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Module Configuration of Rail Freight Transportation with Both Customer Segmentation and Product Family Genealogy in China

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Abstract: The Chinese government is actively restructuring transportation to shift towards more sustainable rail freight transportation (RFT); however, there is still a lack of more systematic optimization in the whole production chain. This study develops a dual-focus modular configuration approach to explore the integration of customer demand and the production chain to achieve more sustainable operations in RFT. Customers have yielded eleven distinct groups, and operational processes have been segmented into sixteen modules by using the Ant Colony Optimization-based Fuzzy C-Means Clustering (ACOFCM) algorithm. Consequently, a Product Family Genealogy (PFG) model is conducted to identify three tailored product families (i.e., cross-border, multi-modal and general freight product). The developed dual-focus modular configuration approach has been proven to be feasible by utilizing a backtracking algorithm through a case study in an RFT logistics enterprise in China, which provides a standardization and optimization for RFT modular configurations.

Keywords: modular design; customer segmentation; logistics services; railway freight transportation; ACOFCM clustering algorithm

MSC: 90B06



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1. Introduction

Given that the transportation sector ranks as the third-largest emitter of CO_2 in China, it bears significant responsibility for mitigating carbon emissions [1]. Rail transport boasts lower carbon emissions per unit of cargo transported over distance and offers a high capacity for commodity transport [2]. The Chinese government has vigorously promoted the adjustment of the freight transportation structure from road to railway, owing to a cleaner mode of railway transportation [3–5]. Despite efforts by the Chinese government to increase the market share of railways through various policies and strategies (e.g., Multi-modal Transport Incentive Policies (2021–2025), Construction of National Logistics Hub Network), the market share of rail freight transportation still remains relatively low, accounting for only 9% of the total freight transportation [6]. One of the key factors limiting the growth of freight volume is the limited efficiency of the whole production chain in traditional rail freight transportation (RFT) modes [7].

The freight volume of RFT is increased through two primary strategies: (1) boosting cargo capacity to improve freight volume per mile; and (2) streamlining the production chain to optimize overall transportation efficiency. However, increasing freight volume faces inherent limitations and can contribute to environmental problems. Further optimizing the production chain of railway transportation meets significant challenges due to its deeply rooted infrastructure and substantial investment in equipment [8]. Therefore, it is critical to implement modular configurations to better organize the whole production chain in the RFT.

The modular configuration of RFT has garnered increasing attention from scholars. Numerous studies have investigated the potential of modular designs to enhance transport efficiency and reduce operating costs. Tian et al. [9] examined how modular services address various customer needs, thereby improving the flexibility and responsiveness of rail transportation. Eltoukhy et al. [10] highlighted the significance of data-driven modular allocation in minimizing resource waste and enhancing carbon emission reduction efficiency. Ng et al. [11] noted that modular design can significantly boost transport capacity and lower carbon emissions per unit of goods. The aforementioned research mainly focused on the structural relationships within modules to improve their functional coordination and technological integration. However, there is a limited discussion on modular design from a perspective of customer demands.

The railway sector necessitates a dual focus on customer segmentation and product family genealogy to meet customer demands and align with environmental and economic goals [12]. Current research in railways tends to concentrate on either customer segmentation or product family genealogy [13,14]. The limited discussion on the integration of customer segmentation and product family genealogy hinders the ability to fully capture the complexity of market demand. The oversight of modular design requirements across diverse customer groups has inadvertently led to misleading decision-making support for rail freight companies [15]. To address the research gap, this study aims to integrate customer segmentation and product family genealogy to design modular configurations with diverse customer needs, thereby promoting the sustainable development of rail freight services. The primary objective of this study is to identify customer segmentations based on their characteristics and preference of rail freight, and then design product family generation based on a proposed module division scheme, resulting in a dual-focus modular configuration.

2. Literature Review

The relevant modular configuration study is primarily based on two approaches, namely customer demand analysis and modular product design methods. The state-of-art studies have been shown as follows.

2.1. Literature on Customer Demand Analysis

Customer demand analysis is crucial for understanding market dynamics and preferences, particularly in rail freight services, where the diversity and complexity of demand necessitate effective analysis [16–18]. According to Kottler and Keller [19], customer segmentation allows enterprises to identify distinct characteristics of various customer groups, enabling the development of targeted marketing strategies. Additionally, product family genealogy theory highlights the link between product modular design and customer needs, emphasizing that flexibility and customization are essential in modular service design to effectively address these needs [20].

Previous studies have extensively utilized clustering algorithms, such as hierarchical clustering [21], K-means [22], K-means++ [23], Fuzzy Clustering [24], Affinity Propagation Clustering [25], and Co-clustering [26], to investigate various demands in different domains. Yan et al. [27] proposed a coverage-based clustering algorithm by incorporating rough set theory, leading to a higher classification performance. Zheng et al. [28] integrated balanced optimization with extreme learning machines to improve classification efficiency. Li et al. [29] integrated quantum particle swarm optimization into the traditional K-means algorithm, optimizing search intensity and parameter selection through continuous experimentation.

The aforementioned clustering methods are prone to sensitivity regarding the selection of initial cluster centers, which leads to entrapment in local optima. The Ant Colony Optimization-based Fuzzy C-Means Clustering (ACOFCM) algorithm leverages ant colony optimization to identify the best initial cluster centers and clusters from inherent attributes, eliminating the need for preset rules or external influence. Biniaz and Abbasi [30] introduced an Unsupervised Ant Colony Optimization (UACO) integrated with Fuzzy

C-Means (FCM) that adeptly handles noise and efficiently uses spatial neighborhood information for image segmentation. Al and Luis [31] demonstrated that by utilizing the behavioral patterns of real ants, the ACO technique significantly outperforms random initialization methods.

2.2. Literature on Modular Product Design Methods

Recent research on modular design methods has gained significant attention, particularly in addressing complex systems and evolving market environments. Modular design enhances product flexibility and scalability, allowing enterprises to adapt swiftly to market changes [32]. Tuunanen and Li [33] found that modular design enables flexible adjustments to service configurations based on diverse customer needs, ultimately enhancing service quality and customer satisfaction.

In modular product design, numerous studies have investigated various approaches. Baldwin [34] introduced the concept of "modular innovation", highlighting the significance of modular design in new product development. Additionally, Forti and Muniz [35] provided an in-depth analysis of the economics of modular design, demonstrating its performance on the reduction of system complexity and the improvement of product maintainability. Zhang and Yu [36] proposed a new intelligent configuration algorithm to resolve complex customer requirements, which is based on the Product Family Genealogy Model (PFG). The application of modular design has also been explored in specific industries, such as automotive manufacturing [37] and information technology [38].

Rajahonka [39] underscored the growing significance of service modularity in logistics, highlighting its potential to address diverse customer demands and complexities. Wang [40] emphasized modular design in railway logistics as key to enhancing service quality and meeting diverse customer demands. Bilous [41] highlighted the potential of modular technology to enhance efficiency and reduce costs in the railway engineering industry. Sigurjónsson and Granlund [42] primarily focused on identifying challenges within the rail freight process. However, they did not investigate how customer needs are specifically integrated into the product family genealogy model in RFT.

3. Materials and Methodology

This study aims to address the dual focus on both customer demand and product family design, generating a dual-focus modular configuration for the RFT. The research framework includes (1) customer segmentation analysis; (2) a product family generation model; and (3) a product module configuration model. Here is the notation of parameters, as presented in Table 1.

Table 1. Notation of parameters.

Parameters	Interpretation	Parameters	Interpretation
R	The total number of ants	x_{BM}	The basic modules
ρ	The pheromone evaporation rate	x_{AM}	The additional modules
q	The threshold	x_{PT}	The product family platform
α	Adjust the pheromone information	x_{WM}	The external modules
β	Adjust the heuristic information	r_1	The core constraints
K	The number of clusters	r_2	The external constraints
t_{max}	The maximum number of iterations in ACO algorithm	CR_G	The main product characteristics demands
X_{iv}	An input data matrix of ACOFCM algorithm	CR_K	The core product demands
m	Membership degree index	CR_F	The additional product demands
ε_F	Convergence Precision	CR_P	Customer preference demands
U_0	Membership degree matrix	R_{req}	The demand matching constraint set
$t\prime_{max}$	The maximum number of iterations	R_{con}	The module constraint set
x_{KM}	The core modules	R_{log}	The logical constraint set
pls	The local search threshold	$C_{kv}^{t_{max}}$	The cluster center

3.1. Customer Segmentation

3.1.1. Demand Extraction

This study uses a combination of literature review and expert consultations to extract information on customer demand for RFT. A comprehensive literature review is conducted based on the databases CNKI and Web of Science, spanning 2003 to 2023, which covered relevant articles both in Chinese and English. The keywords related to RFT service are used and combined to shape the query. This query, which is based on the scope of the research and previous studies, is ("Rail freight" OR "Rail freight express" OR "Multi-modal transportation" OR "Combined transport by road and rail" OR "Combined transport by sea and rail" OR "Combined transport by air and rail"), resulting in 13,510 articles available in two used datasets. The results of the query are refined by relevant keywords related to customer demand in RFT, resulting in 110 articles remaining. Then, we exclude 44 articles by manual screening of titles. After reading the abstracts, 5 articles are excluded, and further abstract reviews lead to the selection of 31 papers for in-depth reading. Additionally, expert consultations involve 10 professionals from academia and the industry, with demographic data summarized in Table S1 in the Supplementary Materials, indicating a majority of male participants (66.6%) and a high level of educational attainment (25% doctoral, 41.6% master's), with 83.3% possessing railway research experience.

This study classifies demands into transportation, shuttle, warehousing, logistics processing, business and service, and individualized demands. Customer demand is transformed into configuration variables and categorized into main product features CR_G, core product demand CR_K, additional product demand CR_F and customer preference demand CR_P. A survey is designed to gather demand information from transport agents, transportation companies, logistics enterprises, commercial distribution enterprises, and industrial enterprises, aiming to assess rail freight users' service demands based on their preferences and expectations. The survey consists of four sections aligned with the rail freight customer demand segmentation, as shown in Table S2 in the Supplementary Materials.

3.1.2. ACOFCM Algorithm

To optimize clustering dynamically and address the ambiguity in customer data effectively, this study uses the ACOFCM algorithm to segment rail freight customers into distinct groups. The algorithm steps have been listed as follows:

Algorithm 1 The ACO Algorithm

Input: the customer demand information X_{iv} of size (N, V), the number of clusters K, number of ants R, maximum iterations t_{max}, local search threshold pls, the pheromone evaporation rate ρ, the threshold q, and number of paths for local search L.
Output: the cluster center $C_{kv}^{t_{max}}$.

for all iterations $t \in [1, t_{max}]$ **do**
  Initialize *solution_string* as a zero matrix of size $R \times (N+1)$.
  for all ant $r \in [1, R]$ **do**
    for all sample $i \in [1, N]$ **do**
      Generate random number r_i.
      Calculate the path selection probability $p_{ik}^t = \frac{\left(T_{ik}^t\right)^{\alpha} \times (\eta_{ik})^{\beta}}{\sum_{k \in allowed}\left(\left(T_{ik}^t\right)^{\alpha} \times (\eta_{ik})^{\beta}\right)}$
      if $r_i < q$ **then**
        Assign sample i to the cluster k with the highest pheromone.
      else
        Select cluster k based on pheromone probability distribution.
      end if
    end for
    Calculate cluster centers $C_{kv}^t = \frac{\sum_{i=1}^{N}\left(w_{ik}^r \times X_{iv}\right)}{\sum_{i=1}^{N} w_{ik}^r}$.
    Calculate the fitness function $F_r = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{v=1}^{V} d\left(X_{iv}, C_{kv}^r\right)$.
    Store F_r in *solution_string(r, end)*.

Algorithm 1 *Cont.*

end for
Sort solutions based on their fitness values in ascending order.
for each solution in top L **do**
  Generate a random array rp of size $1 \times N$
  for all sample $i \in [1, N]$ **do**
    if $rp_i \leq pls$ **then**
      Select a random cluster change cluster from current cluster number.
      Calculate cluster centers $C_{kv}^{t}{}'$ and fitness $F_r{}'$.
      if $F_r{}' > F_r$ **then**
        Update *solution_string*.
      end if
    end if
  end for
end for
Update $T_{ik}^{t+1} = (1-\rho) \times T_{ik}^{t} + \frac{1}{\tau_F}$
end for

Algorithm 2 The FCM Algorithm

Input: the customer demand information X_{iv} of size (N, V), cluster center $C_{kv}^{t_{max}}$, the number of clusters K, membership degree index m, maximum iterations t'_{max}, and convergence precision ε_F.
Output: the cluster center $C'^{t'_{max}}_{kv}$ and clustering results R_k.

for all iterations $t \in [1, t'_{max}]$ **do**
  $C'^{1}_{kv} = C_{kv}^{t_{max}}$.
  Calculate the cluster centers $C'^{t'_{max}}_{kv} = \frac{\sum_{i=1}^{N}((u_{ik}^{t'})^m \cdot X_{iv})}{\sum_{i=1}^{N}(u_{ik}^{t'})^m}$.
  Calculate the membership matrix $u_{ik}^{t'+1} = \frac{1}{\sum_{j=1}^{K}(\frac{d(X_{iv}, C'^{t'}_{kv})}{d(X_{iv}, C'^{t'}_{jv})})^{\frac{2}{m-1}}}$.
  if $\left|\left|u_{ik}^{t'+1} - u_{ik}^{t'}\right|\right| < \varepsilon_F$ **then**
    break
  end if
end if

The ACOFCM algorithm analyzes the sample based on the customers' main features using collected data from designed questionnaire. To assess the clustering quality, the Silhouette Coefficients of different cluster numbers have been shown in Figure 1a, which are compared with SAGAFCM, FCM and K-means to demonstrate the effectiveness of the ACOFCM approach in clustering performance. Figure 1b represents the Silhouette Coefficients ranging from 1 to 100 iterations in ACOFCM, SAGAFCM, FCM and K-means to show the stability of ACOFCM. To decide on the number of classes, this study analyzes the Silhouette Coefficients ranging from 2 to 20 classes and employs the elbow criterion to identify optimal cluster numbers. The Silhouette Coefficients stabilize around 10 clusters. Thus, selecting 11 clusters is ideal.

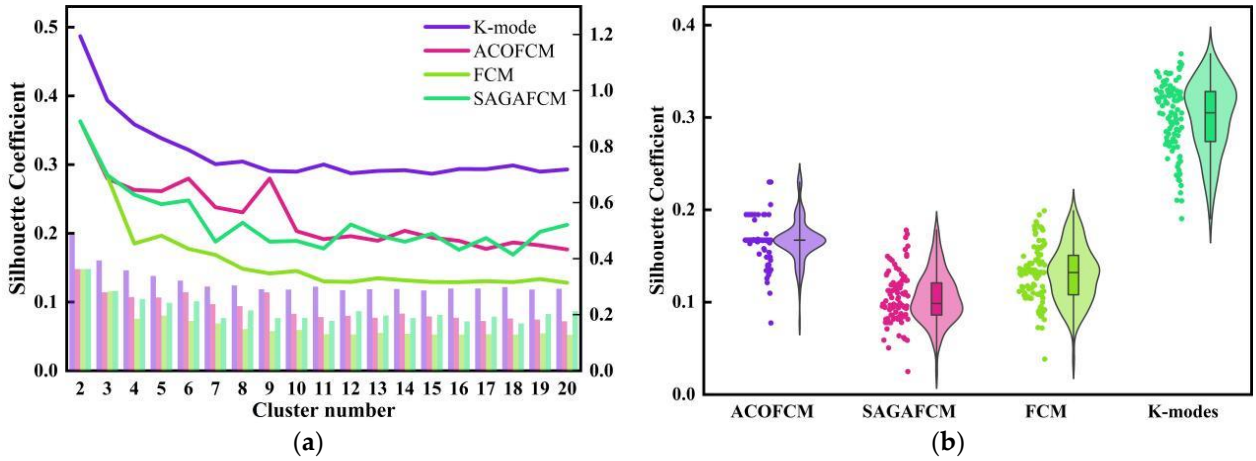


Figure 1. Comparison of different cluster numbers. (**a**) Silhouette Coefficients of different cluster numbers. (**b**) Comparison of external indicator iterations.

3.1.3. Demand Analysis

A correlation analysis is conducted to understand the relationships among various demands. This study used the Kendall coefficient for correlation analysis, as shown in Figure 2, as the collected data does not follow a normal distribution and has many tied ranks. Figure 2 illustrates the correlation coefficient between different demands, which labels the demands in the order of main product features CR_G, core product demands CR_K, additional product demands CR_F, and customer preference demands CR_P as numbers from 1 to 80. The correlation coefficient close to 1 indicates a strong positive linear relationship, that close to −1 indicates a strong negative linear relationship, and that close to 0 indicates almost no linear relationship.

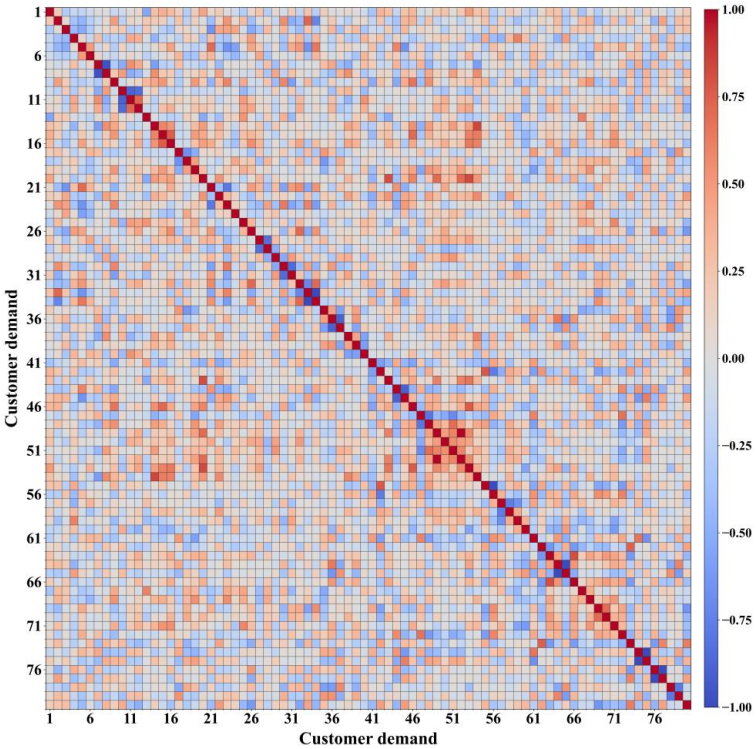


Figure 2. Correlation coefficient of customer demands.

3.2. Product Family Genealogy Model

3.2.1. Structural Evaluation Matrix by DSM

Considering the product characteristics and functional features of RFT, and incorporating experts' suggestions, a structural evaluation system for operational processes is developed. According to the detailed operational processes of the RFT production chain in Table S3 in the Supplementary Materials, the established system consists of three primary indicators and twelve secondary indicators, as shown in Table 2. Demand attributes reflect customer expectations and satisfaction, serving as indicators of service quality and user experience. Functional attributes define the relationship between modules and product functions, distinguishing core, basic, and additional modules. Physical attributes describe the continuity of operational processes in terms of time, space, and resources, aiding in module classification.

Table 2. The weight of the structural evaluation system for operational processes.

Grade I	Grade II	Interpretation	Weight	*CR*
Demand attributes W_1	Satisfaction W_{11}	The link between the process and customer satisfaction	43.63%	0.02
	Convenience W_{12}	How easily customers engage with the process	17.48%	
	Personalization W_{13}	How well individual needs are met	7.76%	
	Informatization W_{14}	How the process meets digital service demands	11.37%	
	Cost W_{15}	The expenses	10.41%	
	Time W_{16}	The duration required	9.35%	
Functional attributes W_2	Core function W_{21}	The process's alignment with the transportation product's primary function	66.07%	0.06
	Formal function W_{22}	Its connection to the product's formal attributes	23.70%	
	Additional function W_{23}	The link to supplementary features	10.23%	
Physical attributes W_3	Spatial displacement W_{31}	The continuity of processes in space	58.94%	0.05
	Temporal continuity W_{32}	Sequence	28.83%	
	Service resources W_{33}	Shared resources among processes	12.22%	

This study employs the Analytic Hierarchy Process (AHP) to determine the importance of each secondary indicator, owing to its effective performance in integrating qualitative and quantitative analysis within each attributes (i.e., demand attributes, functional attributes and physical attributes) [43]. The scale values a_{ij} are used to assess the relationship between two elements and range from 1 to 9. The weight of each index is usually calculated by the method of normalization, as shown in Equation (1).

$$\text{weight}_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \tag{1}$$

The consistency ratio CR is used to evaluate the judgment matrix in Equations (2) and (3). If CR < 0.1, this indicates that the consistency test is acceptable. The results of the consistency test are presented in Table 2.

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{2}$$

$$CR = \frac{CI}{RI} \tag{3}$$

where λ_{max} represents the maximum eigenvalue of the judgment matrix, n represents the number of indicators, CI represents the consistency index, and RI represents the random index, which depends on the order of n.

This study constructs a structural matrix for operational processes by collecting data from rail freight experts, customers, staff, and researchers. The data collection is conducted

in two stages. Firstly, each operational process is evaluated based on its correlation with indicators W_1 and W_2, using four levels: "0" for none, "3" for weak, "6" for moderate, and "9" for strong. In the second stage, a numerical Design Structure Matrix (DSM) is developed based on indicator W_3 to assess the relationships between operational processes. Correlation levels are classified as "strong", "fairly strong", "moderate", "fairly weak", and "none", with corresponding values of "1", "0.75", "0.5", "0.25", and "0".

After consolidating the scoring results and applying weight calculations, the comprehensive structural matrix is generated, as shown in Tables S4 and S5 in the Supplementary Materials. Due to the independence and flexibility of operational processes 120–141 within the rail freight workflow, they are more suitable as standalone modules and are excluded from the module division model.

3.2.2. Results of Module Division

Using the comprehensive structural matrix from Table S2 and the ACOFCM algorithm in Section 3.1.2. The maximum initial number of clusters $c_{max} = 13$, and each module division scheme is run independently 20 times to select the optimal result. The results of rail freight product module division model are presented in Table 3.

Table 3. Results of the RFT module division.

c [1]	Obj [2]	Silhouette Coefficient	CH Index	c	Obj	Silhouette Coefficient	CH Index
2	82.21	0.18	22.99	8	1.28	0.18	22.99
3	24.36	0.18	22.99	9	0.90	0.11	14.10
4	10.28	0.18	22.99	10	0.66	0.18	22.99
5	5.26	0.18	22.99	11	0.49	0.08	12.54
6	3.04	0.08	12.09	12	0.38	0.18	19.93
7	1.92	0.09	12.14	13	0.30	0.18	22.99

[1] c represents the number of clusters. [2] Obj represents the objective function of ACOFCM algorithm.

After comparing all the indicators, it is determined that when the number of module divisions reaches 13, the modular division scheme for operational processes is optimal. Based on this analysis, operational processes 120–141, which are not included in the module division model, are categorized into three modules:

- The Information Service Module (120,121,122,123,124,125);
- The Value-added Service Module (126,127,128,129,130,131,132,133,134);
- The Consultation Service Module (135,136,137,138,139,140,141).

This study labels the modules in the order of GM_1, GM_2, …, GM_{16}, as shown in Table 4.

Table 4. The name of each module.

Modules	Name	Modules	Name
GM_1	The user interface module	GM_9	The storage module
GM_2	The payment method module	GM_{10}	The intermodal preparation module
GM_3	The transportation cost collection module	GM_{11}	The goods delivery module
GM_4	The intermodal application module	GM_{12}	The domestic transportation module
GM_5	The outbound application module	GM_{13}	The domestic and international transportation module
GM_6	The goods pickup and delivery module	GM_{14}	The information service module
GM_7	The loading and unloading module	GM_{15}	The value-added service module
GM_8	The circulation processing module	GM_{16}	The consultation service module

The detailed results, combining the proposed scheme with the actual operational processes, are shown in Figure 3. The dark blue grid indicates that the operational process

on the abscissa belongs to the module on the ordinate. The results of demand attributes for the segmented modules are shown in Figure 4a, and functional attributes for the segmented modules are shown in Figure 4b. In terms of demand attributes, all modules have high values for satisfaction and convenience, but lower values for cost and time. Regarding functional attributes, the types of modules are categorized based on core functions, formal functions, and additional functions.

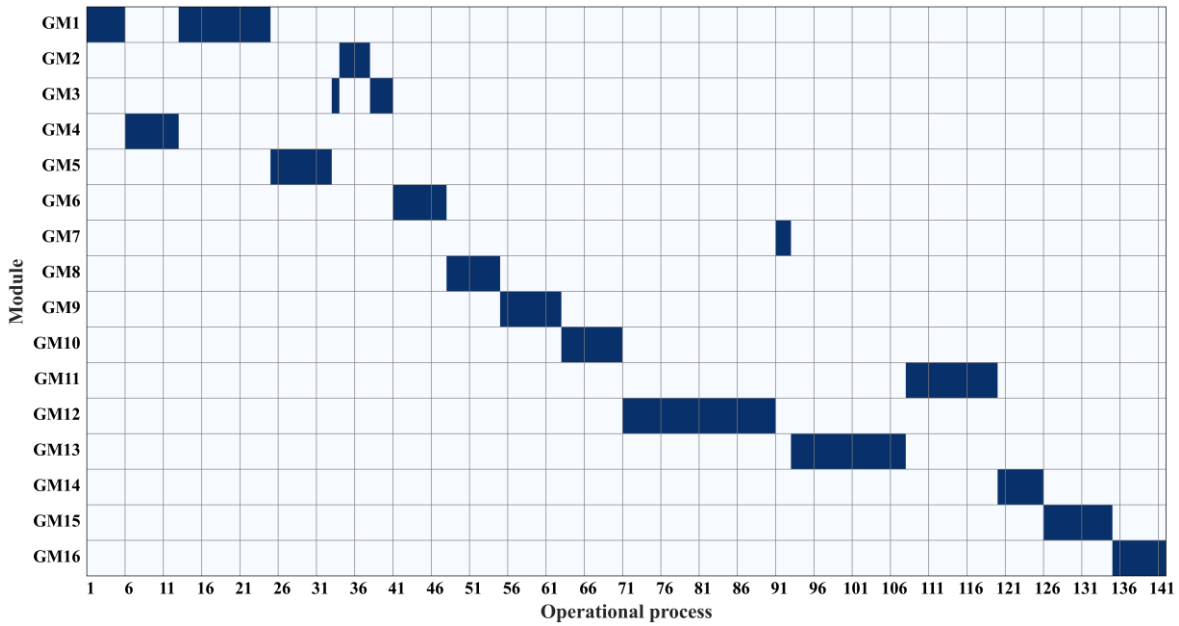


Figure 3. The modular division results of RFT product.

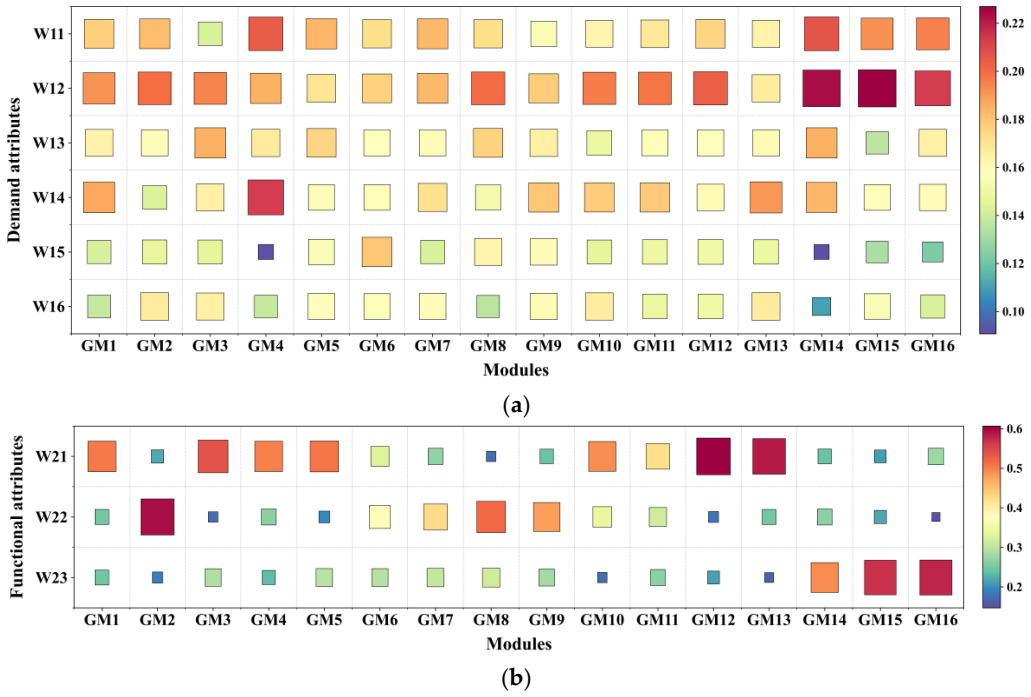


Figure 4. Demand and functional attributes of each modules. (**a**) Demand attributes of each modules. (**b**) Functional attributes of each modules.

3.2.3. Model Construction

Product family genealogy is a configuration area distribution system obtained by planning the configuration space of the product family based on the aggregation of configurable

modules according to the demand characteristics of customer groups. A constraint satisfaction problem (CSP) is defined by a triplet (X, A, R) to solve the problem of establishing the rail freight product family genealogy model, such that:

- $X = \{x_{KM}, x_{BM}, x_{AM}, x_{PT}, x_{WM}\}$ is a finite set of variables, which are called constraint variables.
- $A = \{a_{KM}, a_{BM}, a_{AM}, a_{PT}, a_{WM}\}$ is a finite set of variable value domains of X.
- $R = \{r_1, r_2\}$ is a finite set of constraints. Core constraints facilitate the integration and operation of these modules, ensuring the realization of essential functions, enabling the construction of various levels and series of RFT platforms. Core constraints are binary constraints, defined as $\hat{R}_{PT}^{KM} = f(KM, PT), \forall KM_i, KM_j \in PT, i \neq j; (KM_i, KM_j) \in \hat{R}_{PT}^{KM}$. External constraints allow additional modules to connect flexibly to the platform, permitting the addition or modification of external modules based on customer needs. Like core constraints, external constraints are also binary, defined as $\hat{R}_{PT}^{WM} = f(WM, PT), \forall WM_i \in GP, (WM_i, PT) \in \hat{R}_{PT}^{WM}, PT \in GP$.

This model is built on a triple $GP = \{X^*, A^*, R^*\}$ and is represented as $PFG = \{GP, PT, WM\}$. The process for generating the rail freight product family follows these steps.

Step 1: Module function division. The division of rail freight modules is based on three functional coefficients: core, basic, and additional. For each module, the coefficient with the highest value determines its classification. The module division results are detailed in Table 5, with each module represented by a symbol.

Table 5. Module function division.

Classification	Description	Module
Core modules x_{KM}	The essential functions of the rail freight product, serving as a vital component of the rail freight system	$GM_1, GM_3, GM_4, GM_5, GM_{10}, GM_{11}, GM_{12}, GM_{13}$
Basic modules x_{BM}	Consists of indispensable components necessary for the rail freight product's operation	$GM_2, GM_6, GM_7, GM_8, GM_9$
Additional module x_{AM}	Offers optional features that enhance the customer experience and cater to specific demand, thereby boosting satisfaction	$GM_{14}, GM_{15}, GM_{16}$

Step 2: Establishing Core Module Constraints. To evaluate relationships between core modules, the study considers their structure, functionality, and alignment with customer needs. Conflicting modules, such as GM_{12} and GM_{13}, are identified, and constraints are established accordingly, as shown in Table 6. These two modules overlap in function: GM_{12} handles domestic transport, while GM_{13} covers both domestic and international transport. Additionally, the scheduling of tasks within the modules is not coordinated.

Table 6. Core module constraints.

	GM_4	GM_5	GM_{10}	GM_{12}	GM_{13}
GM_4	0	0	1 [1]	1	0
GM_5	0	0	0	0	1
GM_{10}	1	0	0	1	1
GM_{12}	1	0	1	0	0
GM_{13}	0	1	1	0	0

[1] 1 indicates that the modules can be connected, while 0 indicates that the modules cannot be connected.

In this model, outbound operations take priority over intermodal operations. If a product is designated for both, it defaults to the intermodal platform. The constraints guide the construction of the rail freight product family platform, as shown in Table 7.

Table 7. The rail freight product family platform.

The Product Family Platform x_{PT}	Core Module x_{KM}
Cross-Border Platform x_{PT1}	GM_1, GM_3, GM_5, GM_{11}, GM_{13}
Multimodal Platform x_{PT2}	GM_1, GM_3, GM_4, GM_{10}, GM_{11}, GM_{12}
General Freight Platform x_{PT3}	GM_1, GM_3, GM_{11}, GM_{12}

Step 3: Designing the Product Family Lineage. The product family is defined by its platforms and external modules, which includes identifying suitable customer segments and specifying product characteristics, forming the attribute domain of the product family.

Step 4: Ensuring Uniqueness. The designed configurations are checked for uniqueness. If uniqueness is not achieved, adjustments are made. The finalized rail freight product family is presented in Table S6 in the Supplementary Materials. Also, the whole scheme of the production chain linking product family group (3 groups), operational processes (16 modules), and customers (11 groups) is shown in Figure 5. The blue grid indicates that the column belongs to this row.

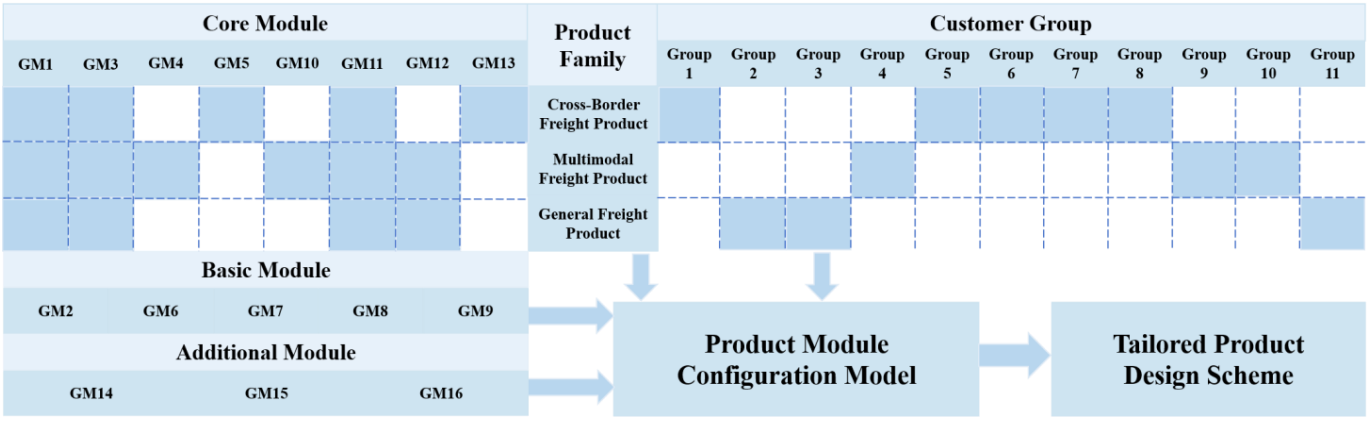


Figure 5. The whole scheme of product family group, modules and customer groups.

3.3. Product Module Configuration Model

3.3.1. Module Configuration Model

A CSP is defined by a triplet $RFG = (C, R, D)$ to solve the problem of establishing the rail freight module configuration model, as shown in Figure 6.

- $C = \{CR, Val\}$ is a finite set of variables and its optional values. This study defines the following four variables: $CR = \{CR_G, CR_K, CR_F, CR_P\}$.
- $R = \left\{R_{req}, R_{con}, R_{log}\right\}$ is a finite set of constraints. R_{req} defines the mapping between customer demands and the product family: $G_1(R) : \{CR_G\} \rightarrow \{GP\}; G_2(R) : \{CR_K\} \rightarrow \{KM\}; G_3(R) : \{CR_F\} \rightarrow \{WM\}; G_4(R) : \{CR_P\} \rightarrow \{WM\}$. Modules are configured sequentially in the order of $G_1(R)$, $G_2(R)$, $G_3(R)$, and $G_4(R)$. Depending on the specific customer requirements, the structure of the rail freight product family is adjusted from general to specific levels, effectively translating customer needs into concrete configurations. R_{con} can be found in Section 3.2.3. R_{log} outlines the logical relationships governing the combination and sequence of modules. This set of constraints arise from the inherent logical order required by the operational processes as well as from any logical sequence dictated by customer preferences, serving as overarching constraints.
- $D = \{k \times GM | CR = Val_i\}$ is a finite set of the value domain of CR.

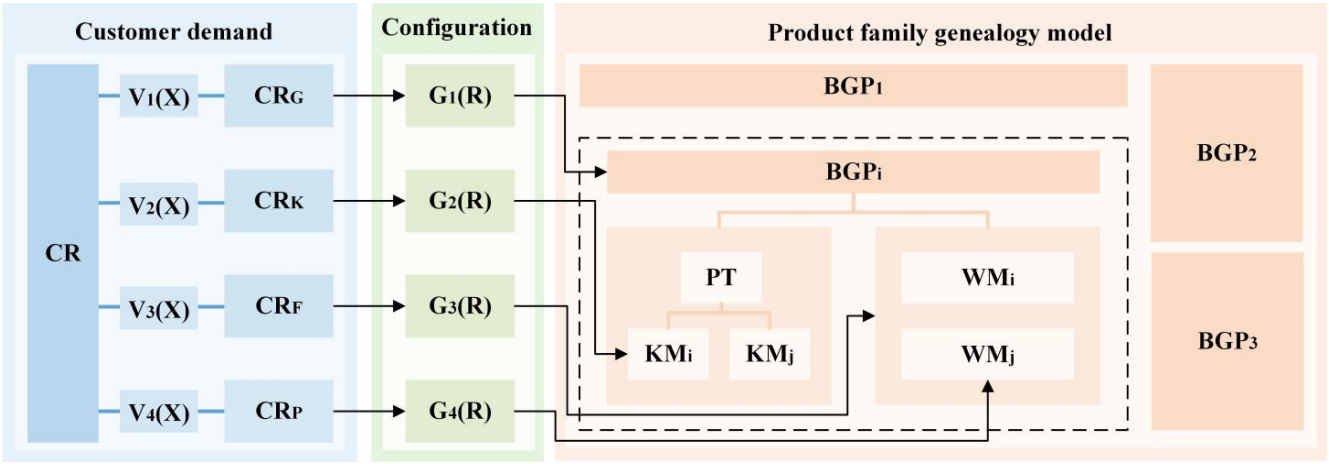


Figure 6. The framework for product module configuration model building.

3.3.2. A Resolution for the CSP

Common approaches for solving CSP include the Generate-and-Test (GT) method [44], Backtracking [45], the Min-Conflicts algorithm [46], and the Genetic/Systematic Arc-Revising Hybrid Algorithm (GSA) [47]. With only 13 modules, the problem has a manageable computational scale, making the classic backtracking algorithm an ideal choice for solving the model [48].

The backtracking algorithm works by selecting potential solutions step by step. When a newly generated node fails to meet the constraints, the algorithm backtracks to the previous node and explores the next available option. If no valid solutions remain, it continues to backtrack until either a target node is reached or all possible solutions have been exhausted. The execution process for each step is described as follows.

Step 1. Identify selective constraints from Section 3.3.1. R_{req} is classified as selective, while R_{con} and R_{log} are normative. R_{req} serves as the filtering condition in the algorithm's constraint mechanism.

Step 2. Initialize i = 1 and assign values to the configurable units CR_{ij} in $G_i(R)$. Use the constraints identified in Step 1 to filter the domain of variable values, discarding those that do not meet the criteria and skipping them in subsequent checks.

Step 2.1. Set j = 1 and select an instance $D(CR_{ij})$ from the candidate set $d(CR_{ij})$ of unassigned units CR_{ij}. If $D(CR_{ij})$ satisfies all constraints, assign it to the unit CR_{ij}.

Step 2.2. Increment j and find an instance $D\left(CR_{i(j+1)}\right)$ in the alternative set $d\left(CR_{i(j+1)}\right)$. Verify $D\left(CR_{i(j+1)}\right)$, and if it does not conflict with any constraints, consider it valid.

Step 2.3. If an instance conflicts with a constraint, choose another from the candidate set and check for conflicts. If all options conflict, backtrack and reassign the unit.

Step 2.4. If none of the instances conflict with any constraints, proceed with calculating the configurable cells until all configurable units are assigned values.

Step 3. Increment i, assign values to the configurable unit CR_{ij}, and repeat Steps 2-1 through 2-4 until all configurable units are assigned.

Step 4. Continue recursive backtracking until all units CR_{ij} in $G_i(R)$ are assigned, providing a complete solution to the CSP model that meets customer requirements for the rail freight product family.

4. Case Study

Company A, a logistics enterprise based in Sichuan in China, is a key customer of rail freight services. With operations spanning Sichuan and Europe, its freight needs align with the customer group Cluster 1, as outlined in Section 3.1.3. Detailed information on Company A's rail freight requirements is provided in Table 8.

Table 8. Details of company A's rail freight demand.

Demand Category	Subcategory	Specification	Customer Preference
Product main features	Types of goods	Non-bulk cargo	None
	Transportation Regions	China; Europe	None
	Modes of transportation	Railway	None
Core product demand	Transport speed	Fast	None
	Freight Type	Container	None
Additional product demands	Storage	Cold chain warehousing; Short-term storage	Sichuan
	Processing	Packaging required	None
		Measurement required	None
	Service acceptance	Online acceptance and confirmation required	Time-sensitive [1]
	Information consultation	Transportation plan consultation required	None
		Pricing consultation required	None
		Transportation technology consultation required	None
	Value-added transportation	Railway value-added transportation selected	None

[1] "Time-sensitive" means the online acceptance and confirmation have a time limitation, which is restricted within a certain period of time.

Using the proposed backtracking approach method, this study designs the product module configuration for Company A with six steps.

Step 1. Employ the demand matching constraint set as a selective constraint to filter the configured modules based on Company A's demand variables.

Step 2. Based on the demand in Table 8, the product family is incorporated into the configurable unit. The selected set consists of: BGP_1 for the cross-border express product, with a core module set of $\{GM_1, GM_3, GM_5, GM_{11}, GM_{13}\}$ and an external module set of $\{GM_8, GM_9, GM_{14}, GM_{15}, GM_{16}\}$.

Step 3. Choose the instance GM_1 from the alternative set to verify compliance with constraints R_{con} and R_{log}. The results indicate that this instance satisfies the constraints.

Step 4. Select the instance $\{GM_1, GM_2\}$ from the alternative set to confirm compliance with the constraint rules R_{con} and R_{log}. The results show that this instance also meets the constraints.

Step 5. After conducting retrospective and recursive calculations, the feasible module combinations for Company A's product family are identified as follows:

$\{GM_1, GM_3, GM_5, GM_8, GM_9, GM_{13}, GM_{11}\}$
$\{GM_1, GM_3, GM_5, GM_9, GM_8, GM_{13}, GM_{11}\}$
$\{GM_1, GM_3, GM_5, GM_8, GM_{13}, GM_9, GM_{11}\}$
$\{GM_1, GM_3, GM_5, GM_9, GM_{13}, GM_8, GM_{11}\}$
$\{GM_1, GM_3, GM_5, GM_{13}, GM_8, GM_9, GM_{11}\}$
$\{GM_1, GM_3, GM_5, GM_{13}, GM_9, GM_8, GM_{11}\}$

Step 6. Adjust the module combinations according to customer preferences. As Company A specifies the storage location "Sichuan" in the customer preference demand column, it is more logical for GM_9 to precede GM_{13}, given that the storage service occurs before transportation. There is no sequential relationship between GM_8 and GM_9. Additionally, GM_{14}, GM_{15} and GM_{16} are included based on the transportation demands. After these adjustments, the final module configuration scheme for Company A is as follows:

$\{GM_1, GM_3, GM_5, GM_8, GM_9, GM_{13}, GM_{11}\}$
$\{GM_1, GM_3, GM_5, GM_9, GM_8, GM_{13}, GM_{11}\}$

$\{GM_1, GM_3, GM_5, GM_9, GM_{13}, GM_8, GM_{11}\}$

5. Conclusions and Implication

This study designed a dual-focus modular configuration approach based on the customer segmentation method and product family genealogy model. The customer segmentation method had been conducted based on a three-level demand structure by using the ACOFCM clustering algorithm. For the product family genealogy model, this study designed a module division scheme based on a structural evaluation system on the RFT product operational process. Consequently, this study developed a modular configuration model that aligned customer needs with the product family. A case study had been conducted in a logistics enterprise in Sichuan province in China, and it proved the feasibility of the dual-focus modular configuration approach by backtracking algorithm in a CSP problem.

This study employed the ACOFCM algorithm to segment railway freight customers into 11 distinct groups. Regarding the types of transport enterprises, transport agents were typically price-sensitive and required efficient information services, while transportation companies focused more on transport efficiency and service quality. In terms of goods, small-batch transport customers had a higher demand for flexibility and immediacy, whereas bulk cargo customers tended to establish long-term cooperative relationships and placed greater emphasis on cost control. Geographically, domestic transport customers were more concerned with balancing cost and timeliness, while international transport customers faced more complex service demands.

By utilizing the PFG model, this study ultimately identified three product families: Cross-Border Freight Product, Multi-modal Freight Product, and General Freight Product. The cross-border freight product offered efficient and stable international transportation, accommodating diverse cargo needs while providing advantages in terms of high capacity and frequency. The multi-modal freight product integrated various transportation modes to flexibly address complex logistics demands, offering customized transportation solutions and efficient node connections. The general freight product was cost-effective and met the short-distance transportation needs of small and medium-sized enterprises, covering a variety of cargo types.

This study achieved the alignment of customer needs with operational processes by adopting a dual-focus modular configuration approach. By employing the ACOFCM algorithm to segment customers based on their diverse and dynamic demands, this study introduces an innovative approach to understanding customer heterogeneity in the railway freight sector. The application of the PFG model further enhances this framework by systematically generating modular product families tailored to the specific needs of each customer group. This integration of advanced clustering techniques and modular design principles ensures a more precise alignment between customer expectations and service offerings, thereby optimizing the demand-matching process. Additionally, this study establishes an evaluation system for RFT operation processes. The evaluation system is designed to assess key operational aspects, ensuring a systematic approach to identifying demand attributes, functional attributes and physical attributes and constructing modules. This multi-dimensional framework not only contributes to better operational decision-making but also facilitates the design of robust and adaptable railway freight services capable of responding to evolving market demands. Through a systematic analysis of customer demands, the product configuration model provides scientific decision support for RFT enterprises, promoting the standardization and optimization of modular configurations.

To tailor services more closely to customer needs, future studies are suggested to collect more detailed data across a broader range of demand dimensions and customer types. The expanded data collection should include not only quantitative metrics (e.g., usage patterns and transaction volumes) but also qualitative insights (e.g., customer preferences, feedback, and satisfaction levels). By incorporating a more diverse set of customers, it will allow for

a deeper understanding of the nuanced needs and behaviors of different user segments, enabling the development of more targeted and effective services.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/math12243947/s1, Table S1: Information from the expert; Table S2: Rail freight customer demand segmentation; Table S3: The operational process of railway freight train products; Table S4: The structural matrices W1 and W2; Table S5: The structural matrix W3; Table S6: The characteristics of rail freight train product family.

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