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Application of Strength Pareto Evolutionary Algorithm II in Multi-Objective Water Supply Optimization Model Design for Mountainous Complex Terrain

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Abstract: Water distribution networks (WDN) model optimization is an important part of smart water systems to achieve optimal strategies. WDN optimization focuses on the nonlinearity of the discharge head loss equation, the availability of discrete properties of pipe sizes, and the conservation of constraints. Multi-objective evolutionary algorithms (MOEAs) have been proposed and successfully applied in the field of WDN design optimization. Previous studies have focused on comparing the optimization effects of algorithms in water distribution networks, ignoring the problems of unbalanced pressure distribution and water hammer at the nodes of the pipe network caused by the complex terrain in mountainous areas. In this paper, a multi-objective water supply optimization model that integrated cost, reliability, and water quality was established for a mountainous WDN in real engineering. The method of traversing the nodes to solve the water age was introduced to find a more scientific and practical water age solution model, with setting the weight function to evaluate the water age of the water supply model comprehensively. Strength Pareto Evolutionary Algorithm II (SPEA-II) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) were adopted to optimize the WDN design model in the mountainous complex terrain. The significance levels of the number of Pareto solutions (NOPS) and running time are 0.029 and 0.001, respectively, indicating that the two algorithms have significant differences. Compared to NSGA-II, SPEA-II has a better convergence rate and running time in multi-objective water supply optimization design. The solution set distribution of SPEA-II is more concentrated than that of NSGA-II, also the numerical value is better. The number of SPEA-II optimization schemes is larger and the scheme is more effective. Among them, the Pareto solution set of SPEA-II can obtain more desirable optimization results on cost, reliability index (RI) and water age. In summary, the study provides valuable information for decision makers in WDN with complex terrain.

Keywords: water distribution network; optimization design; mountainous complex terrain; SPEA-II; NSGA-II

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1. Introduction

Water distribution networks (WDNs) are vital infrastructure in cities, requiring considerable investment. The primary function of WDNs is to transport water from the reservoir or tank to the nodes (consumers), and its main components are pipes, pumping stations, valves, etc. According to the present research, constructing a WDN costs 70% of the total cost [1]. WDNs constructed in territories with a certain height (relative and absolute) and a certain slope tend to be different from those in the plains. There is also a lack of a uniform definition of mountainous cities internationally. There are relatively little literature and case studies of WDNs in mountainous complex terrain. The design of WDNs in mountainous complex terrain is more onerous than in plains, due to differences in node elevation and low-flow of node demand. On the one hand, this leads to enormous energy consumption and extreme operation costs for the overall WDN. On the other hand, it leads to excessive pressure and frequent pipe burst accidents in the node of low area, while it is arduous to ensure pressure and demand in the node of high area [2]. In addition, the hazard of laying pipelines is increased by the specificity of the terrain. To overcome this difficulty, designers usually adopt multi-pressurization and pressurization WDN zoning [3]. Moreover, WDNs in mountainous complex terrain still face other problems, such as the sudden stoppage of the pumping station of the network, and the network will face huge water hammer pressure.

The optimal design of WDNs is to reduce the cost of the pipe network as much as possible, provided that water quantity, water pressure, and water quality requirements of WDNs are ensured. WDNs' optimization design on mountainous complex terrain can be challenging due to node elevation and demand constraints. Few researchers are currently focusing on this aspect. However, the construction of mountain WDNs is hampered by high cost and low hydraulic reliability. In this paper, a model based on the SPEA-II algorithm is developed to optimize WDNs of the case in the mountainous complex terrain, achieving considerable results in water supply design. In addition, an in-depth comparison of SPEA-II with another multi-objective optimization algorithm, NSGA-II, is presented. The two types of algorithms are combined with EPANET 2.0, a WDN analysis software. EPANET 2.0 performs the model analysis to obtain nodal pressures and pipe flow rates. The optimal design of WDNs is considered as an optimization problem with pipe diameter as the decision variable.

2. Literature Review

The optimal design of WDNs has attracted a lot of interest in the past decades. Breakthroughs in algorithmic frameworks and computational efficiency are the main reasons for the continuous development of water supply optimization research, as its optimization problem complexity and search space become larger with the increase in pipe network size. Liu et al. [4] proposed a head loss-based preprocessing method for the optimal design of WDNs and compared such a method with the initial design method preprocessing based on velocity and simple genetic algorithm without preprocessing, and the comparison results showed that the head loss-based method outperformed the other two methods regarding processing quality and computational efficiency. Bi et al. [5] proposed a genetic algorithm based on the pre-screening heuristic sampling method and applied it to optimize seven different scale WNDs, indicating that the advantages of this method will increase with the size of the mountain pipe network. The optimization results showed that the improved genetic algorithm not only had the optimal computer efficiency and the ability to search for the optimal solution, but also its advantages gradually emerged as the scale of WDNs grew.

Although cost reduction is the primary objective of WDN construction, numerous research scholars have built on this by proposing innumerable objectives, such as minimizing water age and maximizing reliability. During the shift from single-objective optimization to multi-objective optimization, multi-objective evolutionary algorithms (MOEAs) and Swarm Intelligence (SI) have played a significant role. They have been widely used in the field of engineering. Strength Pareto Evolutionary Algorithm II (SPEA-II) [6] and Non-dominated Sorting Genetic Algorithm II (NSGA-II) [7] are typical MOEAs, while multi-objective particle swarm optimization (MOPSO) [8] is SI. Zarei et al. [9] developed a multi-objective optimization model for the arithmetic pipe network using the NSGA-II and MOPSO algorithms. In optimizing the two-looped and Lansey networks, the optimization results of both algorithms satisfy the multi-objective ideal optimization results, but NSGA-II is more than MOPSO. Torkomany et al. [10] developed a hybrid fast convergent MOPSO, which enhances the convergence and diversity of the algorithm by introducing strategies such as adaptive particle swarm optimization (PSO) parameters, collision regeneration, etc. This algorithm is compared with the original MOPSO. The results show that the new MOPSO algorithm is more suitable for the optimization of medium-sized WDNs. Reca et al. [11] considered both cost and resilience indices and used several multi-objective metaheuristics for the optimization of the benchmark pipe network. This research showed that SPEA-II outperformed the remaining methods in terms of Pareto dominance. Shirzad et al. [12] introduced a dynamic design method that can optimize both initial design and rehabilitation schedule during the life cycle of WDNs, and applied this method to arithmetic pipe network optimization. The optimization results showed that dynamic network design could produce lower cost and more reliable optimization solutions. Fathollahi-Fard et al. [13] applied a sustainable closed-looped supply chain to an integrated water supply and wastewater collection system based on uncertainty. Models consider sustainable development factors such as economic, environmental, and social impacts. A multi-objective optimization model is developed to improve the mismanagement of closed-looped supply chain waters. The paper also proposes an improved social optimizer algorithm and uses it for model solution optimization, suggesting that the optimization model should consider more sustainability factors. Fathollahi-Fard et al. [14] used a two-stage stochastic mixed-integer linear programming method to demonstrate the feasibility of considering location-allocation-inventory strategies in water supply and wastewater collection networks. And a Lagrangian relaxation-based algorithm with an adaptive strategy is used to optimize the solution, and metrics evaluate the performance of the model and algorithm. Ghebi et al. [15] developed a Gaussian mathematical model for chlorine dosing corresponding to three different cyanide concentration levels, calibrated the residual cyanide prediction equation for chlorine injection by GA, and finally estimated the residual cyanide concentration under different conditions by machine learning. The results showed that the residual cyanide concentration showed a strong positive correlation with the chlorine dose. However, applying other meta-heuristic algorithms has not validated this class of algorithms. Zhang et al. [16] proposed a demand-weighted modified elasticity index (IMRI). The IMRI is defined as an integral of nodal demand-weighted MRI. They used it as one of the objective functions in a multi-objective optimization model. It is shown that this index effectively quantifies the elasticity of system operation in the time dimension. Jabbary et al. [17] proposed an improved central force optimization algorithm for the multi-objective optimization of WDNs, which treats cost minimization and reliability maximization as objective functions. The algorithm uses non-dominated ranking and congestion distance calculation to generate the Pareto frontier and obtain the optimal Pareto scheme. Cimorelli et al. [18] compared entropy and elasticity indices for their alternative reliability measures and evaluated the reliability of both measures in the face of limited WDN rehabilitation budget conditions. Zhang et al. [19] developed an optimization model with cost, reliability, and water quality as objective functions and performed a 24 h simulation analysis of the model and multiple load conditions.

Previous studies mostly carry out optimization analysis for benchmark WDNs, and the mathematical model they established is not used in actual engineering, and only the algorithm optimization effect is compared. The optimal design of water supply network is generally based on plain cases, while there are few studies on the optimization model of mountain water supply network. Moreover, there are still fewer studies using multi-objective optimization algorithms for WDN optimization in mountainous areas. Therefore, the effectiveness of SPEA-II and NSGA-II for multi-objective water supply optimization model need to be verified. And the comparison of convergence effect in multi-objective water supply optimization design needs to be further addressed.

The aim of this work was to investigate the WDN optimization by SPEA-II in mountainous area, as compared to NSGA-II. The pipeline flow rate limit was adjusted to reduce the impact on the pipeline caused by the water hammer from the pump stoppage. The operation of each step in the two algorithms is clarified and a practical case of constructing a WDN in a mountainous area is optimized. Finally, the adaptability of SPEA-II was evaluated for WDNs in mountainous complex terrain. This study provides a better understanding of the pipe network for mountainous urban project like one in Q city, China, that assists in their applications of the multi-objective optimization design for mountainous WDNs.

3. Materials and Methods

The current design of WDN optimization focuses on the optimization effect of the algorithm in the comparison of the benchmark pipe network, ignoring the optimization effect of the actual pipe networks. In particular, there are differences between the actual mountain WDN and the actual plain WDN. Pumping station heads in mountainous networks are mainly used to overcome the difference of terrain height, while those in the plain networks are mainly used to overcome the head loss. Once the pump station of the mountain WDN stops working, it can be fatal for the whole network system [20]. To mitigate such effects, this paper proposes a multi-objective WDN design model that considers three factors: cost, reliability, and water quality.

3.1. Problem Statement

3.1.1. Notations

The problem is formulated using the notations described in Abbreviations section.

3.1.2. Optimization Model Formulation of Water Supply Network

Three objective functions are established in this study, namely the lowest construction cost, the lowest depreciation and maintenance cost and the lowest operating cost. The specific formula is as follows.

$$
\begin{gathered}
\mathrm{C_1} = \sum_{\mathrm{u}=1}^{\mathrm{U}} \mathrm{c_u}(\mathrm{D_u})\mathrm{L_u} \\
\mathrm{C_2} = \left(\frac{\mathrm{b}(\mathrm{b}+1)^{\mathrm{t}}}{(\mathrm{b}+1)^{\mathrm{t}}-1} + \frac{\mathrm{R_1}}{100}\right)\sum_{\mathrm{u}=1}^{\mathrm{U}} \mathrm{c_u}(\mathrm{D_u})\mathrm{L_u} + \left(\frac{\mathrm{b}(\mathrm{b}+1)^{\mathrm{t}}}{(\mathrm{b}+1)^{\mathrm{t}}-1} + \frac{\mathrm{R_2}}{100}\right)\mathrm{C_p} \\
\mathrm{C_3} = 0.01 \times \frac{8.76\gamma \mathrm{E}\rho \mathrm{g}}{\eta}\mathrm{Q_p}\mathrm{H_p}
\end{gathered}
\tag{1}
$$

Todini [21] defines the concept of network resilience (Ir) as the ability of a WDN to overcome a failure (customer demand or head change, improper pipe size, pipe rupture, inoperable valve or pump station) during operation, and treats the resilience factor as a reliability metric. In addition, Todini [21] defined the failure factor (If) to assess the impact of pipeline failure on the network. Parasad [22] considers the effect of redundancy in WDNs and proposes the network resilience index (In) as a reliability metric for WDNs. The nodal surplus head indicates the portion of the nodal free head that is exceeded under the condition that the minimum service head is satisfied. Its formula is expressed as follows.

$$
\bar{I} = \frac{\sum_{i=1}^{N} H_i - H_i^{min}}{N} \tag{2}
$$

Without regarding the influence of other external forces, the probability of pipe burst, leakage and failure of pipe network components shows a positive correlation with the affluent head, which leads to the waste of water resources and electric energy. However, when the affluent head is negative, the normal water supply to the customers is impossible, and the water demand of some nodes cannot be satisfied. In the WDN of a mountainous town, it is effortless to have uneven pressure leading to various accidents. Therefore, the node rich head variance is too large, which not only leads to water wastage, but also accelerates the WDN breakdown. Therefore, this paper uses the variance of the nodal surplus head as the reliability index (RI).

$$
RI = \sum_{i=1}^{N} \left(H_i - H_i^{min} - \bar{I}\right)^2 \tag{3}
$$

Water quality and water age show a negative correlation. As the water age increases, turbidity, color, odor, COD_{Mn}, and other conventional indicators are showing an increasing trend, the water quality gradually becomes worse. Node water age refers to the water flow from the water source to the time of each node. Node water age size indicates the node of water quality security. Most of the current studies on water age use EPANET 2.0 for simulation analysis. However, EPANET 2.0 water age analysis in the face of large scale and complex topological relationship of water supply pipe network when the problem of computational redundancy. To address this problem, Wang et al. [23] proposed a node-by-node traversal method to calculate the water age. The method is based on the definition of water age and traversal from the known node water age to the unknown node water age to find the node water age, which has the characteristics of simplicity and efficiency.

$$T_j = \begin{cases} 0 & j \in MT \\ \frac{\sum_{i \in S_j} q_{ij}\left(t_i + \frac{L_{ij}}{v_{ij}}\right)}{\sum_{i \in S_j} q_{ij}} & j \in M \end{cases} \tag{4}$$

The end nodes of the WDN generally have a small water consumption, resulting in excessive water age at the end nodes. The optimization effect of using the weight method for nodes with a small flow at the end nodes of the pipe network is poor. To avoid this problem, Xin et al. [24] proposed a comprehensive water age index to optimize the water age of the water supply pipe network, which divides the pipe network into near the water source node area, the middle node area and the end node area of the pipe network according to the node water age, and obtains the comprehensive water age index by setting a reasonable weighting factor λ. The water age objective function of the pipe network node is formulated as follows.

$$Age = \sum_{m=1}^{3} \lambda_m \left(\frac{\sum_{i \in S_j} T_i q_i}{\sum_{i \in S_j} T_i q_i} \right) \tag{5}$$

The formula of λ is as follows.

$$\lambda_m = \frac{\frac{1}{\sum_{i \in S_m} q_i}}{\frac{1}{\sum_{i \in S_1} q_i} + \frac{1}{\sum_{i \in S_2} q_i} + \frac{1}{\sum_{i \in S_3} q_i}} \tag{6}$$

S_m is the set of nodes in area m and the classification formula is as follows.

$$\begin{cases} Near\ the\ water\ node\ area:\ S_1 & \frac{T_{max}}{3} \geq T_i \geq 0 \\ Mid-pipe\ network\ node\ area:\ S_2 & \frac{2T_{max}}{3} \geq T_i \geq \frac{T_{max}}{3} \\ Pipe\ network\ end\ node\ area:\ S_3 & T_{max} \geq T_i \geq \frac{2T_{max}}{3} \end{cases} \tag{7}$$

3.1.3. Constraint Condition

The hydraulic values of the pipe network model optimization from the hydraulic simulator of EPANET. From the perspective of engineering design rationality and realism, the model optimization must comply with the conservation law, node flow, and pipe pressure conservation law in EPANET to achieve. The nodal pressure constraint is as follows:

$$h_{min,j} \leq \mathrm{h}_j \leq \mathrm{h}_{max,j} \tag{8}$$

The pipe flow rate constraint is as follows:

$$0 < v_{min,i} < \mathrm{v}_i \leq \mathrm{v}_{max,i} \tag{9}$$

3.2. Multi-Objective Optimization Algorithm in Text

In most cases, the objective functions of multi-objective optimization problems are conflicting, i.e., it is impossible to make all objective functions reach the optimal value at the same time, and only each objective function can be coordinated to make each objective function as optimal as possible, i.e., Pareto optimal. The solution set of single-objective optimization function is usually a single solution set, called the optimal global solution. In contrast, the solution set of multi-objective optimization is a set of the equilibrium solution set, which is primarily a non-dominated solution or Pareto optimal solution. In addition to the fact that the number of objective functions is different from that of a single objective optimization problem, the solution is also not unique but is a Pareto optimal solution set consisting of several non-dominated solutions. In practical engineering applications, decision-makers must select one or more solutions from the Pareto optimal solution set for comparison and choose the solution that best suits their needs. To increase the possibility of searching for the optimal solution, the key to the multi-objective optimization problem is to ensure that the number of Pareto-optimal solutions is as large as possible.

3.2.1. NSGA-II

NSGA-II (Elitist Non-dominated Sorting Genetic Algorithm-II) is an improved algorithm based on a genetic algorithm [25–27]. Whereas the basic ideas are all to simulate the biological evolution process in nature, treating the independent variables as genes of chromosomes, and finally to obtain the optimal solution of the optimization problem through the operations of selection, crossover and mutation.

The crowding degree is introduced and used as the comparison criterion of non-dominated individuals in the same layer. The crowding degree is performed to distribute the individuals in the Pareto domain evenly, improving the science and rationality of the algorithm [28]. The fast non-dominated sorting method is proposed to reduce the complexity of the algorithm and shorten the running time of the algorithm. The elite strategy is introduced to generate the next generation population after elite selection to ensure its heritability. And the individuals are stored in a hierarchy to improve the population level. The specific process is shown in Algorithm 1 in the following table.

Algorithm 1: NSGA-II.

The initialization of the parameters of the algorithm;
Initialization of population Parent$_{\xi}$;
Initialization of iteration $\xi = 1$;
while iteration $\xi \leq \xi_{max}$
  Update the values of Pc and Pr according to ξ;
  Crossover and mutation on Parent to generate new population Child$_{\xi}$;
  Merge parent and child as total population Family$_{\xi}$;
  Rank population Family$_{\xi}$ in Pareto front;
  Select best non-dominant group form Family$_{\xi}$ as Parent$_{\xi+1}$ with crowding distance function;
  $\xi = \xi + 1$;
end;
Return the most solution

3.2.2. SPEA-II

SPEA-II (Strength Pareto Evolutionary Algorithm-II) is one of the most powerful multi-objective algorithms. This algorithm provides excellent results compared to other multi-objective algorithms, such as its first version. SPEA-II not only introduces the concept of Pareto dominance when calculating fitness but also considers the number of individuals dominated by the population individuals and the number of individuals dominated by them and uses the k-nearest neighbor strategy to calculate the density of individuals, which makes the Pareto solution uniformly distributed.The specific process is shown in Algorithm 2 in the following table.

Algorithm 2: SPEA-II.

The initialization of the parameters of the algorithm;
Initialization of population Pop$_{\xi}$;
Generate an empty external archive set ε_{ξ};
Initialization of iteration $\xi = 1$;
while iteration $\xi \leq \xi_{max}$
  Calculate the fitness of population and external archive set ε_{ξ};
  Select the non-dominated solution to store in $\varepsilon_{\xi+1}$;
  If the size of $\varepsilon_{\xi+1}$ does not meet the requirements, the size is adjusted;
  ε_{ξ} for tournament selection;
  Update the values of Pc and Pr according to ξ;
  Crossover and mutation on ε_{ξ} to generate new population $\varepsilon_{\xi+1}$;
  $\xi = \xi + 1$;
end;
Return the most solution

3.3. Improvement of Algorithm in WDN Optimization

In order to understand the model structure more intuitively, the flow chart of the algorithm optimization model structure is shown in Figure 1. The range of decision variables available is a discrete set of pipe diameters. The current encoding methods are binary encoding, real number encoding, floating point encoding, etc. In this paper, real number encoding is used for pipe diameter. The crossovers are divided into point crossover, uniform crossover, and arithmetic crossover. The variances are classified into several types: basic position variation, uniform variation, boundary variation, non-uniform variation, and Gaussian approximation variation. This paper chooses uniform crossover and uniform variation as the crossover and variation, respectively. The crossover probability (Pc) and variable probability (Pr) are set as follows: The Pc is ξ_{max} values in decreasing order from 0.5 to 0.3, and the Pr is ξ_{max} values in decreasing order from 0.9 to 0.5.

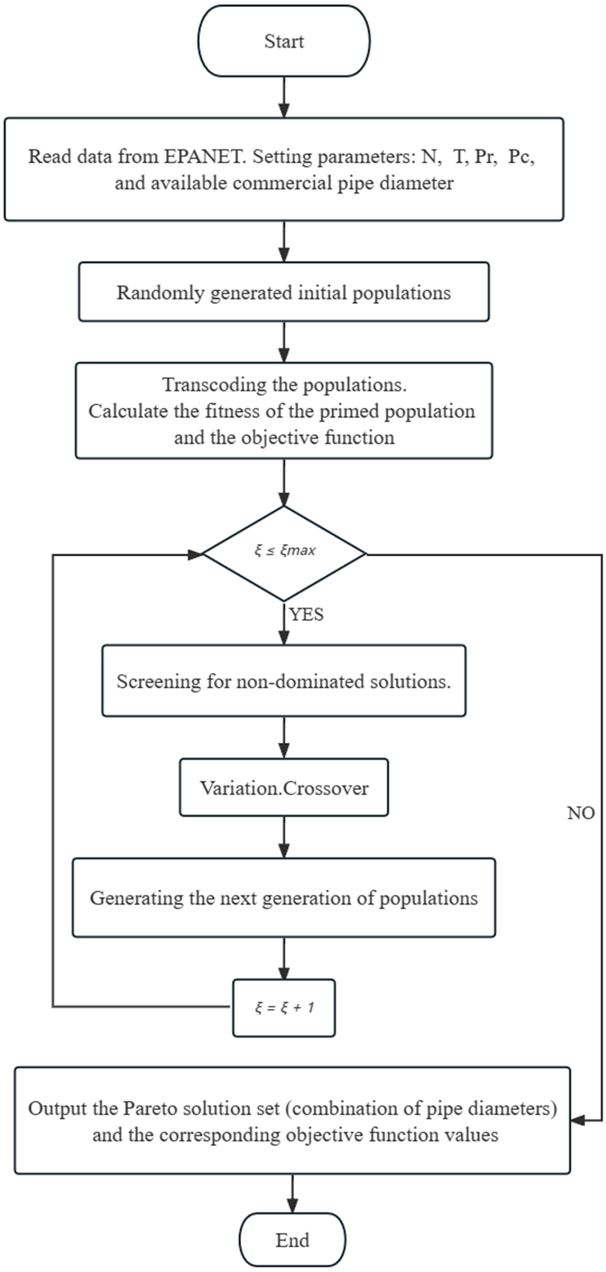

Figure 1. Model Structure Flow Chart.

4. Results

4.1. Case Study

The terrain nodes in this case have large elevation differences and distinct topographic undulations. To visually reflect the topographic changes, a satellite map of the case area was selected (see Figure 2). According to the water supply characteristics and topographic constraints and other factors, a WDN topology relationship map was established (see Figure 3). The preliminary design of this network includes 26 pipe sections, 21 nodes and one municipal water supply point, with a maximum water supply volume of 112.78 L/s, which belongs to a small-town pipe network. The node flow of the pipe network is determined based on the historical water consumption of the town, and the length of the proposed pipe sections as well as the node elevation, minimum service head and other basic data are also determined (see Table 1). In mountainous and hilly areas, steel pipes cannot be buried under soil. Considering that pipelines in actual engineering cases are laid along mountain roads and cannot be buried under soil, steel pipes are selected for water supply engineering in this case. The loss calculation of pipe section in the hydraulic calculation of pipe network adopts the Heizen–Williams formula, and the Heizen–Williams coefficient of steel pipes is 130.

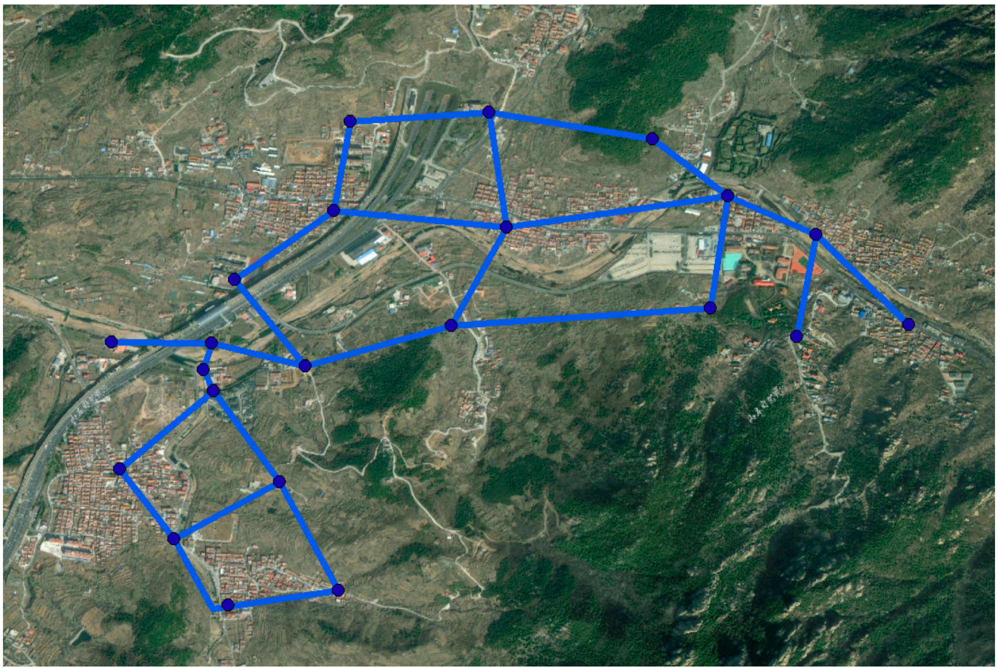

Figure 2. Satellite map of the case study area.

Table 1. The basic information of the case nodes and pipe sections.

Node ID	Elevation (m)	Base Demand (L/s)	The Minimum Free Head	Link ID	Length (m)
2	335.267	1.39	14	1	531
3	356.081	5.04	14	2	646
4	315.681	5.46	14	3	584
5	336.775	6.36	14	4	457
6	348.718	4.68	14	5	672
7	312.915	5.82	14	6	836
8	307.31	5.253	14	7	493
9	301.736	3.684	14	8	513
10	349.048	7.92	14	9	769
11	364.141	10.41	14	10	913
12	327.06	5.22	14	11	497

Table 1. *Cont.*

Node ID	Elevation (m)	Base Demand (L/s)	The Minimum Free Head	Link ID	Length (m)
13	316.13	4.658	14	12	467
14	338.582	6.27	14	13	481
15	351.64	0	-	14	536
16	377.526	7.53	28	15	488
17	389.647	9.96	28	16	706
18	446.004	6.66	28	17	471
19	418.267	5.73	28	18	263
20	427.144	5.67	28	19	238
21	456.713	5.07	28	20	524
22	351.64	0	28	21	966
1	380 (total head)	−112.78	-	22	874
				23	893
				24	836
				25	574
				26	915

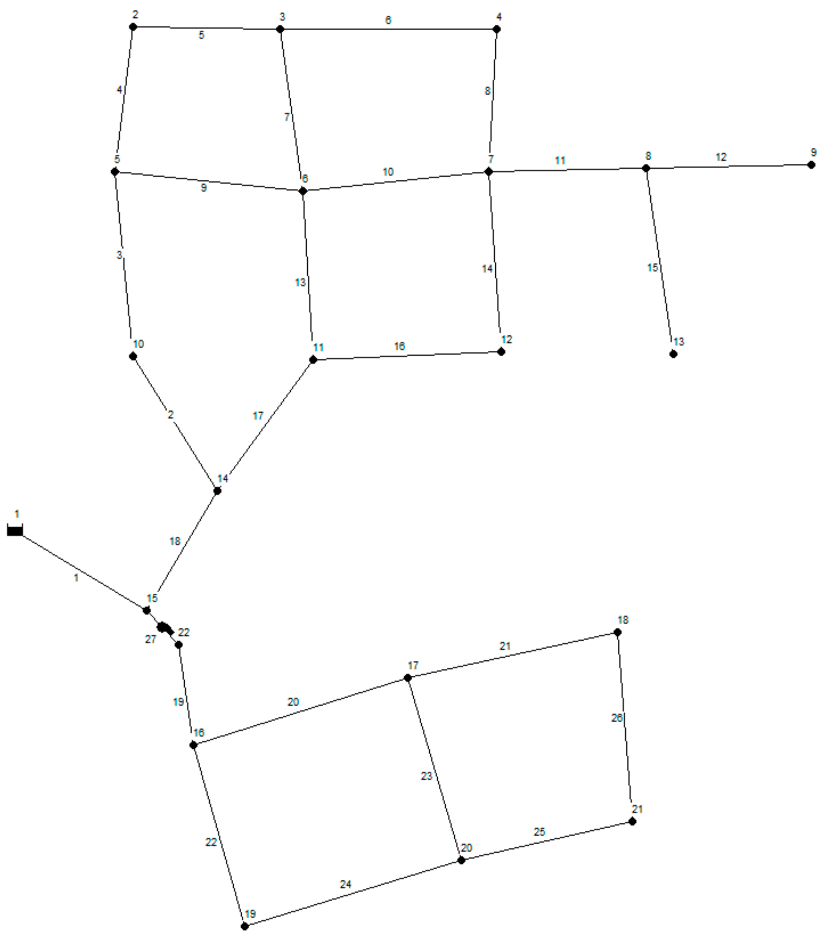

Figure 3. Case pipe network topology diagram.

4.1.1. Decision Variables and Objective Function

The case is a hilly area with more complex terrain changes and higher requirements for pipeline pressure resistance level. So, two types of steel pipe with pressure resistance levels of 1.6 MPa and 2.5 MPa are used in this case. Due to the local policy, the water pressure of steel pipe design pipe is equal to the maximum working pressure of the pipe plus 0.5 MPa. Thus, the case proposes two types of nominal values of 1.6 MPa and 2.5 MPa. And the maximum working pressure of steel pipe shall not be greater than 1.1 MPa and 2.0 MPa. Local pipe prices as shown in Table 2.

Table 2. Local pipe prices.

Pipe Diameter (mm)	Price (1.6 MPa)	Price (1.6 MPa)	Pipe Diameter (mm)	Price (1.6 MPa)	Price (1.6 MPa)
40	77.70	91.80	200	469.40	611.11
50	83.40	109.54	250	688.65	992.91
65	105.37	135.14	300	850.88	1307.55
80	129.69	172.20	350	1121.67	1585.15
100	172.98	228.43	400	1334.51	1812.36
125	253.00	345.09	450	1558.67	2135.73
150	368.91	496.71	500	1895.82	2564.20

The 1.6 MPa and 2.5 MPa grade of steel pipe were selected for the sections when the maximum value of the head at the ends of the sections was less than 110 m and 200 m, respectively. So, the cost of the pipe section can be expressed in the following equation.

$$C = \sum_{u=1}^{U} \{x_u\,(27.57 + 5318.81 * D_u^{1.52}) + [1 - x_u]\,(48.15 + 9724.13 * D_u^{1.69})\}L_u \tag{10}$$

Each pipe diameter size corresponds to one variable, and to avoid processing redundancy, real numbers are coded with a total of 26 decision variables.

The pumping station construction price is not considered because it is relatively stable and does not change significantly. Also pump station depreciation and overhaul costs are not included in the cost function of this case.

At this time, $v_{min,j}$ is 0, and, $v_{max,j}$ is 2.5 m/s. $h_{min,j}$ is the minimum free head of node j, $h_{max,j}$ is 200 m.

4.1.2. The Difference of Compared to Other Systems

The height difference of the case area is large, so the zoning water supply is chosen. The gravity water supply is chosen for the low zone water supply area, while pressure water supply is determined for the high zone water supply area. The head of water supply pumping station, namely '27' pumping station, needs to meet the most unfavorable node minimum service head in the high zone water supply area.

4.2. Result Analysis

4.2.1. Overall Effect Comparison

The parameters for the adopted multi-objective evolutionary algorithm are set as follows. The initial population size, NP, is 100 and the number of iterations, ξ_{max}, is 200, depending on the need for accuracy of calculation results. To avoid the influence of the initial population on the optimized population, the optimization procedures of SPEA-II and NSGA-II are both run ten times. The optimal solution sets of the ten calculations are merged to obtain the Pareto optimal solution of the case. The results of the optimization calculation for both algorithms were confirmed to be Pareto surfaces, as shown in Figure 4. There are considerable differences between the two algorithms in the number of non-dominated solutions, with the SPEA-II obtaining 534 solutions and the NSGA-II obtaining 94 solutions. In terms of optimization quality, the convergence of the theoretical optimal point ((Cost, RI, Water Age) = (0,0,0)) obtained from Pareto optimal point of SPEA-II is better than that of the NSGA-II. Therefore, it is concluded that SPEA-II achieves better results in the face of multi-objective water supply optimization design.

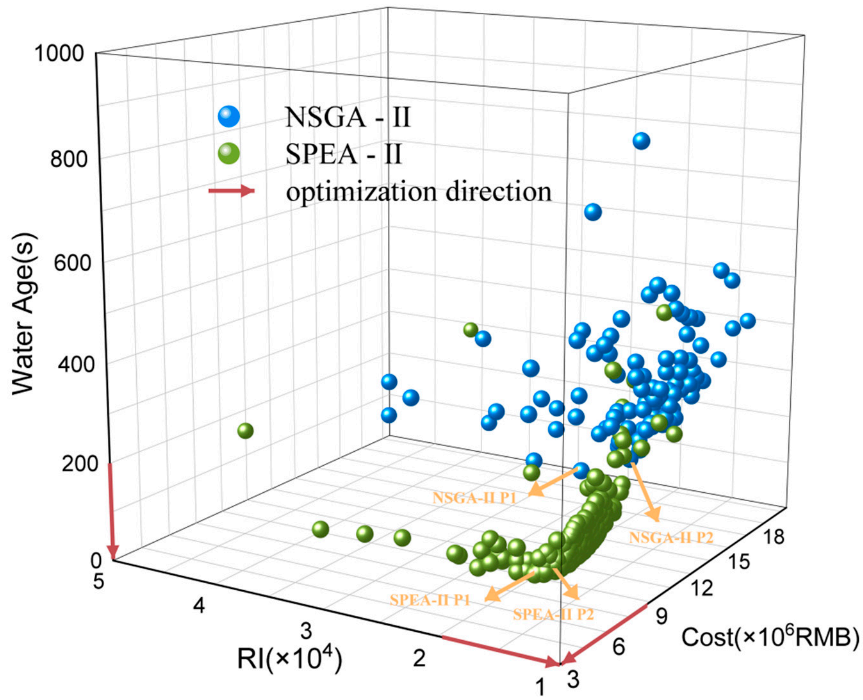

Figure 4. The optimal set of solutions for ten independent runs of SPEA-II and NSGA-II.

Figure 5 shows the violin plots of the optimization results of the two algorithms for ten independent runs. As shown in Figure 5a, the median of the box plot for cost produced by SPEA-II is 7.102798×10^6, and the other median of the box plot produced by NSGA-II is 1.32791445×10^6. The median values of the box plot for RI (Figure 5b) produced by two algorithms are 1.52236×10^4, 1.41232×10^4, indicating the difference between the optimization results of the two algorithms in outliers is insignificant. Moreover, SPEA-II is more concentrated around the median distribution than NSGA-II regarding RI. Meanwhile, the box plot for water age (Figure 5c) shows that the media value optimized by SPEA-II is lower than NSGA-II. Figure 5d shows the differences in running times between the two algorithms, the box value of SPEA-II for runtime is much lower than NSGA-II. The results show that the median of the optimization results of SPEA-II is better than that of NSGA-II. In terms of cost, water age and running time, the SPEA-II optimization results box is lower than NSGA-II. Based on the above results, it is shown that SPEA-II can obtain lower cost, higher hydraulic reliability, and safer water supply optimization solution for pipeline network water quality in a shorter time. And it is further indicated that SPEA-II has a good optimization effect in multi-objective water supply optimization design.

There are some evaluating metrics in this research to compare the performance of multiple algorithms in a multi-objective optimization problem. In addition to the number of Pareto solutions, the distance index, which indicates the relative distance of consecutive solutions, can also be used to evaluate the performance of algorithm. Lower values of this index are more desirable. The distance index is calculated by [28]:

$$\mathrm{SM} = \frac{\sum_{i=1}^{NUM-1} \left| \overline{d} - d_i \right|}{(NUM-1)\overline{d}} \tag{11}$$

where NUM is the number of Pareto solutions, di is the spacing between the two sequential solutions in optimal front by each algorithm, and d is the average distance. The diversity index is another method to evaluate the number of solutions. The better it is if the index has a large value. This index can be computed as follows [29]:

$$DM = \sqrt{\left(\frac{max\ f_{1i} - min\ f_{1i}}{max\ f_{1,total} - min\ f_{1,total}}\right)^2 + \left(\frac{max\ f_{2i} - min\ f_{2i}}{max\ f_{2,total} - min\ f_{2,total}}\right)^2 + \left(\frac{max\ f_{3i} - min\ f_{3i}}{max\ f_{3,total} - min\ f_{3,total}}\right)^2} \quad (12)$$

In order to avoid the impact of the initial population on the direction of evolution, the two algorithms were independently run ten times each, forming Table 3. The method evaluation metric values for the ten-run generation sample are given in Table 3. Figures 6–9 is a more intuitive representation of the four indicators in Table 3 to better analyze the impact of the indicators.

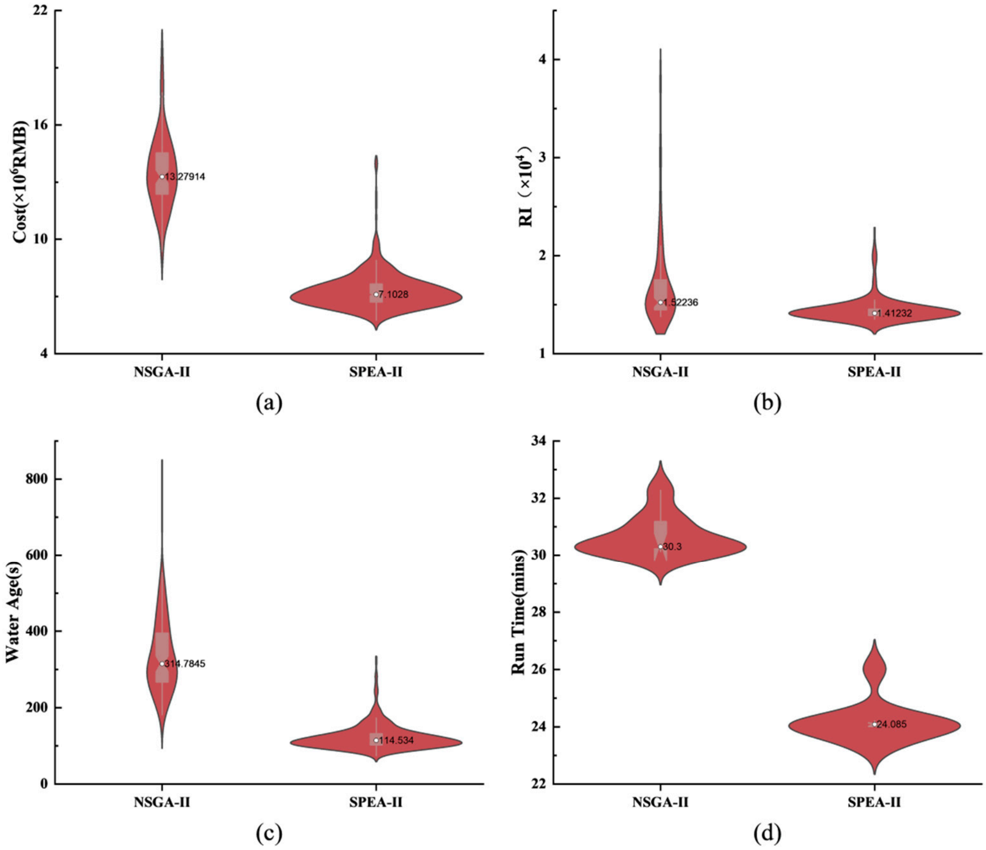

Figure 5. Distribution of algorithm optimization results in terms of Cost (**a**), RI (**b**), Water Age (**c**) and Running Time (**d**).

Table 3. Obtained values for ten tests by NSGA-II and SPEA-II.

Run NO.	NSGA-II				SPEA-II			
	SM	DM	NOPS	Run Time	SM	DM	NOPS	Run Time
1	0.5605345	1.0560663	8	32.22	0.5605548	0.3892499	100	25.29
2	0.767305	0.7499839	11	33.15	0.6171902	0.7812316	100	25.4
3	0.7253668	0.8265837	9	32.12	0.6880164	0.721118	91	25.52
4	0.4610114	1.1747089	12	32.57	0.593714	1.0367978	46	25.38
5	0.5070672	0.770535	9	31.17	0.6750568	1.6367351	100	26.38
6	0.6462196	0.7959993	7	31.1	0.4800687	1.0867432	8	25.45
7	0.8974586	1.5233356	11	31.54	0.787881	1.0315251	11	25.55
8	0.5621243	0.488824	9	31.5	0.6850569	1.0402223	18	26
9	0.6102167	0.8936668	10	31.42	0.6550387	1.0508704	100	25.54
10	0.5938924	0.7295313	11	32.45	0.2891572	0.592205	4	25.11
Average	0.6331197	0.9009235	9.7	32.8	0.6031735	0.9366698	57.8	25.44

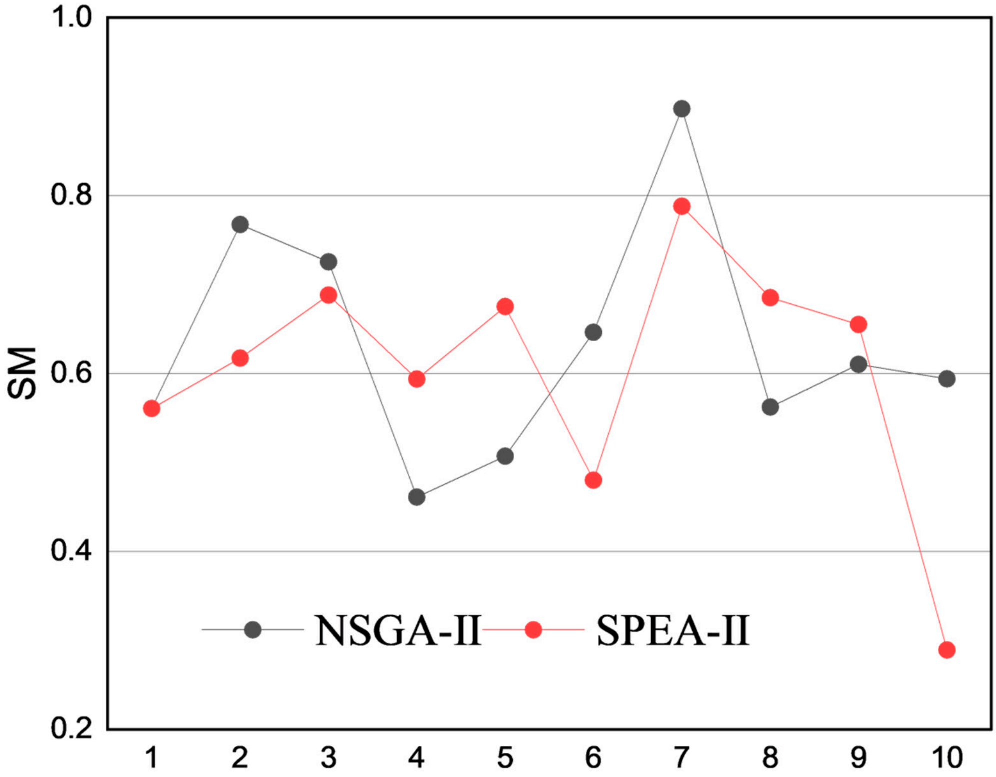

Figure 6. Comparison between NSGA-II and SPEA-II according to the distance index.

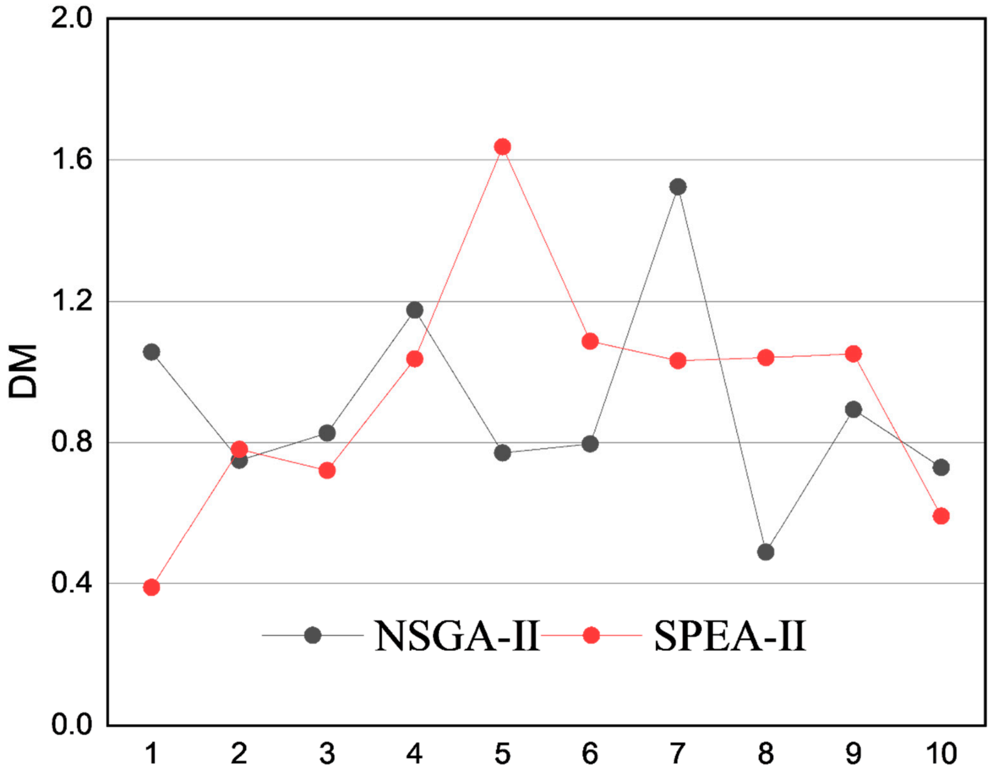

Figure 7. Comparison between NSGA-II and SPEA-II according to the diversity metric.

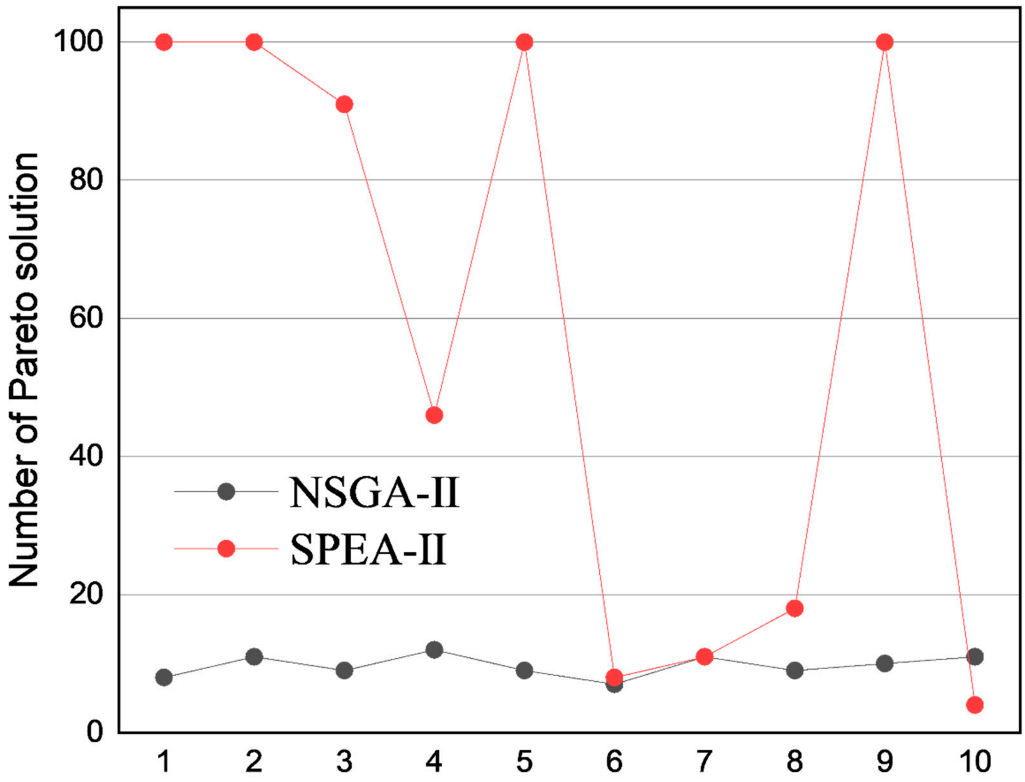

Figure 8. Comparison between NSGA-II and SPEA-II according to the number of Pareto solutions.

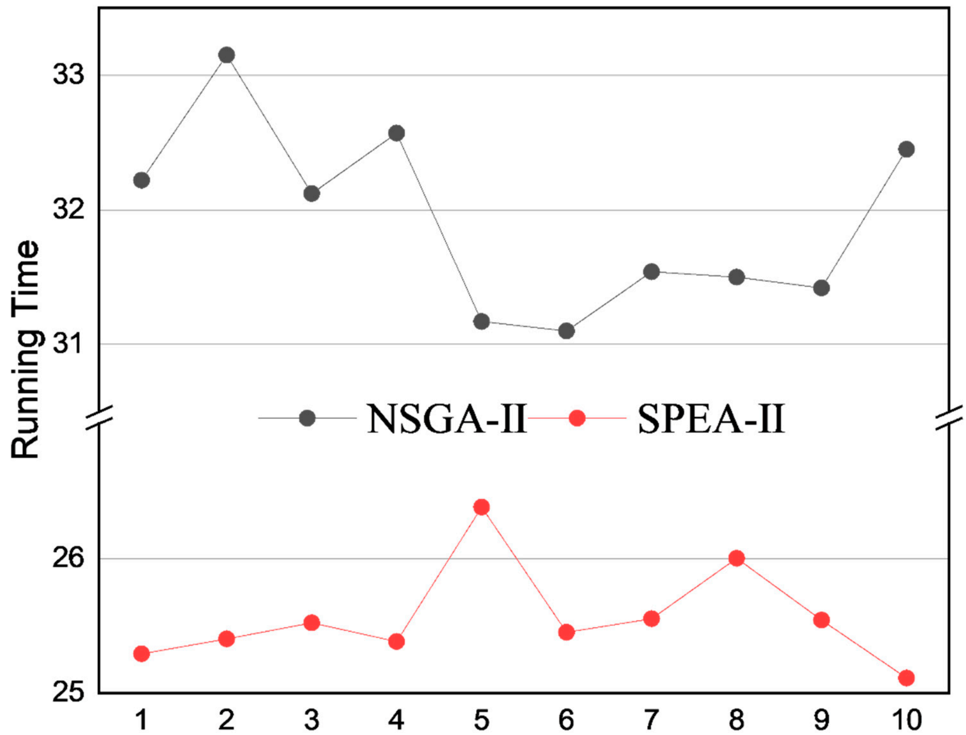

Figure 9. Comparison between NSGA-II and SPEA-II according to running time.

As shown in Figures 6 and 7, there is no significant difference between the distance index and diversity metric of two algorithm. The overall trend of SM values of SPEA-II was slightly lower than that of NSGA-II, while the general direction of DM values for SPEA-II was marginally higher than that for NSGA-II. The number of Pareto solutions obtained from the algorithm is shown in Figure 8. The number of SPEA-II non-dominated solutions is much higher than that of NSGA-II, which illustrates the superior performance of SPEA-II. The result of the running time shows that the SPEA-II takes the least time to search for the optimal solution, further proving the better overall performance of the SPEA-II. (Figure 9)

The above results show that SPEA-II can perform well in optimizing mountainous WDNs, effectively reducing pipeline costs while improving network reliability and water quality safety.

4.2.2. Statistical Test

Ten run tests were conducted to determine whether there is a significant difference between these two algorithms in optimizing mountain WDN. The results of the significance tests of the algorithms are shown in Tables 4–7.

Table 4. Normality test results.

	Normal Distribution					
	Kolmogorov–Smirnova			**Shapiro–Wilk**		
	Statistics	**df**	**Sig.**	**Statistics**	**df**	**Sig.**
SM	0.131	20	0.200 *	0.977	20	0.885
DM	0.142	20	0.200 *	0.943	20	0.273
NOPS	0.361	20	0	0.653	20	0
Run Time	0.263	20	0.001	0.766	20	0

* This is the lower limit of true significance.

Table 5. Results of statistical hypothesis test to compare the performance of algorithms (independent *t*-test).

		Levene's Test for Equality of Variances		*t*-Test for Equality of Means						
		F	**Sig.**	**t**	**df**	**Sig. (2-Tailed)**	**Mean Difference**	**Std. Error Difference**	**95% Confidence Interval of the Difference**	
									Lower	**Upper**
SM	Equal variances assumed	0.006	0.939	0.497	18	0.625	0.02995	0.0602	−0.09653	0.15643
	Equal variances not assumed			0.497	17.95	0.625	0.02995	0.0602	−0.09656	0.15645
DM	Equal variances assumed	0.228	0.639	−0.254	18	0.803	−0.03575	0.14088	−0.33173	0.26024
	Equal variances not assumed			−0.254	17.499	0.803	−0.03575	0.14088	−0.33234	0.26085

Table 6. Statistical characteristics of the three criteria for both algorithms (independent *t*-test).

	Method	N	Mean	Std. Deviation	Std. Error Mean
SM	NSGA-II	10	0.6331	0.131	0.04143
	SPEA-II	10	0.6032	0.13814	0.04368
DM	NSGA-II	10	0.9009	0.28713	0.0908
	SPEA-II	10	0.9367	0.34064	0.10772

Table 7. Results of statistical hypothesis tests used to compare algorithm performance (non-parametric tests).

	H_0	Test	Significance	Decision
1	The assignment of NOPS is the same between NSGA-II and SPEA-II	Mann–Whitney U test	0.029 [1]	Reject H_0
2	The assignment of Running Time is the same between NSGA-II and SPEA-II	Mann–Whitney U test	0.001 [1]	Reject H_0

Showing progressive significance. Significance level is 0.05; [1] This test showed exact significance.

As shown in Table 4, SM and DM conform to the normal distribution, and the Number of Pareto Solutions (NOPS) and Running Time does not conform to the normal distribution. Therefore, independent sample *t*-tests were conducted for SM and DM (see Table 5), and nonparametric tests were conducted for NOPS and Running Time (see Table 6).

According to the results reported in Table 5, it can be seen that the significant level of Levene's test for equality of variance for SM, DM are 0.939, 0.639. The *p*-values for the Levene's test for SM and DM are well above the significance level of 0.05, indicating no difference between the variances. Based on the significance level of the independence test, the values of SM and DM are 0.625 and 0.803, respectively, which are greater than the significance level value of 0.05. It indicates that there is no significant difference between the performance of the two algorithms under the criteria of SM and DM.

As shown in Table 7, the significant levels of NOPS and Running Time were well below 0.05, so the hypothesis that NOPS and Running Time are the same in SPEA-II and NSGA-II is rejected.

As shown in Table 6, in the NOPS criterion, the algorithm with the highest value is preferred, and the mean value of SPEA-II is much lower than that of NSGA-II, so SPEA-II is better than NSGA-II. In the Running Time criterion, the algorithm with the lowest value is preferred, so SPEA-II is better than NSGA-II. In the optimization of mountain water supply, SPEA-II is recommended based on the results of each metric. SPEA-II is recommended to be used.

4.2.3. Comparison of Representative Solutions

Four representative schemes (indicated in Figure 4) were selected for each of the two algorithms and are analyzed in Tables 8 and 9 and Figure 10. Two different schemes of two algorithms are selected from Figure 4 to compare a pipe diameter, as shown in Table 8. The pipe diameters (see Table 8) in both cases of SPEA-II are approximately the same, with only minor variations in local pipe diameters.

Table 8. Comparison of four water supply options pipe diameter.

Pipe ID	SPEA-II P1	SPEA-II P2	NSGA-II P1	NSGA-II P2
1	450	400	500	400
2	200	250	500	350
3	125	125	250	300
4	125	65	100	125
5	80	50	350	150
6	50	50	125	100
7	100	100	50	40
8	100	100	65	100
9	50	40	150	450
10	40	65	65	250
11	150	150	250	150
12	80	80	50	250
13	200	150	250	150
14	150	150	200	65
15	100	125	300	200
16	200	200	500	100
17	300	300	300	500
18	350	400	400	350
19	300	300	150	400
20	200	350	150	200
21	80	80	200	400
22	65	65	250	125
23	200	200	65	400
24	65	65	50	50
25	150	150	50	200
26	65	80	350	65

Table 9. Comparison of the indicators of the three types of programs.

Optimized Index	SPEA-II	NSGA-II	Optimized Program
Cost ($\times 10^6$ RMB)	5.996344	11.455565	91.04%
RI ($\times 10^4$)	1.56216045	1.696171	8.58%
Water Age (**s**)	**83.8025**	200.7085	139.50%

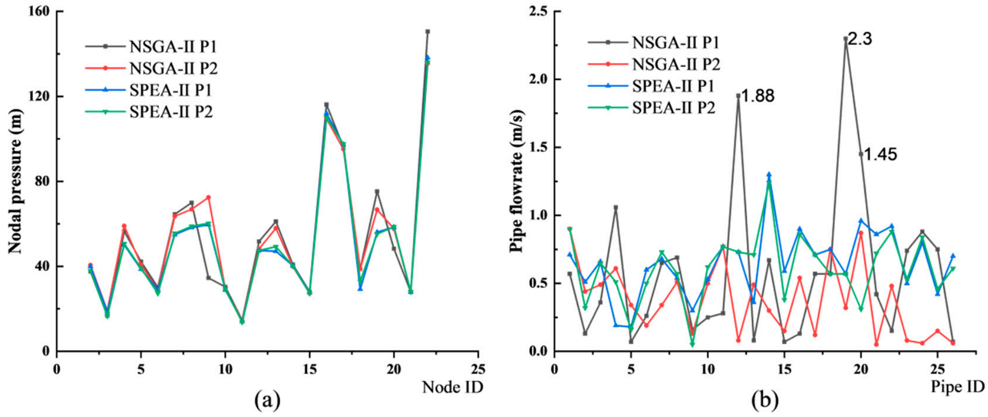

Figure 10. Nodal pressure (**a**) and pipe section flowrate (**b**).

Detailed information on nodal pressure and pipe section flow rate is shown in Figure 10. The two optimized representative schemes of SPEA-II have approximately the same nodal head values as NSGA-II and there are several values overlapping; however, the partial pipe flow velocities of the two schemes of NSGA-II are much higher than those of SPEA-II, and have large variation differences, especially the NSGA-II P1 scheme, which has pipe flow velocity values of 1.88, 2.3, and 1.45 for 12, 19, and 20 pipes, respectively; although their pipe section flow velocities do not violate the pipe section flow rate constraints, which means that the two optimized representative schemes of NSGA-II are more prone to pipe burst accidents. The nodal pressure variability is small in all four schemes, and all of them are able to meet the nodal-free head requirement well. Considering the safety of the pipe network, the SPEA-II scheme has a slow change in pipe section flow velocity. In contrast, the NSGA-II scheme has a drastic change in pipe section flow velocity, which makes the occurrence of water hammer very probable. As a result, the SPEA-II solution performs a higher level of safety. From the perspective of the three objective functions, the two SPEA-II schemes are similar in reliability. However, compared to SPEA-II P1, SPEA-II P2 offers designers a variety of options by sacrificing cost for lower water age.

In order to evaluate the optimization performance of the two algorithms in WDN design, the average values of the indicators of the two schemes are compared. The simulated data are shown in Table 9. Compared with the NSGA-II representative scheme, the SPEA-II representative scheme was relatively significant, with an average cost reduction of 5.459221×10^6 RMB, an improvement of 91.04%; the reduction in variance for the nodal-rich head is not outstanding, with a reduction of 1340.1055, an improvement of only 8.58%; the average water age is effectively reduced by 116.9055 s, with an improvement of 139.50%. In summary, it can be seen that the optimization effect of SPEA-II is better than NSGA-II in the economy, hydraulic reliability, and water quality safety.

5. Conclusions

In this paper, two standard multi-objective optimization algorithms were used to solve the multi-objective WDN optimization model. To evaluate the performance of the algorithm for optimization in WDNs, metrics were used to evaluate its performance. The results show that SPEA-II gives better optimization results than NSGA-II. In addition to this, two representative schemes were selected from the Pareto sets generated by each of the two algorithms. The variability of the nodal pressure variation is not significant for the four schemes, but the differences in the NSGA-II pipe section flow rates are obvious in terms of the pipe section flow rate. This variability increases the probability of water hammer in the pipe network, and the safety of the WDN cannot be guaranteed. This further demonstrates that SPEA-II performs better than NSGA-II in the optimized design of mountain water supply.

To reduce the probability of water hammer in complex mountainous terrain, the flow velocity of the pipe section needs to be reduced in the design. With the solution space vector unchanged, the solution set of the optimization scheme for mountainous WDNs is diminished. It was found that SPEA-II outperforms NSGA-II both in terms of convergence speed and Pareto optimal solution. The model is suitable for mountainous complex terrain, where the Pareto solution set of SPEA-II can achieve a more desirable optimization effect and effectively reduce the probability of water hammer.

The Pareto solution set of SPEA-II could yield more reasonable optimization results in terms of cost, reliability index (RI) and water age. In conclusion, the study provides a more reliable construction solution for decision makers in WDNs under complex terrain.

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Abbreviations

C_1	the construction cost
C_2	the depreciation and maintenance cost
C_3	the operation cost
$c_u(D_u)$	the cost per unit length of pipe diameter D_u
L_u	the length of pipe u
U	the number of pipes in the network
b	the benchmark yield
t	the payback period of pipe network construction
R_1	the depreciation and maintenance rate of the pipe network
R_2	the depreciation and maintenance rate of the pump
C_p	the construction cost of the pump
γ	the energy factor
E	electricity tariff prices
ρ	the density of water
g	the acceleration of gravity
η	combined efficiency of the pump station
Q_p	the pump station flow
H_p	the pump station head
H_i	the free water head of node i
H_i^{min}	the minimum free head of node i
N	the number of nodes of the water supply system
MT	the set of water source node
M	the set of non-water source node

S_j	the set of all nodes adjacent to node j that flow to node j
t_i, t_j	the water ages of nodes i, j
i	the node adjacent to node j
q_{ij}	the pipe flow between nodes i and j
L_{ij}	the pipe length between nodes i and j
v_{ij}	the pipe flowrate between nodes i and j
λ_1	the coefficients near the water source node area of the WDN
λ_2	the coefficients near the middle node area of the WDN
λ_3	the coefficients near the end node area of the WDN
$h_{min,j}$, $h_{max,j}$	respectively lower and upper bound of the pressure head of node j
v_i	the velocity of pipe i
$v_{min,j}$, $v_{max,j}$	the minimal and maximal velocity of pipe i
NP	the population size
ξ	the number of iterations

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