

Original Paper

Multi-objective optimization of oilfield water injection operations under dynamic electricity prices: For equivalent reduction of carbon emissions



Shuang-Qing Chen^a, Chao Chen^{a,*}, Yu-Chun Li^b, Lan Meng^c, Li-Xin Wei^a, Bing Guan^{d,e}

^a Key Laboratory of Enhanced Oil and Gas Recovery, Ministry of Education, Northeast Petroleum University, Daqing, 163318, Heilongjiang, China

^b Daqing Oilfield Design Institute Co., Ltd., Daqing, 163712, Heilongjiang, China

^c New Energy Division, Daqing Oilfield Co., Ltd., Daqing, 163453, Heilongjiang, China

^d Key Laboratory of Continental Shale Hydrocarbon Accumulation and Efficient Development, Northeast Petroleum University, Daqing, 163318, Heilongjiang, China

^e Postdoctoral Programme of Daqing Oilfield, Daqing, 163318, Heilongjiang, China

ARTICLE INFO

Article history:

Received 22 January 2026

Received in revised form

23 May 2026

Accepted 4 August 2026

Available online 7 September 2026

Edited by Xi Zhang

Keywords:

Water injection system

Multi-objective optimization

Time-of-use electricity pricing

QLFFOA

Reduction of harmful gas emissions

Low-carbon operation

ABSTRACT

Low-carbon oilfield requires the water injection system with huge electricity consumption to reduce carbon emissions, and there is an urgent need to establish an operation optimization method with low-carbon goals. This paper constructs a multi-objective optimization model of time-segmented water injection in oilfield water injection systems considering time-of-use electricity pricing that minimizes carbon emissions and electricity cost under time-of-use electricity pricing. The model comprehensively considers local head losses, pipeline network hydraulic balance, water balance constraint, pressure constraint of water injection well, pump flow rate constraint, water injection volume constraint, and time period priority constraint. Traditional solvers are prone to falling into local optima when solving the water injection optimization model. This paper proposes the innovative algorithm named Quantum Leader-Follower Formation Optimization Algorithm (QLFFOA). Compared with 10 classical algorithms, QLFFOA exhibits better solution performance. Finally, the proposed method was applied to a real oilfield water injection system containing 131 water injection wells and 2 water injection stations, and time-segmented water injection optimization was performed for 4 injection pumps over 13 independent time periods throughout the day under the time-of-use (TOU) electricity pricing mechanism. Under the premise of satisfying the core constraints of the water injection system, the optimized schedule decreased system energy consumption by about 7.3%, saved electricity costs by 10.8%, decreased carbon emissions by 7.2%, decreased unit energy consumption by 0.4 kWh/m³, and raised the system average pump efficiency by 1.84%. The optimized scheme avoided night-time peak periods, effectively reduced electrical energy consumption and correspondingly decreased CO₂ emissions. The results indicate that this model and algorithm can scientifically guide the time-segmented operation management of oilfield water injection systems, thereby reducing harmful gas emissions from the electricity demand side.

© 2026 The Authors. Publishing services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

* Corresponding author.

E-mail address: cchao0317@163.com (C. Chen).

Peer review under the responsibility of China University of Petroleum (Beijing).

1. Introduction

1.1. Energy consumption and carbon emissions in water injection systems

The energy consumption of the oilfield water injection system is directly related to the carbon emissions and operating costs of oilfield production. Therefore, optimizing water injection systems to conserve energy is equivalent to reducing greenhouse gas emissions from the source. The International Energy Agency points out that improving energy efficiency can simultaneously enhance the economy, safety, and sustainability of energy, and regards it as the primary tool for addressing the dual challenges of energy and climate. The current global share of fossil fuel consumption remains excessively high, which implies that industrial electricity demand continues to be closely linked to the combustion of fossil resources and the resulting CO₂ emissions (Dong et al., 2025; Hannah and Pablo, 2025; Zou et al., 2021). For oilfields, the water injection system is usually the main component of electricity consumption, so optimizing the water injection system can directly reduce electricity consumption and synchronously reduce carbon emissions (Wang et al., 2019).

1.2. Existing optimization studies in water injection systems

The optimization of water injection systems is to construct an optimization model and solving algorithms to obtain the optimal operating parameter scheme. In recent years, researchers have conducted extensive studies on energy-consumption modeling for water injection systems, but system carbon emissions have not been considered as an optimization objective. Many studies aim to minimize system energy consumption while accounting for operational constraints such as pressure and flow rate. For example, Bai et al. incorporated constraints such as wellhead pressure, injection–production balance, and reservoir flow characteristics to develop an integrated injection–reservoir–production energy-optimization model that emphasizes the coupling between reservoir flow and surface energy consumption (Bai et al., 2022). Zhou et al. (2019) targeted the overall benefit of water injection development, considering pipeline network structure constraints, injection–production allocation relationships, and reservoir response characteristics, and formulated the MINLP model that focuses on joint optimization of the surface injection network and the subsurface reservoir. Almeida et al. (2010) considering constraints such as reservoir heterogeneity and delayed injection–production responses, developed the optimization model aimed at maximizing net present value.

However, existing optimization studies exhibit notable limitations. First, the aforementioned research primarily focuses on the dynamic response of underground reservoirs or the minimization of a single energy consumption metric. These studies lack the systematic integration of surface water injection networks under time-segmented dispatching, rendering them inadequate for the refined operational requirements of short-cycle management. Second, most current models employ extended optimization horizons and lack the responsiveness to short-term electricity price fluctuations or time-of-use power variations. Consequently, they fail to achieve a short-term synergistic optimization of economic efficiency and environmental sustainability.

1.3. Existing intelligent algorithms

The optimization model for water injection systems is characterized by strong non-linearity and multiple constraints.

Consequently, intelligent optimization algorithms have become the mainstream solution approach. Common algorithms include Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), Ant Colony Optimization (ACO) (Dorigo et al., 2006), Sparrow Search Algorithm (SSA) (Xue and Shen, 2020), and Crowned-Porcupine Optimization (CPO) (Abdel-Basset et al., 2024), among others. However, oilfield water injection networks often exhibit the ring-type topological structure, with coupled pressure variations and a large number of decision variables, which makes conventional algorithms often perform poorly in dealing with nonlinear problems (Zhou et al., 2025). To address this issue, the recent research has begun to explore hybrid and enhanced intelligent algorithms. Liang et al. (2018) put forward an integrated approach that brings together ant colony optimization, linear approximation techniques, and the simplex method to tackle the developed MINLP model. Azamipour et al. (2018) developed a optimization method that integrates a genetic algorithm with polyhedral search to optimize oil production and water injection rates. Yasari and Pishvaie (2015) derived water-injection strategies using a Monte Carlo simulation coupled with a genetic algorithm. Chen et al. (2025) proposed a hybrid PSCPA algorithm which reduced system energy consumption by approximately 6.8% in the optimization of water-injection operational parameter models. Chen et al. (2024b) established a water scheduling model for sewage systems and proposed a hybrid PSO-CS algorithm to solve this model. Swarm intelligence algorithms, owing to their global search capability and model generality, have been widely applied in nonlinear, non-convex, multi-modal, and multi-peak scenarios (Chen et al., 2024a).

However, although hybrid and improved intelligent algorithms have enhanced the solution quality to a certain extent, when dealing with high-dimensional ring-type oilfield water injection pipe networks, the proliferation of decision variables causes traditional swarm intelligence algorithms and their improved variants to be highly susceptible to falling into local optima, accompanied by a sharp increase in computational cost. Therefore, there is an urgent need to introduce an advanced algorithm that possesses both a strong capability to escape local optima and high convergence efficiency. In recent years, the emergence of quantum-inspired algorithms has provided a new opportunity to break through this bottleneck, and the integration of quantum mechanisms with swarm intelligence has been demonstrated to effectively improve global optimization performance (Iovane, 2025).

1.4. Research gap and novelty

With the advancement of optimization research in complex industrial systems, an increasing number of studies have incorporated machine learning, robust optimization, and multi-objective optimization concepts (Ala and Goli, 2024; Davoodi et al., 2026; Goli, 2023, 2024a, 2024b; Rahmani and Goli, 2023). These efforts demonstrate that multi-objective optimization, robust design, and the fusion of intelligent algorithms have emerged as pivotal developmental trends in complex industrial system optimization.

With the diversification of energy pricing mechanisms, time-of-use (TOU) electricity pricing has been generally applied in industrial power consumption. In existing pipeline network optimization studies, incorporating time-segmentation and load peak-shaving into scheduling models has been shown to effectively improve operational economy. Currently, operational optimization studies for surface water injection systems rarely consider time-of-use electricity pricing. Most existing research focuses on municipal water supply systems (Abdelsalam and Gabbar, 2021;

Chen et al., 2021; Hu et al., 2023; Napierała, 2022; Ngancha et al., 2022; Wang et al., 2021). Moreover, the energy systems field has also gradually begun to pay attention to dynamic electricity pricing and water-energy nexus issues (Gheouany et al., 2025a, 2025b; Mokhtare and Keysan, 2025). These works provide important references for dynamic energy management and demand-side optimization. However, the aforementioned studies differ significantly from oilfield water injection systems in terms of both problem characteristics and engineering objects. First, oilfield water injection systems are typical high-pressure ring-type pipeline network systems with complex pressure coupling relationships, and their water allocation tasks must meet strict formation development requirements. Second, flow regulation in water injection systems exhibits continuous dynamic characteristics, rather than being the discrete resource allocation problem encountered in traditional scheduling issues. Finally, peak-shaving and valley-filling operations in oilfield water injection cannot be achieved by simply interrupting or drastically curtailing flow rates. The optimization process must not only satisfy hydraulic balance and equipment operation constraints but also ensure stable reservoir pressure, making its optimization difficulty far higher than that of municipal water supply or general energy management systems.

At present, most oilfield water injection optimization studies still remain at the level of single-objective energy consumption optimization. Although reducing energy consumption is inevitably accompanied by carbon emission reduction, very few studies have directly quantified carbon emissions and taken them as the primary optimization objective. Particularly in annular water injection pipeline networks, how to achieve the peak shifting and valley filling operation under complex hydraulic constraints while simultaneously reducing carbon emissions and operating costs remains a gap in current research. Regarding intelligent algorithms, very few studies in the field of oilfield water injection optimization have developed and employed hybrid algorithms integrating quantum mechanisms with swarm intelligence to solve optimization models.

In summary, to address the aforementioned research gaps, the main contributions of this paper are as follows.

- (1) Construction of multi-objective optimization model of time-segmented water injection in oilfield water injection systems considering time-of-use electricity pricing

The objective functions of the model aim to minimize carbon emissions and electricity costs of water injection systems. It is the first to use carbon emission minimization as the objective function in the oilfield water injection system optimization model. It introduces a time-of-use electricity pricing mechanism and considers constraints such as local head loss constraint, pipeline network hydraulic balance constraint, water balance constraint, time period priority.

- (2) Proposal of a Quantum Leader-Follower Formation Optimization Algorithm (QLFFOA)

The algorithm integrates probabilistic and non-local search features derived from quantum mechanics and introduces a leader-follower cooperative mechanism within the swarm intelligence framework, thereby significantly enhancing global optimization performance and convergence speed. Through comparative experiments with various classic intelligent algorithms, the superior global optimization capability of QLFFOA has been validated.

- (3) Significant engineering application value and energy conservation and emission reduction effects

The effectiveness of the proposed model and algorithm is validated by empirical application to a typical ring-type oilfield water injection system. The results show that while satisfying the water injection requirements, the optimized schedule decreased system energy consumption by about 7.3%, saved electricity costs by 10.8%, decreased carbon emissions by 7.2%, decreased unit energy consumption by 0.4 kWh/m³, raised the system average pump efficiency by 1.84%, and avoided night-time peak periods. This provides scientific decision-making tools and practical operational schemes for oilfield managers to achieve green and low-carbon transformation on the electricity demand side.

2. Model building

2.1. Basic assumptions for hydraulic modeling

To ensure the computational efficiency and physical feasibility of the optimization model, the following hydraulic assumptions are formulated based on the actual operating conditions of oilfield water injection systems.

- (1) Steady-state flow

It is assumed that the pressure and flow rate within the pipeline network remain constant over time during each independent optimization period.

- (2) Incompressible fluid

The injection medium is treated as an incompressible fluid, and minor volume compression caused by abrupt pressure changes is neglected.

- (3) Constant density

The fluid density is set to remain unchanged throughout the entire transportation process.

- (4) Exclusion of thermal effects

Since water injection pipelines are generally buried below the frost line with relatively limited transmission distances, this model does not consider the influences of fluid temperature fluctuations on viscosity and pipeline deformation.

- (5) Constant pipeline characteristics

It is assumed that no significant changes occur in the scaling and corrosion degree of the pipeline inner wall during the optimization cycle, thus the Darcy friction coefficient and Hazen-Williams coefficient remain constant.

- (6) Constant short-term allocated injection volume

The allocated water injection volume of each individual injection well is assumed to remain relatively stable in the short term.

2.2. Hybrid hydraulic modeling method

To balance physical rigor and computational efficiency, this study adopted a hybrid hydraulic modeling method, in which the Darcy equation and the Hazen-Williams equation were

strategically applied to flow characterization in different regions of the water injection system. Specifically, the Darcy equation was used to simulate the hydraulic characteristics of local components within the pumping stations. Since the pressure drops in these local components are mainly dominated by complex geometric flow separation and intense local turbulence, the strict dependence of the Darcy equation on kinetic energy ensures high-fidelity physical representation of local head losses.

Conversely, the Hazen-Williams equation was employed to characterize the macroscopic hydraulic characteristics of long-distance pipeline networks outside the control stations. For long-distance water transmission systems dominated by frictional head loss along the pipelines, the Hazen-Williams equation exhibits higher applicability. Its constant empirical flow velocity exponent avoids the nested sub-iterations required by the Darcy equation when solving for the friction factor. This significantly simplifies the formulation process of the system's overall governing equations and corresponding matrices, thereby ensuring high numerical stability and fast convergence rate when solving the high-dimensional nonlinear hydraulic balance equations of looping networks.

2.3. Optimization model

The multi-objective optimization of time-segmented water injection in oilfield water injection systems considering time-of-use electricity pricing refers to using the time-of-use electricity pricing to adjust the operation parameters of water injection pumps in each time period to satisfy the system's injection demands, while taking carbon emissions and total electricity costs as two optimization objectives for optimization decision-making. It should be noted that the system boundary for energy consumption and carbon emission accounting in the optimization model constructed in this study is strictly defined as the electricity consumption end on the demand side, that is, starting from the injection pump motors in the water injection stations and covering the entire downstream water injection pipeline network and injection wells. The energy consumption in the model is mainly calculated based on the active power generated by motor work and internal equipment losses. The transmission and distribution losses at the front end of the motors (grid side), as well as the additional grid burdens and marginal carbon emission changes caused by the reactive power consumed during the operation of industrial induction motors, are not included in the system accounting boundary at the current stage.

The main idea of optimizing the process can be described as: equating electricity consumption with carbon emissions, considering the impact of time-of-use electricity prices on total electricity costs, and based on actual production data of water injection systems, calculating the operating parameter schemes through computer. The optimization results can achieve staggered operation during peak electricity prices, improve average pump efficiency, reduce electricity consumption and carbon dioxide emissions, provide detailed parameter scheme guidance for on-site operations, and promote low-carbon oilfield construction. Fig. 1 shows the detailed optimization process.

2.3.1. Optimization objective

In this optimization problem, the optimization objectives aim to minimize the total carbon emissions and electricity cost of water injection systems, as expressed in Eqs. (1) and (2). The descriptions of all variables and symbols used in the equations throughout this paper are presented in Table A1 of Appendix A.1. For the total carbon emission objective function, this study adopts an accounting model based on the emission factor method. Its

physical meaning is that the electrical energy consumed by the i -th injection pump during period k is converted into carbon emissions through the CO₂ emission factor of the local power grid supply. To ensure the rigor of the research and the authenticity of the results, this study uses the 2022 Electricity Carbon Dioxide Emission Factors issued by the Ministry of Ecology and Environment of the People's Republic of China (China, 2024). This coefficient is based on the latest statistics of China's power generation structure and can scientifically reflect the indirect carbon dioxide emissions generated by the electricity consumption of water injection pump stations.

$$\min E = \xi E_F \sum_{i=1}^{N_p} \sum_{k=1}^M \frac{Z_{i,k} F_{i,k} \rho g t_{i,k}}{\eta_{i,k}^p \eta_{i,k}^m} = \sum_{i=1}^{N_p} \sum_{k=1}^M W_{i,k} \cdot E_F \quad (1)$$

$$\min C = \xi \sum_{i=1}^{N_p} \sum_{k=1}^M \frac{Z_{i,k} F_{i,k} \rho g t_{i,k} \lambda_k}{\eta_{i,k}^p \eta_{i,k}^m} = \sum_{i=1}^{N_p} \sum_{k=1}^M W_{i,k} \cdot \lambda_k \quad (2)$$

2.3.2. Constraint condition

Appropriate physical and operational constraints must be incorporated into the optimization model to ensure that the obtained results are practically implementable.

(1) Local head loss constraint

In a water injection station, on-site components including pipelines and valves lead to localized energy losses of high-pressure water emitted by pumps as it flows through the pipeline system. The pressure-energy loss correlation derived from the station's local head loss model should be consistent with this hydraulic loss.

$$P_{out,k} - P_{in,k} = \Delta \Psi_{\chi,k}(\chi, \zeta, F_k, d, l), \quad k = 1, \dots, M \quad (3)$$

For pipelines, the frictional loss along the pipe can be derived from the Darcy equation.

$$h_f = \chi \frac{l}{d} \frac{v^2}{2g} = \chi \frac{8F_k^2}{\pi^2 d^5 g}, \quad k = 1, \dots, M \quad (4)$$

The fundamental expression for local head loss can be derived from the Bernoulli equation with empirical corrections. For local components such as valves, elbows, and tees, the corresponding head loss is expressed by Eq. (5).

$$h_{loc,i} = \zeta_i \frac{v^2}{2g} = \zeta_i \frac{8F_k^2}{\pi^2 g d^4}, \quad k = 1, \dots, M \quad (5)$$

If there are multiple local components connected in series within the station, the comprehensive local resistance coefficient can be defined as Eq. (6).

$$\zeta = \sum_i \zeta_i \quad (6)$$

The total local head loss is expressed by Eq. (7).

$$h_{loc} = \zeta \frac{8F_k^2}{\pi^2 g d^4}, \quad k = 1, \dots, M \quad (7)$$

The total head loss of the station unit, which is the sum of the frictional and local losses, is shown in Eq. (8).

$$h_{tot} = \chi \frac{8F_k^2}{\pi^2 d^5 g} + \zeta \frac{8F_k^2}{\pi^2 g d^4}, \quad k = 1, \dots, M \quad (8)$$

Eq. (8) is converted into its pressure form, yielding Eq. (9).

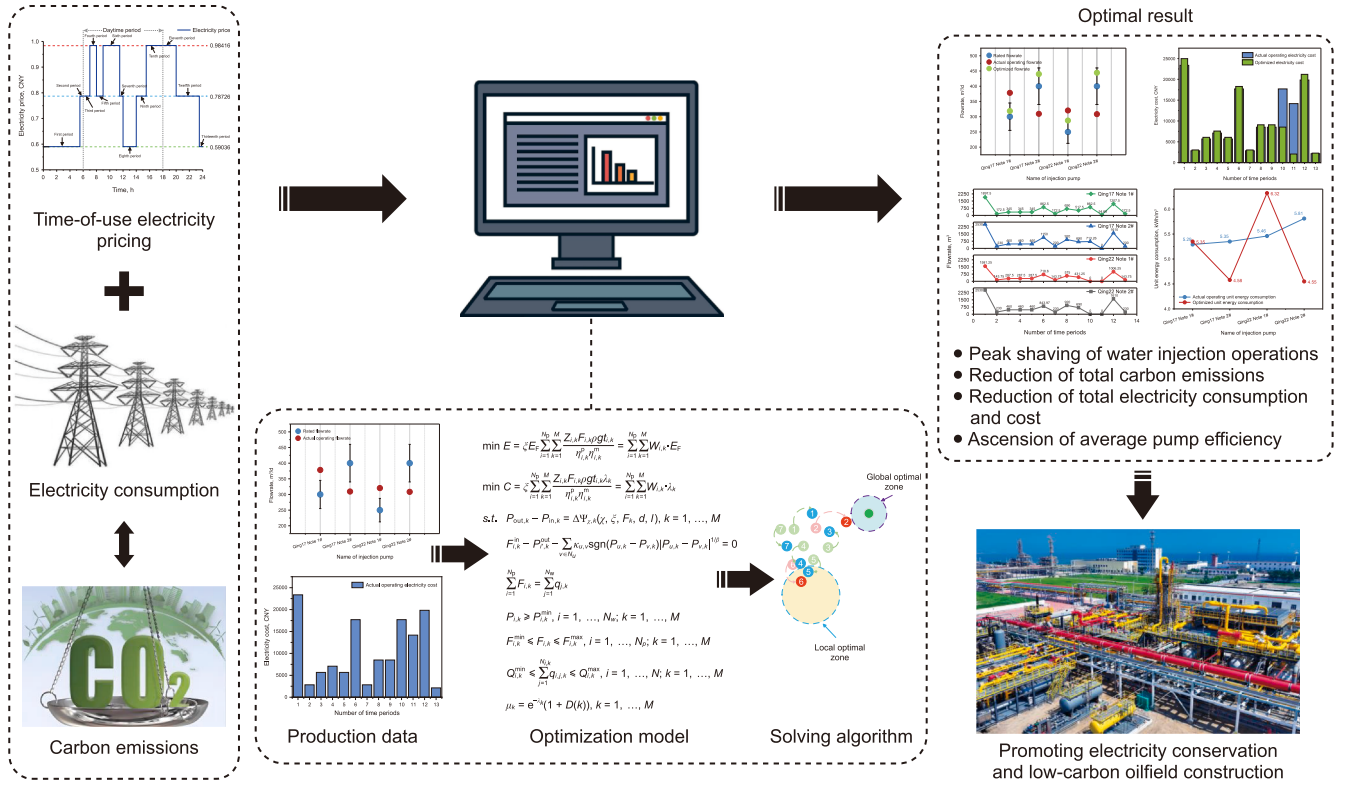


Fig. 1. Detailed optimization process.

$$\Delta\Psi_{\chi,k} = \rho g h_{\text{tot}} = \left[\rho \frac{8l_{\chi}}{\pi^2 d^5} + \rho \frac{8\zeta}{\pi^2 d^4} \right] F_k^2 = K_p F_k^2, \quad k = 1, \dots, M \quad (9)$$

(2) Pipeline network hydraulic balance constraint

In a water injection system with m nodes, Eq. (10) displays the i -th node's equilibrium equation.

$$F_{i,k}^{\text{in}} - F_{i,k}^{\text{out}} - \sum_{v \in N_u} \kappa_{u,v} \text{sgn}(P_{u,k} - P_{v,k}) |P_{u,k} - P_{v,k}|^{1/\beta} = 0, \quad i = 1, \dots, m-1; \quad k = 1, \dots, M \quad (10)$$

In this expression, sgn denotes the sign function specified by Eq. (11).

$$\text{sgn}(X) = \begin{cases} +1, & X \geq 0 \\ -1, & X < 0 \end{cases} \quad (11)$$

(3) Water balance constraint

For each period k , the total water supply of all pumps in that time period must match the total water injection volume of all wells during that time period, as shown in Eq. (12).

$$\sum_{i=1}^{N_p} F_{i,k} = \sum_{j=1}^{N_w} q_{j,k} \quad (12)$$

(4) Pressure constraint of water injection well

For each time period k , the nodal pressure of every injection well must meet or exceed its required minimum injection pressure, as shown in Eq. (13).

$$P_{i,k} \geq P_{i,k}^{\min}, \quad i = 1, \dots, N_w; \quad k = 1, \dots, M \quad (13)$$

(5) Pump flow rate constraint

During each time period, the flow rate of every pump should remain within its corresponding high-efficiency operating range, that is, between the minimum and maximum efficient flow rates of the pump in that period, to ensure operational energy efficiency and system stability.

$$F_{i,k}^{\min} \leq F_{i,k} \leq F_{i,k}^{\max}, \quad i = 1, \dots, N_p; \quad k = 1, \dots, M \quad (14)$$

(6) Water injection volume constraint

Each station's water injection volume is restricted by factors including sewage reinjection and incoming water volume. Therefore, during each time period, each station's water injection volume must meet the constraints defined in Eq. (15) to maintain the balance of water supply and return in the system as well as operational stability.

$$Q_{i,k}^{\min} \leq \sum_{j=1}^{N_{i,k}} q_{i,j,k} \leq Q_{i,k}^{\max}, \quad i = 1, \dots, N; \quad k = 1, \dots, M \quad (15)$$

(7) Priority constraints for time periods

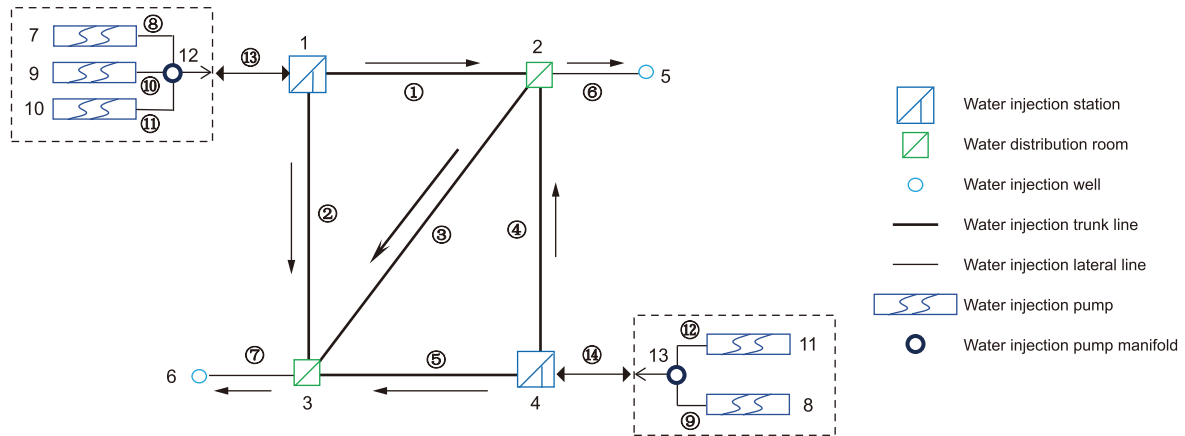


Fig. 2. The fluid network of simple water injection system.

To further enhance the engineering practicality and economy of the model, a time-period priority constraint is introduced by incorporating the time-of-use electricity pricing mechanism and considering the operational and monitoring advantages during daytime periods.

$$\mu_k = e^{-\lambda_k} (1 + D(k)), \quad k = 1, \dots, M \quad (16)$$

2.4. Simulation model

In the water injection system, stations are abstracted as nodes, the pumps are modeled as virtual nodal elements and pipelines are represented as connecting edges. Fig. 2 presents a

schematic diagram of the fluid network for the water injection system.

Within this depicted water injection system, the outlet points for water injection stations are node 1 and node 4, while node 2 and node 3 correspond to the water distribution rooms. The water injection wells are identified by node 5 and node 6. Node 7 to node 11 represent water injection pump units that also function as virtual water-source nodes. Node 12 and node 13 act as the manifold nodes for the water injection pumps. Edges labeled ① to ⑦ correspond to off-station pipeline sections, edges ⑧ to ⑫ connect the outlets of the various pumps to the manifold. Edges ⑬ to ⑭ denote on-station pipeline sections. The

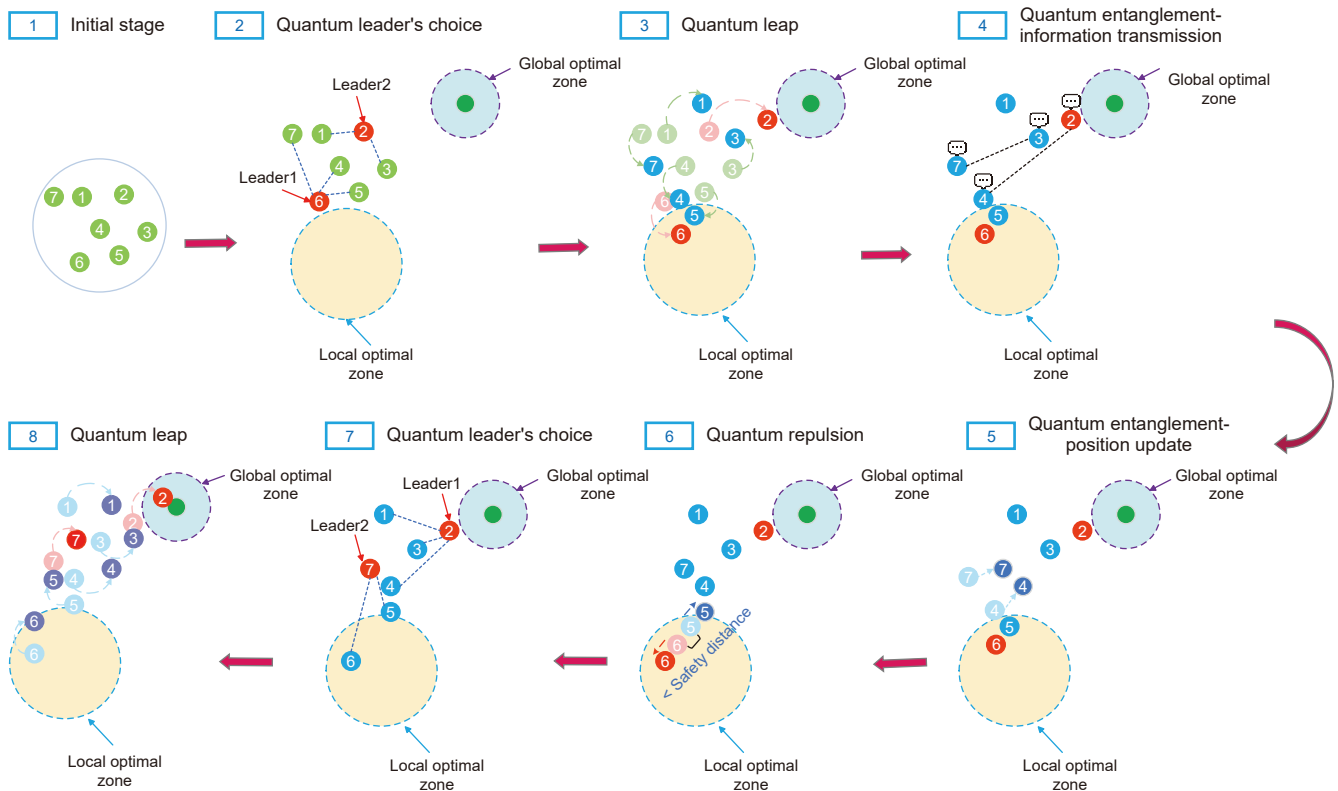


Fig. 3. Schematic of algorithm working mechanism.

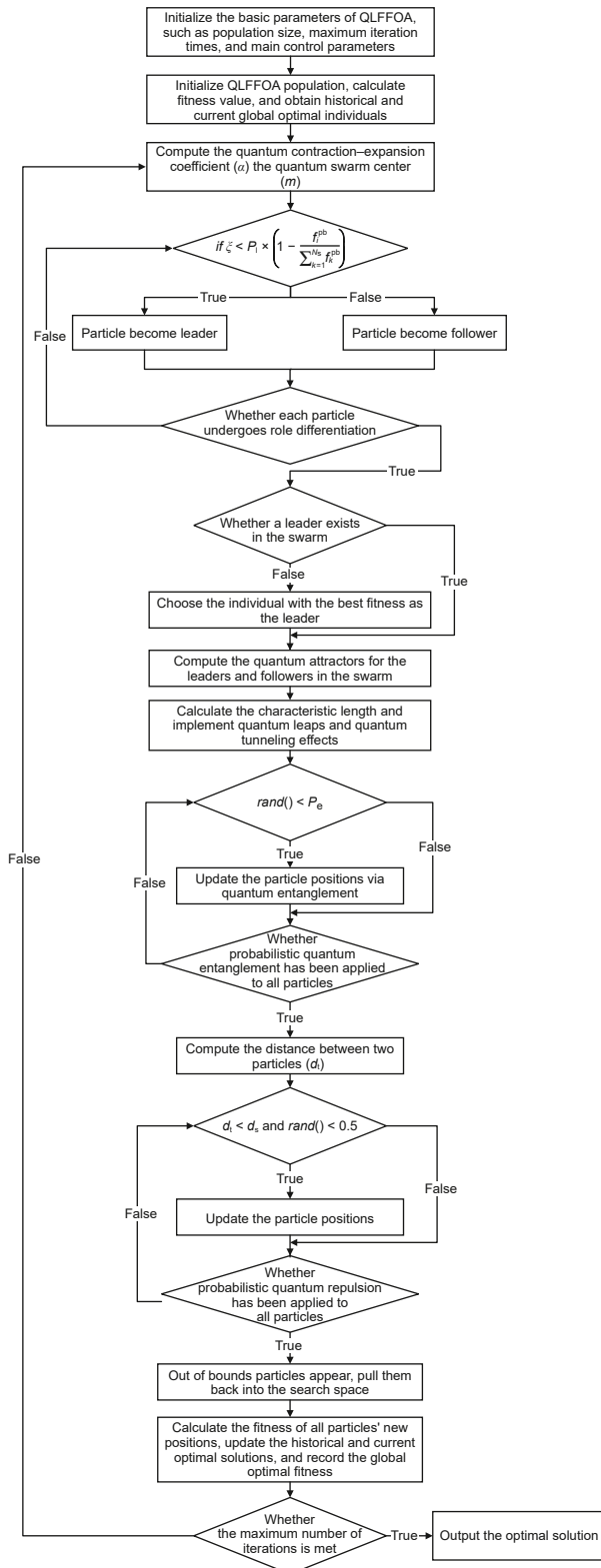


Fig. 4. Flowchart of the QLFFOA.

arrows show the direction of fluid flow in the pipelines, implying that the system can be viewed as a small-scale fluid network. In this network, the 5 virtual water-source nodes supply fluid to the 2 wells via the water injection stations, water distribution rooms, and both on-station and off-station pipeline sections.

Using the Hazen-Williams equation as a basis, Eq. (17) represents the energy equation of pipeline element i .

$$\Delta H_i = P_k - P_j = \frac{\varsigma q^{1.852} l}{\chi_h^{1.852} \delta_{kj}^{4.87}} \quad (17)$$

Based on Eq. (17), a method for determining the flow rate from the pressure loss between two nodes within the application unit can be developed. Firstly, Eq. (18) can be obtained.

$$q^{1.852} = \frac{\Delta H_i \chi_h^{1.852} \delta_{kj}^{4.87}}{10.67} \quad (18)$$

$$\chi_i = \sqrt[1.852]{\frac{\chi_h^{1.852} \delta_{kj}^{4.87}}{10.67 (\Delta H_i)^{0.852}}} \quad (19)$$

When Eq. (19) holds, then Eq. (20) is obtained by Eq. (18).

$$q_i = \chi_i \Delta H_i \quad (20)$$

For flow moving from node k to node j , the flow rate is treated as positive, which indicates $H_k > H_j$. Under the assumption that a positive flow rate indicates outflow from a node, the following relationship can be established.

$$\begin{cases} q_{i,k} = \chi_i \Delta H_i = \chi_i (H_k - H_j) \\ q_{i,j} = \chi_i \Delta H_i = -\chi_i (H_k - H_j) \end{cases} \quad (21)$$

Eq. (21) can be reformulated into its matrix equivalent, as shown in Eq. (22).

$$\begin{Bmatrix} q_{i,k} \\ q_{i,j} \end{Bmatrix} = \chi_i \begin{bmatrix} +1 & -1 \\ -1 & +1 \end{bmatrix} \begin{Bmatrix} H_{i,k} \\ H_{i,j} \end{Bmatrix} \quad (22)$$

Eq. (23) represents the flow conservation equation for node 3 in Fig. 2.

$$F_3 = -q_{2,3} - q_{3,3} + q_{7,3} - q_{5,3} \quad (23)$$

Considering the properties of the pipeline segment and assuming a positive flow direction outward from the node, the relationship described in Eq. (24) is derived.

$$\begin{cases} q_{2,3} = -\chi_2 (H_1 - H_3) \\ q_{3,3} = -\chi_3 (H_2 - H_3) \\ q_{5,3} = -\chi_5 (H_4 - H_3) \\ q_{7,3} = +\chi_7 (H_3 - H_6) \end{cases} \quad (24)$$

Substituting Eq. (23) into Eq. (24) and simplifying yields Eq. (25).

$$\begin{bmatrix}
 \chi_1 + \chi_2 + \chi''_{13} & -\chi_1 & -\chi_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\chi''_{13} & 0 \\
 -\chi_1 & \chi_1 + \chi_3 + \chi_4 + \chi_6 & -\chi_3 & -\chi_4 & -\chi_6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 -\chi_2 & -\chi_3 & \chi_2 + \chi_3 + \chi_5 + \chi_7 & -\chi_5 & 0 & -\chi_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & -\chi_4 & -\chi_5 & \chi_4 + \chi_5 + \chi''_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\chi''_{14} \\
 0 & -\chi_6 & 0 & 0 & \chi_6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & -\chi_7 & 0 & 0 & \chi_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & \chi'_8 & 0 & 0 & 0 & 0 & -\chi'_8 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & \chi'_9 & 0 & 0 & 0 & 0 & -\chi'_9 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \chi'_{10} & 0 & 0 & -\chi'_{10} & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \chi'_{11} & 0 & -\chi'_{11} & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \chi'_{12} & 0 & -\chi'_{12} \\
 -\chi''_{13} & 0 & 0 & 0 & 0 & 0 & -\chi'_8 & 0 & -\chi'_{10} & -\chi'_{11} & 0 & \chi'_8 + \chi'_{10} + \chi'_{11} + \chi''_{13} & 0 \\
 0 & 0 & 0 & -\chi''_{14} & 0 & 0 & 0 & -\chi'_9 & 0 & 0 & -\chi'_{12} & 0 & \chi'_9 + \chi'_{12} + \chi''_{14}
 \end{bmatrix}
 \begin{pmatrix}
 H_1 \\
 H_2 \\
 H_3 \\
 H_4 \\
 H_5 \\
 H_6 \\
 H_7 \\
 H'_8 \\
 H'_9 \\
 H'_{10} \\
 H'_{11} \\
 H'_{12} \\
 H'_{13}
 \end{pmatrix}
 =
 \begin{pmatrix}
 F_1 \\
 F_2 \\
 F_3 \\
 F_4 \\
 F_5 \\
 F_6 \\
 F_7 \\
 F_8 \\
 F_9 \\
 F_{10} \\
 F_{11} \\
 F'_{12} \\
 F'_{13}
 \end{pmatrix}
 \quad (26)$$

$$F_3 = -\chi_2 H_1 - \chi_3 H_2 + (\chi_2 + \chi_3 + \chi_5 + \chi_7) H_3 - \chi_5 H_4 - \chi_7 H_6 \quad (25)$$

This expression constitutes a component of the global equation set, and the same approach can be systematically applied to formulate balance equations for all nodes within the pipeline network. Eq. (26) presents the complete set of governing equations for the system shown in Fig. 2.

Given the structural complexity of water injection systems and the high dimensionality of the system equations, to ensure computational reliability, a simple iterative method is employed for solution. The solution procedure is as follows.

- (1) Choose a reference point and designate its pressure value. Pre-estimate a group of initial nodal pressures H_0 , specify the required computational precision γ , and initialize the iteration counter $i = 0$.
- (2) Compute the χ_k value for every pipe component and combine the overall set of equations.
- (3) To determine each nodal pressure values H , apply the boundary conditions and solve the overall set of equations.
- (4) Calculate the flow rate of each pipeline component and check whether the precision requirement given by Eq. (27) is satisfied.

$$\max \left| \sum_{j \in I_k} q_{kj} - F_k \right| \leq \gamma, k = 1, \dots, N \quad (27)$$

If the condition is satisfied, move to step (5). If not, set $i = i + 1$, update $H_0 = H$, and repeat step (2).

- (5) Make H^* be equal to H to acquire all nodal pressure values, and terminate the iteration.

3. Feasibility analysis of QLFFOA

As shown in Fig. 3, the QLFFOA performs optimization by simulating quantum motion characteristics and incorporating the Leader-Follower mechanism. After the particle swarm completes the initial phase (Phase 1), particles 2 and 6 are assumed to be selected as leaders, particles 1 and 3 are randomly chosen as followers of particle 2, while particles 4, 5, and 7 are randomly chosen as followers of particle 6 (Phase 2). Followers perform quantum leaps toward their designated leader positions, with the leap direction deviating slightly to the left or right of the leader's position. Leaders perform quantum leaps based on both the current global optimum and their own historical best experience (Phase 3). After the leaps, particles 5 and 6 are located within local optimum regions, while particle 4 is positioned at the edge of a local optimum region. At this point, a certain probability of particles engages in quantum entanglement (i.e., the Position Sharing). Assuming particles 7 and 4 choose to engage in quantum entanglement with particles 3 and 2 respectively, particles 7 and 4 will slightly move toward particles 3 and 2 (Phase 5). Since the positions of particles 5 and 6 are closer than the safety distance, quantum repulsion may occur with a certain probability. The quantum repulsion will cause particles 5 and 6 to move in opposite directions (Phase 6). At this point, the iteration is finished, and thus the subsequent iteration starts. In the second iteration, the particle swarm reselects leaders. Particles 2 and 7 are assumed to be chosen as leaders, particles 1, 3, and 4 are randomly assigned as followers of particle 2, and particles 5 and 6 are randomly assigned as followers of particle 7 (Phase 7). Phase 8 is consistent with Phase 3, where followers perform quantum leaps toward their designated leader positions with the

leap direction slightly offset to the left or right of the leader's position, while leaders execute quantum leaps based on both the current global optimum and their own historical best experience. At this point, particle 2 leaps into the global optimum region, while particle 6 exits the local optimum region. By continuing the above steps, the particle swarm gradually approaches and explores the global optimum region, obtaining results closer to the optimal solution.

4. Algorithm design

The core of the QLFFOA is to deeply integrate the probabilistic and non-local characteristics of quantum mechanics with the Leader-Follower hierarchical collaboration framework of swarm intelligence. The algorithm takes the Leader-Follower mechanism as its core framework and the quantum motion characteristics endow the swarm with efficient optimization capabilities. This integration not only avoids the imbalance between exploration and exploitation present in conventional swarm intelligence algorithms, but also breaks through the limitations of insufficient group collaboration in quantum optimization algorithms, providing an efficient solution for high-dimensional, multi-modal complex optimization tasks.

4.1. Probabilistic dynamic selection mechanism for leaders

As the decision-making core of the swarm, the selection logic of the leader directly determines the optimization direction and efficiency of the swarm. QLFFOA abandons the static mode of deterministic selection of the top N optimal individuals in traditional algorithms and proposes a dynamic selection mechanism based on fitness weighted probability, which ensures the guiding position of elite individuals while preserving population diversity.

The criterion for selecting individual i as a leader can be expressed by Eq. (28).

$$\text{if } \xi < P_1 \times \left(1 - \frac{f_i^{\text{pb}}}{\sum_{k=1}^{N_s} f_k^{\text{pb}}} \right), \text{ then individual } i \in L_s \quad (28)$$

4.2. Quantum motion characteristics

4.2.1. Dynamic regulation of the quantum contraction–expansion coefficient (α)

The QLFFOA algorithm dynamically adjusts the contraction–expansion coefficient to emulate the quantum-state evolution from diffuse distributions to localized collapse, thereby enabling adaptive control of the search range and balancing global exploration with local exploitation.

$$\alpha = \alpha_{\max} - (\alpha_{\max} - \alpha_{\min}) \times \frac{I_t}{\text{Max.iteration}} \quad (29)$$

The dynamic decay mechanism of α corresponds to the quantum-state transition from diffusion to contraction as follows.

- (1) Early iterations (α close to $\alpha_{\max}$): the search step length is relatively large, simulating the broad dispersion of the quantum state and enhancing the algorithm's exploration capability in unknown regions.
- (2) Late iterations (α close to $\alpha_{\min}$): the search step length contracts, simulating the localized collapse of the quantum state and strengthening the algorithm's exploitation capability in promising regions.

Table 1
Pseudocode of QLFFOA.

Algorithm 1: Quantum leader-follower formation optimization algorithm
Input: Population size N_s , maximum number of iterations Max_iteration , search space boundaries $[lb, ub]$, objective function f_{obj} Output: Global optimal solution and its fitness value 1. Initialization phase a. Set main control parameters: $\alpha_{\max}, \alpha_{\min}, P_l, P_e, d_s = 0.1 \times (ub - lb)$ b. Randomly generate initial population positions within the search space c. Initialize personal best position of each individual x_i^{pb} and global best position gBest 2. While $I_t < \text{Max_iteration}$ do Step I: Fitness evaluation and parameter calculation Calculate the fitness value of each individual, update personal best position x_i^{pb} and global best position gBest Calculate quantum contraction-expansion coefficient: $\alpha = \alpha_{\max} - (\alpha_{\max} - \alpha_{\min}) \times \frac{I_t}{\text{Max_iteration}}$ Calculate quantum swarm center of the current population: $m = \frac{1}{N_s} \sum_{i=1}^{N_s} x_i^{pb}$ Step II: Role assignment Select leader set based on the probabilistic dynamic screening mechanism of leaders: If $\xi < P_l \times \left(1 - \frac{f_i^{pb}}{\sum_{k=1}^{N_s} f_k^{pb}}\right)$, then individual $i \in L_s$ Step III: Position update For each individual $i = 1$ to N_s do a. Calculate quantum attractor p_i : If $i \in L_s$, then $p_i = \phi \times x_i^{pb} + (1 - \phi) \times \text{gBest}$ If $i \notin L_s$, randomly select a leader k from L_s , $p_i = \phi \times x_k^{pb} + (1 - \phi) \times \text{gBest}$ b. Quantum leap and quantum tunneling effect: Calculate characteristic length: $L = \alpha \times m - x_i $ Perform position update: $x'_i = p_i + \text{dir} \times L \times \lg\left(\frac{1}{\theta}\right)$ c. Quantum entanglement operation: If $\text{rand} \notin P_e$, then x_i generates entanglement displacement towards a random individual d. Quantum repulsion operation For each pair of individuals (i, j) do If $d_t < d_s$, apply quantum repulsion force to separate the individuals End for End for Step IV: Boundary handling and optimal fitness update Pull any out-of-bounds individuals back into the search space Calculate the fitness values of all individuals at their new positions, update the global best fitness gBestScore $I_t = I_t + 1$ 3. End while 4. Return gBest, gBestScore

4.2.2. Design of quantum attractors for leaders and followers

The algorithm designs distinct quantum attractors to assign different behavioral objectives to the two role types, establishing a division of labor of “leaders for exploration, followers for refinement”, thereby ensuring efficient allocation of swarm resources.

- (1) For leaders (the high-quality individuals in the population), their attractors integrate both their personal historical best information and the global best information.

$$p_i = \phi \times x_i^{pb} + (1 - \phi) \times \text{gBest} \quad (30)$$

- (2) For followers (ordinary individuals), their attractors integrate the historical best of a randomly assigned leader together with the global best information.

$$p_i = \phi \times x_k^{pb} + (1 - \phi) \times \text{gBest} \quad (31)$$

4.2.3. Quantum leap and quantum tunneling effect

Position updates in conventional swarm intelligence algorithms are typically deterministic. QLFFOA integrates quantum leap and tunneling effect to formulate non deterministic position-update rules for leaders and followers, thereby increasing the flexibility of individual movement directions, mitigating the limitations of unidirectional search, and enabling the swarm to escape local optima.

$$m = \frac{1}{N_s} \sum_{i=1}^{N_s} x_i^{pb} \quad (32)$$

$$L = \alpha \times |m - x_i| \quad (33)$$

$$x'_i = p_i + \text{dir} \times L \times \lg\left(\frac{1}{\theta}\right) \quad (34)$$

As θ approaches 0, this term tends to infinity, enabling individuals to perform long-range jumps and thereby escape local optima.

4.2.4. Information sharing in quantum entanglement and quantum repulsion mechanism

Quantum entanglement manifests as non-local correlations between the states of two (or more) quantum systems, and QLFFOA simulates this characteristic using Eq. (35). In physical formations, individual collision avoidance usually follows deterministic rules (such as moving in the opposite direction if the distance is less than a threshold), while QLFFOA introduces the uncertainty principle of quantum measurement and designs a probabilistic exclusion mechanism. If two individuals are at an excessively small separation, their positions are adjusted along mutually repulsive directions. The computation of the repulsion direction vector is given by Eq. (37), and Eqs. (38) and (39) provide the position updating equations for the two individuals.

$$x'_i = x_i + 0.1 \times (x_e - x_i) \quad (35)$$

In the equation, the coefficient 0.1 represents the influence weight of quantum entanglement, controlling the degree of information synchronization and preventing drastic updates that may induce group oscillations.

$$d_t = \|x_i - x_j\| \quad (36)$$

$$d_{\text{disp}} = \frac{x_i - x_j}{d_t + 10^{-10}} \quad (37)$$

$$x'_i = x_i + 0.05 \times d_{\text{disp}} \quad (38)$$

$$x'_j = x_j - 0.05 \times d_{\text{disp}} \quad (39)$$

4.3. Algorithm's pseudocode

The pseudocode of the proposed algorithm is presented in Table 1.

5. Algorithm solving

5.1. Feasibility criteria

The feasibility criterion for optimization algorithms is a standard for evaluating individual performance by integrating the objective function value and the constraint violation degree. In addressing constrained optimization problems, simple constraint transformation enables the conversion of complex constrained cases into unconstrained ones for subsequent solution. The optimization model for such problems is presented in Eq. (40).

$$\begin{aligned} \min \quad & \text{Fea}(A) \\ \text{s.t.} \quad & f_p(A) \leq 0, \quad p = 1, 2, \dots, P \\ & g_m(A) = 0, \quad m = P + 1, P + 2, \dots, M \end{aligned} \quad (40)$$

The optimization problem described above includes P inequality constraints and $M - P$ equality constraints. Equality constraints are convertible to inequality constraints. Based on the introduced tolerance constant, the equality constraint is rewritten as the subsequent inequality constraint.

$$|g_m(A)| - \alpha_c \leq 0, \quad m = P + 1, P + 2, \dots, M \quad (41)$$

Through the transformation defined in Eq. (41), the optimization problem presented in Eq. (40) is converted into a nonlinear optimization problem involving M inequality constraints. For the constrained optimization problem presented in Eq. (40), its fundamental task is to determine the D -dimensional optimization variable A^* —which meets all M inequality constraints—such that the objective function value is minimized. For the population within optimization algorithms, a constraint violation function $F_i(A)$ is formulated to quantify the deviation of individuals from the constraint requirements.

$$F_i(A) = \begin{cases} \max\{f_i(A), 0\} & i = 1, 2, \dots, P \\ \max\{|g_i(A)| - \alpha_c, 0\} & i = P + 1, P + 2, \dots, M \end{cases} \quad (42)$$

Through the use of the constraint violation function, the constraint violation degree $V(A)$ of an individual with regard to all constraints can be determined.

$$V(A) = \sum_{p=1}^M F_p(A) \quad (43)$$

Through the computation of an individual's constraint violation

degree, the quality of the solutions it holds can be quantitatively assessed. Based on the comparison of the constraint violation degree and fitness function values of all individuals, the individuals who will enter the next iteration are determined. For any two arbitrary individuals A_i and A_j in the swarm, the specific comparison criteria are presented below.

- (1) Both A_i and A_j correspond to infeasible solutions. When the constraint violation degree of A_i is smaller than that of A_j , A_i is considered superior to A_j .
- (2) The fitness function value is mainly determined based on the goal of minimizing carbon emissions. For the two feasible solutions A_i and A_j , A_i outperforms A_j if the objective function value of A_i is smaller than that of A_j .
- (3) A_i corresponds to a feasible solution, while A_j is an infeasible solution. A_i outperforms A_j .

Through the feasibility criterion, all individuals in the swarm can be effectively evaluated. Consequently, solving such constrained optimization problems is transformed into an optimization process that progresses from infeasible to feasible solutions and ultimately converges to the optimal solution. This process achieves the efficient resolution of complex nonlinear constrained optimization tasks.

5.2. Algorithm convergence criteria and tolerance

The algorithm program sets the maximum number of iterations Max_iteration as the primary termination criterion. Meanwhile, a fitness tolerance mechanism is adopted. If the global optimal fitness value remains unchanged for 10 consecutive iterations, the algorithm is deemed to have entered the steady-state convergence region and the iteration is terminated early.

5.3. Algorithm solving process

The specific hybrid algorithm solving process is shown below. The solution flowchart of the algorithm is shown in Fig. 4.

- (1) Initialize the search space boundaries, maximum iteration times, and population size of the QLFFOA. And assign values to the algorithm's key control parameters, including contraction-expansion coefficients $[\alpha_{\min}, \alpha_{\max}]$, quantum leader selection probability P_l , quantum entanglement probability P_e , safe distance $d_s = 0.1 \times (ub - lb)$, then load and save the objective function and constraint conditions.
- (2) Within the search space, randomly initialize the initial particle positions of the QLFFOA, compute the fitness function values, and save both the population's best individual and historical best individual.
- (3) Compute the quantum contraction-expansion coefficient α and the quantum swarm center m according to Eqs. (29) and (32).
- (4) Select the quantum leaders based on the decision criteria given in Eq. (28).
- (5) Compute the quantum attractors for the leaders and followers in the population according to Eqs. (30) and (31), respectively.
- (6) Calculate the characteristic length L using Eq. (33) and implement quantum leaps and quantum tunneling effects using Eq. (34).
- (7) Perform probabilistic quantum entanglement on the particles. Specifically, if $\text{rand}() < P_e$ holds, update the particle positions via quantum entanglement according to Eq. (35).

Table 2

Comparison of optimization results between QLFFOA and other 10 swarm intelligent algorithms on 30-dimensional benchmark functions.

f		QPSO	PSO	CPO	HO	POA	GOOSE	NRBO	PO	DOA	GJO	QLFFOA
f_1	Mean rank	1	4	10	5	8	2	9	6	11	7	3
	Std rank	1	5	7	4	10	2	9	6	11	8	3
f_2	Mean rank	2	4	10	5	7	3	9	6	11	8	1
	Std rank	2	4	10	5	7	3	9	6	11	8	1
f_3	Mean rank	7	1	11	6	2	10	5	3	9	8	4
	Std rank	8	1	11	2	3	10	5	4	7	6	9
f_4	Mean rank	2	4	10	5	8	3	9	6	11	7	1
	Std rank	2	5	10	4	8	3	9	6	11	7	1
f_5	Mean rank	2	3	9	5	6	10	8	7	11	4	1
	Std rank	10	4	2	9	5	11	3	8	6	7	1
f_6	Mean rank	1	4	8	5	6	11	10	7	9	3	2
	Std rank	2	4	6	3	7	11	9	8	10	5	1
f_7	Mean rank	2	3	8	5	9	11	7	6	10	4	1
	Std rank	3	2	5	6	8	11	7	9	10	4	1
f_8	Mean rank	2	3	11	4	6	10	8	7	9	5	1
	Std rank	10	3	8	2	4	11	6	5	7	9	1
f_9	Mean rank	2	6	10	5	4	9	8	7	11	3	1
	Std rank	2	8	9	4	3	10	7	5	11	6	1
f_{10}	Mean rank	9	2	11	3	4	5	8	6	10	7	1
	Std rank	4	6	1	3	5	8	2	9	7	11	10
f_{11}	Mean rank	2	3	11	5	7	4	8	6	10	9	1
	Std rank	3	2	10	5	8	4	7	6	11	9	1
f_{12}	Mean rank	2	3	10	5	7	4	9	6	11	8	1
	Std rank	1	3	7	5	10	4	8	6	11	9	2
f_{13}	Mean rank	2	3	10	5	7	4	8	6	11	9	1
	Std rank	3	2	9	4	7	5	8	6	11	10	1
f_{14}	Mean rank	5	1	11	7	2	3	6	8	9	10	4
	Std rank	5	1	11	8	2	4	6	7	10	9	3
f_{15}	Mean rank	3	2	11	4	5	6	8	7	10	9	1
	Std rank	4	3	10	2	5	6	8	7	11	9	1
f_{16}	Mean rank	2	3	11	6	4	8	9	7	10	5	1
	Std rank	10	2	3	5	4	8	7	9	11	6	1
f_{17}	Mean rank	2	4	11	7	5	9	8	6	10	3	1
	Std rank	4	9	3	7	2	10	5	6	11	8	1
f_{18}	Mean rank	6	1	11	5	2	3	9	7	10	8	4
	Std rank	6	3	10	4	2	1	8	7	11	9	5
f_{19}	Mean rank	3	1	8	5	6	4	9	7	11	10	2
	Std rank	3	2	11	5	6	4	8	7	10	9	1
f_{20}	Mean rank	2	6	11	3	4	9	8	7	10	5	1
	Std rank	7	9	2	3	1	11	6	4	8	10	5
f_{21}	Mean rank	2	4	9	7	6	11	8	5	10	3	1
	Std rank	3	9	2	10	11	8	6	5	7	4	1
f_{22}	Mean rank	9	3	8	6	5	10	7	1	11	4	2
	Std rank	11	9	5	10	3	4	8	2	1	6	7
f_{23}	Mean rank	2	8	9	6	5	11	7	4	10	3	1
	Std rank	2	9	4	8	5	11	3	7	10	6	1
f_{24}	Mean rank	2	7	9	8	5	11	6	4	10	3	1
	Std rank	2	6	3	9	8	10	5	4	11	7	1
f_{25}	Mean rank	2	3	10	5	7	4	9	6	11	8	1
	Std rank	2	4	10	5	9	3	7	6	11	8	1
f_{26}	Mean rank	2	3	9	5	6	11	8	7	10	4	1
	Std rank	2	10	3	9	6	11	5	8	7	4	1
f_{27}	Mean rank	2	3	10	4	7	11	8	6	9	5	1
	Std rank	2	9	8	7	5	11	4	6	10	3	1
f_{28}	Mean rank	4	3	10	5	8	2	9	6	11	7	1
	Std rank	3	5	10	4	8	2	7	6	11	9	1
f_{29}	Mean rank	2	3	11	8	5	9	7	6	10	4	1
	Std rank	1	3	5	10	7	8	9	6	11	4	2
f_{30}	Mean rank	2	3	10	6	5	4	9	7	11	8	1
	Std rank	2	3	10	6	5	4	9	7	11	8	1

(8) Determine whether probabilistic quantum entanglement has been applied to all particles in the population. If not, return to step (5) to adjust the next particle; if yes, proceed to step (9);

(9) Compute the distance between two particles using Eq. (36), if the distance is smaller than the safety threshold d_s , apply probabilistic quantum repulsion. Specifically, if $\text{rand}() < 0.5$ holds, the positions of the two particles are updated based on Eqs. (38) and (39); if the condition is not satisfied, no position update is performed.

(10) Determine whether probabilistic quantum repulsion has been applied to all particles in the population. If not, return to step (9) to adjust the next group of particles; If yes, proceed to step (11).

(11) After particles move to their new positions, any particles that violate the search bounds are brought back into the search space; then compute the fitness values for all particles at their new positions, replace each particle's historical best fitness when the new fitness is superior, update the

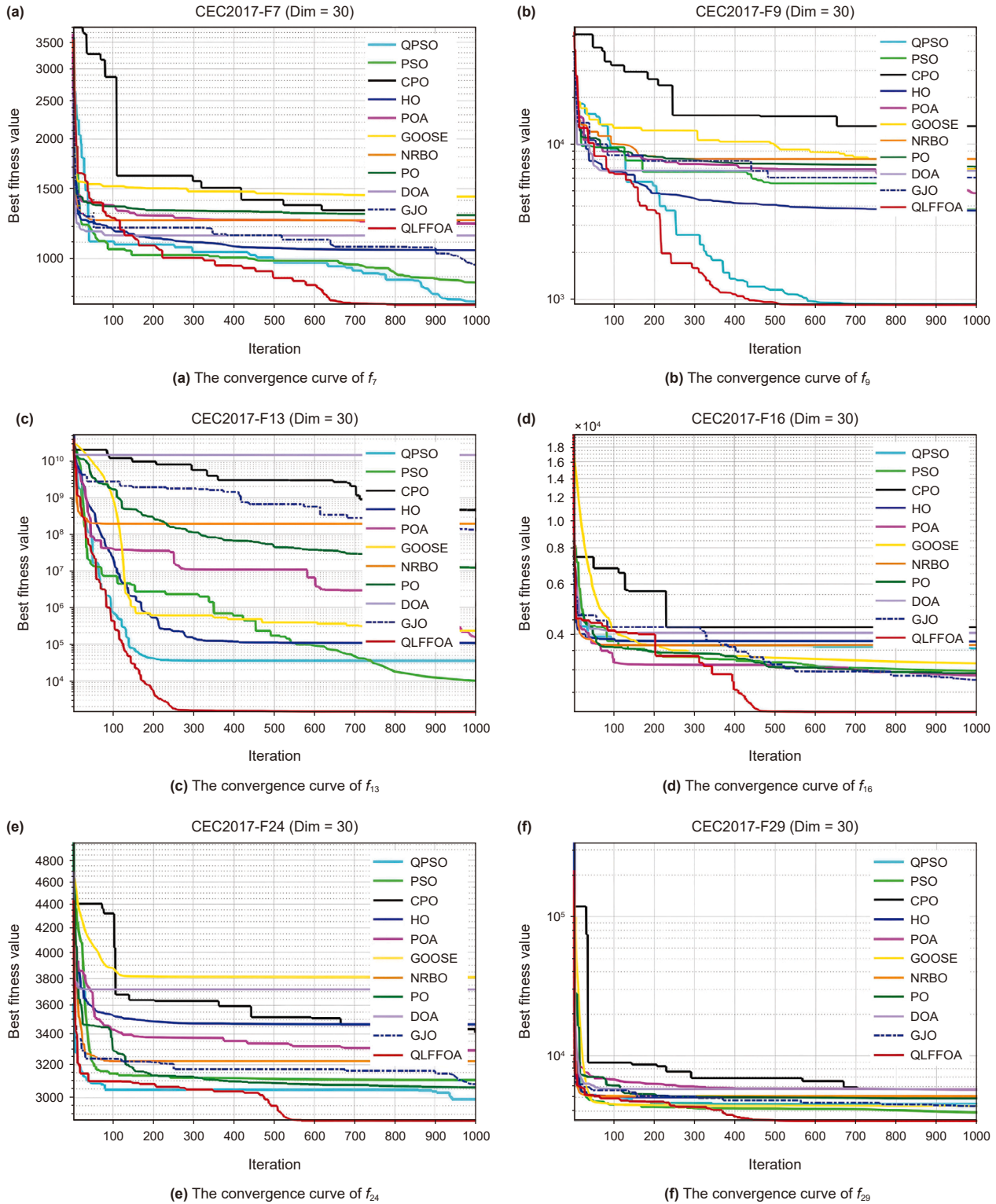


Fig. 5. Convergence curves of the QLFFOA algorithm on the benchmark test functions. (a) The convergence curve of f_7 . (b) The convergence curve of f_9 . (c) The convergence curve of f_{13} . (d) The convergence curve of f_{16} . (e) The convergence curve of f_{24} . (f) The convergence curve of f_{29} .

current global best if a better solution is found, and record the per-generation global best fitness.

- (12) Check whether the maximum number of iterations has been satisfied. If yes, advance to step (13); otherwise, revert to step (3) to commence the subsequent iteration.
- (13) Output the final optimal solution obtained.

6. Algorithmic solving performance analysis and validation

To assess the optimization effectiveness of the QLFFOA, this study conducts comparative experiments against PSO, QPSO, and 8 well-known intelligent optimization algorithms published in the past 5 years. Numerical experiments are performed with

internationally recognized standard test functions, aiming to conduct a horizontal evaluation of the algorithm’s solving capability. The comparative intelligent optimization algorithms are listed below.

The QPSO algorithm proposed by the team of Chinese scholar Sun Jun at the IEEE Congress on Evolutionary Computation in 2004 integrates the principles of quantum mechanics to simulate the quantum behavior characteristics of particles (Jun et al., 2004). The PSO algorithm, proposed by Kennedy and Eberhart (1995) at the IEEE International Conference on Neural Networks in 1995, simulates the collective cooperative behavior of bird flocks during foraging. The CPO algorithm, published by Mokhtare and Keysan (2025) in Knowledge Based Systems in 2024, simulates the Crested Porcupine’s 4 defense strategies in natural environments and achieves optimization goals through unique exploration and development mechanisms (Abdel-Basset et al., 2024). The HO algorithm proposed by Iranian scholar Mohammad Hussein Amiri’s team in Scientific Reports in 2024 simulates the activity characteristics of hippopotamus water bodies (Amiri et al., 2024). The POA, published in Sensors in 2022, aims to simulate the hunting behavior and activity characteristics of pelicans in natural environments (Trojovský and Dehghani, 2022). The GOOSE Algorithm, published in Evolving Systems in 2024, was inspired by the migration behavior of geese (Hamad and Rashid, 2024). The Newton-Raphson-Based Optimizer (NRBO), published in Engineering Applications of Artificial Intelligence in 2024, integrates classical numerical calculation methods (Sowmya et al., 2024). Parrot Optimizer (PO) proposed in 2024, inspired by parrot foraging, staying, communication, and fear of life behaviors (Lian et al., 2024). The Dingo Optimization Algorithm (DOA) proposed in 2021, inspired by the hunting strategies of the dingo in natural environments (Peraza-Vázquez et al., 2021). The Golden Jackal Optimization (GJO) algorithm, published in Expert Systems with Applications in 2022, was inspired by the unique survival strategy of the Golden Jackal in grassland ecology (Chopra and Mohsin Ansari, 2022). Through a systematic cross-comparison conducted within the standardized experimental framework, the performance advantages of the Quantum Leader-Follower Formation Optimization Algorithm over these cutting-edge algorithms are objectively assessed.

Table 3
Friedman test results.

/	/	Mean	Std
Test results	N	30	30
	Chi-square	194.5705	98.4639
	p-value	2.1856×10^{-36}	1.1056×10^{-16}
Friedman test value	QPSO	3.200	3.900
	PSO	3.233	4.533
	CPO	9.633	6.767
	HO	5.100	5.267
	POA	5.400	5.433
	GOOSE	6.700	6.700
	NRBO	7.767	6.467
	PO	5.833	6.100
	DOA	9.900	9.300
	GJO	5.933	7.133
	QLFFOA	1.433	2.200

For assessing an algorithm’s problem-solving capability, using internationally recognized standard benchmark functions to compare various intelligent optimization algorithms is a widely adopted approach. In this numerical study, the performance of the algorithms in continuous search spaces is evaluated using the 30 standard benchmark functions from the IEEE CEC 2017 competition benchmark suite (Wu et al., 2016). The 30 benchmark functions were solved using the QLFFOA and other 10 algorithm. All algorithms are run with a maximum iteration count of 1000. The population size is fixed at 30. Each test problem is configured as 30-dimensional. The algorithms are coded and executed in MATLAB, on a computer with a Windows 10 system, Intel(R) Core(TM) i7-9700, and 4 GB of memory. The key control parameters of the Quantum Leader-Follower Formation Optimization Algorithm were set as the contraction-expansion coefficient [$\alpha_{\min} = 0.2$, $\alpha_{\max} = 1.0$], quantum leader selection probability $P_l = 0.3$, and quantum entanglement probability $P_e = 0.3$. Each test function is independently executed 20 times, and the aggregated results are presented in Table 2. Relevant detailed calculation results are illustrated in Table A2 of Appendix A.

Based on the results in Table 2, the following conclusions can be drawn. Compared with the other 10 algorithms, the QLFFOA achieves the best overall numerical solution performance. Among the

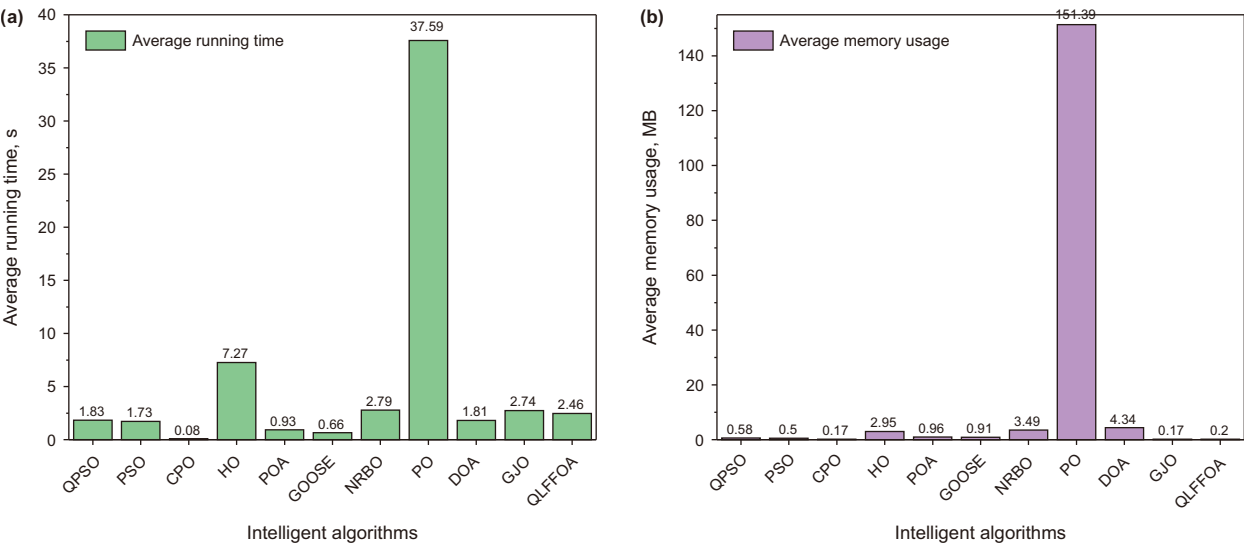


Fig. 6. Comparison of computational costs among the 11 algorithms. (a) Average running time. (b) Average memory usage.

30 standard test functions, it attains the optimal solution for 23 of them, representing over 2/3 of the total. Compared to the QLFFOA, the remaining 10 swarm intelligence algorithms have a significantly lower proportion of test functions where they achieve the optimal solution. Specifically, the QPSO algorithm attains the optimal solution for 2 functions, the PSO algorithm for 4, and the PO algorithm for 1. Moreover, the QLFFOA's mean value and corresponding standard deviation are both superior to those of the other 10 algorithms. This outcome highlights that the QLFFOA possesses excellent robustness and superior adaptability to various categories of optimization problems. To further evaluate the algorithm's convergence performance, several representative functions are selected from the 30 test functions to generate convergence curves, which are presented in Fig. 5.

As shown in Fig. 5, each subgraph depicts the convergence speed of the 11 algorithms, where the QLFFOA is highlighted by a red solid curve and the remaining algorithms are identified using different colored line styles. By observation, in experiments on the six benchmark functions f_7 , f_9 , f_{13} , f_{16} , f_{24} , and f_{29} , the curves indicated by the red solid line consistently lie below the other 10 curves. This indicates that the QLFFOA can reach the optimal solution in the least number of iterations. In particular, the QLFFOA in Fig. 5(b)–(f) attain the optimum in fewer than 600 iterations. It exhibits both a faster convergence speed than the other 10 comparative algorithms and a significantly superior optimal value to the others.

Among the six subgraphs in Fig. 5, the QLFFOA does not exhibit the fastest descent speed during the initial iteration stage among the 11 algorithms in Fig. 5(a) and (d).

In Fig. 5(a), the QLFFOA exhibits a slower descent speed than PSO during the 0–200 iteration phase, but it outperforms PSO with significantly faster descent speed after 200 iterations. In Fig. 5(d), the QLFFOA lags behind POA in descent speed within the 0–300 iterations, yet exhibits significantly faster descent than POA beyond 300 iterations. This is attributable to the integration of quantum motion characteristics with the leader-follower mechanism, enabling the algorithm to escape local optima through quantum leaps and tunneling effects guided by the quantum attractors of leaders and followers. At the same time, the algorithm adopts mechanisms of quantum entanglement and quantum repulsion which effectively enhance the likelihood of escaping local optima and enable the algorithm to have better global search capabilities. From Fig. 5(a), (b), the QLFFOA exhibits a rapid convergence speed in the early stage under multi-modal functions (the fitness value rapidly decreases from a high value), and there is

no obvious stagnation throughout the process. It can continuously break through the trap of local optima, reflecting a good balance between global exploration and local development. The QLFFOA in Fig. 5(c) shows a much greater decrease in both magnitude and rate compared to other algorithms, indicating its ability to efficiently adapt to multi substructure coupling scenarios with mixed functions and strong adaptability to optimization requirements in different subregions. Fig. 5(d)–(f) demonstrate that the QLFFOA algorithm not only experiences a rapid decline in the early stages, but also continues to optimize in the later stages, demonstrating its strong robustness and precise optimization ability in high-dimensional scenarios.

To further evaluate the strengths and weaknesses of these algorithms, a comparison of computational overhead was performed between QLFFOA and the other 10 algorithms. Each of the 11 algorithms was executed 20 times. The mean running time and memory usage were recorded. The results are presented in the bar chart in Fig. 6.

As shown in Fig. 6, The proposed QLFFOA exhibits a mean running time of 2.46 s and a memory usage of 0.2 MB. These performance indicators are substantially lower than the PO algorithm's excessive runtime and high memory consumption. Simultaneously, the QLFFOA's resource requirements are comparable to those of classical lightweight algorithms, including PSO (1.73 s, 0.50 MB) and QPSO (1.83 s, 0.58 MB). Therefore, the QLFFOA can be categorized as a low-latency and low-memory-consumption optimization method.

Moreover, to assess the statistical significance of the performance differences between the QLFFOA and the remaining 10 algorithms, non-parametric test were applied to the ranking outcomes of the 11 algorithms. Specifically, the mean and standard deviation of the optimal values in Table 2 were analyzed using the Friedman non-parametric test, allowing assessment of whether QLFFOA exhibits significantly different optimization performance. The detailed Friedman test results are provided in Table 3, and the best ranking is highlighted in bold.

Based on the results presented in Table 3, the p -values for both the mean and standard deviation rankings are less than the 0.05 significance threshold. This indicates that the performance differences between QLFFOA and the other 10 algorithms are significant. The corresponding test statistics further confirm that QLFFOA delivers the superior overall performance within the 11 methods. The p -values for the mean and standard deviation rankings reach 2.1856×10^{-36} and 1.1056×10^{-16} , respectively, demonstrating that random variation is an implausible

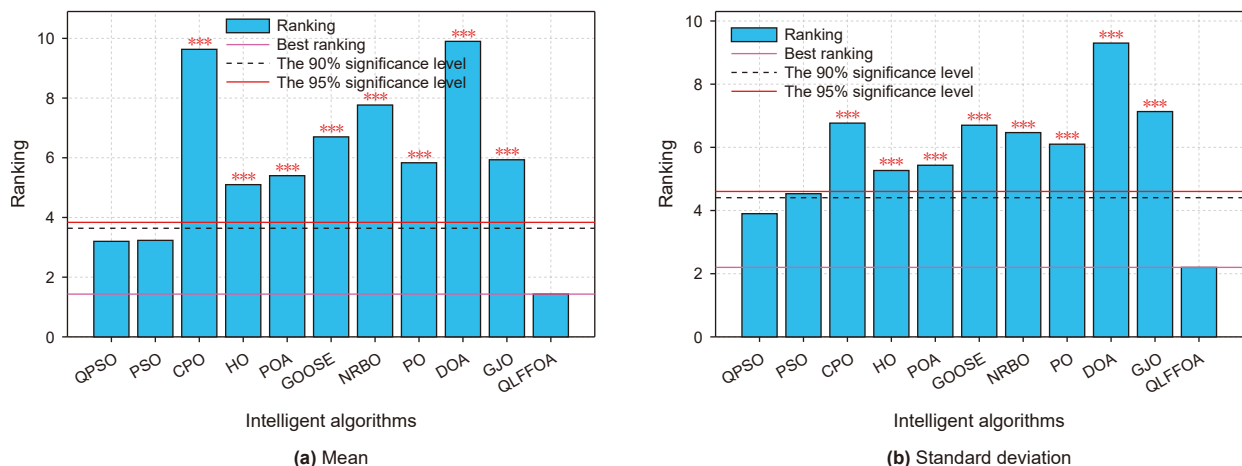


Fig. 7. Bar chart of Bonferroni-Dunn test results. (a) Mean. (b) Standard deviation.

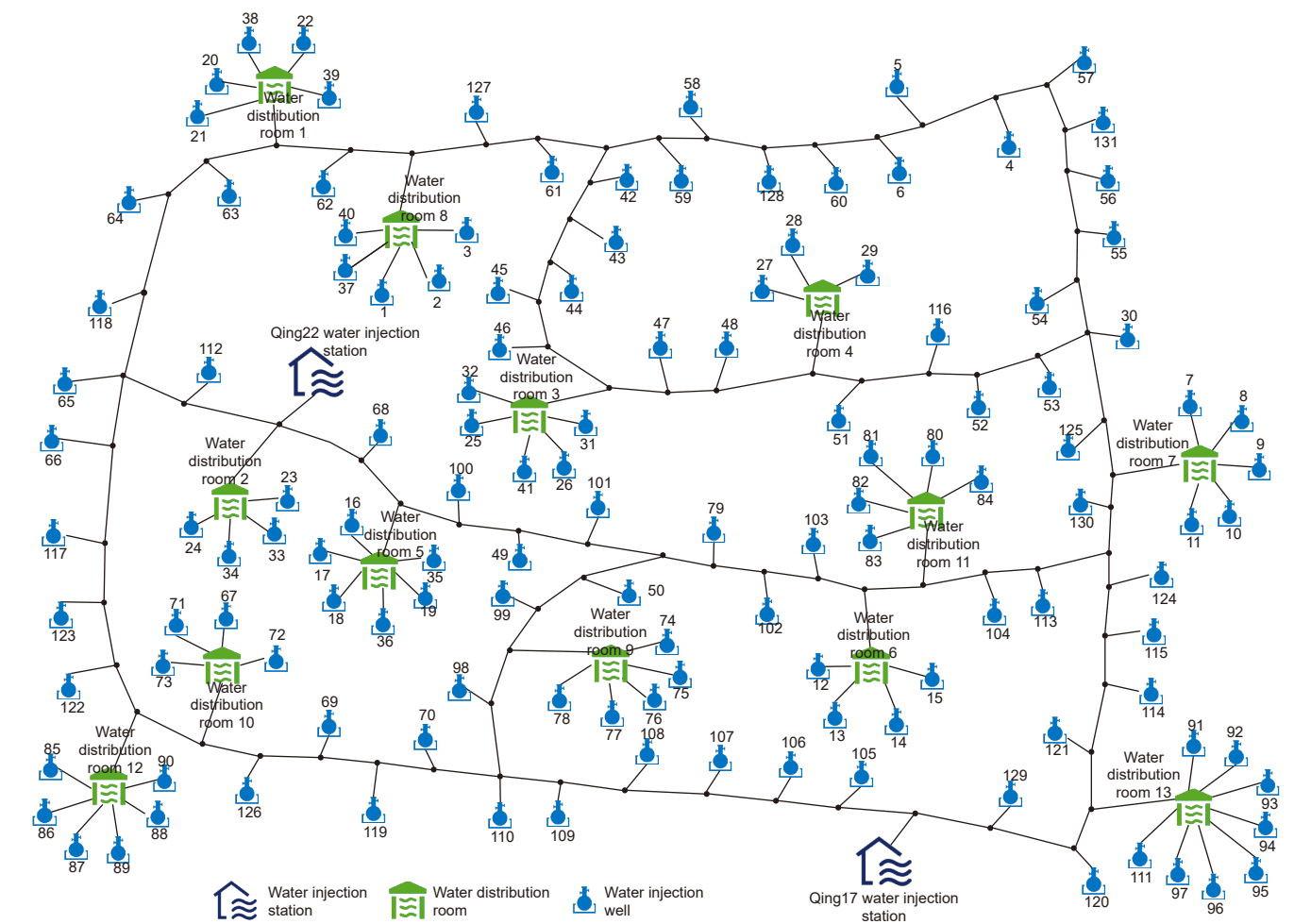


Fig. 8. The topology structure of the water injection pipeline network.

Table 4
Specification parameters of water injection pump.

Pump name	Rated flow rate, m ³ /h	Rated head, m	Rated efficiency, %	Inlet pipe diameter, mm	Export pipe diameter, mm	Motor model
Qing17 Note 1#	300	1650	76	200	300	D300-150×11
Qing17 Note 2#	400	1500	76	200	300	D400-150×10
Qing22 Note 1#	250	1650	75	200	300	DF250-150×11
Qing22 Note 2#	400	1600	81	200	300	DF400-160×10

explanation for the observed differences. Additionally, QLFFOA attains the top rank in both metrics, demonstrating superior solution accuracy and greater stability relative to the other algorithms.

To obtain a more detailed comparison and reinforce the conclusions drawn from the Friedman test, a Bonferroni-Dunn test was subsequently performed. For the test, a significant difference between any two comparative algorithms is determined when the difference in their performance rankings exceeds the critical difference (CD), and the calculated CD values for the test are presented below.

$CD_{0.05} = 2.4$, $CD_{0.1} = 2.21$

Using the critical differences derived from this analysis, along with the Friedman test outcomes, a comparative bar chart of the 11

algorithms was generated, as presented in Fig. 7. In this figure, the black dashed line indicates the 90% significance level, the red line indicates the 95% significance level, and the pink horizontal line marks the Friedman ranking of the best-performing algorithm.

Based on the test outcomes associated with the mean rankings of 30 benchmark functions in Fig. 7(a), at the 95% significance level, the QLFFOA is significantly superior to 8 algorithms HO, CPO, POA, PO, NRBO, GOOSE, GJO, and DOA. This observation confirms that the algorithm exhibits significant differences in the accuracy of optimization problem solving compared with other 8 algorithms, and its excellent global solving ability has been demonstrated. It can also be seen from the figure that the QLFFOA is superior to QPSO and PSO algorithms, but QPSO and PSO algorithms themselves also perform well in solving accuracy. Therefore, the QLFFOA does not

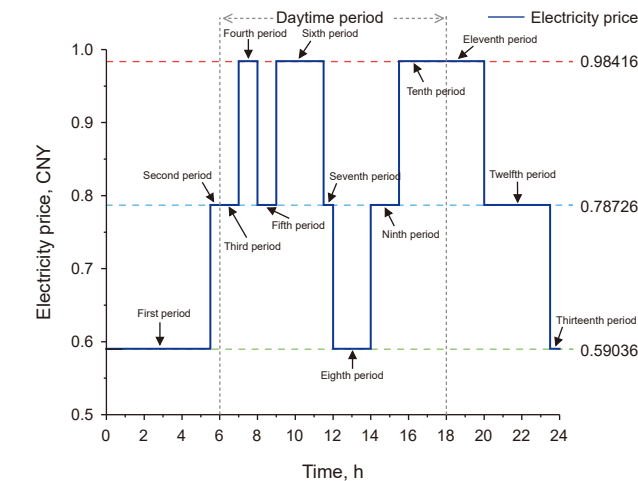


Fig. 9. Local electricity pricing standards and time period differentiation in the oilfield.

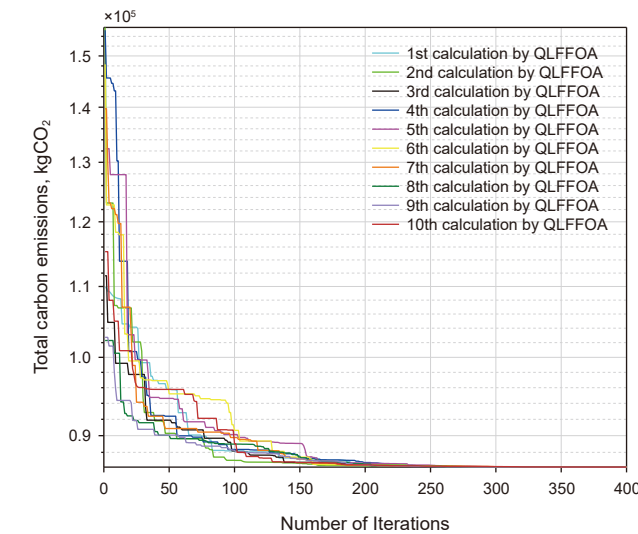


Fig. 10. Iteration diagram of QLFFOA solution.

Table 5
Comparison of water injection system schemes before and after optimization.

Name	Before optimization	After optimization
Total water volume, m ³ /d	31,598	31,598
Total energy consumption, kWh/d	172,720	160,156.26
Total electricity cost, CNY	135,976.24	121,253.25
Total carbon emissions, kgCO ₂	92,716.10	85,971.88
Unit energy consumption, kWh/m ³	5.47	5.07
Average pump efficiency, %	79.59	81.43
Number of pumps turned on	4	4

demonstrate a significant advantage over QPSO and PSO in the test results. In Fig. 7(b), the QLFFOA demonstrates superior robustness compared with the other swarm intelligence optimization algorithms. At both the 95% and 90% significance levels, the QLFFOA is significantly superior to 8 algorithms HO, CPO, POA, PO, NRBO, GOOSE, GJO, and DOA. This confirms that its solution stability of addressing optimization problems is significantly superior to that of other 8 algorithms. Fig. 7(b) shows that the QLFFOA outperforms both QPSO and PSO, and it is significantly superior to PSO at the 90% significance level. However, QPSO and PSO themselves also exhibit

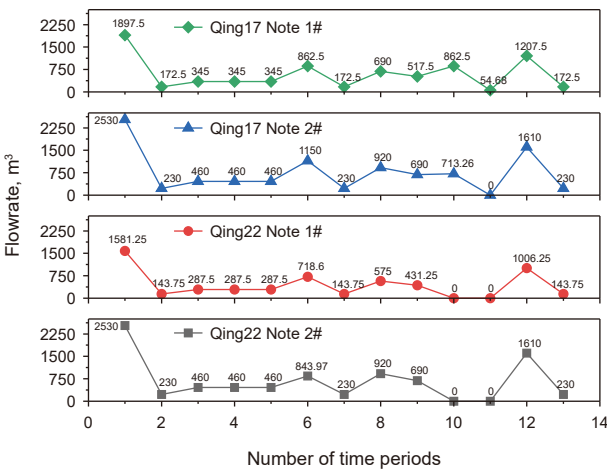


Fig. 11. Optimized time-period water injection results of pumps.

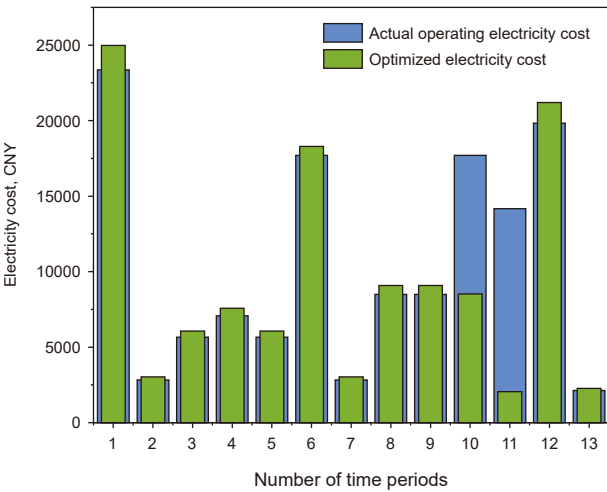


Fig. 12. Optimized time-period water injection electricity cost results of pumps.

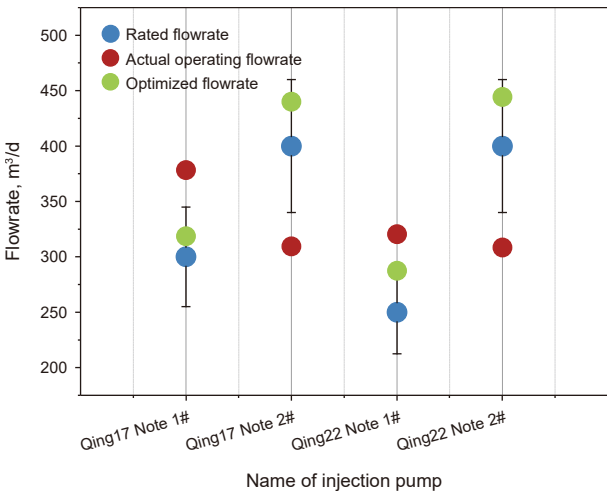


Fig. 13. Comparison of flow rate for water injection pumps before and after optimization.

strong robustness. Therefore, at the 95% significance level, the QLFFOA does not exhibit a significant advantage over QPSO and PSO. Through comparative experiments, it has been proven that the

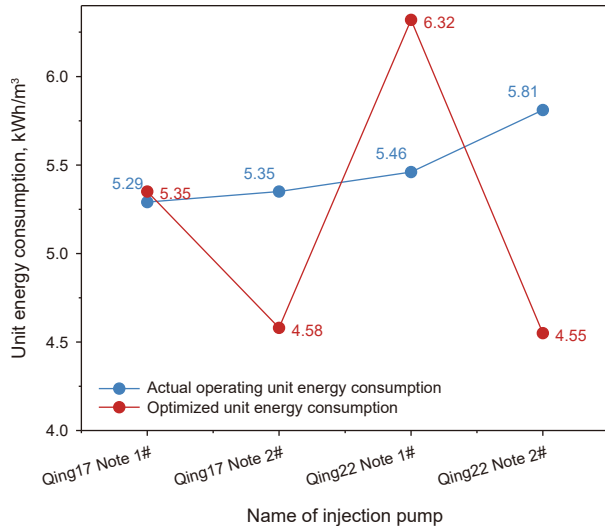


Fig. 14. Comparison of unit energy consumption for water injection pumps before and after optimization.

QLFFOA is a robust and efficient approach for addressing complex optimization problems. Furthermore, it is well-suited for solving the complex nonlinear optimization model presented in the subsequent sections of this work.

7. Case study

To validate the practical applicability of the proposed algorithm and model in real-world engineering scenarios, a specific block in Oilfield C is selected as the case study. The system's total daily flow rate demand is 31,598 m³/d. The water injection system comprises 13 distribution rooms, 131 injection wells, 2 water injection stations, and 4 injection pumps, with its topology depicted in Fig. 8. Table 4 provides the specifications of the injection pump.

To ensure that the optimization results reflect practical operating conditions, field-measured operating parameters for the 131 injection wells were incorporated into the analysis, with the required wellhead flow rates ranging from 125 to 267 m³/d. Based on the daily charging standards in the location of the oilfield, considering the daytime period from 6am to 6pm, the entire day is divided into 13 time periods for optimization, as shown in Fig. 9. Meanwhile, the model is solved based on the average CO₂ emission factor for electricity (0.5368 kgCO₂/kWh) in the location of the oilfield last year. Using the simulation model established in this paper, simulation calculations were performed on the 131 wells of this water injection system to obtain the calculated pressures, which were compared with the measured pressures. The comparison results are presented in Table A3 in Appendix A.3. It can be seen from Table A3 that the relative errors between the calculated pressures and the measured pressures of the 131 wells in this

water injection system are less than 5%, and the mean relative error is less than 3%.

Considering the positive correlation between total carbon emissions and total electricity cost, this study adopts minimizing the total carbon emissions as the primary optimization objective to solve the optimization model. The QLFFOA was applied to solve the established model 10 times, and the resulting iterative convergence curves are shown in Fig. 10. The computational time required for the QLFFOA to solve this water injection pipeline network optimization model is approximately 21 min. Table 5 presents a comparison of the water-injection system's original operation scheme and the optimized scheme. Table 5 demonstrates that with constant number of pumps and total water volume, the optimized result decreases the power consumption of 12,563.74 kWh/d, saves a total electricity cost of 14,722.99 CNY, reduces total carbon emissions of 6,744.22 kg CO₂, decreases the system unit energy consumption of 0.4 kWh/m³, and increases the average pump efficiency of 1.84%. As shown in Fig. 11, the optimized time-segmented water injection distribution indicates that all four pumps inject most of the water during off-peak periods, while also prioritizing daytime injection when electricity prices are equal. It can be seen that all four pumps inject most of the water during off-peak periods, and prioritize water injection during the daytime when electricity prices are equal. As shown in Fig. 12, the optimized electricity cost is concentrated in the daytime off-peak periods, while largely avoiding the evening peak periods, consistent with the expected outcome. Fig. 13 depicts the optimized flow rate outcomes of the water injection pumps. Compared to before optimization, the deviation between optimized flow rate and rated flow rate is less than 15%. The optimized scheme demonstrates superior flow rate control accuracy, complying with on-site hydraulic demands. Fig. 14 presents the unit energy consumption of the water injection pumps. As shown in Fig. 14, the optimized results indicate that only two pumps have lower unit energy consumption than before optimization. This outcome stems from the algorithm focus on the lowest total carbon emissions under the existing water-injection network connection conditions. This may lead to higher unit energy consumption for certain individual water-injection pumps compared to before optimization. However, the optimized total unit energy consumption (20.8 kWh/m³) outperforms the actual operating unit energy consumption (21.91 kWh/m³). This confirms the rationality of such individual pump performance fluctuations, as the optimization simultaneously achieves energy consumption reduction and flow rate deviation minimization.

Furthermore, to comprehensively and objectively evaluate the solution performance of the QLFFOA, it is imperative to mitigate the limitations in relying solely on comparisons with the actual operational scheme. The analysis and validation presented in Chapter 6 demonstrate that PSO and QPSO exhibit better performance relative to the other eight algorithms. Therefore, this case study introduces the classical PSO algorithm and QPSO algorithm as baseline algorithms for comparative analysis. All comparison algorithms are run under identical constraint conditions, population sizes and maximum numbers of iterations, and all strictly satisfy the daily total water injection allocation requirements of the oilfield. The comparison of the optimization results of the three algorithms is presented in Table 6. The results show that under the premise of the same number of operating pumps and all meeting the allocation requirements, the QLFFOA optimization result achieves the best optimization performance. This further proves that the QLFFOA also possesses higher solution accuracy in high-dimensional and strongly coupled oilfield water injection optimization problems.

To further quantify the demand-side flexible regulation capacity of the water injection system in response to time-of-use electricity

Table 6
Comparison of optimization schemes between other algorithms and the QLFFOA.

Name	QPSO	PSO	QLFFOA
Total water volume, m³/d	31,598	31,598	31,598
Total energy consumption, kWh/d	165,480.04	166,821.99	160,156.26
Total electricity cost, CNY	125,283.83	126,299.81	121,253.25
Total carbon emissions, kg CO ₂	88,829.68	89,550.04	85,971.88
Number of pumps turned on	4	4	4

pricing, this paper introduces the peak-valley electricity transfer rate (η_{transfer}) for quantitative evaluation. The specific calculation formula is shown in Eq. (44). According to the time-of-use pricing structure of the oilfield distribution network, time periods 4, 6, 10 and 11 are designated as peak electricity price periods. Statistical data shows that the total electricity consumption of the system during peak periods before optimization was 57,573.33 kWh; after optimal scheduling with the QLFFOA algorithm, the peak electricity consumption was significantly reduced to 37,025.11 kWh, achieving a peak electricity load reduction of 35.69%. The peak-valley electricity transfer rate of the QLFFOA optimization scheme reaches 11.90%. The results indicate that the proposed optimization strategy does not merely rely on reducing the total energy consumption of the system, but rather realizes the temporal reconstruction and flexible transfer of industrial power loads through accurate collaborative optimization of time period combinations.

$$\eta_{\text{transfer}} = \frac{E_{\text{peak}}^{\text{base}} - E_{\text{peak}}^{\text{opt}}}{E_{\text{total}}^{\text{base}}} \times 100\% \quad (44)$$

8. Conclusions

This study addresses the issue of continuous increase in energy consumption and electricity expenses of oilfield water injection systems during high water-cut periods. The multi-objective optimization model of time-segmented water injection in oilfield water injection systems considering time-of-use electricity pricing was constructed with the objective functions of minimizing total carbon emissions and total electricity costs. This model is the first to use carbon emission minimization as the objective function in the optimization model of oilfield water injection system. It introduces a time of use electricity pricing mechanism and considers constraints such as time period priority and time period water volume.

This paper proposes the QLFFOA to address the non-linearity, multiple constraints, and tendency to get stuck in local optima of the model. The algorithm introduces the probability superposition and non-local search characteristics of quantum mechanics into the Leader-Follower hierarchical collaboration mechanism, avoiding the problem of the exploration and exploitation imbalance in conventional swarm intelligence algorithms and breaking through the limitations of insufficient group collaboration in quantum optimization algorithms. The comparison results with 10 representative swarm intelligence algorithms show that QLFFOA exhibits better performance in convergence accuracy, stability, and global search efficiency.

The results of an engineering case show that, the optimization scheme proposed in this article has achieved three effects.

- (1) The optimized scheme increased the system average pump efficiency by 1.84% and reduced the unit energy consumption by 0.4 kWh/m³, which means that the optimized scheme can improve the operation level of the entire water injection system and enhance the energy-saving potential of the system.
- (2) The optimized scheme reduced electricity consumption by 7.3%, which is equivalent to a reduction of 7.2% in total carbon emissions based on the carbon emission factor. This indicates that the optimization model and algorithm in this paper can effectively reduce electricity demand while ensuring normal production, and reduce greenhouse gas emissions such as carbon dioxide from the source.

- (3) The optimized scheme reduced the total electricity cost by 10.8%, realizing that electricity consumption is mainly distributed in the off-peak electricity price periods, successfully avoiding the peak electricity price period in the evening. The optimized plan complies with the oilfield operation management rules, and the constraint of prioritizing daytime hours also conforms to the engineering operation and maintenance preferences.

In summary, the optimization model and algorithm constructed in this article can scientifically guide the time-segmented operation and management of oilfield water injection systems, helping them achieve low-carbon and efficient operation.

9. Discussions

The optimization model and algorithm proposed in this article have shown excellent energy-saving and cost-saving performance in case studies. The proposed optimization scheme does not change the total water injection volume and the number of configured pumps, and the flow rate deviation of all pumps is controlled within 15% of the rated flow rate, indicating that the optimization results are still within the field-acceptable operating range. Meanwhile, the optimized scheduling scheme strictly satisfies the constraints of pipeline network hydraulic balance, wellhead pressure and water injection allocation, which demonstrates that shifting water injection operations from peak periods to valley periods will not violate the engineering constraints of the system. The results show that 35.69% of the peak-period electricity is transferred to valley periods, and the peak-valley electricity transfer rate reaches 11.90%, indicating that this method achieves the temporal reconstruction and flexible transfer of power loads under the premise of satisfying field operating conditions, rather than simply compressing the water injection scale. Therefore, this optimization strategy has engineering practicability and can provide practical reference for the time-of-use scheduling of oilfield water injection systems.

However, there are still some limitations that need further research.

- (1) The current optimization objectives do not include long-term cost factors such as pump unit start-stop frequency, starting current shock, and equipment wear. In future research, start-stop penalties or equipment lifespan functions will be introduced to balance short-term energy conservation and long-term economy.
- (2) The current optimization model is based on the average carbon dioxide emission factor of electricity, without considering the difference in carbon dioxide emission factors between peak and off-peak periods of electricity prices. In future research, dynamic carbon dioxide emission factors will be considered in the optimization model to improve the accuracy of the total carbon emissions of the optimization scheme.
- (3) The current optimization strategies mainly focus on the macroscopic active power scheduling and energy efficiency improvement of water injection systems. However, in actual operation, frequent adjustment of the operating frequency of injection pump motors may cause fluctuations in system reactive power, thereby imposing additional load impacts and transmission losses on the upstream power grid. In

future work, we will further expand the current system boundary and incorporate the reactive power losses of induction motors, grid-side transmission efficiency, and dynamic marginal emission factors of the power grid into comprehensive consideration to achieve deeper collaborative multi-objective optimization.

CRediT authorship contribution statement

Shuang-Qing Chen: Funding acquisition, Conceptualization. **Chao Chen:** Writing – original draft, Software, Methodology, Formal analysis. **Yu-Chun Li:** Visualization, Validation. **Lan Meng:** Investigation, Data curation. **Li-Xin Wei:** Supervision, Resources. **Bing Guan:** Writing – review & editing, Project administration.

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.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (Nos. 52104065, 51674086), Heilongjiang Province's Basic Research Support Program for Excellent Young Teachers (No. YQJH2023086), Northeast Petroleum University Talent Introduction and Research Initiation Funding Project (No. 2021KQ18), Northeast Petroleum University National Natural Science Foundation Cultivation Fund (No. 2023GPL-14), Heilongjiang Outbound Postdoctoral Funding (No. 216240064), Qingyan Talent Support Program Project of Daqing Heilongjiang Province (No. DQXY202403).

Appendix A

Appendix A.1

Table A1 shows the detailed definitions and descriptions of all variables and symbols involved in the optimization model, simulation model, algorithm design, and algorithm solving in this article.

Table A1
Nomenclature of variables and symbols.

Category	Symbol	Description	Unit
Optimization model	E	The carbon emissions	kg CO ₂
	C	The total electricity cost	CNY
	M	The total number of time periods	-
	N_p	The count of operational water injection pumps in operation	-
	λ_k	The electricity price during period k	CNY/h
	$Z_{i,k}$	The i -th water injection pump's head during period k	m
	$F_{i,k}$	The i -th pump's flow rate during period k	m ³
	g	The gravitational acceleration	m/s ²
	$\eta_{i,k}^p$	The i -th pump's operational efficiency corresponding to its flow rate during period k	%
	ρ	The density of the fluid	kg/m ³
	$t_{i,k}$	The i -th pump's runtime during period k	h
	$\eta_{i,k}^m$	The motor efficiency of the i -th water injection pump during period k	%
	ξ	The unit conversion coefficient, which is 3.6×10^{-6}	-
	E_F	The CO ₂ emission factor for electricity	kgCO ₂ /kWh
	$W_{i,k}$	The power consumption of the i -th water injection pump during period k	kWh
	$P_{out,k}$	The pump's outlet pressure during period k	MPa
	$P_{in,k}$	The outlet pressure of the station during period k	MPa
	$\Delta\Psi_{\chi,k}(\cdot)$	Unit model for local head loss within the station	-
	h_f	The frictional loss along the pipe	m
	l	The pipeline length	m
	χ	The pipeline friction coefficient	-
	d	The pipeline inner diameter	m
	v	The fluid's average flow velocity	m/s
	F_k	The volumetric flow rate in the pipe during period k	m ³ /s
	ζ	The comprehensive local resistance coefficient	-
	ζ_i	The resistance coefficient for the i -th local component	-
	$h_{loc,i}$	The head loss for the i -th local component	m
	h_{loc}	The total local head loss	m
	h_{tot}	The total head loss of the station unit, which is the sum of the frictional and local losses	m
	K_p	The comprehensive loss coefficient of the simulation unit	-
	$F_{i,k}^{in}$	The inflow rate at node i during period k	m ³ /s
	$F_{i',k}^{out}$	The outflow rate at node i' during period k	m ³ /s
	N_u	The collection of node identifiers linked to node u	-
	$\kappa_{u,v}$	The pipeline resistance coefficient between nodes u and v	-
	$P_{u,k}$	The pressure at node u during period k	MPa
	$P_{v,k}$	The pressure at node v during period k	MPa
	β	The constant coefficient	-
	N_w	The total count of wells in the system	-
	$p_{i,k}^{min}$	The i -th well's minimum demand pressure during period k	MPa
	$P_{i,k}$	The i -th well's pressure during period k	MPa

Table A1 (continued)

Category	Symbol	Description	Unit
Simulation model	$f_{i,k}^{\min}$	The lower bound of the flow rate of the i -th pump operating within its high-efficiency region during period k	m^3/s
	$f_{i,k}^{\max}$	The upper bound of the flow rate of the i -th pump operating within its high-efficiency region during period k	m^3/s
	$N_{i,k}$	The count of operational pumps at the i -th station during period k	-
	$Q_{i,k}^{\min}$	The minimum water injection volume at the i -th station during period k	m^3/s
	$Q_{i,k}^{\max}$	The maximum water injection volume at the i -th station during period k	m^3/s
	N	The total count of water injection stations	-
	μ_k	The priority level of period k , where a larger value indicates a higher priority;	-
	$D(k)$	The day–night indicator for period k , where $D(k) = 1$ corresponds to the daytime period and $D(k) = 0$ corresponds to the nighttime period	-
	P_k	The pressure value at node k	MPa
	P_j	The pressure value at node j	MPa
	q	The pipeline section's flow rate	m^3/s
	χ_h	The Hazen-Williams coefficient	-
	δ_{kj}	The pipe's hydraulic diameter taking into account pipe-wall thickness	m
	$q_{i,k}$	The flow rate at node k for unit i	m^3/s
	$q_{i,j}$	The flow rate at node i for unit j	m^3/s
Algorithm design	$\chi_1 \sim \chi_7$	The calculation coefficients corresponding to the pipeline unit located outside the station	-
	$\chi'_8 \sim \chi'_{12}$	The coefficients associated with the pipeline unit from the pump outlet to the manifold	-
	χ'_{13}, χ'_{14}	The coefficients for the pipeline unit from the manifold to the water injection station outlet	-
	$H_1 \sim H_6$	The pressures at the injection wells and at the intersection nodes	MPa
	$H'_j \sim H'_{11}$	The pressure of the virtual water-source nodes, which correspond to pump outlet pressure	MPa
	H''_{12}, H''_{13}	The pressures at the water injection station internal manifold	MPa
	$F_1 \sim F_4$	The aggregated inflow and outflow rates at the pipeline nodes	m^3/s
	F_5, F_6	The injection volumes at the injection wells	m^3/s
	$F'_j \sim F'_{11}$	The flow rates at the virtual water-source points, namely flow rates at the outlets of the injection pumps	m^3/s
	F''_{12}, F''_{13}	The flow rates at station internal manifold	m^3/s
	ξ	A random number uniformly distributed over the interval $[0,1)$, $\xi \sim U(0,1)$	-
	P_l	The quantum leader selection probability, which controls the overall proportion of leaders	-
	f_i^{pb}	The historical best fitness of individual i	-
	$\sum_{k=1}^{N_s} f_k^{\text{pb}}$	The sum of historical best fitness values for all individuals within the population	-
	N_s	The population size	-
Algorithm solving	L_s	The leader set	-
	$\alpha_{\max}, \alpha_{\min}$	The upper and lower bounds of the coefficient	-
	I_t	The current iteration index	-
	Max_iteration	The maximum number of iterations	-
	p_i	The quantum attractor of individual i	-
	ϕ	A random weight in the interval $[0,1)$;	-
	$gBest$	The global-best position	-
	x_k^{pb}	The historical-best position of a randomly assigned leader k	-
	m	The center of the quantum swarm	-
	x_i^{pb}	The historical-best position of individual i	-
	L	The characteristic length	-
	α	The quantum contraction–expansion coefficient	-
	x_i	The current position of individual i	-
	p_i	The quantum attractor of individual i	-
	dir	A random direction vector (taking values ± 1) that models the directional randomness of quantum transitions	-
Peak-valley electricity transfer rate	$\lg\left(\frac{1}{\theta}\right)$	The quantum tunneling effect, where θ is a random number in the interval $[0,1)$.	-
	x'_i	The updated position of the i -th individual	-
	x_e	The position of the randomly selected “entanglement partner” (the e -th individual).	-
	d_t	The distance between two individuals	-
	$\ \cdot\ $	The Euclidean norm, which is used to quantify the straight-line distance between two individuals in space	-
	d_{disp}	The repulsion direction	-
	x_j	The current position of the j -th individual	-
	x'_j	The updated position of the j -th individual	-
	A	The D -dimensional optimization variable, where $A = (a_1, a_2, \dots, a_D)$	-
	$f_p(A)$	The p -th inequality constraint	-
	$g_m(A)$	The m -th equality constraint	-
	α_c	The tolerance constant, it is generally a small positive number	-
	$E_{\text{peak}}^{\text{base}}$	Cumulative electricity consumption during peak periods before optimization	kWh
	$E_{\text{peak}}^{\text{opt}}$	Cumulative electricity consumption during peak periods after optimization	kWh
	$E_{\text{total}}^{\text{base}}$	Total daily electricity consumption before optimization	kWh

Appendix A.2

Table A2 shows the specific optimization results of QLFFOA and other intelligent algorithms in solving benchmark functions with dimension $D = 30$.

Table A2The specific optimization results of QLFFOA and other intelligent algorithms in solving benchmark functions with dimension $D = 30$.

f		QPSO	PSO	CPO	HO	POA	GOOSE	NRBO	PO	DOA	GJO	QLFFOA
f_1	Mean	6.7818×10^3	1.1896×10^8	2.0016×10^{10}	1.3659×10^8	1.5158×10^{10}	7.5191×10^3	1.6497×10^{10}	4.1957×10^9	5.2432×10^{10}	1.1438×10^{10}	2.0309×10^5
	Std	6.3786×10^3	3.6434×10^8	3.2027×10^9	3.0579×10^8	5.2903×10^9	4.0758×10^3	4.6102×10^9	1.9586×10^9	9.4084×10^9	4.1578×10^9	6.7131×10^4
	Mean rank	1	4	10	5	8	2	9	6	11	7	3
	Std rank	1	5	7	4	10	2	9	6	11	8	3
f_2	Mean	1.0814×10^{14}	8.2674×10^{26}	2.6793×10^{39}	4.2959×10^{29}	7.2881×10^{32}	2.0771×10^{17}	8.4924×10^{34}	3.2708×10^{32}	6.2376×10^{42}	1.9668×10^{33}	1.8032×10^{12}
	Std	2.1447×10^{14}	3.6971×10^{27}	1.0614×10^{40}	1.1929×10^{30}	2.8772×10^{33}	5.4524×10^{17}	2.6974×10^{35}	1.0812×10^{33}	1.996×10^{43}	4.6737×10^{33}	5.8658×10^{12}
	Mean rank	2	4	10	5	7	3	9	6	11	8	1
	Std rank	2	4	10	5	7	3	9	6	11	8	1
f_3	Mean	5.2928×10^4	1.4672×10^4	1.2839×10^5	5.2476×10^4	3.3834×10^4	7.4350×10^4	4.8513×10^4	3.7522×10^4	7.2074×10^4	5.7469×10^4	4.1995×10^4
	Std	1.8401×10^4	5.1340×10^3	3.1781×10^4	5.7627×10^3	7.4707×10^3	2.9906×10^4	1.0207×10^4	7.5592×10^3	1.2342×10^4	1.1354×10^4	1.9852×10^4
	Mean rank	7	1	11	6	2	10	5	3	9	8	4
	Std rank	8	1	11	2	3	10	5	4	7	6	9
f_4	Mean	499.5859	513.0414	4.2481×10^3	615.4720	1.8816×10^3	505.9621	2.1464×10^3	781.3142	1.2076×10^4	1.4536×10^3	489.9977
	Std	13.2219	89.7443	1.1122×10^3	70.9363	1.0080×10^3	18.4776	1.0231×10^3	196.5705	4.4954×10^3	894.1797	6.4023
	Mean rank	2	4	10	5	8	3	9	6	11	7	1
	Std rank	2	5	10	4	8	3	9	6	11	7	1
f_5	Mean	597.1354	688.7358	849.5201	735.4802	757.3665	872.3163	831.6002	777.7343	872.9200	704.8057	548.8892
	Std	55.7278	35.3400	31.1252	48.0787	36.2813	73.0408	31.8017	46.4390	38.1368	38.8415	9.0850
	Mean rank	2	3	9	5	6	10	8	7	11	4	1
	Std rank	10	4	2	9	5	11	3	8	6	7	1
f_6	Mean	600.0825	647.1381	667.9590	658.5097	660.2591	676.7810	675.5265	661.7348	675.2867	636.0466	600.2450
	Std	0.2100	6.5502	7.2542	5.8060	7.5623	11.9023	10.1450	9.8409	11.7001	7.0978	0.1686
	Mean rank	1	4	8	5	6	11	10	7	9	3	2
	Std rank	2	4	6	3	7	11	9	8	10	5	1
f_7	Mean	853.9007	864.0376	1.2610×10^3	1.1687×10^3	1.2615×10^3	2.0406×10^3	1.2365×10^3	1.2252×10^3	1.3654×10^3	1.0294×10^3	772.1784
	Std	54.4772	39.5212	57.4600	58.0093	78.3182	927.9320	76.9109	79.7388	82.7438	55.8577	11.3093
	Mean rank	2	3	8	5	9	11	7	6	10	4	1
	Std rank	3	2	5	6	8	11	7	9	10	4	1
f_8	Mean	879.1558	944.3865	1.1065×10^3	954.8784	990.2773	1.1027×10^3	1.0852×10^3	1.0096×10^3	1.0924×10^3	961.3425	841.4628
	Std	46.4482	25.6171	34.1905	25.2234	25.6605	84.4991	30.0269	29.2192	31.1145	36.7881	12.0895
	Mean rank	2	3	11	4	6	10	8	7	9	5	1
	Std rank	10	3	8	2	4	11	6	5	7	9	1
f_9	Mean	935.8407	6.0775×10^3	9.7482×10^3	5.4518×10^3	5.4606×10^3	7.6245×10^3	7.1068×10^3	6.3654×10^3	9.8873×10^3	5.2960×10^3	919.4754
	Std	73.2668	2.1582×10^3	2.2541×10^3	494.0883	465.8166	2.6466×10^3	1.4961×10^3	968.6339	2.7023×10^3	1.4952×10^3	22.7107
	Mean rank	2	6	10	5	4	9	8	7	11	3	1
	Std rank	2	8	9	4	3	10	7	5	11	6	1
f_{10}	Mean	8.2797×10^3	4.9755×10^3	9.3185×10^3	5.1582×10^3	5.3422×10^3	5.9014×10^3	8.0673×10^3	6.5627×10^3	8.5749×10^3	6.9688×10^3	4.4318×10^3
	Std	576.7848	608.4938	432.1646	574.9088	578.1344	658.5562	524.3758	754.3116	632.2674	1.4061×10^3	993.4072
	Mean rank	9	2	11	3	4	5	8	6	10	7	1
	Std rank	4	6	1	3	5	8	2	9	7	11	10
f_{11}	Mean	1.1591×10^3	1.2425×10^3	8.7178×10^3	1.6010×10^3	2.0680×10^3	1.3017×10^3	2.1898×10^3	1.6532×10^3	6.3594×10^3	3.1722×10^3	1.1587×10^3
	Std	34.3677	34.1852	2.1500×10^3	166.5841	727.0803	62.0910	350.6996	245.6775	2.2507×10^3	1.0470×10^3	32.8537
	Mean rank	2	3	11	5	7	4	8	6	10	9	1
	Std rank	3	2	10	5	8	4	7	6	11	9	1
f_{12}	Mean	1.1838×10^6	1.4090×10^6	2.7048×10^9	6.2339×10^7	1.1316×10^9	3.9877×10^6	1.3713×10^9	1.3994×10^8	8.7487×10^9	1.3554×10^9	1.0048×10^6
	Std	9.0921×10^5	1.2658×10^6	6.5664×10^8	7.0025×10^7	1.1173×10^9	2.4625×10^6	8.6127×10^8	9.3900×10^7	4.2810×10^9	1.1133×10^9	9.3570×10^5
	Mean rank	2	3	10	5	7	4	9	6	11	8	1
	Std rank	1	3	7	5	10	4	8	6	11	9	2
f_{13}	Mean	1.8441×10^4	1.9694×10^4	7.7920×10^8	1.3939×10^5	1.4040×10^7	1.1884×10^5	2.9795×10^8	2.9453×10^5	1.9254×10^9	3.7609×10^8	9.5347×10^3
	Std	1.6018×10^4	1.3995×10^4	3.3540×10^8	9.4800×10^4	3.5023×10^7	1.2461×10^5	2.3436×10^8	3.6736×10^5	2.3599×10^9	6.6800×10^8	9.3855×10^3
	Mean rank	2	3	10	5	7	4	8	6	11	9	1
	Std rank	3	2	9	4	7	5	8	6	11	10	1
f_{14}	Mean	5.6150×10^4	2.1492×10^4	1.7583×10^6	2.4021×10^5	2.4380×10^4	3.9590×10^4	1.0302×10^5	2.4549×10^5	4.6391×10^5	4.7897×10^5	4.0823×10^4
	Std	5.2226×10^4	1.9813×10^4	1.3056×10^6	3.4739×10^5	2.8494×10^4	3.2303×10^4	9.1219×10^4	2.5934×10^5	8.5870×10^5	6.0256×10^5	3.0450×10^4
	Mean rank	5	1	11	7	2	3	6	8	9	10	4
	Std rank	5	1	11	8	2	4	6	7	10	9	3

f_{15}	Mean	9.2541×10^3	8.2303×10^3	8.8764×10^7	1.8236×10^4	2.8433×10^4	5.8400×10^4	3.5742×10^6	7.2708×10^4	3.4047×10^7	9.2828×10^6	6.0627×10^3
	Std	1.0775×10^4	7.8402×10^3	6.5837×10^7	7.3840×10^3	1.4831×10^4	4.0239×10^4	6.9893×10^6	6.6455×10^4	9.3168×10^7	2.0644×10^7	5.7827×10^3
	Mean rank	3	2	11	4	5	6	8	7	10	9	1
	Std rank	4	3	10	2	5	6	8	7	11	9	1
f_{16}	Mean	2.6232×10^3	2.7205×10^3	4.4596×10^3	3.4386×10^3	2.9698×10^3	3.5823×10^3	3.8034×10^3	3.5124×10^3	4.2672×10^3	3.0089×10^3	2.2688×10^3
	Std	519.6743	275.2623	280.0111	327.5936	309.4064	466.9579	447.7405	483.9221	760.3301	342.8465	258.7014
	Mean rank	2	3	11	6	4	8	9	7	10	5	1
	Std rank	10	2	3	5	4	8	7	9	11	6	1
f_{17}	Mean	1.9955×10^3	2.3013×10^3	2.9705×10^3	2.4919×10^3	2.3742×10^3	2.8342×10^3	2.5426×10^3	2.4240×10^3	2.9673×10^3	2.2952×10^3	1.8934×10^3
	Std	187.6153	267.3135	184.0000	253.2525	178.6562	438.4304	233.6204	244.2975	805.5215	265.9545	98.8241
	Mean rank	2	4	11	7	5	9	8	6	10	3	1
	Std rank	4	9	3	7	2	10	5	6	11	8	1
f_{18}	Mean	1.5267×10^6	4.4220×10^5	2.0775×10^7	8.5810×10^5	3.2210×10^5	3.8463×10^5	2.7129×10^6	2.3609×10^6	1.0348×10^7	2.6813×10^6	7.8872×10^5
	Std	1.7270×10^6	3.6092×10^5	9.4493×10^6	6.2412×10^5	3.5500×10^5	3.3726×10^5	3.3773×10^6	2.3498×10^6	2.1933×10^7	3.4989×10^6	9.6459×10^5
	Mean rank	6	1	11	5	2	3	9	7	10	8	4
	Std rank	6	3	10	4	2	1	8	7	11	9	5
f_{19}	Mean	1.7408×10^4	8.6846×10^3	7.6685×10^7	1.3620×10^6	1.1956×10^6	5.8754×10^5	9.1652×10^6	3.4817×10^6	2.9661×10^7	1.4250×10^7	1.1502×10^4
	Std	2.1336×10^4	1.2156×10^4	5.4216×10^7	8.6878×10^5	1.3198×10^6	2.8256×10^5	9.0222×10^6	2.5023×10^6	4.9498×10^7	2.8057×10^7	8.5481×10^3
	Mean rank	3	1	8	5	6	4	9	7	11	10	2
	Std rank	3	2	11	5	6	4	8	7	10	9	1
f_{20}	Mean	2.4289×10^3	2.6332×10^3	3.2185×10^3	2.5171×10^3	2.5370×10^3	2.9798×10^3	2.7705×10^3	2.6457×10^3	2.9944×10^3	2.6098×10^3	2.2729×10^3
	Std	184.2754	197.1188	128.3229	135.1220	112.7754	324.5267	180.2825	141.9171	188.6167	260.2995	154.4483
	Mean rank	2	6	11	3	4	9	8	7	10	5	1
	Std rank	7	9	2	3	1	11	6	4	8	10	5
f_{21}	Mean	2.3680×10^3	2.4984×10^3	2.6286×10^3	2.5297×10^3	2.5245×10^3	2.6726×10^3	2.5951×10^3	2.5002×10^3	2.6583×10^3	2.4908×10^3	2.3421×10^3
	Std	39.3906	53.1524	18.2224	56.8484	90.8049	52.6911	46.6017	42.2518	49.2001	40.2284	14.3356
	Mean rank	2	4	9	7	6	11	8	5	10	3	1
	Std rank	3	9	2	10	11	8	6	5	7	4	1
f_{22}	Mean	6.6982×10^3	4.6606×10^3	6.4209×10^3	5.4137×10^3	5.2172×10^3	7.2538×10^3	5.7632×10^3	3.9129×10^3	8.1646×10^3	4.9606×10^3	4.1700×10^3
	Std	3.4104×10^3	2.2430×10^3	1.7412×10^3	2.4725×10^3	1.5319×10^3	1.5679×10^3	2.2063×10^3	1.3264×10^3	1.2964×10^3	1.8271×10^3	1.9959×10^3
	Mean rank	9	3	8	6	5	10	7	1	11	4	2
	Std rank	11	9	5	10	3	4	8	2	1	6	7
f_{23}	Mean	2.7172×10^3	3.1894×10^3	3.2052×10^3	3.0209×10^3	2.9882×10^3	3.5847×10^3	3.0568×10^3	2.9859×10^3	3.3484×10^3	2.8967×10^3	2.6985×10^3
	Std	42.6500	132.9379	63.8502	91.7700	65.0483	225.4629	61.8776	86.1339	148.3072	66.6771	15.6807
	Mean rank	2	8	9	6	5	11	7	4	10	3	1
	Std rank	2	9	4	8	5	11	3	7	10	6	1
f_{24}	Mean	2.9400×10^3	3.2202×10^3	3.3925×10^3	3.2724×10^3	3.1801×10^3	3.7165×10^3	3.2149×10^3	3.1112×10^3	3.4869×10^3	3.0792×10^3	2.8655×10^3
	Std	54.8673	80.0755	68.9490	101.4932	81.6440	127.3600	76.6819	71.4338	170.4763	80.7663	14.8320
	Mean rank	2	7	9	8	5	11	6	4	10	3	1
	Std rank	2	6	3	9	8	10	5	4	11	7	1
f_{25}	Mean	2.8894×10^3	2.9049×10^3	3.8040×10^3	3.0133×10^3	3.2194×10^3	2.9263×10^3	3.3486×10^3	3.0422×10^3	5.0287×10^3	3.2372×10^3	2.8874×10^3
	Std	3.3328	18.7560	246.8686	40.1518	184.3722	18.1506	142.8886	48.4488	642.9500	159.9487	0.9557
	Mean rank	2	3	10	5	7	4	9	6	11	8	1
	Std rank	2	4	10	5	9	3	7	6	11	8	1
f_{26}	Mean	4.1797×10^3	5.5710×10^3	8.4065×10^3	6.9086×10^3	7.2650×10^3	1.0226×10^4	7.4389×10^3	7.2883×10^3	1.0080×10^4	6.0151×10^3	4.1228×10^3
	Std	243.0664	1.9679×10^3	612.5739	1.5616×10^3	1.2785×10^3	3.2911×10^3	1.2311×10^3	1.4248×10^3	1.3310×10^3	730.8054	125.4679
	Mean rank	2	3	9	5	6	11	8	7	10	4	1
	Std rank	2	10	3	9	6	11	5	8	7	4	1
f_{27}	Mean	3.2176×10^3	3.4439×10^3	3.8265×10^3	3.4751×10^3	3.3697×10^3	4.0144×10^3	3.4112×10^3	3.3669×10^3	3.7309×10^3	3.3510×10^3	3.2171×10^3
	Std	13.1537	152.0413	142.4332	120.9425	82.2183	399.3626	73.3343	117.3005	294.8433	69.9031	8.5884
	Mean rank	2	3	10	4	7	11	8	6	9	5	1
	Std rank	2	9	8	7	5	11	4	6	10	3	1
f_{28}	Mean	3.2542×10^3	3.2487×10^3	5.0577×10^3	3.3951×10^3	3.9441×10^3	3.2430×10^3	4.1426×10^3	3.5191×10^3	6.4303×10^3	3.8858×10^3	3.2229×10^3
	Std	44.9222	68.0805	456.2352	61.7186	400.3160	27.7652	302.7653	125.9934	798.0094	402.7795	22.2009
	Mean rank	4	3	10	5	8	2	9	6	11	7	1
	Std rank	3	5	10	4	8	2	7	6	11	9	1
f_{29}	Mean	3.6235×10^3	4.1520×10^3	5.6864×10^3	4.9292×10^3	4.6252×10^3	5.1534×10^3	4.9158×10^3	4.6783×10^3	5.5298×10^3	4.2632×10^3	3.5863×10^3
	Std	141.2209	263.9384	284.6051	540.1071	432.4219	434.2850	536.6100	351.9617	728.0358	270.9924	166.1460
	Mean rank	2	3	11	8	5	9	7	6	10	4	1

(continued on next page)

Table A2 (continued)

<i>f</i>	QPSO	PSO	CPO	HO	POA	GOOSE	NRBO	PO	DOA	GJO	QLFFOA
Std rank	1	3	5	10	7	8	9	6	11	4	2
<i>f</i> ₃₀	1.1465 × 10 ⁴	4.9477 × 10 ⁴	1.1482 × 10 ⁸	1.5163 × 10 ⁷	1.0515 × 10 ⁷	2.3181 × 10 ⁶	6.6001 × 10 ⁷	2.8556 × 10 ⁷	1.4686 × 10 ⁸	3.2911 × 10 ⁷	9.0303 × 10 ³
Mean	4.9425 × 10 ³	2.5637 × 10 ⁴	5.8130 × 10 ⁷	2.0589 × 10 ⁷	8.4216 × 10 ⁶	1.4871 × 10 ⁶	4.5074 × 10 ⁷	2.0872 × 10 ⁷	1.1340 × 10 ⁸	2.5152 × 10 ⁷	3.0125 × 10 ³
Std	2	3	10	6	5	4	9	7	11	8	1
Mean rank	2	3	10	6	5	4	9	7	11	8	1
Std rank	2	3	10	6	5	4	9	7	11	8	1

Appendix A.3

Table A3 shows the simulation calculation results of 131 wells in the water injection system in the case study.

Table A3
Simulation calculation results of 131 wells.

Water injection well number	Measured pressure, MPa	Calculated pressure, MPa	Absolute error, MPa	Relative error, %
1	13.6	13.589	0.011	0.081
2	13.2	13.589	−0.389	2.947
3	13.5	13.589	−0.089	0.659
4	13.6	13.588	0.012	0.088
5	13.3	13.588	−0.288	2.165
6	13.4	13.587	−0.187	1.396
7	13.6	13.728	−0.128	0.941
8	13.6	13.728	−0.128	0.941
9	13.4	13.728	−0.328	2.448
10	13.5	13.728	−0.228	1.689
11	13.5	13.728	−0.228	1.689
12	13.3	13.649	−0.349	2.624
13	13.3	13.649	−0.349	2.624
14	13.4	13.649	−0.249	1.858
15	13.2	13.649	−0.449	3.402
16	13.3	13.636	−0.336	2.526
17	13.3	13.636	−0.336	2.526
18	13.5	13.636	−0.136	1.007
19	13.2	13.636	−0.436	3.303
20	13.4	13.679	−0.279	2.082
21	13.6	13.678	−0.078	0.574
22	13.4	13.679	−0.279	2.082
23	13.4	13.760	−0.360	2.687
24	13.3	13.760	−0.460	3.459
25	13.4	13.635	−0.235	1.754
26	13.3	13.634	−0.334	2.511
27	13.2	13.619	−0.419	3.174
28	13.6	13.619	−0.019	0.140
29	13.3	13.619	−0.319	2.398
30	13.2	13.628	−0.428	3.242
31	13.3	13.635	−0.335	2.519
32	13.6	13.635	−0.035	0.257
33	13.5	13.760	−0.260	1.926
34	13.4	13.759	−0.359	2.679
35	13.6	13.636	−0.036	0.265
36	13.4	13.636	−0.236	1.761
37	13.3	13.589	−0.289	2.173
38	13.6	13.679	−0.079	0.581
39	13.2	13.679	−0.479	3.629
40	13.3	13.589	−0.289	2.173
41	13.6	13.635	−0.035	0.257
42	13.5	13.834	−0.334	2.474
43	13.3	13.776	−0.476	3.579
44	13.4	13.728	−0.328	2.448
45	13.3	13.699	−0.399	3.000
46	13.2	13.661	−0.461	3.492
47	13.3	13.629	−0.329	2.474
48	13.6	13.624	−0.024	0.176
49	13.5	13.629	−0.129	0.956
50	13.4	13.629	−0.229	1.709
51	13.4	13.622	−0.222	1.657
52	13.3	13.623	−0.323	2.429
53	13.4	13.626	−0.226	1.687
54	13.5	13.615	−0.115	0.852
55	13.6	13.606	−0.006	0.044
56	13.6	13.598	0.002	0.015
57	13.4	13.593	−0.193	1.440
58	13.4	13.588	−0.188	1.403
59	13.5	13.588	−0.088	0.652
60	13.5	13.588	−0.088	0.652
61	13.4	13.591	−0.191	1.425
62	13.3	13.631	−0.331	2.489
63	13.5	13.755	−0.255	1.889
64	13.3	13.834	−0.534	4.015
65	13.6	13.872	−0.272	2.000

Table A3 (continued)

Water injection well number	Measured pressure, MPa	Calculated pressure, MPa	Absolute error, MPa	Relative error, %
66	13.6	13.803	−0.203	1.493
67	13.4	13.721	−0.321	2.396
68	13.6	13.663	−0.063	0.463
69	13.4	13.639	−0.239	1.784
70	13.1	13.623	−0.523	3.992
71	13.5	13.721	−0.221	1.637
72	13.6	13.721	−0.121	0.890
73	13.4	13.721	−0.321	2.396
74	13.5	13.595	−0.095	0.704
75	13.4	13.596	−0.196	1.463
76	13.5	13.595	−0.095	0.704
77	13.3	13.595	−0.295	2.218
78	13.3	13.595	−0.295	2.218
79	13.4	13.634	−0.234	1.746
80	13.2	13.698	−0.498	3.773
81	13.3	13.698	−0.398	2.992
82	13.4	13.698	−0.298	2.224
83	13.6	13.698	−0.098	0.721
84	13.3	13.698	−0.398	2.992
85	12.9	12.365	0.535	4.147
86	12.9	12.365	0.535	4.147
87	12.9	12.364	0.536	4.155
88	12.9	12.364	0.536	4.155
89	12.9	12.364	0.536	4.155
90	12.9	12.364	0.536	4.155
91	13.3	13.305	−0.005	0.038
92	13.5	13.305	0.195	1.444
93	13.2	13.305	−0.105	0.795
94	13.2	13.305	−0.105	0.795
95	13.3	13.305	−0.005	0.038
96	13.1	13.305	−0.205	1.565
97	13.3	13.305	−0.005	0.038
98	13.3	13.602	−0.302	2.271
99	13.4	13.611	−0.211	1.575
100	13.4	13.634	−0.234	1.746
101	13.3	13.628	−0.328	2.466
102	13.2	13.641	−0.441	3.341
103	13.4	13.677	−0.277	2.067
104	13.3	13.706	−0.406	3.053
105	13.2	13.580	−0.380	2.879
106	13.5	13.580	−0.080	0.593
107	13.6	13.582	0.018	0.132
108	13.4	13.585	−0.185	1.381
109	13.4	13.592	−0.192	1.433
110	13.2	13.602	−0.402	3.045
111	13.1	13.305	−0.205	1.565
112	13.1	13.059	0.041	0.313
113	12.9	12.832	0.068	0.527
114	12.9	12.686	0.214	1.659
115	12.9	12.626	0.274	2.124
116	12.9	12.551	0.349	2.705
117	12.9	12.502	0.398	3.085
118	12.8	12.465	0.335	2.617
119	12.7	12.438	0.262	2.063
120	13.0	12.417	0.583	4.485
121	12.9	12.392	0.508	3.938
122	12.8	12.376	0.424	3.313
123	13.0	12.375	0.625	4.808
124	13.1	12.749	0.351	2.679
125	13.1	12.750	0.350	2.672
126	13.2	12.752	0.448	3.394
127	13.1	12.756	0.344	2.626
128	13.1	12.760	0.340	2.595
129	13.2	12.770	0.430	3.258
130	13.3	12.781	0.519	3.902
131	13.1	12.809	0.291	2.221
Mean value	13.490	13.450	−0.110	2.055

References

Abdel-Basset, M., Mohamed, R., Abouhawwash, M., 2024. Crested porcupine optimizer: A new nature-inspired metaheuristic. *Knowl. Base Syst.* 284, 111257. <https://doi.org/10.1016/j.knsys.2023.111257>.

Abdelsalam, A.A., Gabbar, H.A., 2021. Energy saving and management of water pumping networks. *Heliyon* 7, e07820. <https://doi.org/10.1016/j.heliyon.2021.e07820>.

Ala, A., Goli, A., 2024. Incorporating machine learning and optimization techniques for assigning patients to operating rooms by considering fairness policies. *Eng. Appl. Artif. Intell.* 136, 108980. <https://doi.org/10.1016/j.engappai.2024.108980>.

Almeida, L.F., Vellasco, M.M.B.R., Pacheco, M.A.C., 2010. Optimization system for valve control in intelligent Wells under uncertainties. *J. Petrol. Sci. Eng.* 73, 129–140. <https://doi.org/10.1016/j.petrol.2010.05.013>.

Amiri, M.H., Mehrabi Hashjin, N., Montazeri, M., et al., 2024. Hippopotamus optimization algorithm: A novel nature-inspired optimization algorithm. *Sci. Rep.* 14, 5032. <https://doi.org/10.1038/s41598-024-54910-3>.

Azamipour, V., Assareh, M., Mittermeir, G.M., 2018. An improved optimization procedure for production and injection scheduling using a hybrid genetic algorithm. *Chem. Eng. Res. Des.* 131, 557–570. <https://doi.org/10.1016/j.cherd.2017.11.022>.

Bai, Y., Hou, J., Liu, Y., et al., 2022. Energy-consumption calculation and optimization method of integrated system of injection-reservoir-production in high water-cut reservoir. *Energy* 239, 121961. <https://doi.org/10.1016/j.energy.2021.121961>.

Chen, L., Megow, N., Rischke, R., et al., 2021. Optimal algorithms for scheduling under time-of-use tariffs. *Ann. Oper. Res.* 304, 85–107. <https://doi.org/10.1007/s10479-021-04059-3>.

Chen, S., Chen, C., Li, Y., et al., 2025. Optimization of operating parameters scheme for water injection system based on a hybrid particle swarm-crested porcupine algorithm. *Sustainability* 8057. <https://doi.org/10.3390/su17178057>.

Chen, S., Liu, T., Dong, H., et al., 2024a. Generic layout optimization design methodology for China's loop-star natural gas field pipeline network. *Nat. Gas Ind. B* 11, 616–629. <https://doi.org/10.1016/j.ngib.2024.09.005>.

Chen, S., Zhou, S., Li, Y., et al., 2024b. Optimization method for digital scheduling of oilfield sewage system. *Water* 2623. <https://doi.org/10.3390/w16182623>.

China, M.o.E.a.E.o.t.P.s.R.o., 2024. Announcement on the release of 2022 electricity carbon dioxide emission factors. https://www.mee.gov.cn/xxgk2018/xxgk/xxgk01/202412/t20241226_1099413.html (in Chinese).

Chopra, N., Mohsin Ansari, M., 2022. Golden jackal optimization: A novel nature-inspired optimizer for engineering applications. *Expert Syst. Appl.* 198, 116924. <https://doi.org/10.1016/j.eswa.2022.116924>.

Davoodi, S., Eremyan, G., Mohammadi, A.H., et al., 2026. Machine-learning models for classification of mudcake thickness in oil-based drilling fluids. *Nat. Gas Ind. B* 13, 206–227. <https://doi.org/10.1016/j.ngib.2026.03.007>.

Dong, X., Gong, Q., Li, Y., et al., 2025. The process and trends of China's energy transition and the strategic repositioning of natural gas. *Nat. Gas Ind. B* 12, 750–765. <https://doi.org/10.1016/j.ngib.2025.11.004>.

Dorigo, M., Birattari, M., Stutzle, T., 2006. Ant colony optimization. *IEEE Comput. Intell. Mag.* 1, 28–39. <https://doi.org/10.1109/MCI.2006.329691>.

Gheouany, S., Ouadi, H., Bakali, S.E., 2025a. Experimental and comparative study on optimal active and reactive energy management in microgrid: moroccan VS time of Use Tariff. *Renew. Sustain. Energy Rev.* 212, 115414. <https://doi.org/10.1016/j.rser.2025.115414>.

Gheouany, S., Ouadi, H., El bakali, S., et al., 2025b. Novel strategy for optimal active and reactive power flows management in a small-scale microgrid system under forecasting uncertainties. *IFAC-PapersOnLine* 59, 229–234. <https://doi.org/10.1016/j.ifacol.2025.08.141>.

Goli, A., 2023. Integration of blockchain-enabled closed-loop supply chain and robust product portfolio design. *Comput. Ind. Eng.* 179, 109211. <https://doi.org/10.1016/j.cie.2023.109211>.

Goli, A., 2024a. Efficient optimization of robust project scheduling for industry 4.0: a hybrid approach based on machine learning and meta-heuristic algorithms. *Int. J. Prod. Econ.* 278, 109427. <https://doi.org/10.1016/j.ijpe.2024.109427>.

Goli, A., 2024b. Optimization of renewable energy project portfolio selection using hybrid AIS-AFS algorithm in an international case study. *Sci. Rep.* 14, 17388. <https://doi.org/10.1038/s41598-024-68449-w>.

Hamad, R.K., Rashid, T.A., 2024. GOOSE algorithm: A powerful optimization tool for real-world engineering challenges and beyond. *Evolv. Syst.* 15, 1249–1274. <https://doi.org/10.1007/s12530-023-09553-6>.

Hannah, R., Pablo, R., 2025. Share of primary energy consumption from fossil fuels. <https://ourworldindata.org/fossil-fuels>.

Hu, S., Gao, J., Zhong, D., et al., 2023. Real-time scheduling of pumps in water distribution systems based on exploration-enhanced deep reinforcement learning. *Systems* 56. <https://doi.org/10.3390/systems11020056>.

Iovane, G., 2025. Quantum-inspired algorithms and perspectives for optimization. *Electronics* 2839. <https://doi.org/10.3390/electronics14142839>.

Jun, S., Bin, F., Wenbo, X., 2004. Particle swarm optimization with particles having quantum behavior. In: *Proceedings of the 2004 Congress on Evolutionary*

- Computation (IEEE Cat. No.04TH8753), Vol 321, pp. 325–331. <https://doi.org/10.1109/CEC.2004.1330875>.
- Kennedy, J., Eberhart, R., 1995. Particle swarm optimization. In: Proceedings of ICNN'95 - International Conference on Neural Networks, vol 1944, pp. 1942–1948. <https://doi.org/10.1109/ICNN.1995.488968>.
- Lian, J., Hui, G., Ma, L., et al., 2024. Parrot optimizer: Algorithm and applications to medical problems. *Comput. Biol. Med.* 172, 108064. <https://doi.org/10.1016/j.compbiomed.2024.108064>.
- Liang, Y., Zhou, X., Qiu, R., et al., 2018. Optimal operation study on the large-scale looped and branched waterflooding pipeline network system of oilfields. *J. China Univ. Petrol. (Edit. Nat. Sci.)* 42, 121–132. <https://doi.org/10.3969/j.issn.1673-5005.2018.06.014> (in Chinese).
- Mokhtare, M.H., Keysan, O., 2025. Optimal sizing of a grid-connected DC microgrid for agricultural applications with water-energy management system considering battery cycle life. *Energy Nexus* 18, 100445. <https://doi.org/10.1016/j.nexus.2025.100445>.
- Napierala, M., 2022. A study on improving economy efficiency of pumping stations based on tariff changes. *Energies* 15 (3), 799. <https://doi.org/10.3390/en15030799>.
- Ngancha, P.B., Kusakana, K., Markus, E.D., 2022. Optimal pumping scheduling for municipal water storage systems. *Energy Rep.* 8, 1126–1137. <https://doi.org/10.1016/j.egyr.2021.10.111>.
- Peraza-Vázquez, H., Peña-Delgado, A.F., Echavarría-Castillo, G., et al., 2021. A bio-inspired method for engineering design optimization inspired by dingoes hunting strategies. *Math. Probl. Eng.* 2021, 9107547. <https://doi.org/10.1155/2021/9107547>.
- Rahmani, S., Goli, A., 2023. Robust sustainable canola oil-based biodiesel supply chain network design under supply and demand uncertainty. *Environ. Sci. Pollut. Control Ser.* 30, 86268–86299. <https://doi.org/10.1007/s11356-023-28044-4>.
- Sowmya, R., Premkumar, M., Jangir, P., 2024. Newton-Raphson-based optimizer: A new population-based metaheuristic algorithm for continuous optimization problems. *Eng. Appl. Artif. Intell.* 128, 107532. <https://doi.org/10.1016/j.engappai.2023.107532>.
- Trojovský, P., Dehghani, M., 2022. Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications. *Sensors* 855. <https://doi.org/10.3390/s22030855>.
- Wang, B., Liang, Y., Yuan, M., 2019. Water transport system optimisation in oilfields: Environmental and economic benefits. *J. Clean. Prod.* 237, 117768. <https://doi.org/10.1016/j.jclepro.2019.117768>.
- Wang, Y., Too Yok, K., Wu, W., et al., 2021. Minimizing pumping energy cost in real-time operations of water distribution systems using economic model predictive control. *J. Water Resour. Plann. Manag.* 147, 04021042. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0001399](https://doi.org/10.1061/(ASCE)WR.1943-5452.0001399).
- Wu, G., Mallipeddi, R., Suganthan, P., 2016. Problem definitions and evaluation criteria for the CEC 2017 competition and special session on constrained single objective real-parameter optimization. https://www.researchgate.net/publication/317228117_Problem_Definitions_and_Evaluation_Criteria_for_the_CEC_2017_Competition_and_Special_Session_on_Constrained_Single_Objective_Real-Parameter_Optimization.
- Xue, J., Shen, B., 2020. A novel swarm intelligence optimization approach: Sparrow search algorithm. *Syst. Sci. Contr. Eng.* 8, 22–34. <https://doi.org/10.1080/21642583.2019.1708830>.
- Yasari, E., Pishvaie, M.R., 2015. Pareto-based robust optimization of water-flooding using multiple realizations. *J. Petrol. Sci. Eng.* 132, 18–27. <https://doi.org/10.1016/j.petrol.2015.04.038>.
- Zhou, J., Li, Z., Liu, S., et al., 2025. Hybrid genetic algorithm for parametric optimization of surface pipeline networks in underground natural gas storage harmonized injection and production conditions. *Nat. Gas Ind. B* 12, 234–250. <https://doi.org/10.1016/j.ngib.2025.03.009>.
- Zhou, X., Liang, Y., Xin, S., et al., 2019. A MINLP model for the optimal waterflooding strategy and operation control of surface waterflooding pipeline network considering reservoir characteristics. *Comput. Chem. Eng.* 129, 106512. <https://doi.org/10.1016/j.compchemeng.2019.106512>.
- Zou, C., Xue, H., Xiong, B., et al., 2021. Connotation, innovation and vision of “carbon neutrality”. *Nat. Gas Ind. B* 8, 523–537. <https://doi.org/10.1016/j.ngib.2021.08.009>.