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Enhanced Method for Emergency Scheduling of Natural Gas Pipeline Networks Based on Heuristic Optimization

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Abstract: Safety and disturbance issues in system engineering have garnered substantial attention. This study focuses on the analysis of the distinct characteristics of emergency dispatch problems in Natural Gas Pipeline Networks (NGPS). Graph theory serves as a tool to transform the NGPS topology and establish an optimization model for NGPS emergency dispatch. The model also integrates user weights, satisfaction, and reduction factors into the user modeling approach. Its objective is to maximize overall system satisfaction while considering factors such as demand-side requirements and operational constraints. To solve this optimization model, the Particle Swarm Optimization (PSO) method is employed. An in-depth exploration of four unique disturbance scenarios provides solid evidence of the effectiveness and practicality of the PSO method. Compared to other methods, the PSO method consistently boosts overall user satisfaction and aligns more fluidly with the real-time demands of emergency scheduling, regardless of reduced supply capacity, complete supply interruptions, sudden surges in user demand, or pipeline connection failures. The developed emergency scheduling optimization method presents two key advantages. Firstly, it proficiently mitigates potential losses stemming from decreased supply capacity at local or regional levels. By adeptly adjusting natural gas supply strategies, it minimizes economic and production losses while ensuring a steady supply to critical users. Secondly, the method is superior at swiftly reducing the affected area and managing the increased demand for natural gas, thus maintaining NGPS stability. This research underscores the importance of considering user characteristics and demands during emergencies and demonstrates the effectiveness of employing the PSO method to navigate emergency scheduling challenges. By strengthening the resilience of the pipeline network and ensuring a sustainable natural gas supply, this study constitutes a significant contribution to energy security, economic development, and the promotion of clean energy utilization, ultimately propelling the achievement of sustainable development goals.

Keywords: natural gas supply assurance; emergency scheduling; user satisfaction; user reduction; optimization model

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1. Introduction

Natural gas is a globally utilized, clean, and efficient energy source that plays a crucial role in industries and commercial and residential areas. Ensuring the reliability and efficiency of natural gas supply, optimizing the production and operation processes of the Natural Gas Pipeline Network (NGPS) becomes paramount. However, a series of challenges associated with the optimization of emergency scheduling in the NGPS can limit the improvement of gas supply efficiency and transportation capacity following accidents.

The optimization of emergency scheduling in the NGPS requires addressing unforeseen circumstances. Sudden events, such as extreme weather, equipment failures, and supply interruptions, can have a severe impact on the NGPS [1]. In such emergency situations, the prompt development of effective scheduling plans is crucial to ensure the continuity and reliability of natural gas supply [2]. The formulation of optimized scheduling plans needs to consider various factors, including supply–demand balance and emergency requirements, to minimize the impacts of supply interruptions and reduce economic losses.

The accurate identification of critical users and the determination of supply prioritization are crucial issues involved in the optimization of emergency scheduling in NGPS [3]. Different users have diverse demands for natural gas and varying degrees of reliance on its supply. However, allocating the limited natural gas supply to effectively meet the needs of critical users poses a significant challenge. It is essential to carefully consider factors such as the industry nature of users, supply interdependencies, and their levels of importance. This approach ensures that the requirements of critical users are prioritized and fulfilled, especially in emergency situations.

Moreover, the scale and complexity of the pipeline network further contribute to the difficulty of optimizing emergency scheduling [4]. Large-scale pipeline networks consist of numerous interconnected nodes, pipelines, and connections, resulting in a considerable number of decision variables. Making scheduling decisions on a global scale requires a comprehensive understanding of the interactions and impacts among different network nodes to achieve overall optimization. Additionally, the complexity of pipeline network scheduling is influenced by various aspects of NGPS, including production, storage, transportation, and distribution [5,6].

In addressing the optimization problem within the NGPS, various approaches are commonly employed to solve the model. These approaches include mathematical programming methods [7], as well as heuristic algorithms [8], which have gained widespread application in the field of optimization. Heuristic algorithms, being optimization methods based on experience and heuristic rules, iteratively search for the optimal or approximately optimal solution to a given problem. Researchers have explored and implemented various heuristic algorithms to effectively tackle the optimization problems in NGPS. For instance, Mohsen [9] utilized Artificial Neural Networks (ANN) to model the natural gas transmission and distribution networks, thereby aiming to enhance the operational performance and stability of the gas pipeline network. Zhang [10] conducted a study using an improved Genetic Algorithm (GA) to develop an optimal operational model for NGPS. Through experiments, the study demonstrated the superior performance of the improved algorithm in terms of maximizing both profit and flow rate. Adarsh [11] employed an Ant Colony Optimization (ACO) strategy to minimize the operational costs of NGPS. This approach not only reduced costs, but also provided valuable guidance to pipeline managers in selecting the best solution. Abolfazl [12] optimized the NGPS by utilizing the Simulated Annealing Algorithm (SA), aiming to achieve the optimal pipeline operation strategy and energy distribution. These examples collectively showcase the successful utilization of heuristic algorithms in solving scheduling optimization problems. More details of practical application cases are shown in Table 1.

The aforementioned methods have demonstrated exceptional performance in various optimization problems. However, when it comes to emergency scheduling optimization in NGPS, several factors need to be considered:

(1) Complexity of NGPS: Scheduling optimization problems in NGPS often involve complex constraints with high dimensions. These problems require the comprehensive optimization of multiple factors, including supply–demand matching, pressure management, pipeline transport capacity, and operational costs. The inherent complexities of these problems make it challenging for traditional optimization methods to find global optimal solutions.

(2) Real-time requirements: NGPS operate in real-time and necessitate prompt scheduling decisions. ANN require extensive training and computation times, rendering them unsuitable for providing real-time scheduling strategies. Methods such as GA, ACO,

and SA typically involve a substantial number of iterations and search operations, making them less suitable for real-time emergency scheduling optimization in pipeline networks.

(3) Complexity and implementation difficulty of algorithms: Algorithms like ANN and GA possess high algorithmic complexity and implementation difficulty. They often require extensive parameter tuning and optimization and significant computational resources.

Table 1. Application of intelligent algorithms in various areas.

Objective	Applied Area	Solving Method	Reference
Minimize total costs	NGPS	Mixed Integer Linear Programming (MILP)	[5]
Maximize operational efficiency and gas delivery		Particle Swarm Optimization (PSO)	[13]
Minimize the total economic cost of the pipe network		ACO	[14]
Minimize the total cost of reliability	Power system	GA	[15]
Maximize the critical load of the grid		MILP	[16]
Minimize the cost of operation	Integrated energy system	MILP	[17]
Maximize meeting demands in emergencies		Linear Programming (LP)	[18]
Predict target displacements for mid-rise regular reinforced concrete buildings under various seismic risks	Construction field	PSO	[19]
Predict risk priorities for reinforced concrete buildings		GA-ANN	[20]

This study highlights the importance of meeting computational speed requirements, overcoming local optima traps, and swiftly identifying superior global optimal solutions in emergency scheduling optimization for NGPS. Simultaneously, it emphasizes the need to reduce the complexity of adjustment and optimization by selecting algorithms with comparatively simpler implementation processes and fewer algorithm parameters.

In the field of scheduling optimization, Particle Swarm Optimization (PSO) has been widely applied in various domains and achieved notable results. Here are some areas and examples where PSO has been used to solve scheduling optimization problems: Production scheduling optimization: PSO has been applied to optimize production scheduling in manufacturing industries, specifically in tasks such as workshop scheduling [21] and job sequencing [22]. By optimizing production schedules, it is possible to enhance production efficiency, reduce costs, and improve resource utilization. Energy scheduling optimization: PSO has been effectively utilized in optimizing the scheduling of energy systems, including power system [23] scheduling and hydrothermal power generation system [24] scheduling. By strategically planning the production, transmission, and distribution of energy, it is possible to achieve efficient energy utilization and ensure a reliable energy supply. Logistics scheduling optimization: PSO has found extensive applications in the logistics field, particularly in optimizing delivery routes and vehicle scheduling [25]. By optimizing logistics scheduling, it is possible to minimize transportation costs, shorten delivery times, and enhance overall logistics efficiency. Traffic scheduling optimization: PSO has been successfully employed in public transportation scheduling [26] and optimizing traffic signal systems [27]. By efficiently managing traffic flow and optimizing traffic signals, it is possible to alleviate traffic congestion, improve traffic efficiency, and enhance the overall travel experience.

Taking into account existing application cases, this paper proposes the application of PSO in the emergency scheduling of NGPS. The aim is to achieve the following objectives: (i) Reduce the complexity of scheduling problems—The optimization problem of NGPS scheduling involves multiple interconnected factors, such as supply–demand matching, pressure management, and pipeline transportation capacity. To address these complexities, PSO can perform a global search in the solution space by coordinating the search of particle positions. This optimization approach ensures efficient operation and resource utilization of NGPS. (ii) Meet real-time requirements: NGPS requires real-time scheduling decisions to respond to constantly changing supply–demand situations and network conditions. With its fast convergence speed and iterative updating capability, PSO enables rapid emergency scheduling optimization in real-time scenarios, effectively meeting the real-time requirements of NGPS. (iii) Adaptability and flexibility: The scheduling problems of NGPS may involve different constraints and objective functions, which can vary over time and under different conditions. PSO exhibits strong adaptability and flexibility, allowing parameter adjustments and optimization based on actual situations. This adaptability ensures effective scheduling optimization under diverse conditions. In summary, PSO offers several advantages for optimizing NGPS scheduling, including its global search capability, algorithm simplicity, good parallel performance, and robustness.

This article proposes an emergency scheduling optimization method aimed at enhancing the emergency response capability and supply efficiency of NGPS. The method serves as both a theoretical exploration and holds practical application potential. By optimizing the scheduling of natural gas demand during emergency situations and making real-time scheduling decisions based on the status of NGPS, our method can significantly improve the emergency response capability of the pipeline network, ensure the supply to critical users, and reduce economic losses caused by production interruptions.

The overall approach of this study involves a detailed analysis of the characteristics of NGPS and emergency scheduling issues. It establishes an NGPS model that considers user characteristics and incorporates the PSO for optimization, resulting in an optimized emergency scheduling strategy. The effectiveness and practicality of the method are validated through case studies.

Ultimately, the goal of this study is to ensure the stability and sustainability of natural gas supply. This outcome is not only significant for energy security and economic development, but also beneficial for promoting and applying clean energy, thereby contributing to the achievement of sustainable development goals.

2. Methodology

To effectively solve the optimization problem of NGPS, it was crucial to precisely define the optimization goal, construct a suitable mathematical model, and select an appropriate solution method. The analysis and application of the optimization results could then guide the scheduling decisions for the practical pipeline network, leading to improved gas supply efficiency and operational performance of NGPS. Figure 1 illustrates the comprehensive workflow of emergency scheduling optimization in NGPS.

NGPS need to consider user characteristics because different types of users have varying needs and importance for natural gas supply. Users could be categorized into four groups: residential, commercial, industrial, and peak-shaving [3]. Assigning different weights to each user type could reflect their criticality in the emergency scheduling process of NGPS. The weight value could be quantitatively determined by taking into account factors such as the user's gas consumption scale, usage patterns, characteristics, and importance.

To prioritize the welfare of the population, China mandates that residential gas supply has the highest priority. However, certain industrial users can reduce their reliance on NGPS by decreasing or temporarily suspending their gas demand during emergency situations, thus warranting a lower weight assignment. The reduction in natural gas supply that users can accommodate during emergencies is referred to as user reduction. Based on the operational experience of NGPS, implementing appropriate user reduction measures can effectively minimize the loss of gas supply. The order of reduction, from least to most affected, is as follows: residential users, key infrastructure; automobiles (excluding public transportation) and commercial users; select power generation and industrial users; LNG plants, chemical fertilizers, and chemical users.

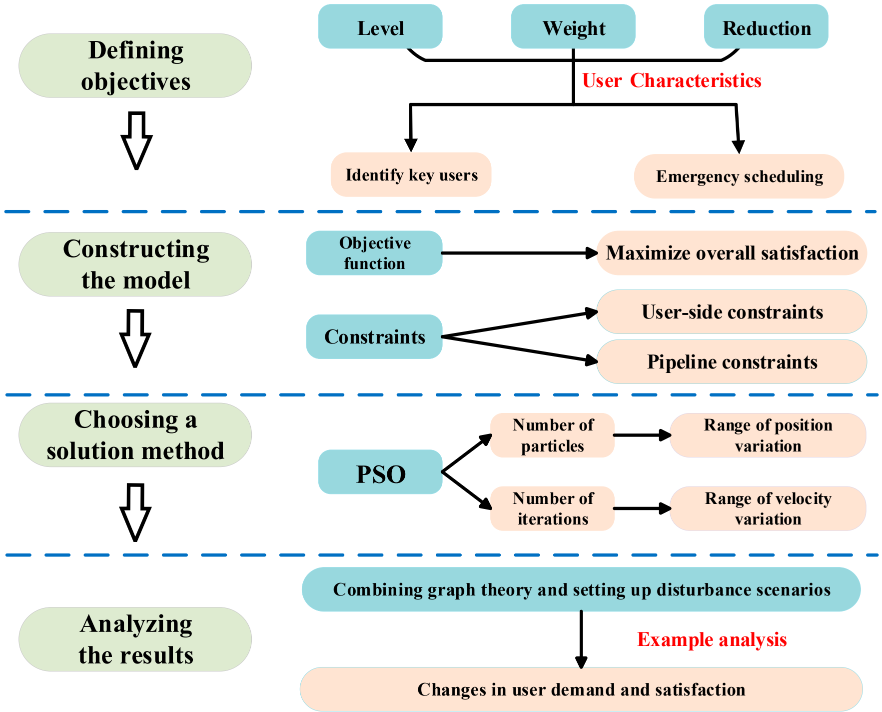


Figure 1. The process of the emergency scheduling optimization method.

By comprehensively considering user characteristics and weight values, natural gas resources could be more efficiently allocated. By reducing gas supply to secondary users, the gas supply for critical users and those with critical demand could be ensured. Such a strategy enabled effective emergency response, ensuring the gas supply capacity and stable operation of the pipeline network.

This paper incorporated the concepts of user classification, weights, and satisfaction, considering the characteristics of different users. It divided different users into the following levels, as shown in Figure 2. The first level of users included residential users, hospitals, schools, welfare institutions, etc., which had the highest importance. The maximum allowable reduction for these users was 0% of their demand, and the user weight was set at 5. The second level of users comprised commercial and some industrial users, with slightly lower importance compared to the first type. The maximum allowable reduction for this type of users was 10% of their demand, and the user weight was set at 4. The third level consisted of industrial users, with a maximum allowable reduction of 10–50% of their demand, and the user weight was set to 3. The fourth level included energy substitutable users or interruptible users, which had the lowest importance. The maximum allowable reduction for this type of user was 100% of their demand, and the user weight was set at 2 or 1.

Furthermore, user satisfaction was defined as the ratio of practical gas supply to user demand. The range of user satisfaction was determined based on the reducible amount for different types of users. A lower user satisfaction level indicated a reduced actual gas supply to the user. It was important to note that unexpected events could cause disruptions that lead to extreme cases of complete loss of gas supply capacity at certain nodes. In such cases, user satisfaction at other nodes could also be partially or completely lost. It was crucial to consider situations in which there was a significant decrease or complete loss of user satisfaction. A large number of low user satisfaction levels could have a detrimental impact on the production and operation of NGPS. Additionally, it was absolutely unacceptable for critical users to experience a complete loss of satisfaction, as this would result in severe economic losses.

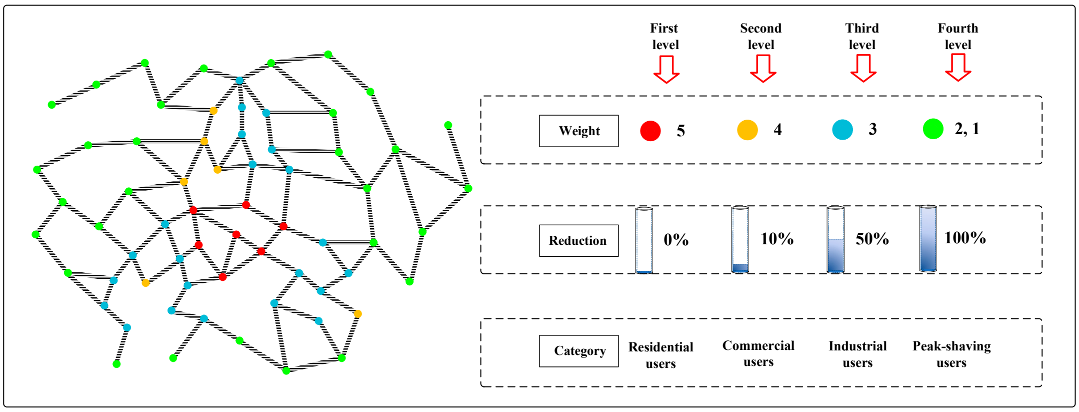


Figure 2. The classification of users [3].

Based on the PSO process depicted in Figure 3, it could be inferred that the PSO studied in this paper considered a search space of D dimensions with a total of N particles. The position of particle i is denoted as $X_i = (X_{i1}, X_{i2}, \ldots\ldots, X_{iD})$. In PSO, X_i is substituted into the fitness function $f(X_i)$ to obtain the fitness value. The velocity of particle i is represented as $V_i = (V_{i1}, V_{i2}, \ldots\ldots V_{iD})$. The best position experienced by the individual particle i is denoted as $pbest_i = (p_{i1}, p_{i2}, \ldots\ldots p_{iD})$, while the best position experienced by the entire population is denoted as $gbest = (g_1, g_2, \ldots\ldots g_D)$. In each iteration, the d-dimensional velocity update formula of particle i contained three terms. The first term was the previous velocity of particle i; the second term was the 'cognitive' part of the particle's thinking about its own state, which could be interpreted as the distance between the current position of particle i and its own best position; and the third term was the information shared between particles, which could be interpreted as the distance between the current position of particle i and the best position of the group.

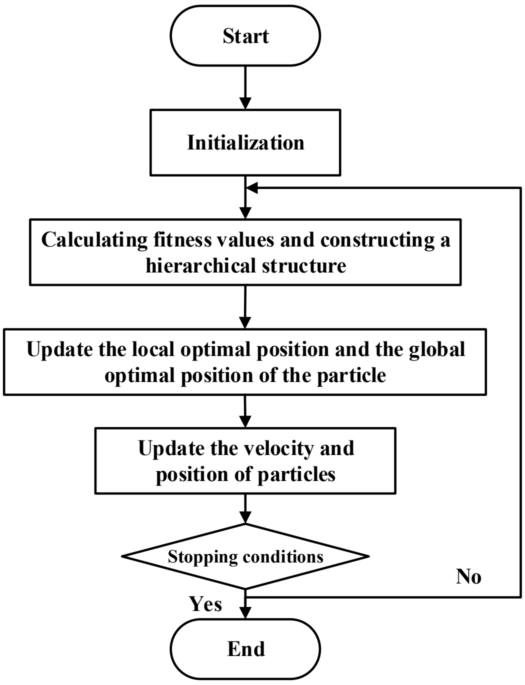


Figure 3. The process of particle swarm algorithm [28].

The velocity V_i update formula used during the iteration process was as follows:

$$V_{id}^{k} = WV_{id}^{k-1} + C_1 r_1 (pbest_{id} - X_{id}^{k-1}) + C_2 r_2 (gbest_d - X_{id}^{k-1}) \tag{1}$$

The position X_i update formula used during the iteration process was as follows:

$$X_{id}^{k} = X_{id}^{k-1} + V_{id}^{k-1} \tag{2}$$

where X_{id}^{k} is the d-dimensional component of the position vector of particle i in the kth iteration, and V_{id}^{k} is the d-dimensional component of the velocity vector of particle i in the kth iteration. C_1 and C_2 are acceleration constants that regulate the maximum learning step. r_1 and r_2 are random functions that take values in the range [0, 1], introducing search randomness. W is the inertia weight, a non-negative parameter that regulates the search range of the solution space.

Typically, the range of position variation in the dth dimension ($1 \leq d \leq D$) was limited to $[X_{\min,d}, X_{\max,d}]$, and the range of velocity was limited to $[-V_{\max,d}, V_{\max,d}]$. This observation meant that if the velocity or position of a certain dimension exceeded the boundary values, it would be constrained to the maximum velocity or boundary position of that dimension.

3. PSO Modeling

3.1. Objective Function

Emergency scheduling optimization measures are implemented to ensure the gas supply capacity of NGPS while aiming to maximize overall user satisfaction. The paper focuses on optimizing emergency scheduling strategies to achieve this goal. Overall user satisfaction is measured by considering various factors, including the degree of supply satisfaction and the importance of the user. By adjusting the gas supply strategy, the aim is to meet the user's needs to the fullest extent possible. Additionally, the importance of each user is a crucial factor that needs to be taken into consideration.

$$F = \sum_{i=1}^{N} \omega_i \frac{Q_{si}}{Q_{di}} \tag{3}$$

where ω_i is the weight of ith user; Q_{si} is the actual gas supply of ith user, 10^4 m^3/d; and Q_{di} is the demand of ith user, 10^4 m^3/d.

3.2. Constraints

When solving the problem of emergency scheduling optimization, researchers must take into account various constraints, including user-side constraints and pipe network constraints. These constraints must be satisfied during the optimization process to ensure the feasibility and rationality of the scheduling solution.

User-side constraints encompass actual supply, user reduction, and user satisfaction. The actual supply constraint ensures that each user receives an appropriate amount of gas to prevent oversupply. The user reduction constraint sets a maximum acceptable reduction for each user. Additionally, the user satisfaction constraint can be defined within a specific range to ensure that it meets the minimum requirements.

In addition to the user-side constraints, it is crucial to consider pipe network constraints. These constraints pertain to pipe network operation parameters, such as pipe flow, pressure, and capacity. For instance, the pipeline flow rate should not exceed its maximum capacity to avoid overloading. Maintaining the pressure of the pipeline network within the appropriate range is essential for ensuring the stability and safety of the gas supply. The pipe network condition constraints guarantee the effectiveness and reliability of the pipe network operation.

The user-side constraints are as follows:

$$S_{\min} \leq \frac{Q_{si}}{Q_{di}} \leq 1.0 \left(i = 1, 2, 3, \ldots N\right) \tag{4}$$

$$Q_{si} = Q_{ssi} + Q_{gci} + Q_{stoi} - Q_{ri} \tag{5}$$

$$\sum_{i}^{N} Q_{\mathrm{r}i} = C_{\mathrm{r}} \tag{6}$$

$$Q_{\mathrm{r}i\mathrm{min}} \leq Q_{\mathrm{r}i} \leq Q_{\mathrm{r}i\mathrm{max}} \tag{7}$$

where S_{min} denotes the minimum satisfaction of the ith user; N is the number of user nodes; $Q_{\mathrm{ss}i}$ denotes the gas supply at the ith user, 10^4 m^3/d; $Q_{\mathrm{gc}i}$ denotes the volume of gas taken out of the ith pipeline storage, 10^4 m^3/d; $Q_{\mathrm{sto}i}$ denotes the gas extraction from gas storage at node i, 10^4 m^3/d; $Q_{\mathrm{r}i}$ denotes the user reduction at the node ith, 10^4 m^3/d; $\mathrm{C_r}$ denotes the total amount of gas reduction, 10^4 m^3/d; Q_{ri} denotes the reduction at the ith user, 10^4 m^3/d; $Q_{\mathrm{r}i\mathrm{min}}$ denotes the minimum reduction at the ith user, 10^4 m^3/d; and $Q_{\mathrm{r}i\mathrm{max}}$ denotes the maximum reduction at the ith user, 10^4 m^3/d.

Equation (1) represents the constraint for ensuring user gas supply satisfaction. During the natural gas supply process, a minimum satisfaction requirement is established as the lower limit for each user, guaranteeing a certain level of user satisfaction. In other words, no user should experience satisfaction below this threshold. An essential user-side constraint is the adherence to the actual gas demand, ensuring that it does not surpass the required amount. This process entails matching the gas supply to the users' actual demand, avoiding oversupply or undersupply to maintain the stable operation of NGPS.

Equation (2) represents the actual gas supply constraint, which is derived from the total amount of gas stored in the gas source, storage, and pipelines minus the user reduction. This constraint ensures the proper allocation and efficient use of natural gas supply required to meet the users' overall demand. When the gas supply is sufficient to meet the users' demand, there is no need for the users' natural gas supply to rely on gas stored in storage and pipelines. However, if the gas supply cannot meet the users' demand, the users will rely on the gas stored in reservoirs and pipelines for their natural gas supply. In such cases, the gas stored in storage and pipelines is deployed to bridge the supply gap and fulfill the natural gas demand of users.

Equations (3) and (4) represent user reduction constraints, which address issues such as emergencies and gas shortages in the natural gas supply. These constraints help to identify the sources of natural gas to be used for scheduling. In the event of a contingency, the natural gas operator must uniformly plan to ensure that the sum of all user reductions equals the total planned reduction. Additionally, each user has an interval range for their reduction, meaning that the level of reduction may vary based on the user type and their natural gas demand situation. The purpose of these constraints is to allocate natural gas resources in a rational manner, prioritizing the needs of people's livelihoods and critical infrastructure during supply shortages.

The pipeline constraints are as follows:

$$\sum_{i}^{N} Q_{\mathrm{in}-i} = \sum_{i}^{N} Q_{\mathrm{out}-i} \tag{8}$$

$$Q_{\mathrm{sto}i} \leq C_{\mathrm{sto}i} \cdot V_{\mathrm{sto}i} \tag{9}$$

$$Q_{\mathrm{gc}i} \leq C_{\mathrm{gc}i} \cdot V_{\mathrm{gc}i} \tag{10}$$

where $Q_{\mathrm{in}-i}$ denotes the gas inlet at node ith, 10^4 m^3/d; $Q_{\mathrm{out}-i}$ denotes the gas outlet at node ith, 10^4 m^3/d; $C_{\mathrm{sto}i}$ denotes the maximum extraction factor at the gas storage ith; $V_{\mathrm{sto}i}$ denotes the gas storage at storage ith, 10^4 m^3/d; $Q_{\mathrm{gc}i}$ denotes the line-pack extracted by the node ith, 10^4 m^3/d; $C_{\mathrm{gc}i}$ denotes the line-pack extraction coefficient of the node ith; and $V_{\mathrm{gc}i}$ denotes the line-pack of the node ith, 10^4 m^3/d.

Equation (6) represents a node flow balance constraint, which ensures that at any node of NGPS, the flow rate of the inflow node is equal to the flow rate of the outflow node.

Equation (7) represents a storage reservoir constraint. In situations where the natural gas supply cannot meet user demand, natural gas from the storage reservoir is used to bridge the supply gap. However, to maintain the proper functioning and storage capacity of the reservoir, a portion of the natural gas is reserved as bedding gas volume. This volume of bedding gas is essential for maintaining stable pressure and volume within the storage reservoir. During times of supply constraint, this reserved bedding gas volume cannot be withdrawn to avoid excessively depleting the reservoir, which could lead to issues such as pressure drop or volume reduction. This constraint ensures the reliability and stability of the natural gas supply while maintaining the operational efficiency and safety of the storage reservoir.

Equation (8) represents the line-pack constraint. When the natural gas supply is insufficient to meet user demand, the gas stored in the pipeline, known as line-pack, can be used as a supplement. To ensure the normal operation and stability of the pipeline system, a certain amount of line-pack is maintained. However, the variation in the pumped line-pack is limited to within 3% of the available line-pack over a specific period. By controlling the range of variation in the line-pack, the pumped amount can be effectively managed, guaranteeing the operational safety and reliability of the pipeline system.

3.3. Model Solving

The PSO involves several key parameters. These parameters include the population size (N), inertia weight (w), individual learning factor (C_1), social learning factor (C_2), and maximum number of iterations. The settings of these parameters play a crucial role in determining the algorithm's performance and convergence speed. Specifically, the individual learning factor (C_1) and social learning factor (C_2) are responsible for updating the particle's position based on its personal best solution and the group's best solution, respectively. These factors determine the balance between individual experience and group cooperation, and their values range from 0 to 3.

Hyperparameter optimization is one of the difficult aspects of current research into the data-driven method [29]. A reasonable setting of hyperparameters can remarkably improve the performance of the model. The grid search mechanism [30] is employed to conduct a sensitivity analysis of these hyperparameters.

In Figure 4, increasing the particle size enhances the algorithm's exploratory capability and enables it to cover a wider search space. However, larger particle sizes can also lead to higher computational costs and slower convergence. To strike a balance between reducing these drawbacks and ensuring accurate estimations, particle sizes of 500, 1000, and 1500 are tested. Higher inertia weights facilitate global exploration but may result in particles skipping the optimal solution. Conversely, lower inertia weights prioritize local search and convergence but may trap the algorithm in local optima. In this study, inertia weights of 0.3, 0.5, 0.7, and 0.9 are evaluated. The results indicate that the model's performance is scarcely affected by the hyperparameter values, demonstrating its robustness. Optimal optimization performance is achieved when the particle size is set at 1000 and the inertia weight is set at 0.5.

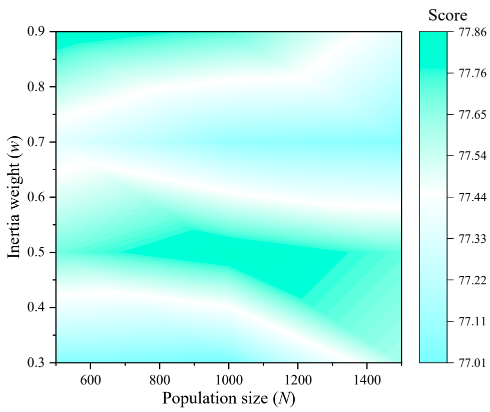


Figure 4. Performance evaluation with inertia weight and population size.

In practical applications, it is often difficult to estimate the minimum value of the fitness function in advance. A common approach is to set a maximum number of iterations to terminate the PSO. However, a high value for the maximum number of iterations significantly increases the computational burden. To address this issue, this paper introduces a new iteration termination condition called the maximum stagnation count. The parameter P_a^s is used as a criterion to assess whether the particle population is concentrated near the minimum value, with a fixed value of 0.0001. After each iteration update of the particle population, the state of P_a^s is checked for any changes. If P_a^s has changed, the stagnation count is reset to zero. Conversely, if P_a^s remains unchanged, the stagnation count is incremented. The iteration process is concluded when the stagnation count surpasses the maximum stagnation count. Figure 5 presents the iteration process for four different scenarios. The number of iterations depends on the problem's complexity and the algorithm's convergence speed. For instance, when optimizing the emergency scheduling of NGPS of various scales, the iteration is typically terminated after 20 to 40 versions in this model.

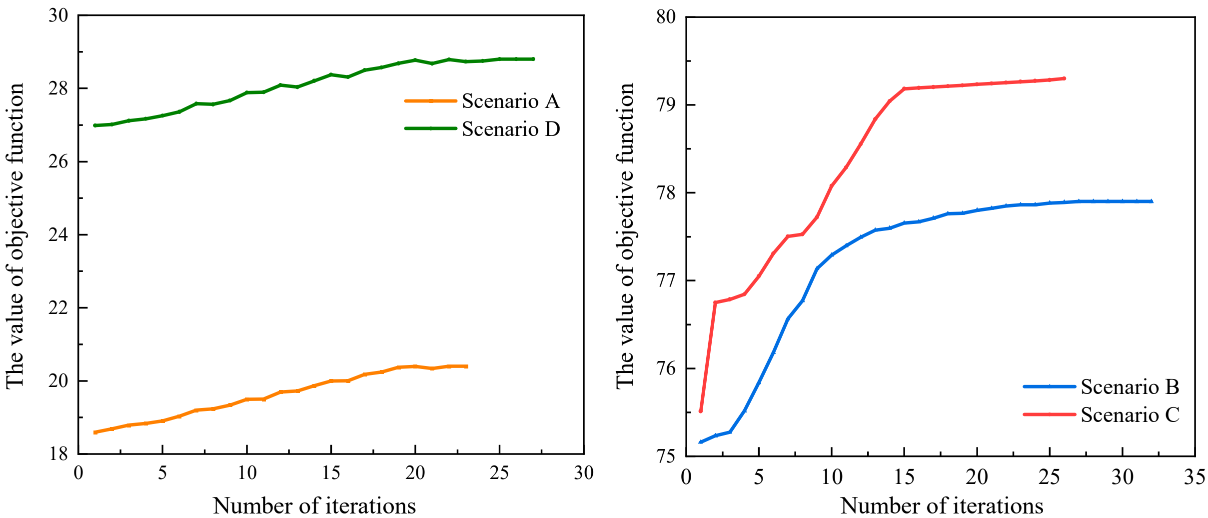


Figure 5. The iterative process in four different scenarios.

4. Numerical Example and Discussion

4.1. NGPS Example

Graph theory is a mathematical tool used to study the relationships between nodes and edges in a graph or network. By employing methods from graph theory, we can effectively model and analyze the physical topology and node characteristics. In the context of NGPS, nodes can represent various components, such as natural gas supply stations and user nodes, while edges symbolize the connections between the natural gas pipelines. Following the assumption of graph theory $G = (N, L)$, where N is the set of n nodes, and L is the set of edges consisting of k pipes, the volume flow rate from node j to node k is denoted as Q_{jk}. By constructing a topological diagram of the pipeline network, we can create a graphical model that facilitates the modeling and analysis of the NGPS.

To assess the feasibility of this research method, we selected a pipeline network system in China. In order to streamline the analysis, we simplified the NGPS by representing it as a topology solely comprising nodes and edges. The pipeline network system encompasses 35 nodes, categorized into two types: user nodes and gas source nodes (S1, S2, LNG, and UGS), as shown in in Figure 6. Table 2 presents the node connections, user demands, and other fundamental parameters.

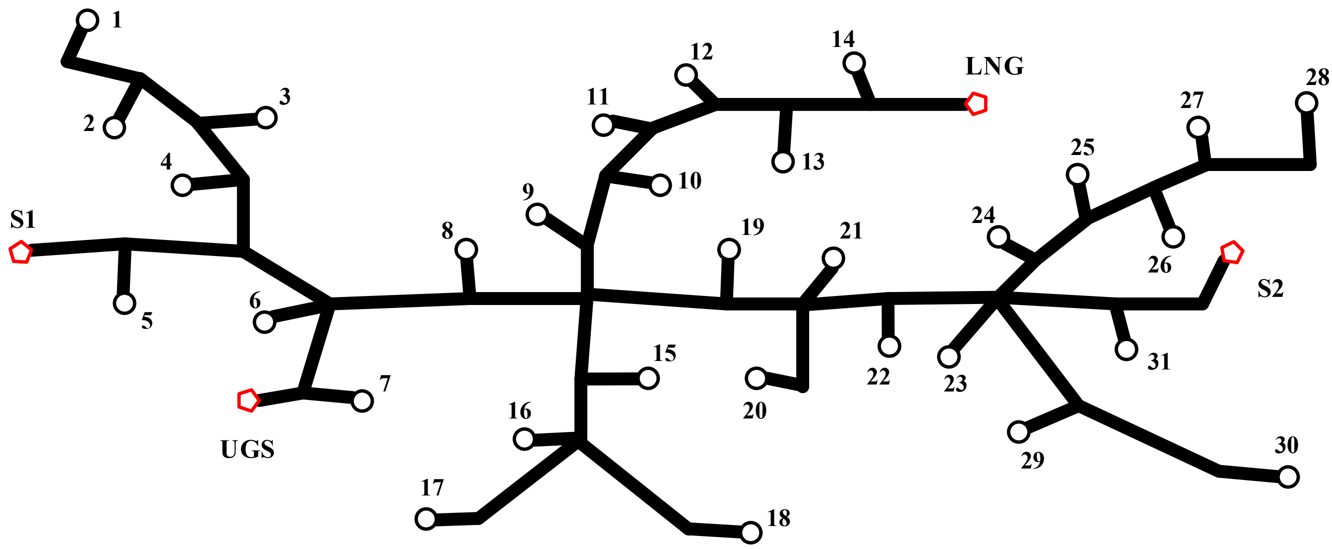


Figure 6. Topology of NGPS [31].

Table 2. Parameters of NGPS.

Node	Source	Demand	Weight	Node	Source	Demand	Weight
1	S1	43.2	1	17	S1	68	4
2	S1	23.2	1	18	S1	43	3
3	S1	33.4	4	19	S2	81	5
4	S1	27.4	1	20	S2	65	1
5	S1	12.4	1	21	S2	74	2
6	S1	73	3	22	S2	53	5
7	S1	12	3	23	S2	12	5
8	S1	99	4	24	S2	70	3
9	LNG	83	1	25	S2	21	4
10	LNG	42	4	26	S2	17	3
11	LNG	74	3	27	S2	24	1
12	LNG	84	5	28	S2	73	3
13	LNG	63	5	29	S2	17	2
14	LNG	76	5	30	S2	24	2
15	S1	53	4	31	S2	93	1
16	S1	88	2				

In conjunction with the research conducted in this paper, we examined the following four disturbance scenarios:

A. Decrease in the gas supply capacity of S1 to 50% of its original capacity;

B. Complete halt in gas supply capacity from S2 (reduced to 0%);

C. A 50% increase in gas supply demand from Level 1 and Level 2 users;

D. Failure in the connection between pipe sections 8 and 15.

4.2. Results and Discussion

This study shows the changes in the practical gas supply and satisfaction of user nodes in the affected area before and after optimization. Figures 7–9 illustrate the actual gas supply variations for different user nodes in the affected areas before and after optimization.

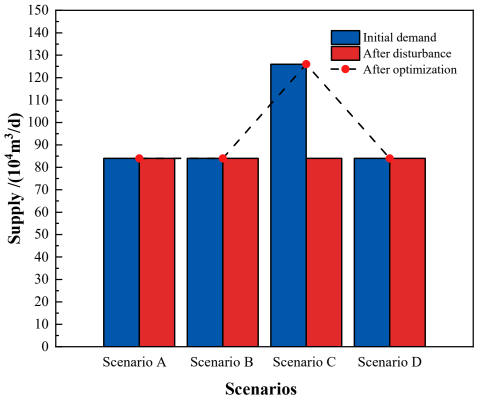


Figure 7. The gas supply of node 12 under different scenarios.

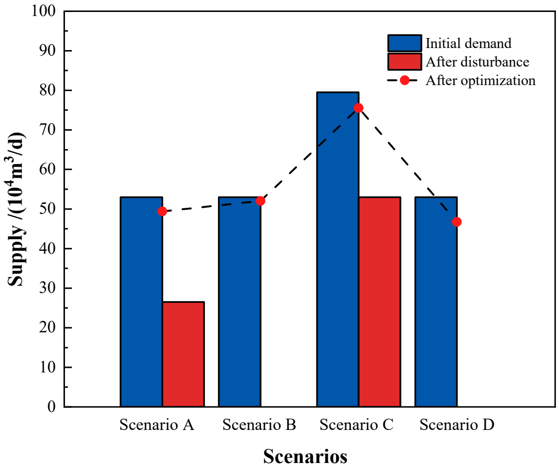


Figure 8. The gas supply of node 15 under different scenarios.

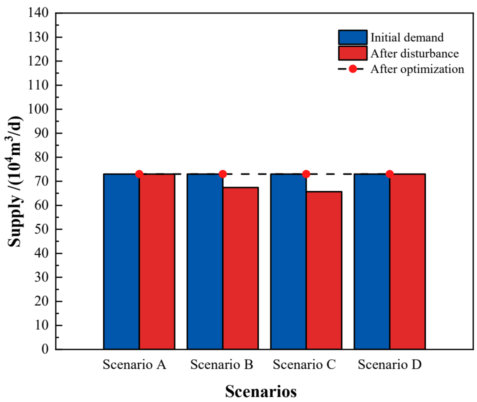


Figure 9. The gas supply of node 28 under different scenarios.

Scenarios B and D lead to the complete deprivation of natural gas supply for certain users. This outcome results in severe consequences for the production and operation of the natural gas pipeline network. These scenarios cause significant disruptions to critical nodes, potentially leading to interruptions in gas supply and posing substantial challenges to the stability and operational efficiency of the pipeline network. However, the disturbance in Scenario C arises from a sudden drop in winter temperatures, which causes a sharp increase in natural gas consumption. Managing this situation requires flexible adjustments to the gas supply plan to meet peak-period user demands while ensuring overall system stability and balance.

In contrast, the impact of Scenario A primarily affects the user group relying on S1 gas source supply. Although seemingly less severe, the needs and satisfaction of this user group should not be disregarded. Since NGPS operates with one-way capability, scheduling can only be conducted within the supply range of S1. During this process, operators must precisely control the gas supply plan to ensure the fulfillment of user needs and optimize gas supply efficiency.

Figure 10 demonstrates the adjustments in Scenario A, where NGPS operates with a one-way capacity. The emergency scheduling optimization for this scenario only considers the coordination among users within S1's supply range. The general trend reveals that the proposed emergency scheduling optimization method focuses on reducing the gas consumption of low-level users to ensure a continuous gas supply for high-level users, given the decrease in the gas source's supply capacity.

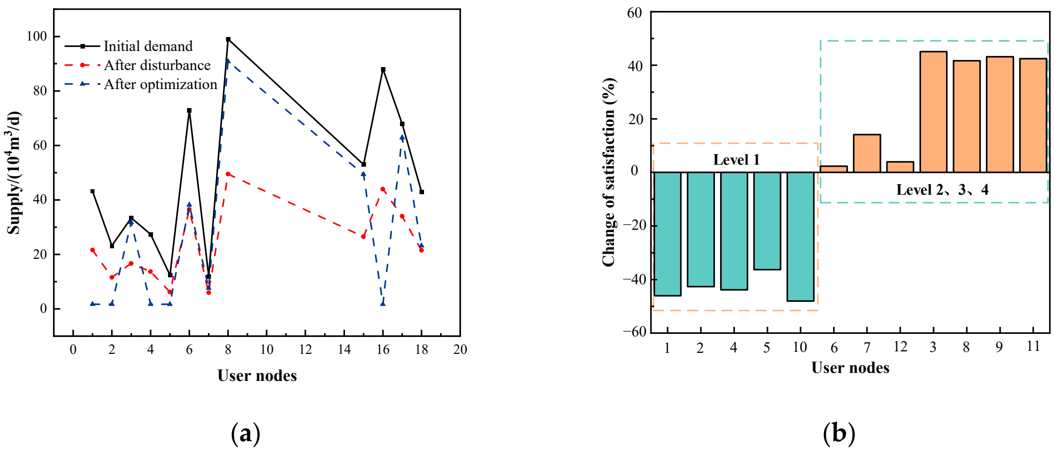


Figure 10. Changes in user supply and satisfaction in Scenario A. (**a**) Changes in user supply. (**b**) Changes in user satisfaction.

Figure 11 presents the modifications occurring in Scenario B. Here, the cessation of the gas supply from S1 necessitates the consideration of alternative gas sources, like S2 and Liquefied Natural Gas (LNG), for users within S1's range. This scenario allows the reduction in gas supply from user nodes with high demand at the same level without significantly impacting the overall trend. This strategy ensures the standard gas supply to high-priority users and maintains a stable gas supply for as many users as possible within the same levels.

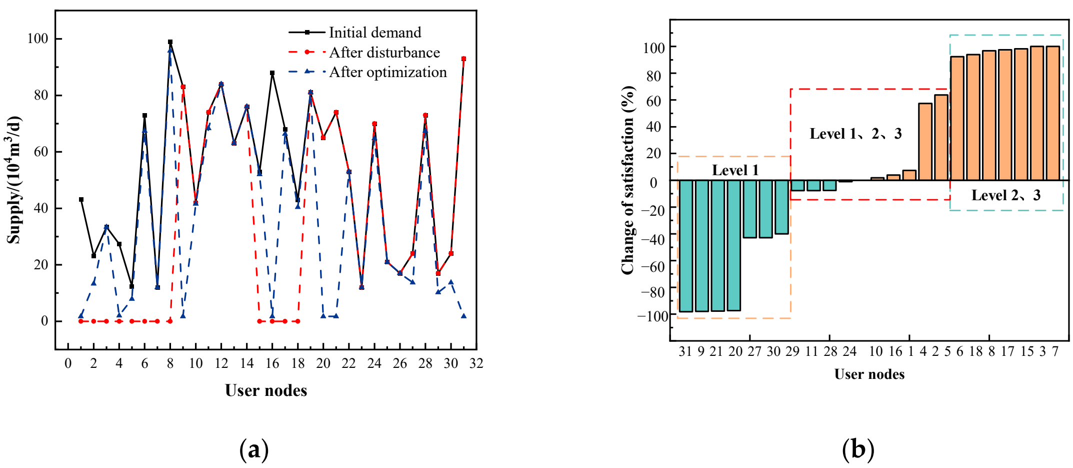
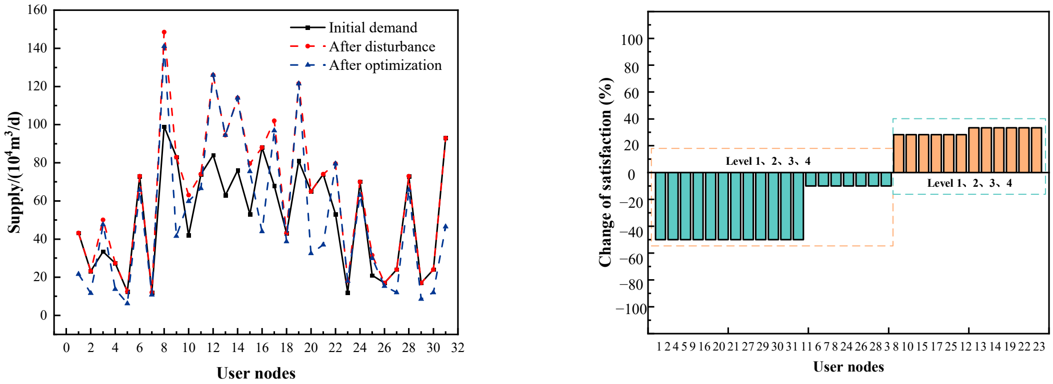


Figure 11. Changes in user supply and satisfaction in Scenario B. (**a**) Changes in user supply. (**b**) Changes in user satisfaction.

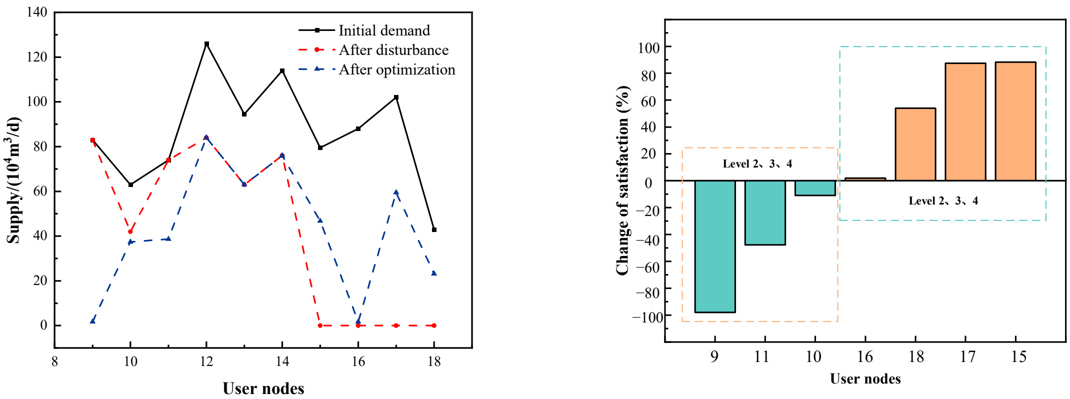
Figure 12 portrays the alterations in Scenario C. Without emergency scheduling measures, the satisfaction levels for all users in Level 1 and Level 2 of the natural gas pipeline system would plummet to 66.7% of the original level. In contrast to the first two disturbance scenarios, Scenario C introduces emergency scheduling following a surge in user demand.



(**a**) (**b**)

Figure 12. Changes in user supply and satisfaction in Scenario C. (**a**) Changes in user supply. (**b**) Changes in user satisfaction.

Figure 13 depicts the changes in Scenario D. In this disturbance scenario, the satisfaction levels for user nodes 15–18 drop to zero. These nodes, originally supplied by S1, are regarded as connected to the LNG gas supply following the failure of the pipe section.



(**a**) (**b**)

Figure 13. Changes in user supply and satisfaction in Scenario D. (**a**) Changes in user supply. (**b**) Changes in user satisfaction.

Emergency scheduling measures are integral in terms of maintaining user satisfaction for those supplied by S1, as their satisfaction would markedly decrease without these measures. The optimization method accounts for user criticality and demand variations, enhancing satisfaction for high-level users while still catering to low-level users. The results highlight the importance of considering the individual characteristics and demands of users during emergency scheduling situations. Moreover, the successful restoration of a stable gas supply for higher-weight users within S1's range is achieved by considering alternative gas sources, such as S2 and LNG, during gas source disruption. Given the varying demands of users at different levels, scheduling optimization might increase satisfaction for some users while decreasing it for others. The optimization method factors increased user demand during winter, a crucial determinant in maintaining user satisfaction with gas supply. Without emergency scheduling measures, both Level 1 and Level 2 users would face a significant decline in satisfaction. However, the application of the emergency scheduling method, prioritizing users with lower demand, effectively mitigates this decline. This approach underscores the importance of considering demand variations in emergency scheduling optimization to maintain user satisfaction during periods of heightened consumption. Lastly, the results underscore the importance of alternative gas sources. While LNG supply partially compensates, Level 4 users still face a reduction in gas supply. This issue highlights the necessity of considering alternative gas sources and user weights during emergency scheduling optimization to ensure user satisfaction amid severe disturbances.

Based on the insights garnered from Table 3, it is evident that the PSO method applied in this study successfully achieves emergency scheduling optimization for NGPS. This result aligns with the effectiveness criteria for solving practical engineering problems. Across four distinct disturbance scenarios, heuristic algorithms consistently enhance overall user satisfaction. The approach proposed in this paper delivers superior performance in terms of numerical results compared to the GA, SA, and ACO methods. Furthermore, our method exhibits faster convergence, aligning better with the real-time requirements of emergency scheduling in natural gas networks.

Table 3. The comparison of several heuristic optimization methods.

Scenario	Initial	Objective Function				Convergence Time (s)			
		PSO	**GA**	**SA**	**ACO**	**PSO**	**GA**	**SA**	**ACO**
A	15.5	20.416	20.135	20.21	20.365	20.576	26.379	23.676	20.156
B	60	77.862	77.316	77.416	77.495	21.233	29.195	27.159	21.125
C	73	79.297	79.015	79.384	79.232	21.792	23.646	21.346	22.258
D	23	28.023	27.845	28.126	27.964	20.217	22.154	21.675	20.897

Figure 14 depicts the variation in the objective function before and after optimization. The red, light blue, dark green, and dark blue cylinders represent scenarios A, B, C, and D, respectively. Compared to scenarios without emergency scheduling optimization measures, the overall user satisfaction for these scenarios witnessed improvements of 31.6%, 29.8%, 8.6%, and 25.2%, respectively. These results validate the positive influence of the emergency scheduling optimization approach on overall user satisfaction across all four scenarios. The different degrees of satisfaction improvement in each scenario underscore the flexibility and adaptability of the optimization method, proving its effectiveness in terms of addressing various disturbance scenarios in the NGPS.

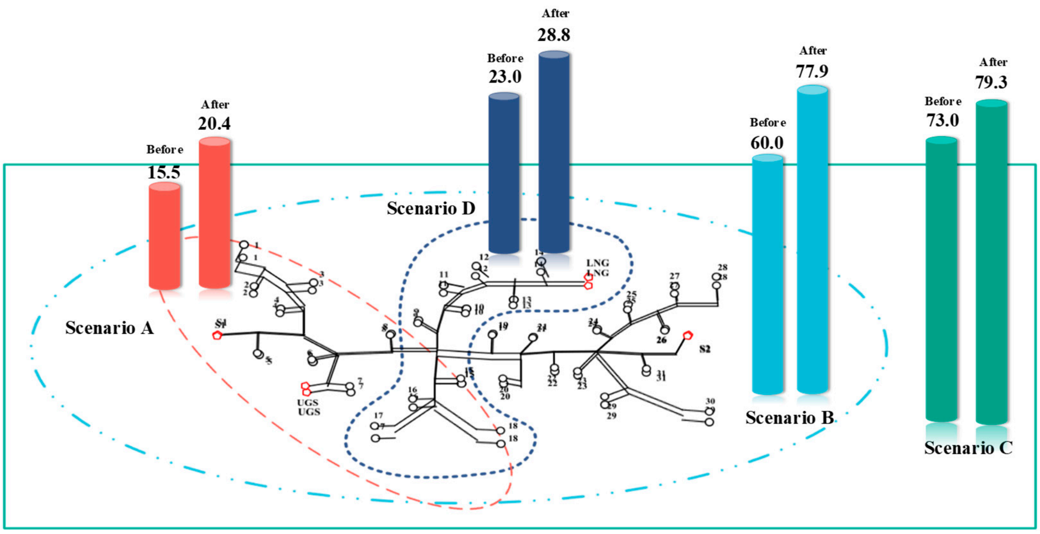


Figure 14. Change in overall satisfaction before and after optimization.

On the whole, the emergency scheduling optimization method in this study offers two key advantages: Firstly, it can reduce local or overall regional losses resulting from disturbances when the supply capacity of gas sources decreases. By efficiently allocating resources and optimizing scheduling decisions, the method helps to minimize the negative impacts of disruptions, contributing to the resilience and sustainability of NGPS operations. Secondly, it can minimize the impact area in a short period of time while maintaining the steady operation of NGPS in response to increased user demand. This capability ensures that the NGPS can effectively meet the growing energy needs of users while minimizing environmental and social consequences. By improving the overall performance, resilience, and sustainability of NGPS through emergency scheduling optimization, this study provides solutions for the efficient and sustainable management of natural gas supply systems.

5. Conclusions

This study delves into the emergency scheduling optimization problem of Natural Gas Pipeline Networks (NGPS). Our objective is to guarantee a stable supply of natural gas during emergencies and maximize user satisfaction. To address this complex issue, we utilize the Particle Swarm Optimization (PSO) method. Through a comprehensive examination of four unique disturbance scenarios, we validate the efficacy and practicality of the PSO method. Whether confronting diminished supply capacity, total supply interruptions, sudden spikes in user demand, or pipeline connection failures, the PSO method consistently enhances overall user satisfaction. It outperforms other methods, like the Genetic Algorithm (GA), Simulated Annealing (SA), and Ant Colony Optimization (ACO), in numerical outcomes. Moreover, it is adept at fulfilling the real-time demands of emergency scheduling, making PSO a powerful tool for managing emergency situations in natural gas supply.

To summarize, the emergency scheduling optimization method developed in this study presents two primary advantages. Firstly, it curbs potential losses that may occur when the supply capacity decreases, whether on a local or regional scale. By skillfully adjusting natural gas supply strategies, we can minimize potential economic and production losses while ensuring a constant supply of natural gas to crucial users. Secondly, this method excels at swiftly reducing the size of the affected area and managing the escalated demand for natural gas, which assists in maintaining the stability of the NGPS.

This study accentuates the importance of considering user characteristics and demands during emergencies. It also underscores the effectiveness of employing the PSO method to address emergency scheduling challenges. Through the proposed approach, we not only enhance the resilience of the pipeline network, but also ensure the sustainability of the natural gas supply. This approach is crucial for energy security, economic development, and the promotion of clean energy utilization, thereby contributing to the achievement of sustainable development goals.

In conclusion, this research provides a robust method and solution for the emergency scheduling of NGPS, making a significant contribution to the reliability and stability of the natural gas supply. Expected to serve as a valuable reference and guide, this research aims to facilitate further investigations and practical applications in related fields. This study will ultimately contribute to the advancement of clean energy and the realization of sustainable development goals.

6. Further Research

In addition to the PSO algorithm used in this study, future research can further explore advanced optimization algorithms to address the decision problems under investigation. For example, customized heuristics and meta-heuristic algorithms, adaptive algorithms, island algorithms, multimodal algorithms, and hyper-heuristic algorithms are of significant importance in terms of solving challenging decision problems. These algorithms have already been successfully applied in multiple domains, such as online learning, scheduling, multi-objective optimization, transportation, medicine, and data classification. Existing research has demonstrated the effectiveness of these advanced optimization algorithms in other fields while also showcasing their potential applications in our research into decision problems. For instance, the adaptive fast fireworks algorithm has shown excellent performance in efficiently solving large-scale optimization problems [32], while the adaptive multimodal fusion algorithm has successfully been applied to truck scheduling problems at cross-docking terminals [33]. Moreover, in a multi-objective setting, precise algorithms and meta-heuristic algorithms have been used for the vehicle routing problem with factories in containers [34]. A hybrid approach based on genetic algorithms and simulated annealing has achieved significant performance improvements in medical image segmentation [35], and ant colony algorithms have been successfully applied to power system scheduling problems [36]. Combinatorial optimization algorithms based on genetic algorithms and simulated annealing have demonstrated outstanding performance in data mining [37]. Therefore, further research into the application of advanced optimization algorithms in decision problems is of great significance, as it is expected to provide a deeper understanding of and more practical contributions to our field of research.

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