Article

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Method for Solving the Pareto Multi-Stakeholder Stable Solution Set of Multi-Objective Optimization for Land-Sea Intermodal Transport

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Abstract: Intermodal transport involving both land and sea encompasses multiple stakeholders and objectives, often leading to mutually exclusive goals and discretely distributed optimal solutions. This complexity makes it challenging to generate stable intermodal transport schemes. To address this, the study proposes a method using Pareto correlation structure analysis to determine the stable solution set for multi-objective optimization in land-sea intermodal transport. By defining the Pareto solution space and employing dimensionality reduction and cluster analysis, a structured correlation model is constructed. This method utilizes projection and transformation operators based on stakeholder preferences to generate a stable Pareto solution set. Using the Shanghai-Qingdao intermodal transport as a case study, the Pareto solution set is generated through a multi-objective particle swarm optimization algorithm. Based on the preferences of various stakeholders, including consignors, carriers, and environmental departments regarding transportation objectives, a multi-stakeholder stable solution set is obtained. The results indicate that, compared to schemes derived through weighted summation, the transportation schemes constructed using the proposed method balance stakeholders' multi-objective requirements, improving overall stability by approximately 30% to 60%. This approach generates stable optimized candidate schemes, facilitating the management of complex intermodal transport scenarios and supporting the selection of multi-stakeholder optimization solutions.

Keyword: Land-Sea Intermodal Transport; Multi-Objective Optimization; Multiple Stakeholders; Pareto Solution Set.

1.0 Introduction

Multimodal Multimodal transport refers to the process of utilizing two or more modes of transportation to coordinate and complete the shipment of goods (Kengpol et al., 2014). Against the backdrop of integrated land-sea transportation, multimodal transport has gradually shifted from inland transportation to cross-sea logistics and international trade. Land-sea intermodal transport plays a crucial role in connecting inland regions with coastal ports for goods transportation. Unlike general multimodal transport, land-sea intermodal transport specifically refers to the interconnection of land and sea routes, indicating that it not only involves coordinating different modes of transport but also addresses the particularities of land and sea transportation. For instance, sea transportation is susceptible to seasonal and weather conditions, while land transportation faces diverse traffic conditions and infrastructure challenges (Kreutzberger et al., 2003). Moreover, the transportation scheme of land-sea intermodal transport involves multiple stakeholders and decision-makers, including carriers, consignors, transportation departments, and environmental departments (Wang, 2003). Therefore, meeting the transportation needs of different stakeholders and selecting suitable transport solutions according to their expectations are key factors in enhancing the effectiveness of land-sea intermodal transport.

Land-sea intermodal transport falls under the broader category of multimodal transport. Based on the number of objectives preferred by different stakeholders, optimization models can be categorized into single-objective optimization and multi-objective optimization. In single-objective optimization methods for multimodal transport, the focus is primarily on a single objective factor, such as transportation time (Boussedjra et al., 2004; Ziliaskopoulos & Wardell, 2000), cost (Liu & Zhu, 2017; Y. Liu & Wei, 2018), or environmental impact (Jiang et al., 2020; Li S. et al., 2019). This is achieved by treating one factor as the primary transportation objective and the others as constraints, constructing an objective function with these constraints, and using optimization algorithms like genetic algorithms (Bin et al., 2023; Deng & Song, 2022) and particle swarm optimization (Wang H. & Wang, 2012) to solve the single-objective optimization model. However, while single-objective optimization can find an optimal solution, it cannot produce a set of optimal solutions for multiple objectives nor flexibly adjust the transportation plan according to varying requirements. Additionally, it ignores the diversity of decision-making objectives in practical situations. Therefore, land-sea intermodal transport emphasizes multi-objective optimization. Currently, there are three main categories of multi-objective optimization methods for multimodal transport: 1. Path optimization with non-dominated solution generation methods, including weighted methods (You et al., 2003), constraint methods (Li et al., 2017), hybrid algorithms (Wan & Wei, 2019), and multi-objective genetic algorithms (Cheng & Jin, 2019; You et al., 2003). These methods generate non-dominated solutions for multimodal transport and utilize stakeholder-assigned weights to find the optimal solution. 2. Interaction methods between different stakeholders and objective factors, such as the Geoffrion method (Medaglia et al., 2007). This approach analyzes the differences between stakeholders and objective factors to gradually identify the optimal solution. 3. Weighting methods based on the relative importance of objective factors in multimodal transport, which involve constructing an objective function by weighting the objectives and transforming the multi-objective problem into a single-objective problem for resolution (Li et al., 2017).

In summary, existing multi-objective solution methods can address the comprehensive path optimization problem of multimodal transport to some extent. However, challenges remain. For instance, most methods that apply genetic algorithms to multi-objective problems have not moved beyond traditional step-by-step approaches to solving them (You et al., 2003). Interaction methods often require significant amounts of time (Medaglia et al., 2007), and weighting methods are susceptible to subjective factors, tending to focus on more desirable environmental species within a region (Li et al., 2017). In contrast, intelligent optimization algorithms for multi-objective optimization problems (Xiao et al., 2011), which transform and project the feasible solution space to generate the Pareto front, are currently the mainstream approach. However, in practical land-sea intermodal transport scenarios, transportation schemes can be influenced by differences in stakeholders' preferences for multi-objective factors due to varying domains and professional backgrounds. Constructing a comprehensive objective function to evaluate transportation schemes is challenging. Additionally, with increasing consideration of external factors such as carbon emissions, environmental concerns, and traffic conditions, the number of Pareto frontier solutions becomes vast, making it difficult to balance optimization results and evaluate them through individual or isolated solutions. Therefore, to address the complexity of land-sea scenarios and assist stakeholders in balancing the importance of objective factors, this paper proposes the concept of a stable solution set for multi-objective optimization in land-sea intermodal transport. By solving for all feasible solutions that meet the transportation objectives of stakeholders, a Pareto solution space is formed. Further analysis is then conducted within this solution space, including similarity measurements and feature analysis, to construct a structured correlation structure for transportation schemes with similar characteristics. This provides structured support for different stakeholders to solve for multi-stakeholder Pareto stable solution sets based on their respective objective requirements.

The paper proposes a definition and solution method for the Pareto stable solution set of multi-objective optimization based on the multi-stakeholder and multi-objective transportation demands of land-sea intermodal transport. By systematically reviewing the transportation objectives of different stakeholders in multimodal transportation, a multi-objective particle swarm algorithm is employed to generate the Pareto solution space. Through dimensionality reduction and similarity measurement of the solution space, structured correlations of multi-stakeholder Pareto solution sets are obtained. Based on the preferences of different stakeholders regarding transportation objectives, the Pareto solution sets with structured relationships are projected and transformed. The k-nearest neighbour Pareto solution sets for each stakeholder are then solved, and their intersection forms a multi-agent Pareto stable solution set, supporting dynamic path planning for the evolving transportation demands and scenarios in multimodal transportation. Aiming to address the deficiencies in existing studies on the comprehensive path optimization problem of multimodal transport within the context of integrated land-sea planning, this research provides a new methodological foundation for multi-objective optimization in land-sea intermodal transport, considering multi-stakeholder constraints and dynamic changes in transportation environments. Compared to existing methods, the transportation scenarios proposed in this study support the personalized transportation objectives of different stakeholders and provide optimized solutions as references for their selection.

2.0 Problem Description

2.1 Definition of Multi-Stakeholder Multi-Objective Optimization Problem in Land-Sea Intermodal Transport

For the path planning problem in land-sea intermodal transport involving multiple stakeholders, it represents a typical multi-objective optimization problem. The different transportation objectives of stakeholders lead to distinct transportation routes and modes. The mathematical formulation of the multi-objective optimization problem for each stakeholder is formally described as (2-1) and (2-2):

$$\text{Min}(\&\,\text{Max})\, y = [\, f_{11}(x), f_{12}(x), \cdots, f_{mn}(x)] \tag{2-1}$$

$$subject.to \begin{cases} g_{ij}(x) \le 0, \; j = 1, 2, \cdots, \; p \\ h_{ij}(x) = 0, \; j = 1, 2, \cdots, \; q \\ x \in D \end{cases} \tag{2-2}$$

Where x is the decision variable, representing the transportation target element, y is the objective variable, n is the total number of optimization objective functions; $f_n(x)$ is the nth sub-objective function; $f_{ij}(x)$ is the jth objective function of the ith entity, $g_{ij}(x)$ and $h_{ij}(x)$ are the inequality constraint and equality constraint of the ith entity respectively, D is the feasible domain of x .

2.2 Definition of Multi-Stakeholder Pareto Stable Solution Set

When solving multi-objective optimization problems, it is typical to compute all possible solutions, forming a solution space. By discussing the solutions within this space, the optimal solution that meets the stakeholders' requirements can be identified (Wang & Peng, 2019). For instance, constructing the Pareto optimal boundary frontier comprises the interval of solution sets that cannot be improved upon by other solutions across all objectives. Since the Pareto optimal boundary frontier encompasses all possible optimal solutions, it only requires discussing stakeholders' preferences regarding the objectives to find the optimal solution that satisfies their needs (Ishibuchi et al., 2019). However, in practical scenarios such as land-sea intermodal transport involving multiple stakeholders, the diversity and partial exclusivity of each stakeholder's objective requirements make it challenging for multi-objective optimization based on a single-stakeholder Pareto solution space to consider the objectives of other stakeholders. Therefore, to construct a correlation structure of Pareto solutions, it is necessary to define the multi-stakeholder Pareto solution space.

Definition 2.1 (Multi-Stakeholder Pareto Solution Space): The multi-stakeholder Pareto solution space refers to the feasible solution space formed by the optimization objectives of multiple stakeholders. Assuming the current number of optimization objectives is n , the solution space $U(a_1e_1, a_2e_2, \cdots, a_ne_n)$ can be defined, where $e_1, e_2, \cdots, e_n$ represents the dimension of objectives and $a_1, a_2, \cdots, a_n$ *a* represents the dimension coefficient. Due to varying demands of different stakeholders on the objectives, there are differences in dimension coefficients for

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different stakeholders. For a given m number of stakeholders, a multi-stakeholder solution space can be constructed, as defined in Equation (2-3)

$$U^{m,n} = \{U^{i,n}\} = U(a_{i1}e_1, a_{i2}e_2, \cdots, a_{in}e_n), i = 1, \cdots, m \quad (2\text{-}3)$$

According to the definition of Pareto solutions, it can be understood that each stakeholder's solution space can construct its corresponding Pareto frontier. The inconsistency of Pareto frontiers is the fundamental reason for the instability of multi-stakeholder multi-objective optimal solutions. By constructing a multi-stakeholder Pareto solution space, utilizing measures of solution similarity and cluster analysis, building a relational structure for Pareto solution sets, and then projecting and transforming the Pareto solution space based on each stakeholder's transportation objective preferences, a stable set of multi-stakeholder Pareto solutions can be generated. Therefore, before constructing a stable Pareto solution set, it is necessary to construct a *k*-nearest neighbour Pareto solution set, defined as follows:

Definition 2.2(*K*-nearest neighbour Pareto solution set): For a given Pareto solution space $U^{i,n}$, assuming x is a feasible solution in the solution space, its *k*-nearest Pareto solution set refers to a subset $T_k = \{x_1, x_2, \cdots, x_k\}(k \le N)$ in $U^{i,n}$, satisfying the condition that $\sum_{j=1}^{k} d(x, x_j)$ is minimized, where $d()$ is a similarity calculation function.

Due to the inconsistency of the dimension coefficients of solution spaces for different stakeholders, the *k*-nearest neighbour Pareto solution sets of corresponding solution spaces also exhibit differences. However, we can use an intersection operator to get the stable solution set of multi-stakeholders: $T_{1k} \cap T_{2k} \cdots \cap T_{mk} = \{x_1, x_2 \cdots x_p\}$, which take into account the needs of all stakeholders. According to the characteristics of the intersection operator, p satisfies the quantitative relation $p \le k$. In order to get the k Pareto stable solution set, it is necessary to dynamically adjust the number of nearest neighbours in each stakeholder 's solution space (Figure 1). Thus, the *k*-multi-stakeholder pareto stable solution set can be defined as follows:

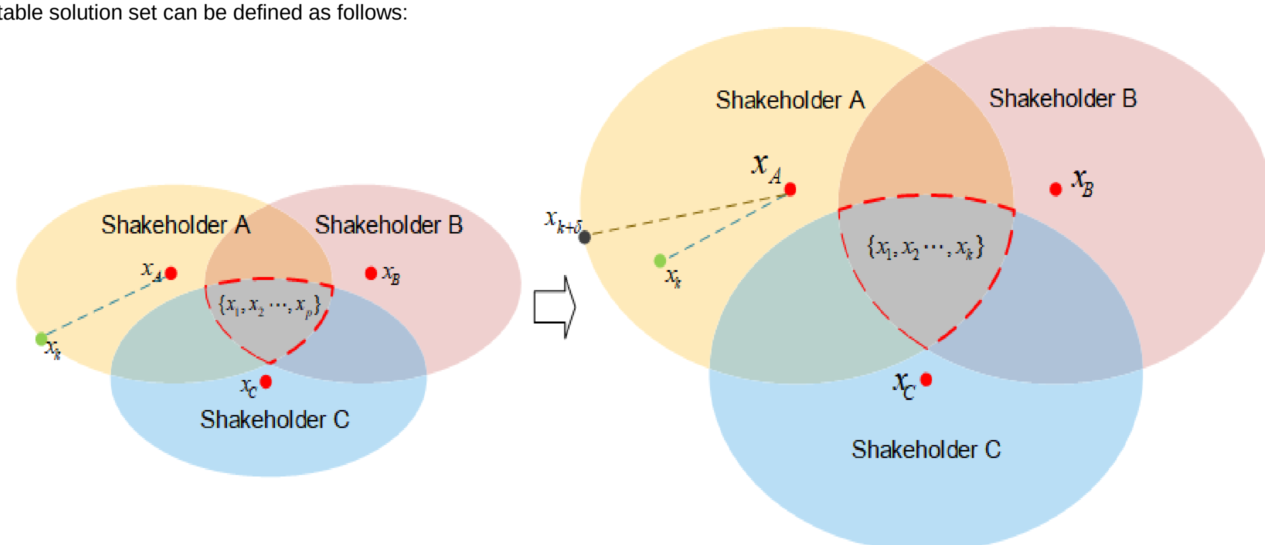

Figure 1: Multi-Stakeholder Pareto Stable Solution Set

Definition 2.3 (*K*-nearest Multi-Stakeholder Pareto Stable Solution Set): For a given Pareto solution space $U^{m,n}$, assuming x is a feasible solution in the solution space, its *k*-nearest multi-stakeholder Pareto stable solution set refers to a subset $M_k = \{x_1, x_2, \cdots, x_k\}(k \le N)$ in $U^{m,n}$, satisfying the needs of all *n* subjects. It can be defined in Equation (2-4):

$$M_k = T_{1(k+\delta_1)} \cap T_{2(k+\delta_2)} \cdots \cap T_{m(k+\delta_m)} = \{x_1, x_2 \cdots x_k\} \quad (2\text{-}4)$$

Where $\delta_i (i = 1, 2, \cdots, m)$ represents the number of additional nearest neighbour solutions added within each agent's solution space.

2.3 Approach to Solving Based on Multi-Stakeholder Pareto Stable Solution Set in Land-Sea Intermodal Transport

Based on the multi-objective optimization problem of multimodal transportation, which involves multiple stakeholders in decision-making, the Pareto solution set obtained from multi-objective optimization algorithms undergoes projection and transformation in the objective space. To accommodate the preferences of different stakeholders regarding objective elements and to obtain a multi-stakeholder Pareto stable solution set, it is necessary to construct multi-stakeholder solution spaces based on the transportation objectives of each stakeholder. Subsequently, through data dimensionality reduction and cluster analysis, transportation schemes with similar features are classified, creating a network of relationships between the Pareto solution sets. Each stakeholder's k Pareto stable solution sets are identified. When each stakeholder selects the nearest transportation scheme based on their preferences, a series of Pareto stable solution sets can be output according to the associated relationships, and the intersection is taken to obtain the multi-stakeholder Pareto stable solution set, as illustrated in Figure 2.

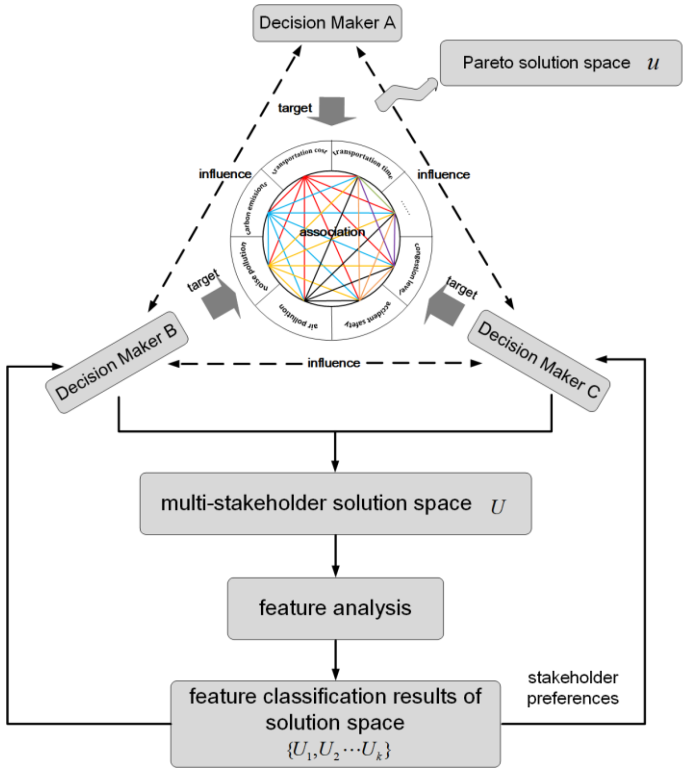

Figure 2: Approach to Solving the Multi-Stakeholder Pareto Stable Solution Set

3.0 Model Construction and Solution

This study addresses the multi-objective path planning problem faced by different entities in land-sea intermodal transport, proposing a structured method for developing the Pareto solution set. The aim is to correlate the multi-objective elements of various entities in land-sea intermodal transport with the non-dominated solutions in the solution set. In this context, multi-objective optimization problems typically involve multiple dimensions, resulting in complex relationships among objective elements, which makes it challenging to associate the multi-objective elements of multiple stakeholders with the Pareto solution set. Therefore, there is a need to analyze the features of the Pareto solution set, construct a structured relationship model for the Pareto solution set, and support the selection of multi-stakeholder transportation path planning schemes.

3.1 The definition of the Pareto Solution Set Structured Correlation Modell

After solving the multi-objective transportation problems in land-sea intermodal transport using multi-objective particle swarm optimization, it is necessary to provide a structured description and organization of the generated Pareto solution set. In graph theory, a graph is defined as a mathematical model representing a certain type of discrete entity set and the connections between each pair of entities within that set (Cai et al., 2021). Therefore, the definition of a graph can be utilized to structure the Pareto solution set.

Definition 3.1 (Structured Correlation model of Pareto Solution Set): The Pareto solution set (denoted as P) is structurally described using a directed graph, where the directed graph G is composed of a binary tuple (V, E). V represents vertices indicating non-empty finite Pareto solution sets, and E represents edges indicating relationships between Pareto solutions. The formal expression is as follows Equation (3-1):

$$\begin{cases} G = (V, E) \\ V = \{v \mid v \in P\} \\ E = \{< v_i, v_j > \mid v_i, v_j \in V \wedge p(v_i, v_j)\} \end{cases} \quad (3\text{-}1)$$

Where $p(v_i, v_j)$ represents a connected path from one point to another. When v_i and v_j are connected, it is represented by the value 1; otherwise, it is represented by 0. The connectivity is determined based on the relationship between Pareto nondominated solutions v_i and

v_j ,denoted as $R(v_i, v_j)$ .When it is less than a specified threshold δ , it is considered connected; otherwise, it is considered disconnected. Therefore, the structured association of the Pareto solution set can be formalized in the form of an adjacency matrix as shown in Equation (3-2):

$$A_{ij} = \begin{cases} 1, R(v_i, v_j) \le \delta, v_i, v_j \, adjacent \\ 0, R(v_i, v_j) > \delta, v_i, v_j \, Non-adjacent \end{cases} \quad (3\text{-}2)$$

Structuring the Pareto solution set via Equation (2-2) entails building structured correlations based on the characteristic information of the solution set. Therefore, an analysis of the feature information contained within the Pareto solution set is necessary. Non-dominated solutions within the Pareto set are mapped onto network nodes, with the partial order relation among non-dominated solutions serving as edges, thereby constructing a structured Pareto correlation model.

3.2 Pareto Solution Set Structured Correlation Model

The multi-objective problem in Land-sea intermodal transport is more complex than traditional multi-objective problems, as it requires the comprehensive consideration of multiple objective elements from different stakeholders. Preferences of different stakeholders regarding transportation elements directly influence various transportation planning schemes. Analysing the relationship between the data characteristics of the Pareto solution set and the multi-objective elements of multiple stakeholders is crucial for achieving structured Pareto solution sets. Firstly, by conducting PCA (Principal Component Analysis) on the Pareto solution set to reduce dimensionality, standardizing the data size to n with dimension m , we obtain $\tilde{x}_{ki}(k=1,2,\cdots,n; i=1,2,\cdots,m)$. Then, calculate the correlation coefficient matrix R , as shown in Equation (3-3):

$$R = (r_{ij})_{m\times m} = \frac{\sum_{k=1}^{n} \tilde{x}_{ki} \cdot \tilde{x}_{kj}}{n-1}, (i, j = 1, 2, \cdots, m) \quad (3\text{-}3)$$

Based on the correlation coefficient matrix R , we calculate the eigenvalues $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_m \ge 0$ and eigenvectors $u_1, u_2, \cdots, u_m$ of the Pareto solution set. Here $u_j = (u_{1j}, u_{2j}, \cdots, u_{nj})^T$. Finally, we solve for the principal components according to Equation (3-4):

$$\begin{cases} y_1 = u_{11}\tilde{x}_1 + u_{12}\tilde{x}_2 + \cdots + u_{1n}\tilde{x}_n \\ y_2 = u_{21}\tilde{x}_1 + u_{22}\tilde{x}_2 + \cdots + u_{2n}\tilde{x}_n \\ \vdots \\ y_m = u_{m1}\tilde{x}_1 + u_{m2}\tilde{x}_2 + \cdots + u_{mn}\tilde{x}_n \end{cases} \quad (3\text{-}4)$$

Where y_m represents the mth principal component. PCA (Principal Component Analysis) is utilized to reduce the dimensionality of objective elements, retaining more data features from the original dataset. This transformation converts the high-dimensional Pareto solution set data into low-dimensional data, facilitating further analysis of the low-dimensional data features. This approach enables the structured analysis of the Pareto solution set based on the relationships among objective elements.

Next, we utilize K-means clustering analysis to analyse the features of the dimension-reduced Pareto solution set data. By randomly setting K feature space points as initial cluster centers, denoted as $\mu_1^{(0)}, \mu_2^{(0)}, \cdots, \mu_k^{(0)}$, we calculate the loss function as shown in Equation (3-5). This involves computing the distance from each point to the K cluster centers.

$$J(c, \mu) = min \sum_{i=1}^{M} \left\| x_i - \mu_{c_i} \right\|^2 \quad (3\text{-}5)$$

Where x_i represents the ith sample data of the Pareto solution set, c_i is the cluster to which x_i belongs, μ_{c_i} is the centroid corresponding to the cluster, and M is the total number of samples in the Pareto solution set. The classification of unknown points involves selecting the nearest cluster center as the label category. The decision criterion is shown in Equation (3-6):

$$c_i^t < argmin_k \left\| x_i - \mu_{c_i} \right\|^2 \quad (3\text{-}6)$$

Where c_i^t represents the sub-cluster c_i after t iterations. By recalculating the new centroid for each cluster and iterating continuously, we ultimately minimize the loss function of the clustering results and obtain sub-cluster $\{c_1, c_2, \cdots, c_n\}$. The Pareto solution set sub-clusters c_i obtained using the K-means clustering method exhibit similar data features, as shown in Equation (3-7):

$$mean(c_i, f_i) = \frac{1}{|C|} \sum_{x \in c_i} x_{f_i} (i = 1, 2, \cdots, n) \quad (3\text{-}7)$$

Where f_i represents the data features of sub-cluster c_i , $|C|$ is the size of sub-cluster c_i , x represents the data within sub-cluster $mean(c_i, f_i)$, and mean represents the mean of sub-cluster c_i on feature f_i . Due to the dominance relationship among sub-clusters and within sub-clusters, denoted as c_i of the objective elements, we utilize the relationships between objective elements among sub-clusters and within sub-clusters to map the Pareto solution set data containing objective elements onto the graph network nodes, as shown in Figure 3.

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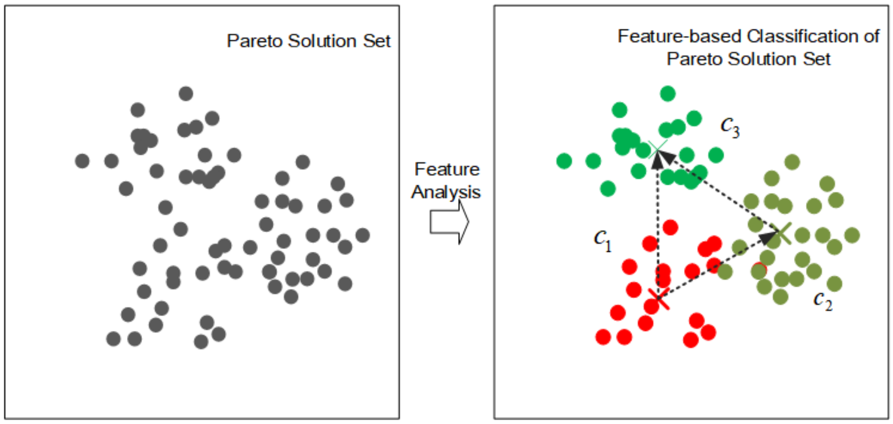

Figure 3 Structuring of the Pareto Solution Set

Where c_1, c_2 and c_3 are sub-clusters constructed based on the Pareto solution set. If sub-cluster c_1 contains objective elements superior to those in sub-cluster c_2, satisfying Equation (3-8):

$$mean(c_1, f_n) \prec mean(c_2, f_n) \quad (3\text{-}8)$$

By using the above equation, the objective elements contained within each sub-cluster are mapped to nodes, and the partial order relation is computed using the mean of the objective elements within each sub-cluster. For sub-cluster c_1, with n objective elements in the Pareto solution set, if m objective elements in non-dominant solution o_1 are all superior to those in o_2, satisfying Equation (3-9):

$$o_1(f_m) \prec o_2(f_m) \text{ and } R(o_1, o_2) \le \delta \Rightarrow A_{12} : o_1 \to o_2 \quad (3\text{-}9)$$

Where $R(o_1, o_2)$ represents the similarity relationship between two solutions, and δ represents the similarity threshold. Within the sub-cluster, the Pareto solution set considers o_1 and o_2 as vertices, with edge A_{12} representing the connectivity between solutions. When the solutions satisfy the partial order relation and the similarity calculation between the objective dimensions of the solutions is less than the threshold, they are considered connected.

3.3 The Multi-Stakeholders Optimization Solution based on the Pareto Solution Set Correlation Model

In actual Land-Sea intermodal transport processes, multi-stakeholder participate and make decisions, leading to complex relationships such as similarity, inclusion, and contradiction among the objective elements of multi-stakeholder transportation. Based on the Pareto solution set, different stakeholders utilize expert experience or comprehensive evaluation methods such as the weighted sum method to assign weights to each objective function, calculating a single optimal solution as shown in Equation (3-10):

$$minZ = \sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij} L_{ij} \quad (3\text{-}10)$$

Where L_{ij} and w_{ij} represent the jth objective element and its corresponding weight for the ith entity, respectively. However, intermodal transport is significantly affected by environmental factors such as weather and traffic during transit, necessitating timely adjustments to transportation routes and modes to cope with unexpected situations. A single transportation plan may not adequately address the complexities of intermodal transport scenarios. Therefore, utilizing Equation (3-10) to solve within the Pareto solution set correlation network allows for the representation of different stakeholder objective solution spaces Ω_k represents all solution spaces of individual objective elements in the Pareto solution set space $\{u_1, u_2, \cdots, u_k\}$, as shown in Equation (3-11):

$$\Omega_k = \left\{ o \in c_i \middle| u_j^T o \le u_k^T o, \forall j = 1, 2, \cdots, N \right\} \quad (3\text{-}11)$$

Where u_j^T represents the expected vector of the jth objective element for the stakeholder. The element o is a solution in the Pareto solution set Ω_k. o and u_k have a small angle α if and only if they satisfy Equation (3-12):

$$u_k^T o = \|u_k\| \bullet \|o\| cos\alpha \quad (3\text{-}12)$$

Where α represents the threshold for multiple transportation objectives of multiple agents, and $u_k^T o$ is the maximum inner product. Based on equation (2-10), the initial solution for multimodal transportation by land and sea for multiple agents is obtained. Then, through the constructed relationship of Pareto solution sets, solution sets with similar relationships and transportation schemes that comply with the transportation objectives of the agents are output.

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3.4 Process for Solving Multi- Stakeholder Pareto Stable Solution Set in Intermodal Transportation

Based on the definition of the multi-stakeholder Pareto stable solution set, solving the *k*-Pareto solution set in practical scenarios involves complex time and space complexities. Therefore, an approximate solution method is adopted to linearly superimpose the multi-stakeholder Pareto solution space to obtain the *k*-Pareto stable solution set. Firstly, utilizing the multi-objective particle swarm optimization algorithm according to the transportation objectives of different agents, optimization is performed for the elements of intermodal transportation, constructing the Pareto solution space for each stakeholder. Then, through transformation and projection of the solution space, and subsequently superimposing according to the optimization strategies of the stakeholders, as shown in Figure 4.

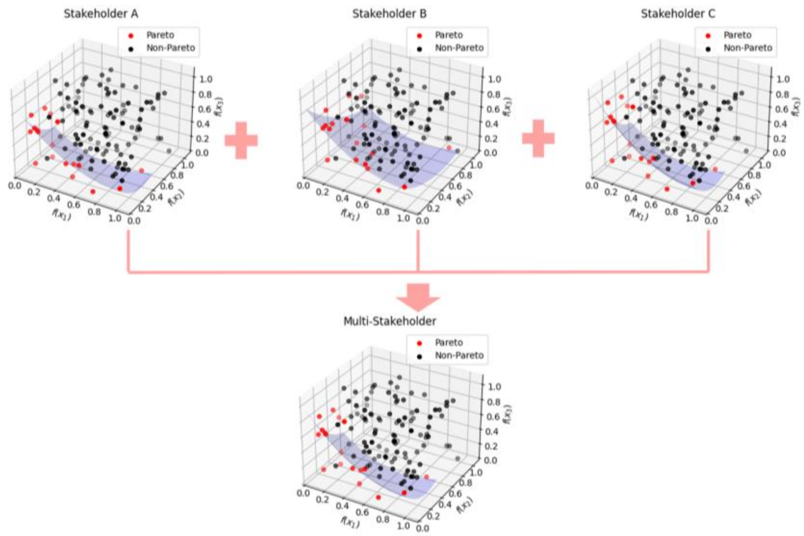

Figure 4 Construction of the Pareto Solution Space

Furthermore, based on the constructed Pareto solution space, analyse the data features of the Pareto solution set within the solution space. Utilize PCA (Principal Component Analysis) and K-means clustering analysis to categorize Pareto solution set data with similar feature attributes in the multi-stakeholder Pareto solution set. Then, select suitable transportation plans from the clustering results according to the objective requirements of different stakeholders. The specific solution approach is depicted in Figure 5.

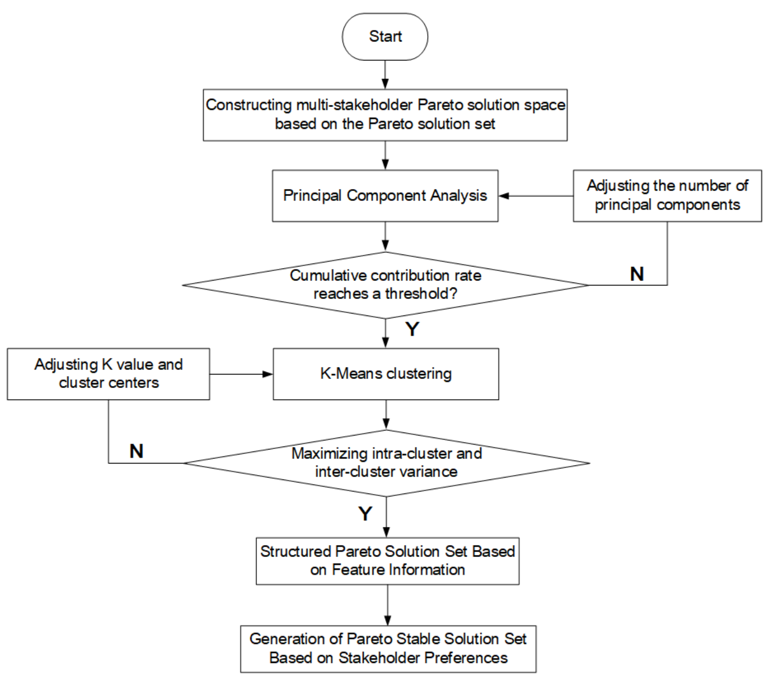

Figure 5 Model Solution Process Flowchart

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4.0 Experiment and Analysis

4.1 Data Collection

Shanghai and Qingdao are important port cities for trade, with advantageous geographical locations and advanced infrastructure, providing necessary support for multimodal transportation. Additionally, both cities have well-developed transportation networks, allowing for the implementation of various multimodal transportation schemes, including combinations of railways, highways, and maritime shipping. In this study, Shanghai and Qingdao are selected as the origin and destination cities for freight transportation. We aim to investigate the multi-objective path optimization problem for logistics trade and cargo transportation along the route between these two cities, which is of significant importance for improving the level of domestic and international intermodal transportation. The specific transportation network is illustrated in Figure 6, and the city nodes are numbered and their coordinates are listed in Table 1.

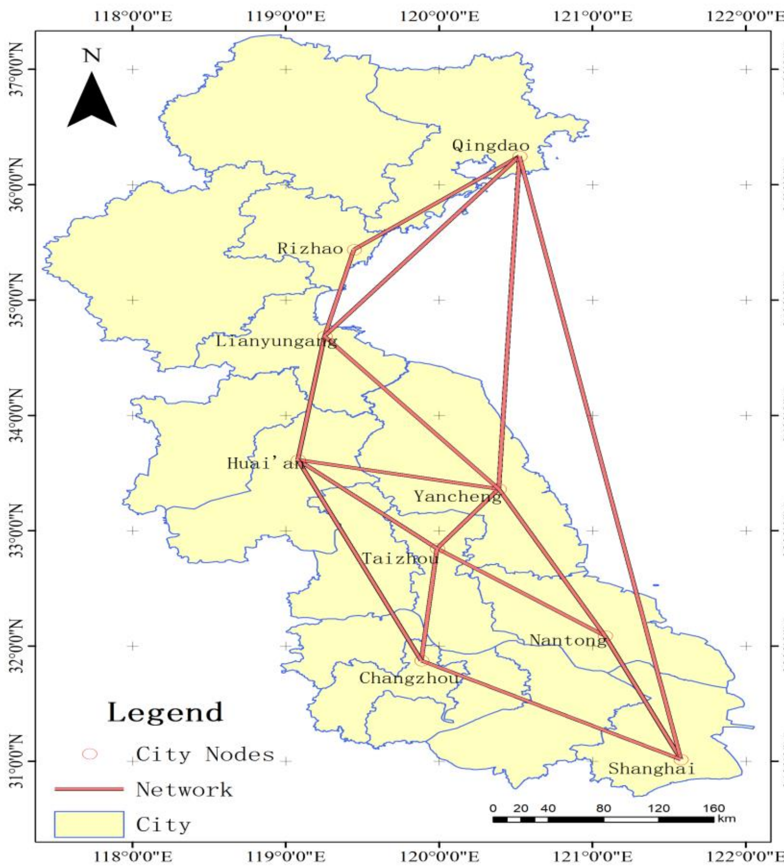

Figure 6: Illustration of Transportation Network Structure

Table 1: Specific Selection of City Nodes and Their Numbers

Serial Number	Node	(Longitude, Latitude)	Serial Number	Node	(Longitude, Latitude)
1	Shanghai	(121.485°E,31.236°N)	6	Huai'an	(119.120°E,33.556°N)
2	Nantong	(120.901°E,31.986°N)	7	Lianyungang	(119.228°E,34.602°N)
3	Changzhou	(119.981°E,31.816°N)	8	Rizhao	(119.533°E,35.423°N)
4	Taizhou	(119.929°E,32.460°N)	9	Qingdao	(120.389°E,36.072°N)
5	Yancheng	(120.167°E,33.355°N)			

The distances between nodes on highways were obtained using the mapping feature of Google Earth software, railway distances were obtained from Train Wiki queries, and sea route distances were measured using Netpas Distance, as shown in Table 2.

Table 2: Transportation Modes and Distances (km) between City Nodes

City pairs	Highway	Railway	Shipping	City pairs	Highway	Railway	Shipping
1-2	127	158	—	4-5	124	155	—
1-3	188	165	—	4-6	196	260	—
1-5	327	316	358	5-6	125	123	—
1-9	—	—	706	5-7	196	186	256
2-4	127	119	—	5-9	—	—	361
2-5	196	166	—	7-9	253	268	187
3-4	102	173	—	8-9	148	180	128
3-6	262	345	—				

Table 3 presents the transportation prices for each mode of transportation. Table 4 displays the transfer time and transfer costs incurred when switching between different modes of transportation. As for the external impact costs caused by transportation processes, due to the lack of calculated data domestically, the transportation's external impacts are computed based on the 2019 edition of the "Handbook on the External Costs of Transport" established by the European Union, as shown in Table 5.

Table 3: Unit Transportation Cost

Transportation mode	Unit transportation cost [$yuan/(t \cdot km)$]	Data source
Highway	0.4	Logistics network
Railway	0.3	China Railway Network
Shipping	0.15	Logistics network

Table 4: Transit Time and Transit Cost

Transportation mode(TEU/h 、 $yuan/t$)	Railway	Highway	Shipping
Railway	0	0.04/3.09	0.05/26.62
Highway	0.04/3.09	0	0.03/5.23
Shipping	0.05/26.62	0.03/5.23	0

Table 5: Unit External Impact Caused by Different Modes of Transportation

Transportation mode	Highway [$g/(t \cdot km)$]	Railway [$g/(t \cdot km)$]	Shipping [$g/(t \cdot km)$]
Carbon emissions	97.60	11.33	8.65
air pollution	5.26	5.89	3.09
Environmental damage	1.47	1.94	1.55

4.2 Algorithm Design

The paper utilizes the multi-objective particle swarm optimization algorithm to solve the case study. The transportation parameters are set as follows: cargo weight is 20 tons, initial population size of the multi-objective particle swarm algorithm is 100, inertia factor is 0.8, local velocity factor is 0.1, global velocity factor is 0.1, grid subdivision quantity is 10, and external archive threshold is set to 300. The algorithm is implemented using Python code. After 30 iterations, the Pareto optimal solution set is obtained. The distribution of the Pareto frontier obtained by the algorithm is shown in Figure 7. In Figure 7a (up), the distribution of effective solutions with transportation time and transportation cost as

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transportation objectives is presented. In Figure 7b (down), the distribution of multiple objective Pareto frontiers including transportation routes and transportation modes is included.

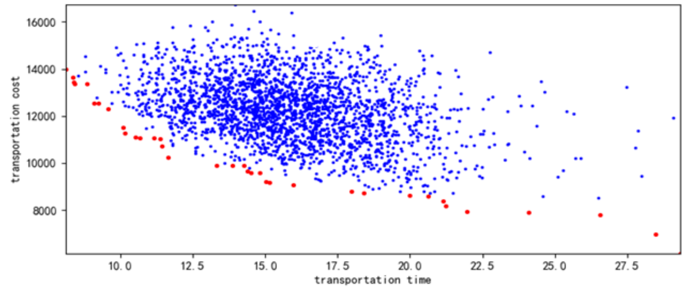

Figure (a)

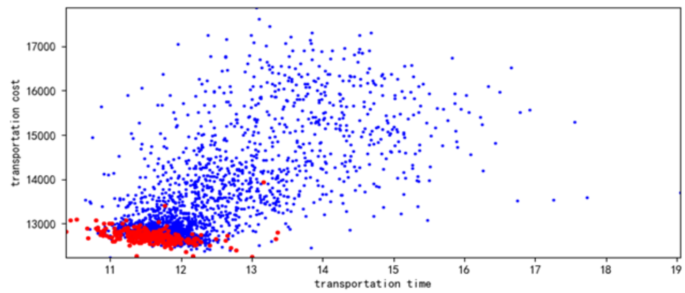

Figure (b)

Figure 7 Distribution of the Pareto Front

Each blue point represents a solution space, while the red points indicate the approximate Pareto frontier. In the actual Pareto solution set, each solution has its own advantages. The representative solution set generated is shown in Table 6. When different stakeholders select the path and mode of intermodal transportation, they can choose the corresponding Pareto solution according to their own needs.

Table 6: Representative Pareto Solutions

Transportation routes	Transportation mode	Transportation time /h	Transportation cost /Yuan	Carbon emissions /kg
1-5-7-9	H-H-H	8.10	18633.310	456.2880
1-9	S	29.33	6144.452	439.6668
1-2-5-9	H-H-S	18.94	11109.880	413.8308
1-2-5-7-8-9	H-H-R-S-S	16.37	13423.010	466.3088
1-2-5-7-8-9	R-T-H-H-H	11.36	15812.150	523.668

In the table, 'H' represents highway transportation, 'S' represents sea transportation, and 'R' represents railway transportation. The first three sets of solutions represent the optimal solutions based on transportation time, transportation cost, and carbon emissions as objective elements, while the last two sets represent compromise transportation solutions. Following the research approach, analyzing the generated Pareto solution set requires dimensionality reduction of the data. In the experiment, principal component analysis (PCA) and K-means clustering analysis were adopted. The optimal number of principal components and the optimal number of clusters were determined using indicators such as the cumulative explained variance ratio, silhouette coefficient, and elbow method. The Pareto solution set data with similar features were categorized and classified, and structured correlations were performed. Table 7 presents the results of the relevant parameters and calculation indicators.

From the above table, it can be observed that when the number of PCA principal components is three, the cumulative explained variance ratio exceeds 90%. At this point, the dimensionality of the objective elements is reduced to three dimensions, with a small number of retained principal components and a relatively good cumulative explained variance ratio. Therefore, the optimal number of principal components for PCA in this dataset is three.

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Furthermore, when the number of clusters is three, it indicates a high inter-cluster density. This suggests that the optimal number of clusters is three, as it maximizes the distance between clusters while maintaining internal density. This simplification reduces the complexity of the multi-objective problem for different entities when considering objective elements.

Table 7: Parameter Analysis of Model Methods

model methodology	evaluation metrics	
	cumulative explained variance	
Principal Component Analysis	(principal component $p=2$), $>80\%$	(principal component $p=3$), $>90\%$
	elbow method	*silhouette coefficient*
K-Means Clustering Analysis	The stable inflection point where the loss value decreases most rapidly when $K=3$.	When $K=3,4$, the difference in silhouette coefficients is small; and the silhouette coefficient is the largest when $K=3$.

After clustering analysis of the Pareto solution set data, the relationships between the Pareto solution set data within each cluster are utilized. Similarity measurements are performed on the Pareto solution set data in each objective dimension. Based on the measurement results, adjacent points are connected to form a network. Figure 8 shows the network structure constructed for each cluster.

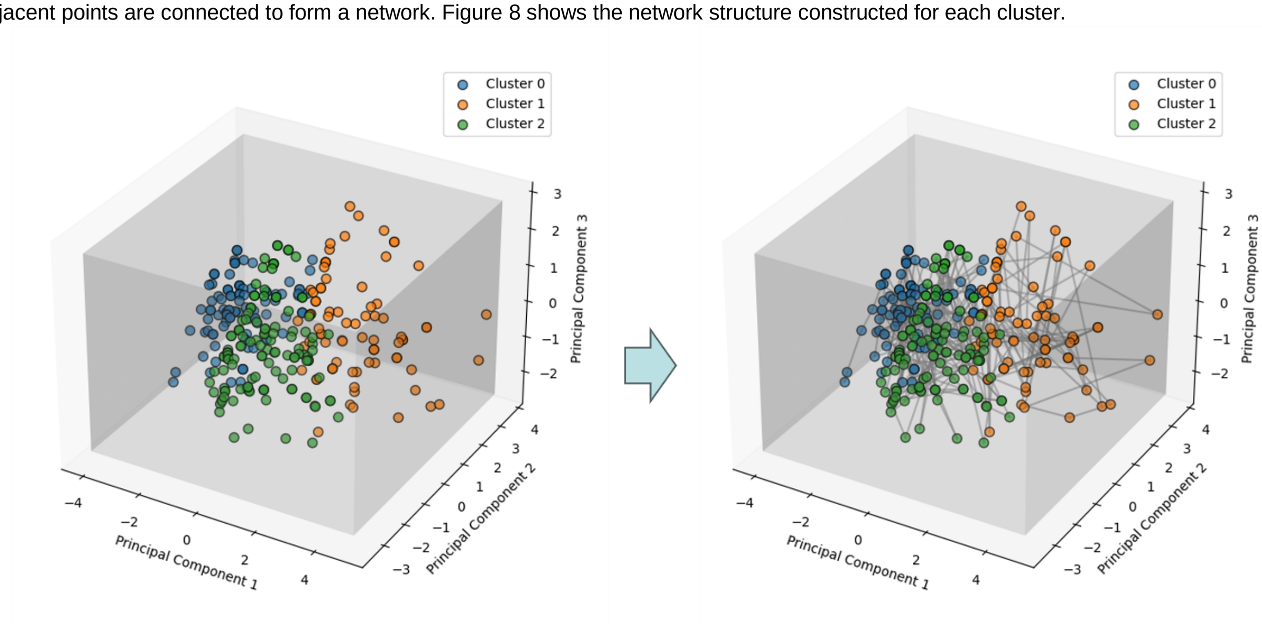

Figure 8 Structuring of the Pareto Solution Set

4.3 Results Analysis

By analyzing the clustering results, the structure of the Pareto solution set is constructed. In practical intermodal transportation processes, carriers typically act as the decision-makers for transportation schemes, while other stakeholders serve as participants, providing corresponding reference schemes. Therefore, transportation time and transportation cost, which are of primary concern to carriers, are set as objective elements. We assign weights to these objective elements and establish acceptable thresholds for the stakeholders. Then, based on the structured relationship of the Pareto solution set, approximate solutions are calculated, forming a stable solution set. The analysis of the stable solution set is presented in Figure 9.

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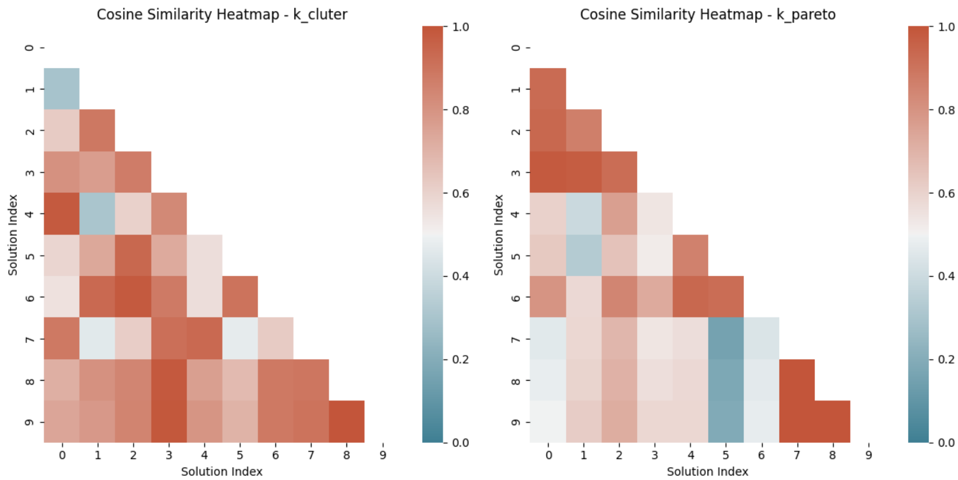

Figure 9 Comparison of Similarity Experiments

Comparison of the Stability of Multiple Solution Sets Obtained from Structured Pareto Solution Set Relationship and Weighted Method: The experimental results indicate that the solution set obtained from the structured Pareto solution set relationship is more stable compared to the solution set obtained directly using the weighted method.

Furthermore, validation of the optimized transportation solutions for multiple stakeholders with multiple objective transportation elements is conducted. Figure 10 illustrates the comparison of experimental results of transportation solution sets obtained through structured Pareto solution set calculation and weighted method, where $o_1 - o_6$ represent the solution sets obtained through Pareto stable solution set calculation method, and $w_1 - w_4$ represent the solution sets obtained through the weighted method.

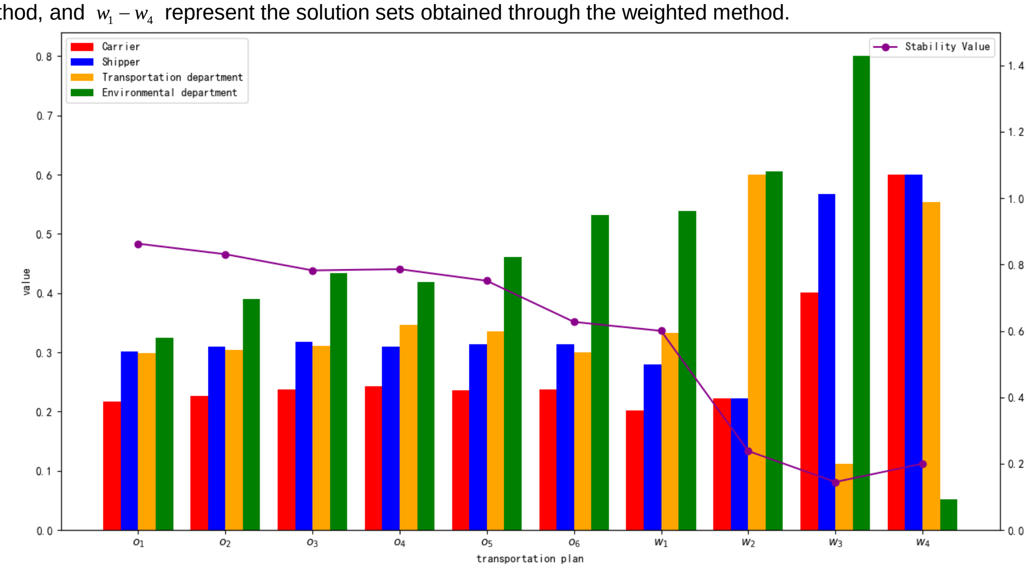

Figure 10 Stability Experiment Comparison

The experiments demonstrate that while the direct weighted method can satisfy the multi-objective requirements of a single stakeholder, it struggles to balance the objectives of other stakeholders. Through comprehensive comparisons, it is evident that transportation solutions obtained using the Pareto structured relationship outperform those derived directly from the weighted preferences of individual stakeholders within the Pareto solution set. The stability of the multi-stakeholder Pareto stable solution set has increased from 0.3 to 0.6, representing an improvement of approximately 30%. This enhancement generates a series of stable optimized candidate solutions for different stakeholders to choose from, facilitating the management of complex intermodal transportation scenarios and supporting the selection of multi-stakeholder optimization solutions.

5.0 Conclusions

In the context of intermodal transportation scenario path planning involving multiple stakeholders and objectives, this paper builds upon the foundation of using multi-objective particle swarm optimization to generate a Pareto solution set. To address the difficulty in selecting

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solutions for different stakeholders due to the unstructured nature of the Pareto solution set, the paper proposes a structured relationship model for the Pareto solution set. The aim is to provide a structured description and organization for the generated Pareto solution set, thereby offering support for the structured selection of transportation solutions by different stakeholders. The experimental results show that the transportation scheme obtained through the structured Pareto solution set exhibits higher similarity and stability compared to the transportation scheme solved by traditional multi-objective optimization algorithms. This approach is conducive to supporting the personalized transportation goals and requirements of different stakeholders, providing optimized solutions as a reference for solution selection.

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Conflicts of Interest: The authors declare that there is no conflict of interest.

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