A new configuration approach to support the technical bid solutions for complex ETO products under uncertainties

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Abstract: This paper proposes a novel two-stage and multi-objective optimization design method for the configuration design of complex Engineering to Order (ETO) product under imprecise matching and other uncertainties. The goal is to support selection of the optimal technical bid solutions while meeting requirements. A new two-stage configuration design framework for complex ETO products is proposed. The stage one is product architecture configuration design, supported by an engineering characteristics design method based on constraint satisfaction problems and Bayesian networks, and the stage two is physical module configuration design , where a multi-objective optimal configuration model of physical modules is developed with the goals of minimum production cost, shortest delivery time, and maximum degree of matching technical requirements under imprecise matching of technical requirements and uncertainties in such as production cost and delivery time. As for the new selection method for obtaining an optimal technical bid solution scheme, it integrates a non-dominated sorting genetic algorithm (NSGA-II) and an approximate ideal solution ranking method (TOPSIS). Our approach has been applied to the design of a technical bid solution of subway's bogie. The results show that this approach enables bidders to quickly select the most interesting solution during a bidding process. The proposed approach aids the bidders to quickly create ETO product scheme designs, and then advise a new selection method for the bidders to quickly obtain a technical bid solution from the above product scheme designs, which has a minimum cost while meeting order requirements.

Key words: Product configuration, ETO products, technical bid solution, multi-objective optimization, uncertainty

1 Introduction

In the current economic and market competition environment, industrial customers are always seeking attractive prices, better performance, and shorter delivery times for products (or systems) via calls for tenders. The call for tenders provides the industrial customer with the opportunity to evaluate multiple potential contractors (bidders) and select the most advantageous one [1]. In a bidding process, the bidders have to identify and evaluate possible technical bid solutions related to the customer's needs, and then select the most compelling solution to submit as an offer to industrial clients [2]. It is crucial for bidders to respond to calls for tenders as quickly as possible with solutions that meet the customer's requirements.

Manufacturing is shifting from mass production to mass customization to swiftly meet ever-growing consumer needs [3] and mass customization can be categorized as assemble-to-order (ATO), make-to-order (MTO), and engineer-to-order (ETO) [4]. Therefore, two types of industrial scenarios can be distinguished when generating a technical bid solution [5]. Firstly, For ATO and MTO, they need assembly-oriented technical bid solutions that result from the assembly of standard sub-systems and components based on existing products configuration modules and configuration systems[6, 7]. While for ETO, it needs product configuration design oriented technical bid solutions that result from a product family design process for producing new product instances based on the existing product platform of an enterprise and expanding the existing product family to meet specific customers' requirements[8-10]. Currently, how to design complex ETO products for an ETO technical bid solution receives less attention, the reason might be that complex ETO products have lower yearly sales averages, higher design complexity, and lower levels of standardization and design automation [11, 12], such as rail vehicles, aircraft, steam turbines, etc. Thus, in this study, we mainly focus on the complex ETO products configuration design issues for technical bid solutions.

When configurating a complex ETO product for a technical bid solution, the key design and production processes include: (1) taking an order (or a call for tenders) as a product design specification(PDS) mainly with engineering requirements; (2) adaptively designing a new product based on an existing product platform with many common sharable parts/subsystems and some adaptable design solutions for updating; and (3) creating a best configurable design solution with shared parts, adaptively redesigned/manufactured, and totally new designed parts to meet the engineering requirements stated in the PDS with the best development costs and time-to-delivery. However, due to some non-standard customer requirements in a complex ETO situation, standard offers (modules) cannot fulfill customer requirements [11, 12]. The ETO technical bid solutions need an adaptive design or re-design of connection features, which makes it difficult to obtain an optimal technical bid solution. In addition, the influence of uncertainty in production costs and delivery times of the product under configuration has not been thoroughly investigated in the available research [13, 14]. For instance, uncertainties in design complexity, logistic circumstances, resource limits, and so on may all effect the estimated cost and delivery time in a technical bid solution [15]. Thus, the key challenges of configuration design of a complex ETO product for a technical bid solution are: (1) customer requirements cannot be precisely matched by the kind of standard offer in ATO/MTO; and (2) the production costs and delivery times of the configured objects are not precisely known under uncertain design and manufacturing capabilities. Therefore, it is difficult to help the bidders make the right decision quickly for a complex ETO technical bid solution under imprecise matching and various uncertainties as mentioned above.

Most of the earlier studies focused on configuration modeling and solving [10] such as product configuration knowledge [16] and conceptual modeling [17], and product configuration process [18]. For complex ETO products, a two-step strategy including product architecture configuration and module configuration is proposed in [19]. For ETO product bidding, Sylla and Guillon [2, 20-22] proposed a new knowledge-based configuration model and multi-criteria decision-making approach to support the definition and estimation of ETO technical bid solutions; while Cicconi [23] proposed a sequential and multi-objective optimization method for the design of ETO steel towers based on three optimization levels including preliminary design, embodiment design and detailed design, which aids designers in developing competitive products that minimize manufacturing and installation costs while meeting performances requirements. Even though numerous researchers have studied ETO configuration, few studies concentrate on how to select the optimal complex ETO product technical bid solutions under imprecise customer-requirements matching and uncertain production costs and delivery times [22].

This paper presents a new ETO product configuration design approach to better overcome the above challenges and support the ETO product bid. Compared with existing research, the proposed new method has the following features and novelties:

(1) A new two-stage configuration design framework for complex ETO products is established.

The first phase is product architecture configuration design supported by an engineering characteristics design method based on constraint satisfaction problems and Bayesian networks, and the second stage is physical module configuration design, which is realized through module key parameter design, physical module multi-objective optimal configuration, and physical module configuration change.

(2) A novel multi-objective optimal configuration model of physical modules is developed for the second stage. Its goals are the minimum production cost, shortest delivery time, and maximum technical requirements matching degree, by considering imprecise matching of technical requirements and uncertainty in production cost and delivery time. The uncertainty production cost and delivery time estimate model is constructed by a normal distribution and the 3σ principle, and the technical requirements matching degree calculation model is constructed to show the match degree of physical module configuration for a complex ETO product under imprecise matching technical requirements.

(3) A new selection method of an optimal technical bid solution is proposed, combining a non-dominated sorting genetic algorithm (NSGA-II) and an approximate ideal solution ranking method (TOPSIS).

The rest of this paper is structured as follows. In the next section, product configuration modeling and solving are reviewed. After that, the proposed method of configuration design of technical bid solution is described. Its application in the subway's bogie is presented in section 4. Section 5 discusses the application results and implications. Finally, conclusions and an outlook are drawn.

2 Related work

2.1 Product configuration modeling

Modeling product configuration is the cornerstone of product configuration design. Product configuration modeling is the process of organizing and expressing configuration knowledge, such as specified modules and association and constraint relationships between modules [24]. The configuration model for a product family describes the product family's customizable space [10].

Song and Kusiak [25] mined configuration rules for required and optional products from historical sales data using association rule mining and K-means clustering. The mined rules predicted customers' future purchases to determine product configuration and common subassemblies. Zhang, et al. [26] created the MTO product configuration model to support configuration and knowledge management by describing product components' aggregation, hierarchical, and association relationships, attributes, ports, resources, constraint rules, and other information. Jannach and Zanker [27] investigated the knowledge modeling technique for constraint fulfillment problems in distributed configuration problems. Yang, et al. [28] used DCSP (Dynamic Constraint Satisfaction Problem) - based configuration modeling to address dynamic module involvement in product configuration. Felfernig, et al. [17] presented an ontology based on the Unified Modeling Language to construct a product configuration model and knowledge base. A general knowledge-based paradigm for configuring commercial offers was suggested by Guillon, et al. [29], and it is flexible enough to accommodate any number of possible solutions. Wang, et al. [30] proposed a new model of extension reasoning for the fast configuration design of complex product schemes. Jiao and Tseng [31] suggested a model of product family architecture that combines functional perspective, technical view, and physical view. To facilitate the preliminary design of ETO goods, Fang and Wei [12] developed a multi-view knowledge model with an expanded functional solution tree as the primary stem, including client requirements, design examples, and constraint rules.

The characteristics of the aforementioned rules, structures, constraints, ontologies, and multi-view configuration modeling methodologies are summarized in Table 1.

Table 1 The summary of the related work in product configuration modeling

Literature	**Method**	**Illustration**	**Feature**
Song and Kusiak [25],	Rule-based configuration modeling	The production rule if< condition >-then< conclusion > is used to describe the relationship between module or attribute parameters	Knowledge representation is intuitive and easy to reason, but it is difficult to extract rules and maintain consistency among complex products
Zhang, et al. [26]	Structure-based configuration modeling	GBOM, and/or tree, classes and features are used to describe the structural relations such as part-of、is-a、has-attribute of product family	The conceptual expression of configuration model is good, and it needs to be combined with rules and constraints
Jannach and Zanker [27], Yang, et al. [28]	Constraint-based configuration modeling	The constraint satisfaction problem is used to express the configuration model, including configuration variables, variable range and constraint relations among variables	The configuration model is an abstract mathematical model with many algorithms and high efficiency, but the model lacks conceptual expression and is difficult to understand
Felfernig, et al. [17]	Ontology-based	Build a configuration model for a particular product by defining a	It can ensure the semantic consistency of configuration knowledge and

	configuration modeling	configuration ontology that normalizes configuration-related concepts and relationships	support model sharing and reuse. The definition of logical structure of model depends on rules and structures
Jiao and Tseng [31]; Fang and Wei [12]	Multi-view based configuration modeling	Multiple interrelated views such as requirements, functions or characteristics, technologies, and physical implementations are used to describe the product family model	Integration of multiple design information improves configuration design, but the diversity of configurable elements and their constraints are still not considered enough.

2.2 Product configuration solving

A configuration solution is the key to obtaining a product design scheme, which has a significant effect on design effectiveness, cost, and quality. Product configuration solution (finding or solving) involves applying specific methods to the feasible configuration scheme to meet requirements and constraints, or the optimal configuration scheme for particular indicators in the configuration model's configuration space, based on the input customer's customized requirements [10, 32, 33]. Yang, et al. [34] used SWRL to design configuration rules, SWRLTab to convert these into JESS rules, and JESS to construct a configuration solution. Yang, et al. [28] utilized backtracking to solve the product configuration issue described by DCSP. Zhu, et al. [35] developed a domain rough set approach to filter the descriptive properties of instances and enhance the precision of CBR solutions. Wang, et al. [36] retrieved instances using self-organizing mapping and fuzzy similarity as the first ratio.

Some researchers have explored product configuration optimization in addition to configuring products that are technically possible. For the purpose of cost-effectively optimizing product configuration, Yeh and Wu [37] introduced a strategy that integrates genetic algorithms, mathematical programming, and tree searching. Long, et al. [38] developed a configuration strategy for product service systems based on a support vector machine that takes customer perception into account; Wei, et al. [39] utilized an improved nondominated Sorting genetic algorithm (NSGA-II) to solve a multi-objective configuration optimization model including cost, delivery time, and performance objectives. Zheng, et al. [40] created a multi-objective optimization model with customer satisfaction, manufacturing cost, and carbon emissions as objectives and solved it to find the Pareto optimum structural solution set. The optimum structural solution was selected by closer to the positive ideal solution. Sigurdarson, et al. [41] presented the method of multi-objective monotonicity analysis to uncover pareto set dependency and trade-off causation in configuration design, hence guiding redesign leading to performance enhancements.

Fang and Wei [12] proposed a preliminary design strategy for ETO products to address comprehensive configuration at product architecture design and module instance selection levels. First, a genetic algorithm found the best functional and technological solutions to reduce information content. Then, a preliminary design plan was established using the parameter design process model to design the module's parameters and structure, but the physical module's reusability was not considered. Levandowski, et al. [19] and Zheng, et al. [42] identified two phases of ETO product configuration design: a modular product architecture and an extendable configuration based on module parameters. This technique can reuse and preserve design flexibility. However, the two articles only describe configuration solution concepts. Kristianto, et al. [18] explored the mass-customization problem of ETO products in two stages: integration configuration of the product and process platform, and module parameter value configuration. They solved the problem using Benders decomposition and double-layer stochastic programming. Du, et al. [43] created a Stackelberg game model to optimize module configuration and parameter optimization in product family design. However, this method is used to plan product series rather than a customer-specific design. Tang, et al. [44] create a new bi-objective optimization model that takes both customer satisfaction and the impact on the environment into account when configuring products. Song, et al. [45] suggest a new uncertain decision model to minimize overall expenses while searching for the best product configuration.

According to the variations in configuration modeling methodologies and the features of configuration challenges, Table 2 summarizes the configuration problem-solving techniques.

Table 2 Product configuration solving methods

Literature	Method	Illustration	Feature
Yang, et al. [34]	Solving based on rule reasoning	Match the design goal to the condition of the rule, and perform forward or backward reasoning to obtain the configuration result	Because of the difficulty of rule extraction and maintenance and the limitation of complex configuration knowledge, rules are rarely used alone
Yang, et al. [28]	Solving based on CSP	Backtracking is utilized to find the variable value combination that meets the	There are many solutions available, but only feasible solutions can be obtained

		requirements and constraints in the variable range space, and the feasible configuration solution is obtained.	
Zhu, et al. [35]; Wang, et al. [36]	Solving based on case-based reasoning	The initial solution to the new requirements is obtained by similarity matching, and the final solution is obtained by example adjustment	Obtaining similarity solution quickly can improve the starting point of custom design, but it is difficult to adjust the example
Yeh and Wu [37], Long, et al. [38], Wei, et al. [39], Zheng, et al. [40]; Sigurdarson, et al. [41]	Solving based on intelligent algorithm	Intelligent optimization algorithm is used to solve the optimal configuration scheme (one or Pareto solution set) for a specific index from the configuration space.	The single or multi-objective optimal configuration scheme can be found. The difficulty lies in establishing the functional relationship between the optimization objective and the configuration variables
Fang and Wei [12], Levandowski, et al. [19]、Zheng, et al. [42], Kristianto, et al. [18], Du, et al. [43]	Two-stage configuration Solving	The product architecture design and module instance selection are considered in series or coupling	It is an extension of the idea and process of configuration solution, and the specific solution still depends on the above methods

2.3 Research gaps

Existing research on product configuration design focuses primarily on the configuration problem as the selection and combination of designed components, i.e., MTO and ATO products, whereas the technical bid solution of ETO products receives less attention. For complex ETO products, the configuration should consider the configurable objects at multiple levels, such as function, technical solution, and physical module; and the configuration of the physical module must also implement variation or new design, resulting in a large design space and a complex solution process. Existing research employs a two-step strategy of product architecture configuration and physical module configuration to gradually decrease the design space and determine the configuration scheme of ETO products. In the configuration of physical modules, traversing the product structure tree, rule reasoning or case reasoning, parametric variant design, etc. are still mostly used to acquire the configuration scheme, which is time-consuming and incapable of optimization. Existing configuration optimization methods, however, do not yet take into account the two characteristics of the physical module configuration of complex ETO products, which prevents them from being directly applied: First, the predefined physical modules in the configuration model often cannot accurately match the personalized technical requirements, leading to the existence of accurate matching and similar matching in the optimization configuration; second, the manufacturing cost and time of the configured physical module are not precisely known because of the effect of many uncertain aspects in the production process and dynamic changes in the supply chain. In order to increase efficiency and assist the search for technical bid solutions, it is important to further investigate the ideal configuration approach for physical modules suited for complex ETO product bidding.

3 Configuration approach of technical bid solution

3.1 Configuration design framework for complex ETO products

For the configuration design of complex ETO product with bidding technical solutions, the configuration process is divided into two stages: product architecture configuration and product physical module configuration, as shown in Figure 1.

In the first phase, according to the requirements of the bid product, the product architecture is also indirectly determined by designing feasible and optimized engineering characteristic (EC) target values (i.e., product design specifications), such as key functions, performance, structural properties parameters, etc. In our previously published article, taking life cycle cost (LCC) as the design goal, an engineering characteristics design method based on the constraint satisfaction problem and Bayesian network is proposed [46]. According to the product family architecture model, configuration rules, expert experience, etc., the design space of engineering characteristics, the constraint satisfaction problem model, and the life cycle cost estimation model based on a Bayesian network are constructed. Main steps are: (1) taking customer requirements as input to solve the constraint satisfaction problem to obtain feasible engineering characteristic design schemes, and (2) using a Bayesian network to evaluate the life cycle cost of the feasible schemes to select the best scheme. The architecture of the order product can be determined based on the engineering characteristic design scheme. For details of how to conduct product architecture configuration design, please refer to our previous work [46].

In the second phase, product physical modules are configured for order requirements. The physical module configuration of complex ETO products is realized through module key parameters design, physical module multi-objective optimal configuration, and configuration change.

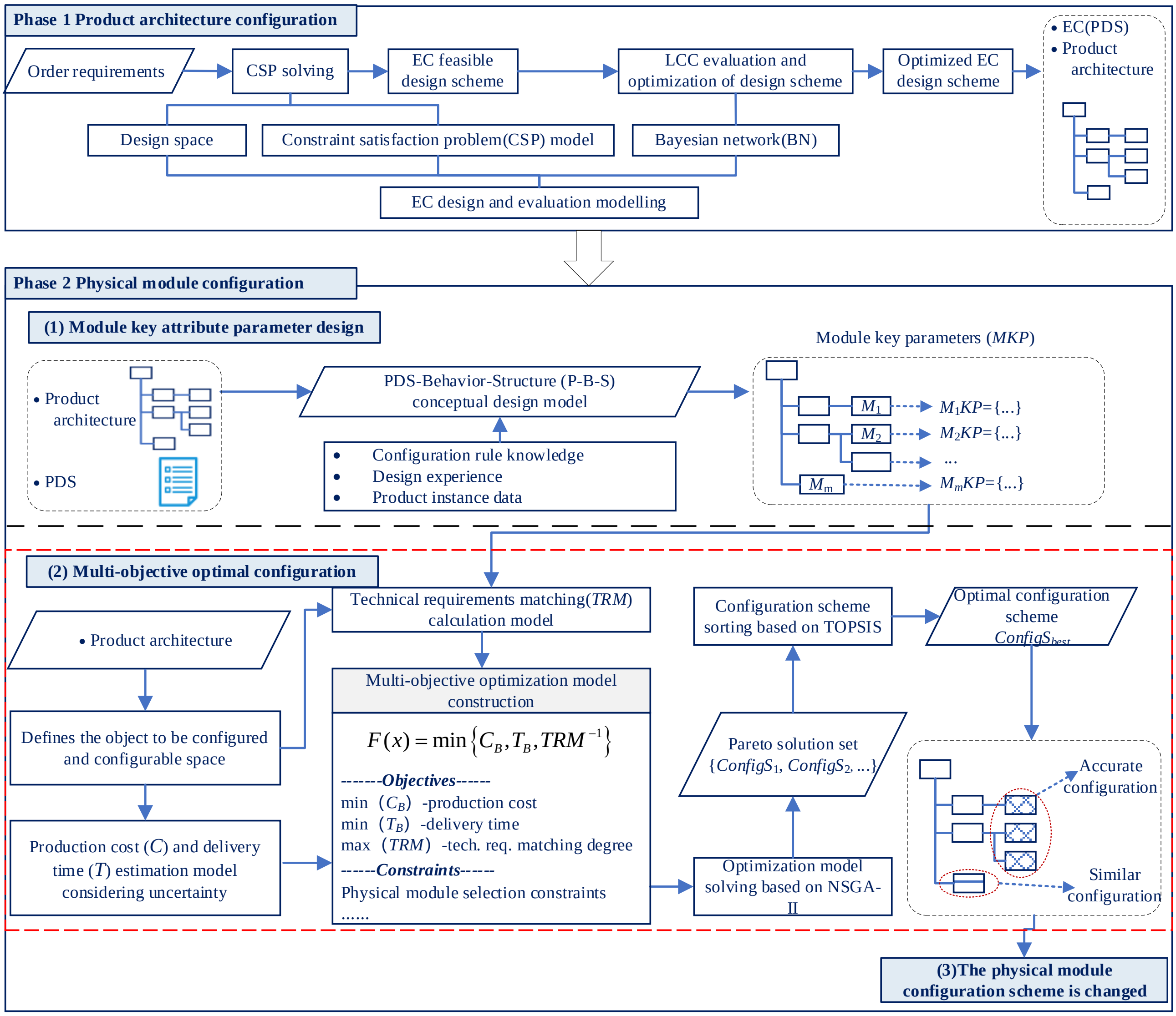

Figure 1 Configuration design framework of complex ETO products

Firstly, module key parameters design should be determined according to the order product architecture, top-level design specifications, and design process model. We established a PDS-Behavior-Structure (P-B-S) conceptual design model and a vector mapping tool for conceptual design analysis and synthesis [47]. Based on the P-B-S conceptual design model and its decomposition process, combined with the black box method, the module key parameters (*MKP*) are obtained, which represent the set of key attribute parameters for module.

Secondly, in order to solve the issue that the final design scheme of a complex ETO product cannot be obtained directly through module configuration design, this study provides a multi-objective optimal configuration method for complex ETO products to facilitate the design of further configuration changes, which considers the trade-offs between price, timeliness, and the degree to which technical criteria are satisfied. This method considers the uncertainty of cost and time data for both self-made and outsourced physical modules due to factors like the uncertainty of the production process and the dynamic change of the supply chain, as shown in Figure 1. The main steps are: (1) building the production cost and delivery time estimation models and the technical requirements matching degree calculation model; (2) using normal distribution and the 3σ principle to describe the uncertainty of cost and time; (3) constructing a multi-objective optimization configuration model of physical modules with the goals of minimum production cost, shortest delivery time, and maximum technical requirements matching degree; (4) utilizing the NSGA-II algorithm to solve the Pareto optimum solution set of the physical module configuration scheme, and evaluating the best and worst instances of the optimization objective value based on the upper and lower boundary values of the cost and time data of the physical module; and (5) in order to determine the optimal configuration scheme, the TOPSIS approach is utilized to quantitatively rank the configuration schemes.

Finally, the optimal solution may precisely fit all technical criteria, or certain physical modules may not precisely satisfy technical requirements, i.e., there are combinations with comparable characteristics. If the technical criteria are precisely met, the evaluation can go directly to simulation. If equivalent settings already exist, they must be modified via configuration adjustments.

In this paper, we mainly focus on the multi-objective optimal configuration in the second phase.

3.2 Configuration modelling

3.2.1 Production cost and delivery time estimation model

To acquire the physical module configuration scheme with the lowest production cost and shortest delivery time, it is important to develop production cost and delivery time estimation models for the physical module configuration scheme. Figure 2 depicts the modeling process of the ETO product development in four phases: *pre-production*, *production*, *assembly,* and *order-to-delivery*. The pre-production phase involves demand analysis, customization design, process design, production planning, etc. The cost C_A and time T_A occurred in this phase are mostly influenced by the management elements of the enterprise, the quantity of information, the use of tools and software, etc., while the design variances of individual orders have a smaller impact. The design variances of products from separate orders influence the production of self-made physical modules, as well as the procurement and shipping of outsourced physical modules. In order to compare the advantages and disadvantages of physical module configuration schemes for various products, this article only addresses the cost and time required to produce C_B and T_B order products.

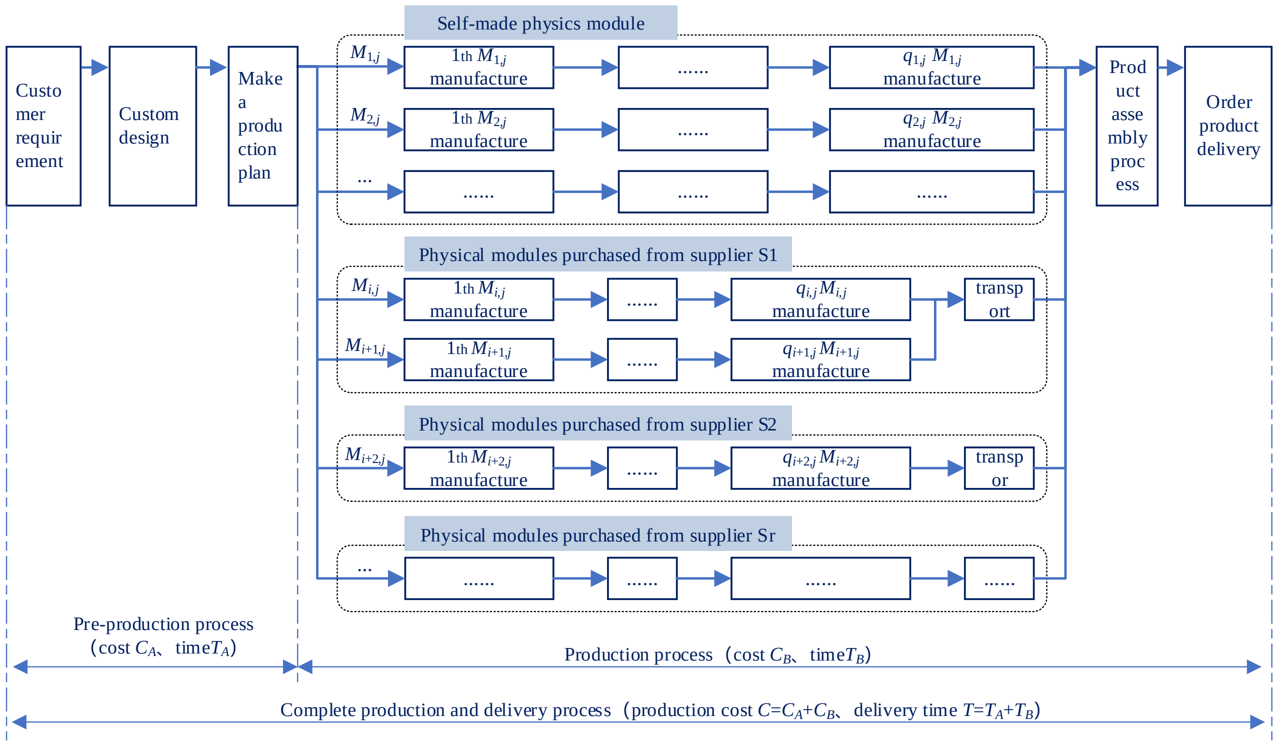

Figure 2 development process of ETO

The variable definition of the data required to estimate the production cost and lead time of the product physical module configuration scheme is shown in Table 3.

Table 3 Data required for production cost and delivery estimates

Data symbol	Description	Sources
M	Physical module	These deterministic data can be directly obtained or calculated based on the order product architecture, configuration model, customer location, supplier location, etc.
M_i	Physical module to be configured in the product	
$M_{i,j}$	Configurable physical module instance	
u	Number of physical module to be configured in the product, $i \in \{1,2,\ldots,u\}$	
v	Number of configurable physical module instance, $j \in \{1,2,\ldots,v\}$	
$q_{i,j}$	Number of $M_{i,j}$ required in the product to be configured	
$W_{i,j}$	The weight of $M_{i,j}$	
D_P	the transportation distance of the product	
$D_{i,j}$	The transportation distance from the supplier to the manufacturer of $M_{i,j}$	
C_T	The unit price of logistics transportation of physical modules	The uncertainty of transport

	or products	unit price and transport speed is small and can be regarded as deterministic data
v_T	The average transport speed of physical modules or products	
$C_{1,i,j}$	The self-made cost of physical module $M_{i,j}$	These data are affected by complex factors in the production process and supply chain, which are uncertain and can be estimated based on the historical production data of the manufacturers and suppliers.
$C_{2,i,j}$	The procurement cost of physical module $M_{i,j}$	
C_3	The assembly cost of the physical module of the product	
$CS_{i,j}$	The selling price of the physical module Mi,j as determined by the supplier	
$T_{1,i,j}$	The manufacturing time of a self-made physical module $M_{i,j}$	
$T_{2,i,j}$	The manufacturing time of an outsourced physical module $M_{i,j}$	
T_3	The assembly time of the physical module of the product	

(1) Production cost estimation model

Let $M_{i,j}$ denote the configurable physical module instance j of module M_i; let $Sel_{i,j}$ denote whether physical module $M_{i,j}$ is selected in the configuration scheme; let $Sel_{i,j}$=1 denote selected; and let $Sel_{i,j}$=0 denote not selected; that is, let $Sel_{i,j}$ be the decision variable for optimizing physical module configuration. In accordance with the preceding analysis of the order product's completion process, the cost C_B is regarded as the order product's production cost. This cost consists primarily of the self-made and outsourced cost of the physical module, the assembly cost, and the product transportation cost. When the physical module is configured for a particular product architecture, the assembly cost of the product is minimally influenced by the change in physical module configuration and can be viewed as a constant value independent of the specific physical module configuration scheme. Consequently, C_B can be computed as follows:

$$\begin{aligned} C_B &= C_1 + C_2 + C_3 + C_4 \\ &= \sum_{i=1}^{u}\sum_{j=1}^{v}\left(C_{1,i,j} + C_{2,i,j}\right) q_{i,j} \cdot Sel_{i,j} + C_3 + C_T D_P \sum_{i=1}^{u}\sum_{j=1}^{v} W_{i,j} \cdot q_{i,j} \cdot Sel_{i,j} \end{aligned} \tag{1}$$

Where: C_1 represents the production cost of all self-made physical modules in the product; C_2 represents the procurement cost of all outsourced physical modules in the product; C_3 represents the assembly cost of the physical module of the product (fixed value); C_4 represents the cost of transporting a product from the OEM to the customer; u indicates the number of modules to be configured for the ordered product; v indicates the number of configurable physical modules of the M_i; $C_{1,i,j}$ represents the self-made cost of physical module $M_{i,j}$ and $C_{1,i,j}$=0 for the outsourced physical module; $C_{2,i,j}$ represents the procurement cost of physical module $M_{i,j}$, and $C_{2,i,j}$=0 for the self-made physical module; $q_{i,j}$ denotes the number of required physical modules $M_{i,j}$; C_T represents the unit price of logistics transportation; D_P represents the transportation distance of the product; $W_{i,j}$ indicates the weight of the physical module $M_{i,j}$.

The procurement cost of the outsourced physical module consists of the selling price of the physical module as defined by the supplier and the cost of delivering the physical module to the manufacturer, which may be calculated using Equation (2).

$$C_{2,i,j} = CS_{i,j} + C_T D_{i,j} W_{i,j} \tag{2}$$

Where: $CS_{i,j}$ represents the selling price of the physical module $M_{i,j}$ as determined by the supplier; $D_{i,j}$ represents the transportation distance from the supplier to the manufacturer.

(2) Delivery time estimation model

The time T_B is regarded as the delivery time of the ordered product, which consists mostly of the production time of the self-made module, the procurement time of the outsourced physical module, the assembly time, and the transportation time of the product. Different modules are manufactured concurrently; therefore, the manufacture time of modules can be calculated based on the largest of the manufacturing times of different self-made physical modules and the manufacturing times of different outsourced physical modules plus transportation time. The assembly time of a product is comparable to the cost of assembly, which can be a fixed amount. The product's transport time is determined by dividing its transport distance by its average transport speed. The formula for calculating T_B is:

$$\begin{aligned} T_B &= \max(T_1, T_2) + T_3 + T_4 \\ &= \max(T_{1,i,j} \cdot q_{i,j} \cdot Sel_{i,j}, \left(T_{2,i,j} \cdot q_{i,j} + \frac{D_{i,j}}{v_T} \right) \cdot Sel_{i,j}) + T_3 + \frac{D_P}{v_T} \end{aligned} \tag{3}$$

Where: T_1 represents the manufacturing time of the self-made physical module; T_2 indicates the procurement time (including manufacturing and transportation time) of outsourced physical modules; T_3 represents the assembly time of the physical module of the product (fixed value); T_4 indicates the time to ship the product from the manufacturer to the customer; $T_{1,i,j}$ represents the manufacturing time of a self-made physical module $M_{i,j}$; $T_{2,i,j}$ represents the manufacturing time of an outsourced physical module $M_{i,j}$; v_T represents the average transport speed of physical modules or products.

According to Formula (1) to (3), the data required to estimate the production cost and delivery time of the product physical module configuration scheme includes 15 parameters. Among them, The

u, v, $q_{i,j}$, $W_{i,j}$, D_P, $D_{i,j}$, C_T, and v_T are determined data that can be obtained directly or by calculation; The $C_{1,i,j}$, $C_{2,i,j}$, C_3, $CS_{i,j}$, $T_{1,i,j}$, $T_{2,i,j}$, and T_3 are the production cost and time data of manufacturers and suppliers. These cost and time data are affected by many complex factors and have uncertainties and can be estimated based on the historical production data of manufacturers and suppliers.

(3) Uncertainty of production cost and delivery time

Numerous complicated factors influence the cost and time required for physical module production. The production cost and time data of self-made and outsourced physical modules cannot be predicted precisely, and there are data uncertainties, such as $C_{1,i,j}$, $C_{2,i,j}$, C_3, $CS_{i,j}$, $T_{1,i,j}$, $T_{2,i,j}$, and T_3. In order to better evaluate the cost and duration of product physical module configuration solutions in support of design decisions, this uncertainty must be accounted for when measuring the cost and time of manufacturing for each physical module and ordered product.

A product platform is a collection of common modules and the relationships between those modules. From the perspective of product platform, physical modules are divided into platform physical modules and non-platform physical modules. Given the frequency with which configurable self-made or outsourced physical modules, particularly platform physical modules, have been manufactured, manufacturers and suppliers have a wealth of information regarding the cost and duration of physical module production. Consequently, the probability distribution of production cost and delivery time for a physical module of a technical specification can be computed using the manufacturer's or supplier's existing production data. Furthermore, there is mutual independence between the various factors that affect the production cost of the physical module and the time, such as the factors that influence the cost of production are raw material prices, processing time, transportation costs, etc. These factors do not interfere with each other and affect the final production costs of physical modules through accumulation. Consequently, according to the central limit theorem, the normal distribution may be utilized to explain the uncertainty of production cost and time data, i.e., production cost and time data of physical modules can be considered as random variables with normal distribution.

The random variable X with a normal distribution is denoted as $X\sim N(\mu,\sigma^2)$, where μ is the mean value and σ is the standard deviation. According to the 3σ principle, the probability of X having a value within the range $(\mu-3\sigma, \mu+3\sigma)$ is 99.73 percent, whereas the probability of X having a value larger or smaller is very low. Therefore, without considering a few extreme values, the upper and lower boundary values of X can be defined as $\mu+3\sigma$ and $\mu-3\sigma$, respectively, and the mean value is μ. On the basis of the normal distribution and the 3σ principle, it is straightforward to determine the lower and upper boundary values and mean values of normal random variables, which may be expressed as a triplet (X_l, X_m, X_u). l, m and u represent, respectively, the lower boundary values, the mean values, and the upper boundary values of X. In this paper, a variable's the upper and lower boundary values and its mean values are obtained, based on subjective experience. For example, the self-made cost $C_{1,i,j}$ of the physical module $M_{i,j}$ can be expressed as ($C_{1,i,j\text{-}l}$, $C_{1,i,j\text{-}m}$, $C_{1,i,j\text{-}u}$), which represents the lower boundary value, mean value, and upper boundary value of $C_{1,i,j}$. After obtaining the triplet of production cost and time data for all physical modules in the configuration space using this method, these data should be organized for use in the optimization configuration of physical modules to facilitate subsequent analysis of the best, most likely, and worst-case scenarios for production cost and delivery time of product configuration schemes.

3.2.2 Technical requirements matching calculation model

Based on the design results of the key attribute parameters of module and the technical attribute parameter values of the physical modules in the configuration space. The weighted Euclidean distance method is used to calculate the similarity between all physical modules and the technical requirement values of the modules, which is then used to determine the degree of conformance of the physical modules to the technical requirements. The matching degree of technical requirements of each physical module is weighted and accumulated for a particular physical module configuration scheme.

(1) Defines the target vector and physical module attribute parameter matrix for module

The target vector is defined as the design outcome $M_iKP=\{KP_{i,1}=d_{i,1,*}$, $KP_{i,2}=d_{i,2,*}$, …, $KP_{i,n}=d_{i,n,*}\}$ of key attribute parameters of module M_i. As shown in Equation (4), the technical attribute parameter values of the physical module associated with module M_i are extracted to create the physical module attribute parameter matrix M_iS, where k represents the k_{th} attribute parameter of the physical module, $k\in\{1,2,\ldots,n\}$, the extracted physical module attribute parameter items correspond to the n attribute parameter items in the target vector.

$$M_iS=\begin{bmatrix} KP_{i,1,1} & KP_{i,1,2} & \cdots & KP_{i,1,n} \\ KP_{i,2,1} & KP_{i,2,2} & \cdots & KP_{i,2,n} \\ \vdots & \vdots & \ddots & \vdots \\ KP_{i,v,1} & KP_{i,v,2} & \cdots & KP_{i,v,n} \end{bmatrix}=(KP_{i,j,k})_{v\times n} \tag{4}$$

If the parameter value is numerical data, the vector value of physical module $KP_{i,j,k}$ is the value of attribute parameter of physical module. If the parameter value is character data, the target vector value $KP_{i,k}$ can be defined as 1, When the value of attribute parameter of physical module is the same as the target value, the vector value of physical module $KP_{i,j,k}$ is 1 otherwise it is 0.

(2) Establish a similar matrix

The scale of various attribute parameters varies. To prevent the annihilation of large-scale data to small-scale data and affect the accuracy of the calculation results, it is necessary to combine the target vector M_iKP with the normalized matrix M_iS to obtain the similarity matrix M_iS'. As demonstrated by Equations (5) and (6).

$$M_iS'=\begin{bmatrix} KP'_{i,1,1} & KP'_{i,1,2} & \cdots & KP'_{i,1,n} \\ KP'_{i,2,1} & KP'_{i,2,2} & \cdots & KP'_{i,2,n} \\ \vdots & \vdots & \ddots & \vdots \\ KP'_{i,v,1} & KP'_{i,v,2} & \cdots & KP'_{i,v,n} \end{bmatrix}=(KP'_{i,j,k})_{v\times n} \tag{5}$$

$$KP'_{i,j,k}=\frac{\left|KP_{i,k}-KP_{i,j,k}\right|}{\sum_{j=1}^{v}\left|KP_{i,k}-KP_{i,j,k}\right|} \tag{6}$$

(3) Calculate the matching degree of the technical requirements of the module

Considering the varying degree of significance of attribute parameters across modules, the effect on the degree of module technical requirements matching is variable. The Analytic Hierarchy Process (AHP) [48] can be used to determine the relative significance of the module attribute parameters $KP_{i,k}$. The attribute parameter importance of module M_i is represented by the vector $\omega_{i,k}$, and the similarity between modules $M_{i,j}$ and the target vector (technical requirement matching degree) is computed using the weighted Euclidean distance method as shown in Equation (7). The calculation results $TRM_{i,j}$ of the technical requirements matching degree of modules $M_{i,j}$ can be recorded for calculating the overall technical requirements matching degree of the configuration scheme during optimization configuration.

$$TRM_{i,j} = 1 - \sqrt{\sum_{k=1}^{n} \omega_{i,k} \cdot \left(KP'_{i,j,k}\right)^2} \quad (7)$$

(4) The technical requirement matching of the physical module configuration solution

Like the module attribute parameters, various modules have varying degrees of importance, which influence the overall technical requirement matching degree of the product's physical module configuration scheme. Using the AHP method to determine the importance of various modules, denoted by the vector ε_i, the overall technical requirement matching degree of the physical module configuration scheme is calculated as follows:

$$TRM = \sum_{i=1}^{u} \sum_{j=1}^{v} \varepsilon_i \cdot TRM_{i,j} \cdot Sel_{i,j} \quad (8)$$

3.2.3 multi-objective optimization model construction

A multi-objective optimization model is created by minimizing the production cost and delivery time of the physical module configuration scheme as well as the degree of matching technical specifications. To facilitate the solution, the reciprocal of the technical requirements matching degree function is converted to be as small as possible, i.e., the fewer the three goals, the better. The configuration scheme is determined by the value of the decision variable $Sel_{i,j}$, so the configuration scheme can be expressed as a decision vector $x=(Sel_{1,1}, Sel_{1,2}, \ldots, Sel_{2,1}, Sel_{2,2}, \ldots, Sel_{i,j}, \ldots)$, $i \in \{1,2,\ldots,u\}$, $j \in \{1,2,\ldots,v\}$. In conjunction with Equations (1) to (8), the following constitutes a multi-objective optimization model of physical module configuration:

$$F(x) = \min\left\{C_B, T_B, TRM^{-1}\right\} \quad (9)$$

$$\text{s.t.} \quad Sel_{i,j} \in \{0,1\}, i = 1,2,\ldots u; j = 1,2\ldots,v; \quad (10)$$

$$\sum_{j=1}^{v} Sel_{i,j} = 1 \quad (11)$$

$$\sum_{k=1}^{n} \omega_{i,k} = 1 \quad (12)$$

$$\sum_{i=1}^{u} \varepsilon_i = 1 \quad (13)$$

$$C_B \le \frac{C_{customer}}{1+\alpha} - C_A \quad (14)$$

$$T_B \le T_{customer} - T_A \quad (15)$$

where: $C_{customer}$ is the highest price that customers can accept; α is the profit margin of the enterprise; and $T_{customer}$ is the maximum delivery time accepted by the customer.

Equations (10) through (15) are physical module configuration constraints, where, Eq. (10) represents the decision variable $Sel_{i,j}$ can only be 0 or 1; Eq. (11) indicates that the pair module M_i can only select one physical module from its configurable space; Eq. (12) indicates that the sum of importance degrees of n attribute parameters of module M_i is 1; Eq. (13) indicates that the sum of importance of m modules to be configured is 1; Eq. (14) indicates that the sum of pre-production cost C_A and production cost C_B should be controlled within the maximum price; and Eq. (15) specifies that the sum of pre-production time T_A and production time T_B must be controlled within the maximum acceptable delivery time to customers. The final two constraints specify the customer's requirements regarding product cost and delivery time. Combined with the optimization objective, the optimization problem can be described as follows: searching for a configuration scheme that satisfies the customer's cost and delivery time requirements with the lowest possible cost, the shortest possible delivery time, and the highest possible degree of matching of technical requirements.

3.3 Configuration solving

3.3.1 Model solving based on NSGA-II

In this paper, the NSGA-II [49] algorithm is utilized to solve the multi-objective optimization configuration problem of physical modules. It has been applied to numerous engineering optimization problems due to its quick solution speed and good convergence.

When NSGA-II is used, the optimization variables need to be encoded as chromosomes, that is, the physical module configuration scheme is represented by chromosome. In this paper, symbols are used to encode chromosomes, as shown in Figure 3. A chromosome represents a configuration scheme (an individual), consisting of several gene locus. A gene locus indicates a module M_i to be configured. A specific value assigned to a gene locus is a selected physical module $M_{i,j}$. The configurable space of the module to be configured constitutes the allele (optional gene value). According to the coding mode way of chromosomes, N chromosomes are randomly generated in the configurable space to form the initial population.

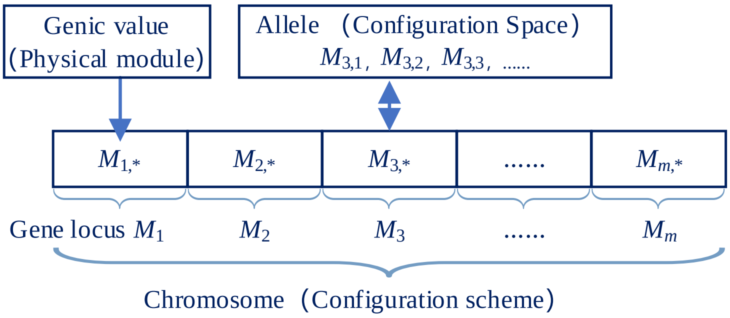

Figure 3 The coding mode way of chromosomes

The parameter setting of NSGA-II algorithm has a great influence on the performance and effect of the algorithm. In the parameter setting range, set an initial population size, number of iterations, crossover probability, and mutation probability. By observing the change of the objective function value during the operation of the algorithm, if the change of the target value fluctuates greatly, the crossover probability or mutation probability is appropriately reduced, and the initial population size and the number of iterations is appropriately increased. If the value of the set parameter is run several times, the value of the objective function tends to be stable or the solution converges to a certain range, then the algorithm reaches the optimal.

Due to the fact that the physical module's production time and cost data have been expressed as a set of three highly uncertain numbers (upper and lower bounds plus the mean), this paper starts by utilizing the mean of these uncertain data for multi-objective optimization to obtain the Pareto optimal configuration scheme set, which is then used in NSGA-II to solve the multi-objective optimal configuration of the physical module. For the obtained configuration scheme, the lower and upper boundary values of uncertain data are used to calculate the worst and best cases of production cost and delivery time, which can be viewed as the most pessimistic and most optimistic evaluations of the configuration scheme under uncertainty, respectively.

The Pareto optimal solution set of the physical module configuration scheme is expressed as $ConfigS=\{ConfigS_1, ConfigS_2, \ldots, ConfigS_l\}$, and the best, most likely, and worst case scenarios of manufacturing cost and delivery time for each configuration scheme are expressed as $ConfigS_i$-$C_B=(C_{i,best}, C_{i,median}, C_{i,worst})$ and $ConfigS_i$-$T_B=(T_{i,best}, T_{i,median}, T_{i,worst})$. In addition, the degree of technical requirement matching for each configuration scheme can be determined by calculating the inverse of the computed target value, whose value range is $0 < TRM \leq 1$.

The Pareto optimal solution set provided by NSGA-II is a collection of configuration schemes from which designers and customers can choose. Each of these configuration schemes is non-dominant. Designers or clients can select the required configuration schemes from the solution set based on their personal preferences or by quantitative rating.

3.3.2 Optimal solution selection based on TOPSIS

To pick an optimal configuration scheme from the Pareto solution set as the basis for the subsequent design, this study employs TOPSIS, an approximation ideal solution ranking approach, to quantitatively rank several non-dominated solutions and to select the best solution based on the ranking. The following is TOPSIS's computation procedure:

(1) Construct the normalized decision matrix

The mean values of production cost and delivery time, as well as the matching degree of technical demand for t Pareto optimal allocation schemes, are constructed into a decision matrix with t rows and 3 columns, as illustrated below:

$$DM = \begin{bmatrix} C_{1,median} & T_{1,median} & TRM_1 \\ C_{2,median} & T_{2,median} & TRM_2 \\ \vdots & \vdots & \vdots \\ C_{t,median} & T_{t,median} & TRM_t \end{bmatrix} \tag{17}$$

The matrix DM is normalized to reduce the influence of dimension discrepancies between various data on the calculation results. The procedure of normalizing is depicted in Equation (18), and the normalized decision matrix is given by the symbol DM'.

$$\begin{cases} C'_{i,median} = \dfrac{C_{i,median}}{\sqrt{\sum_{i=1}^{t}\left(C_{i,median}\right)^2}} \\ T'_{i,median} = \dfrac{T_{i,median}}{\sqrt{\sum_{i=1}^{t}\left(T_{i,median}\right)^2}} \\ TRM'_i = \dfrac{TRM_i}{\sqrt{\sum_{i=1}^{t}\left(TRM_i\right)^2}} \end{cases} \tag{18}$$

(2) Construct positive and negative ideal solutions

The optimal value and the worst value of the aforementioned three indices are selected from the decision matrix DM', with the optimal value combined into a virtual positive ideal solution, $ConfigS^+$, and the worst value combined into a virtual negative ideal solution, $ConfigS^-$. Positive and negative ideal solutions' index values are stated as follows:

$$\begin{cases} ConfigS^{+} = \left(C^{'}_{+,median}, T^{'}_{+,median}, TRM^{'}_{+}\right) \\ ConfigS^{-} = \left(C^{'}_{-,median}, T^{'}_{-,median}, TRM^{'}_{-}\right) \end{cases} \tag{19}$$

(3) Calculate the distance between the non-dominated solution and the positive and negative ideal solution

The Euclidean distance approach is used to calculate the distances D_i^+ and D_i^- between each non-dominated solution $ConfigS_i$ and positive and negative ideal solutions, as illustrated by Equations (20) and (21). In the formula, ω_C, ω_T and ω_{TRM}, respectively, indicate the relative significance that the client places on the production cost, delivery time, and technical demand matching degree of the product, as determined using the AHP approach. The combined relative weight of the three objectives is 1.

$$D_i^{+} = \sqrt{\omega_C\left(C^{'}_{i,median} - C^{'}_{+,median}\right)^2 + \omega_T\left(T^{'}_{i,median} - T^{'}_{+,median}\right)^2 + \omega_{TRM}\left(TRM^{'}_{i} - TRM^{'}_{+}\right)^2} \tag{20}$$

$$D_i^{-} = \sqrt{\omega_C\left(C^{'}_{i,median} - C^{'}_{-,median}\right)^2 + \omega_T\left(T^{'}_{i,median} - T^{'}_{-,median}\right)^2 + \omega_{TRM}\left(TRM^{'}_{i} - TRM^{'}_{-}\right)^2} \tag{21}$$

(4) Calculate the relative closeness between the non-dominated solution and the positive ideal solution

The relative closeness RC_i between each non-dominated solution $ConfigS_i$ and the positive ideal solution is computed as indicated in Equation (22). The greater the degree of relative closeness, the nearer the non-dominated solution is to the positive ideal solution and the further away the negative ideal solution is. Therefore, the set of non-dominated solutions can be organized in descending order based on the relative closeness degree, and the non-dominated solution with the greatest relative closeness degree is chosen as the optimal solution.

$$RC_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{22}$$

If the technology demand matching degree is 1 (i.e., physical modules are accurate configuration) or the technical demand matching degree is less than 1 (i.e., similar configuration), but the configuration scheme is acceptable, it can enter the configuration rules checking and simulation evaluation in order to further verify the functionality, performance, and whether they meet the design scheme's requirements. If the technical requirement matching degree is less than 1 and the configuration scheme is not practicable, the similar physical modules must be modified through the configuration change process to meet all technical criteria.

4 Case study-subway's bogie

Rail transit vehicles, which are classic examples of complicated ETO products, are custom-made to fit customer specifications. The process of customization design requires a great deal of technical engineering design knowledge, and the design is both challenging and time-consuming. This study uses the customization design of a subway bogie to demonstrate the viability of the configuration design process described above.

4.1 Product architecture configuration for subway bogie

According to reference [46], an engineering characteristic design method based on constraint satisfaction Problem (CSP) and Bayesian network (BN) was proposed to design the engineering characteristics (ECs) of subway bogie. Firstly, according to the product family architecture model, we constructed existing maintenance service data, configuration rule knowledge and expert experience, the design space, CSP model and LCC estimation model based on BN of ECs. Then, taking the above customer requirements as input, the CSP model is constructed and solved to obtain the feasible ECs design schemes that satisfy the requirements and constraints, and the corresponding LCC estimation models based on BN are constructed/used to evaluate the LCC of the feasible design schemes to support the selection of the optimal design scheme. Please refer to section 4 of reference [46] for the detailed example calculation process. The obtained final ECs design results of the subway bogie are shown in Table 4.

Table 4 The ECs design results of subway bogie

Classification	**Sub-classification**	**PSS-ECs**	**Value**
Product-related ECs (P-EC)	Function setting	P-EC_1: Intelligent monitoring	Yes
	Technical principle	P-EC_2: Drive device type	Permanent magnet synchronous motor
		P-EC_3: Primary suspension device type	Rotary arm type
	Geometry structure	P-EC_4: Braking device structure	Disc brake
		P-EC_5: Traction device structure	Singe traction rod
	Material	P-EC_6: Frame material	Low-alloy steel
	Performance parameters	P-EC_7: Average acceleration	0.65m/s^2
		P-EC_8: Emergency braking deceleration	1.26m/s^2
		P-EC_9: Axle load	14.4t

		P-EC_{10}: Bogie weight	7.6t
		P-EC_{11}: Maximum Speed	100km/h
	Size parameters	P-EC_{12}: Wheelbase	2300mm
Service-related ECs （S-EC）	Maintenance mode	S-EC_1: Fault detection mode	Intelligent detection
		S-EC_2: Maintenance schedule	MS2
	Spare Parts	S-EC_3: Spare parts inventory level	Level2
	Service quality	S-EC_4: Service response time	4h
		S-EC_5: Fault detection time	FTD2
		S-EC_6: Fault repair time	FRT2

Note[46]： MS2 denotes the balanced schedules that separates biweekly detection, three-month detection, and annual detection into each month. Level2 denotes the stock of redundant spare parts, and the shortage probability is lower than the stock of conventional spare parts; FDT2 denotes the detection time corresponding to intelligent detection; FRT2 denotes the repair time corresponding to MS2.

According to the obtained engineering characteristics design scheme, the subway bogie's product architecture meeting customer needs can be determined, as shown in Figure 4. The product architecture is obtained by selecting the nodes (shoeing as M*x* in Figure 4) of the product family architecture model and assigning the key function attribute parameters and technical attribute parameters according to the engineering characteristics of the design, that is, the function selection, the technical solution selection and the value of the top-level design parameters. The engineering feature design determines the architecture of the ordered product. The next step is to design the key attribute parameters of the module and configure the physical modules based on the architecture (including the ECs design results) and customer customization requirements, and to instantiate the product architecture into a specific product instance.

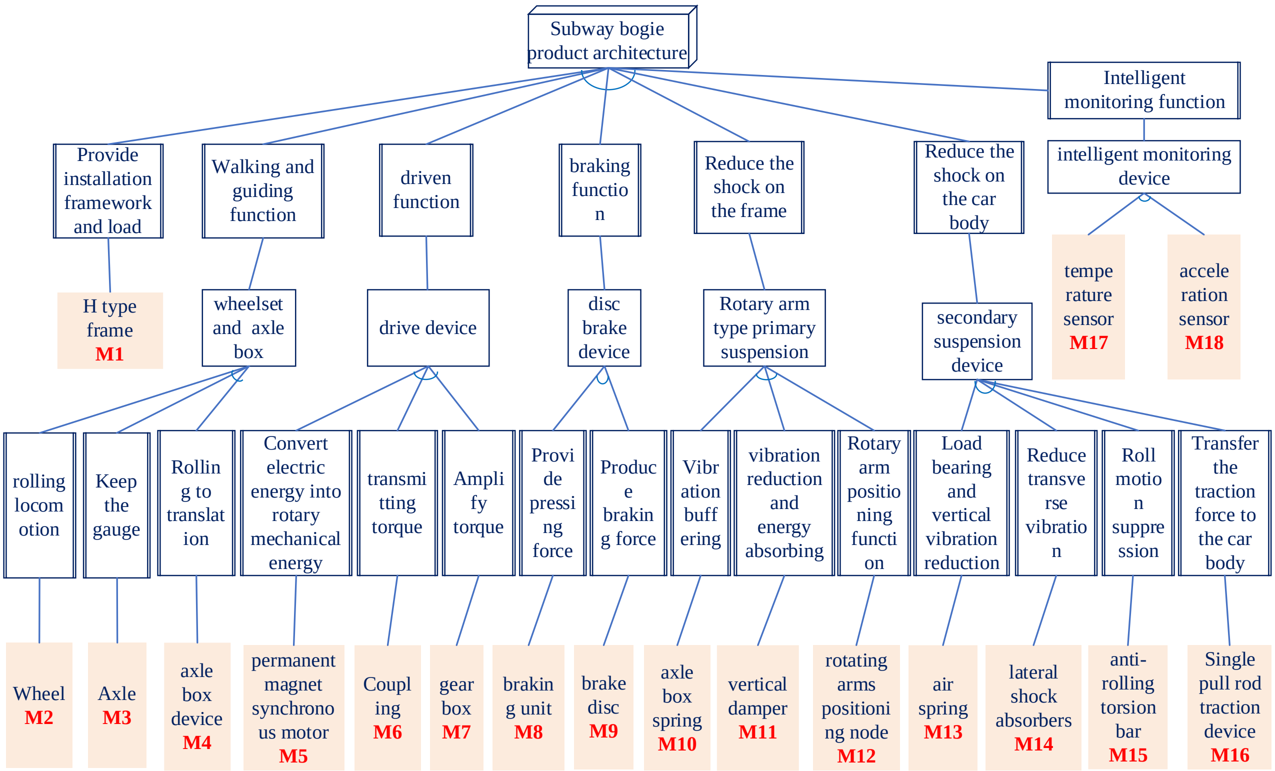

Figure 4 Customer demand-oriented subway bogie's product architecture

4.2 Configurable space for subway bogie modules

The configuration objects consist of 18 subway bogie modules designated. Table 5 displays the design results for important attribute parameters of a specific type of subway bogie module. $M_iKP=\{KP_{i,1}=d_{i,1,*}, KP_{i,2}=d_{i,2,*}, \ldots, KP_{i,n}=d_{i,n,*}\}$ represents the key attribute parameter design findings for module M_i. Where M_iKP represents the set of key attribute parameters for module M_i, $KP_{i,n}$ represents the key attribute parameter for module M_i and $d_{i,n,*}$ represents the exact value of the nth key attribute parameter for module M_i.

Table 5 Design results of key attribute parameters of a subway bogie module

Module to be Configured	Key attribute parameters design results (technical requirements)
M_1（Frame）	M_1KP={Material $KP_{1,1}$=16MnR，Center distance of side beam $KP_{1,2}$=1930mm，The side beam section is wide $KP_{1,3}$=200mm，High section of side beam $KP_{1,4}$=300mm，Center distance of beam $KP_{1,5}$=450mm，Beam steel pipe diameter $KP_{1,6}$=185mm}
M_2（Wheel）	M_2KP={Material $KP_{2,1}$=CL60，Tread shape $KP_{2,2}$=LM，New wheel diameter $KP_{2,3}$=840mm，Full wear wheel diameter $KP_{2,4}$=770mm，Rim width $KP_{2,5}$=135mm，Wheel hub width $KP_{2,6}$=170mm}
……	……

M_{18}（Acceleration sensor）	$M_{18}KP$={Measurement range $KP_{18,1}$=200g，Sensitivity $KP_{18,2}$=10mV/g}

The physical module configurable space of the subway's bogie is formed, as depicted in Table 6, by gathering the platform physical modules in the business product family architecture and the non-platform physical modules available in the product instance.

Table 6 The configuration space of the physical module of the subway bogie

M_i	$M_{i,j}$	M_iKP	$W_{i,j}$ (kg)	$TRM_{i,j}$	$CS_{i,j}$ (10000 yuan)	$D_{i,j}$ (km)	$C_{1,i,j}/C_{2,i,j}$ (10000 yuan)	$T_{1,i,j}/T_{2,i,j}$ (h)
M_1 △ ○	$M_{1,1}$	$KP_{1,1,1}$=S355J2W(H), $KP_{1,1,2}$=1860mm, $KP_{1,1,3}$=180mm, $KP_{1,1,4}$=270mm, $KP_{1,1,5}$=400mm, $KP_{1,1,6}$=170mm	1250	0.398	/	/	29±1.5	52±4
	$M_{1,2}$	$KP_{1,2,1}$=16MnR, $KP_{1,2,2}$=1930mm, $KP_{1,2,3}$=220mm, $KP_{1,2,4}$=340mm, $KP_{1,2,5}$=500mm, $KP_{1,2,6}$=185mm	1500	0.856	/	/	32±1.5	56±4
	$M_{1,3}$	$KP_{1,3,1}$=16MnR, $KP_{1,3,2}$=2010mm, $KP_{1,3,3}$=200mm, $KP_{1,3,4}$=300mm, $KP_{1,3,5}$=450mm, $KP_{1,3,6}$=194mm	1600	0.597	/	/	35±1.5	60±4
M_2 □ ◎	$M_{2,1}$	$KP_{2,1,1}$=CL60, $KP_{2,1,2}$=LM, $KP_{2,1,3}$=840mm, $KP_{2,1,4}$=770mm, $KP_{2,1,5}$=135mm, $KP_{2,1,6}$=170mm	334	1	1.52±0.1	1530 (S1)	1.596±0.1	7±1
	$M_{2,2}$	$KP_{2,2,1}$=CL60, $KP_{2,2,2}$=LM, $KP_{2,2,3}$=840mm, $KP_{2,2,4}$=770mm, $KP_{2,2,5}$=135mm, $KP_{2,2,6}$=170mm	338	1	1.3±0.1	1900 (S2)	1.396±0.1	8.5±1.5
…	…		…	…	…	…	…	…
M_{18} □ ○	$M_{18,1}$	$KP_{18,1,1}$=200g, $KP_{18,1,2}$=10mV/g	10	1	1±0.08	2050(S17)	1.003±0.08	12±1

Under the module to be configured, the symbol △ indicates a self-made module, the symbol □ indicates a purchased module, the symbol ◎ indicates a platform physical module, and the symbol ○ indicates a non-platform physical module. ~~$q_{i,j}$ represents the number of required physical modules to configure an subway bogie; $TRM_{i,j}$ is the matching degree of technical requirements of physical modules, which~~ is determined based on the technical requirements values of each module in Table 5 and Equations (4) to (7). For convenience, the relevance of attribute parameters in each module is determined based on the same significance. The cost and time data of the self-made and purchased physical modules are the upper and lower boundary values and the mean value based on the normal distribution and the 3σ principle, and are abbreviated as "mean value±3σ" for conciseness. For the purchased components, $C_{2,i,j}$ is determined by multiplying $CS_{i,j}$ by the transportation cost (Equation 2), and the unit price of transportation is computed using 1.5 yuan/ton·kilometer. S1, S2, etc., following the transit distance $D_{i,j}$ indicate various suppliers. The manufacturing time of self-made and purchased physical modules is indicated in hours, which is based on an eight-hour workday. By dividing 8 by the time values in the Table 6, working days can be determined.

4.3 Configuration modelling and solving for subway's bogie

The production cost of the physical module configuration strategy for the subway bogie is determined using Equation (1). Among them, the assembly cost can be based on an existing subway's bogie assembly cost data sample of the same architecture in the firm, and the upper and lower boundary values and average value are derived using normal distribution and the 3σ principle, which equals 21.6±1 ten thousand yuan. In addition, the bogie is a component of the subway train and not a standalone item. After the assembly of the primary engine in the plant, it must be assembled into the vehicle as a whole. Therefore, there is no process of conveying the bogie to the consumer, and there is no product transportation cost in this example.

The delivery time of configuration scheme for the subway bogie is computed using Equation 3. Included in the procurement time of outsourced modules are the manufacture and transport times. The average transport speed from the supplier to the main engine factory is 80 km/h, and the travel duration is $D_{i,j}$ divided by 80. The assembly time can also be derived from existing high-speed automobile bogie assembly time data samples of the same architecture, with the top and lower boundary values and mean value, which is 16±2 hours, determined using the normal distribution and 3σ principle. Like the computation of production costs, there is no time to convey the bogie to the consumer.

The matching degree of the total technical requirements of the physical module configuration plan of the subway bogie is computed using Equation (8). The AHP approach is used to calculate the relative weights of the 18 configurable modules as (0.08, 0.06, 0.07, 0.06, 0.08, 0.05, 0.08, 0.06, 0.04, 0.05, 0.05, 0.06, 0.06, 0.05, 0.04, 0.04, 0.035, 0.035)

It is assumed that the customer's maximum acceptable price for a subway bogie is 2.56 million yuan and that the customer's maximum acceptable delivery time is 18 working days. The enterprise's profit margin is estimated to be 20%, and the pre-production cost is estimated to be 100,000 yuan; therefore, the production cost constraint of the physical module configuration scheme in this case is $C_B \leq 2030{,}000$ yuan. The pre-production time is estimated to be 8 working days, hence the production time restriction for the configuration scheme in this case is $T_B \leq 10$ working days, or 80 hours.

In this example, the multi-objective optimal configuration problem is solved by constructing the multi-objective optimization model using Equations (9) through (15), then implementing the NSGA-II algorithm in Python. The mean value of cost and time data for each physical module is utilized as an input for the Pareto optimal configuration search. Taking the size of the optimization issue into account, the parameters of the algorithm are set as follows: population size is 350, iterations number is 800, crossover probability is 0.81, and mutation probability is 0.18. Figure 5 depicts the final collection of Pareto optimal solutions, which includes 28 solutions.

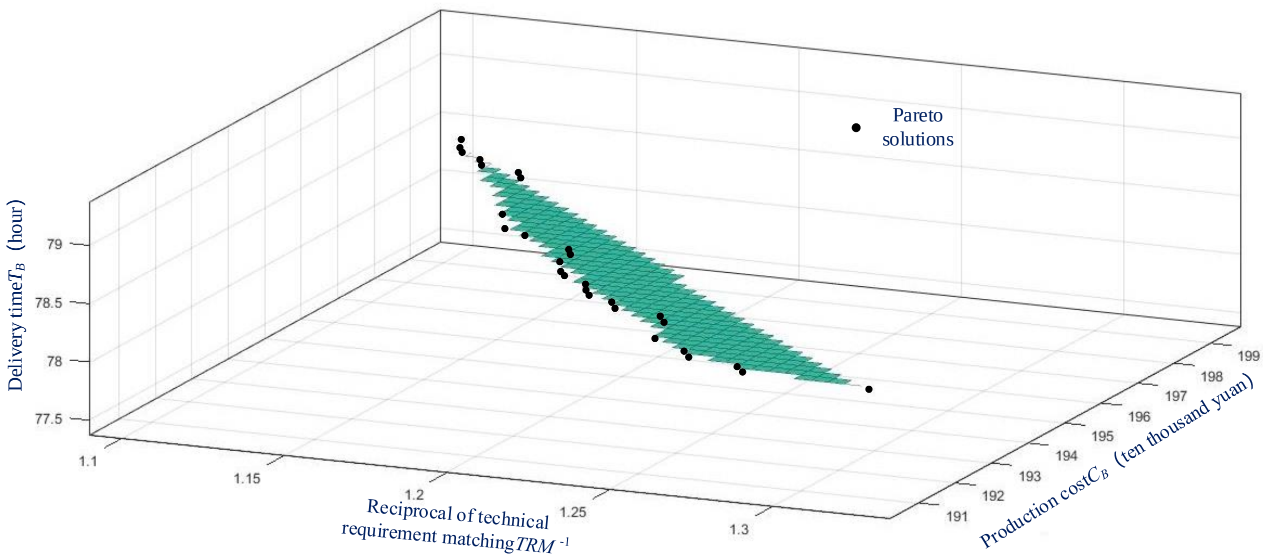

Figure 5 The Pareto solution set of the physical module configuration scheme

Table 7 illustrates the selection of physical modules and their objective values for each configuration scheme in the Pareto solution set. The optimal and worst cases of the production cost and delivery time of the configuration scheme are calculated using the upper and lower boundary values of the production cost and time data of the selected physical modules in each configuration scheme, and the results are displayed in Table 7 as triples.

Table 7 Pareto solution set and target value of physical module configuration of subway bogie

Scheme	Specific Configuration Scheme	C_B（ten thousand yuan）	T_B（hour）	*TRM*
$ConfigS_1$	$M_{1,1}$-$M_{2,2}$-$M_{3,2}$-$M_{4,1}$-$M_{5,1}$-$M_{6,1}$-$M_{7,3}$-$M_{8,3}$-$M_{9,1}$-$M_{10,1}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(181.42, 192.79, 204.16)	(68.375, 78.375, 88.375)	0.80885
$ConfigS_2$	$M_{1,1}$-$M_{2,2}$-$M_{3,2}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,3}$-$M_{8,3}$-$M_{9,1}$-$M_{10,1}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(181.784, 193.154, 204.524)	(68.375, 78.375, 88.375)	0.8215
$ConfigS_3$	$M_{1,1}$-$M_{2,2}$-$M_{3,2}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,2}$-$M_{8,1}$-$M_{9,1}$-$M_{10,1}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(182.456, 193.826, 205.156)	(69.75, 78.375, 88.375)	0.83203
$ConfigS_4$	$M_{1,1}$-$M_{2,2}$-$M_{3,3}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,2}$-$M_{8,3}$-$M_{9,1}$-$M_{10,2}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(184.912, 196.382, 207.852)	(69.75, 78.375, 88.375)	0.87151
$ConfigS_5$	$M_{1,2}$-$M_{2,2}$-$M_{3,2}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,2}$-$M_{8,3}$-$M_{9,1}$-$M_{10,1}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(187.204, 198.574, 209.944)	(69.75, 78.375, 88.375)	0.89615
$ConfigS_6$	$M_{1,1}$-$M_{2,2}$-$M_{3,1}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,3}$-$M_{8,3}$-$M_{9,1}$-$M_{10,1}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(181.578, 192.948, 204.318)	(68.375, 78.375, 88.375)	0.8192
$ConfigS_7$	$M_{1,1}$-$M_{2,2}$-$M_{3,2}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,2}$-$M_{8,3}$-$M_{9,1}$-$M_{10,1}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(184.204, 195.574, 206.944)	(69.75, 78.375, 88.375)	0.85951
…	…	…	…	…
$ConfigS_{28}$	$M_{1,2}$-$M_{2,2}$-$M_{3,3}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,2}$-$M_{8,3}$-$M_{9,1}$-$M_{10,2}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$	(187.912, 199.382, 210.852)	(69.75, 78.375, 88.375)	0.90815

According to Table 7, there is a non-dominant relationship between the 28 schemes, and the mean production cost and lead time of each scheme satisfy the customer-specified criteria. Notable is the fact that the average delivery time for each configuration scheme is 78.375 hours. This is due to the fact that the delivery time is dependent on the longest manufacture or acquisition time of each physical module. In this instance, physical module $M_{5,1}$ has the longest delivery time (M5,1 is chosen for all configuration schemes), hence the average delivery time is the same. This also causes the Pareto front in Figure 5 to be planar, and Figure 6 depicts the projection of the Pareto solution set onto the TRM^{-1}-C_B plane.

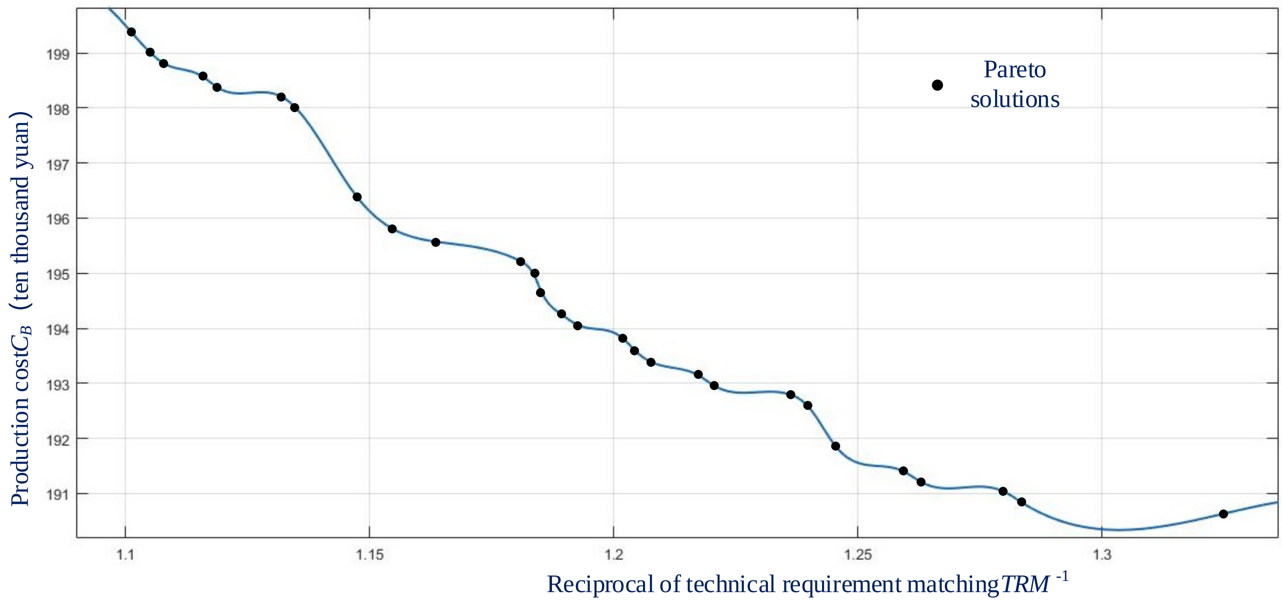

Figure 6 Projection of the Pareto solution set on the TRM^{-1} and C_B planes

The objective values of non-dominated solutions have advantages and disadvantages, but the degree of advantages and disadvantages is different, so the TOPSIS method can be further used to select the best solution. The relative weights of customers to the matching degree of production cost, delivery time and technical demand are set at 0.3, 0.2 and 0.5, respectively. According to Equations (17) and (18), the decision matrix and normalization matrix are constructed as shown in Table 8, from which the positive and negative ideal solutions are respectively $ConfigS^{+}$=(0.18505，0.18898，0.20396)、$ConfigS^{-}$=(0.19355，0.18898，0.16951).

Table 8 Decision matrix and normalization matrix

Scheme	Decision matrix			Normalization matrix		
	$C_{B,median}$	$T_{B,median}$	TRM	$C'_{B,median}$	$T'_{B,median}$	TRM'
$ConfigS_1$	192.79	78.375	0.80885	0.18715	0.18898	0.18166
$ConfigS_2$	193.154	78.375	0.8215	0.1875	0.18898	0.1845
$ConfigS_3$	193.826	78.375	0.83203	0.18815	0.18898	0.18686
$ConfigS_4$	196.382	78.375	0.87151	0.19063	0.18898	0.19573
$ConfigS_5$	198.574	78.375	0.89615	0.19276	0.18898	0.20126
$ConfigS_6$	192.948	78.375	0.8192	0.1873	0.18898	0.18398
$ConfigS_7$	195.574	78.375	0.85951	0.18985	0.18898	0.19303
$ConfigS_8$	194.266	78.375	0.84088	0.18858	0.18898	0.18885
$ConfigS_9$	195.004	78.375	0.84454	0.1893	0.18898	0.18967
$ConfigS_{10}$	191.846	78.375	0.80288	0.18623	0.18898	0.18031
$ConfigS_{11}$	190.836	78.375	0.77906	0.18525	0.18898	0.17496
$ConfigS_{12}$	195.808	78.375	0.86605	0.19008	0.18898	0.1945

$ConfigS_{13}$	198.808	78.375	0.90269	0.19299	0.18898	0.20273
$ConfigS_{14}$	192.584	78.375	0.80654	0.18695	0.18898	0.18114
$ConfigS_{15}$	191.2	78.375	0.79172	0.1856	0.18898	0.17781
$ConfigS_{16}$	193.594	78.375	0.83036	0.18793	0.18898	0.18649
$ConfigS_{17}$	198.21	78.375	0.88349	0.19241	0.18898	0.19842
$ConfigS_{18}$	194.634	78.375	0.84403	0.18894	0.18898	0.18956
$ConfigS_{19}$	194.06	78.375	0.83857	0.18838	0.18898	0.18833
$ConfigS_{20}$	198.368	78.375	0.89384	0.19256	0.18898	0.20074
$ConfigS_{21}$	191.042	78.375	0.78137	0.18545	0.18898	0.17548
$ConfigS_{22}$	190.634	78.375	0.75476	0.18505	0.18898	0.16951
$ConfigS_{23}$	195.21	78.375	0.84685	0.1895	0.18898	0.19019
$ConfigS_{24}$	193.388	78.375	0.82805	0.18773	0.18898	0.18597
$ConfigS_{25}$	199.014	78.375	0.905	0.19319	0.18898	0.20325
$ConfigS_{26}$	198.004	78.375	0.88118	0.19221	0.18898	0.1979
$ConfigS_{27}$	191.406	78.375	0.79403	0.1858	0.18898	0.17833
$ConfigS_{28}$	199.382	78.375	0.90815	0.19355	0.18898	0.20396

In accordance with Equations (20), (21) and (22) the distance between each non-dominated solution and the positive and negative ideal solutions and the non-dominated solution's relative proximity to the positive ideal solution are determined as shown in Table 9. The configuration scheme with the greatest relative closeness is $ConfigS_{25}$ (whose physical module configuration is: $M_{1,2}$-$M_{2,2}$-$M_{3,2}$-$M_{4,2}$-$M_{5,1}$-$M_{6,1}$-$M_{7,2}$-$M_{8,3}$-$M_{9,1}$-$M_{10,2}$-$M_{11,1}$-$M_{12,1}$-$M_{13,1}$-$M_{14,1}$-$M_{15,2}$-$M_{16,2}$-$M_{17,1}$-$M_{18,1}$); hence, it is regarded as the optimal solution.

Table 9 The distance and relative closeness between the non-dominated solution and the positive and negative ideal solution

Scheme	D_i^+	D_i^-	RC_i	**Scheme**	D_i^+	D_i^-	RC_i
$ConfigS_1$	0.01581	0.00928	0.36973	$ConfigS_{15}$	0.01849	0.00731	0.28317
$ConfigS_2$	0.01383	0.0111	0.44534	$ConfigS_{16}$	0.01246	0.01239	0.49872
$ConfigS_3$	0.01221	0.01262	0.50827	$ConfigS_{17}$	0.00562	0.02045	0.7844
$ConfigS_4$	0.00658	0.01861	0.73889	$ConfigS_{18}$	0.01041	0.0144	0.58049
$ConfigS_5$	0.00463	0.02246	0.82892	$ConfigS_{19}$	0.0112	0.01361	0.54845
$ConfigS_6$	0.01418	0.01079	0.43206	$ConfigS_{20}$	0.0047	0.02209	0.82454
$ConfigS_7$	0.00816	0.01676	0.67245	$ConfigS_{21}$	0.02014	0.00613	0.23325
$ConfigS_8$	0.01086	0.01394	0.56217	$ConfigS_{22}$	0.02436	0.00465	0.16039
$ConfigS_9$	0.01037	0.01444	0.58214	$ConfigS_{23}$	0.01004	0.01479	0.59572
$ConfigS_{10}$	0.01673	0.00863	0.34021	$ConfigS_{24}$	0.01281	0.01207	0.4851
$ConfigS_{11}$	0.0205	0.00596	0.22528	$ConfigS_{25}$	0.00449	0.02386	0.84174

$ConfigS_{12}$	0.00723	0.01777	0.71077	$ConfigS_{26}$	0.00581	0.02009	0.77571
$ConfigS_{13}$	0.00443	0.02349	0.84123	$ConfigS_{27}$	0.01813	0.00754	0.29377
$ConfigS_{14}$	0.01617	0.00898	0.35707	$ConfigS_{28}$	0.00465	0.02436	0.83961

4.4 Results

According to the range of values for production cost and delivery time for each configuration scheme in Table 7, designers can more accurately assess the potential scenarios for each scheme, facilitating customer communication and design decisions. Using production cost as an example, the average cost of each configuration scheme in Table 7 meets the customer constraint (≤2.03 million yuan), but the upper limit value does not necessarily, and the upper limit value of the majority of schemes is greater than 2.03 million yuan, so it is possible that the constraint will not be met. If the designer or customer is risk-averse and hesitant to exceed the cost constraint, the scheme with the lowest cost upper limit value can be chosen from the 28 available options. For instance, the cost maximum limit for configuration schemes $ConfigS_{11}$ and $ConfigS_{15}$ is 2.02206 million yuan and 2.0257 million yuan, respectively, which are both less than 2.03 million yuan. Despite the fact that the average delivery time of the aforementioned schemes meets the constraint (≤ 80 hours), there is still a risk of lateness. Therefore, it is also vital to interact with the customer and explain the issue to determine if the possible overdue fee can be accepted or if the delivery date can be extended as necessary.

Comparing $ConfigS_{25}$ to other configuration schemes. For example, compared to $ConfigS_{1}$, $ConfigS_{25}$ has a slightly higher mean production cost, the same mean delivery time, and a higher degree of matching technical requirements, with the degree of matching technical requirements differing more than that of production cost. Concurrently, because the proportional weight of technical requirements matching degree (0.5) is greater than that of production cost (0.3). Therefore, it may be determined that $ConfigS_{25}$ is qualitatively superior to $ConfigS_{1}$ since it is closer to client needs. Likewise, $ConfigS_{25}$ is the superior option when compared to other options. Therefore, it is reasonable to apply TOPSIS to determine the optimal solution in this circumstance.

The degree to which the above-selected configuration scheme $ConfigS_{25}$ matches the technical requirements is 0.905. $ConfigS_{25}$ contains 11 exact configurations and 7 similar configurations based on the matching degree of technical requirements of each module in the configuration space. The similar configurations are: frame $M_{1,2}$($TRM_{1,2}$=0.856), axle $M_{3,2}$($TRM_{3,2}$=0.746), axle box device

$M_{4,2}$($TRM_{4,2}$=0.867), gearbox $M_{7,2}$($TRM_{7,2}$=0.897), rocker positioning node $M_{12,1}$($TRM_{12,1}$=0.802), air spring $M_{13,1}$($TRM_{13,1}$=0.542), single pull rod traction device $M_{16,2}$($TRM_{16,2}$=0.747). The designer first determines whether these similar physical module configurations are acceptable; if they are okay, they do not change; if they are not acceptable, they must alter. This similar configuration module, gear box $M_{7,2}$ and air spring $M_{13,1}$ is an outsourced platform class module, optimization was conducted on the collection platform module, so you can try again from the existing product instance in the search to a higher degree of match physical module; if you can't find the matching solution, you must contact the supplier purchasing to meet the technical specifications of the new physical modules. The frame $M_{1,2}$, single pull rod traction device $M_{16,2}$ are self-made, non-platform modules that can be designed in variants based on the selected physical module to fulfill technical specifications. However, axle $M_{3,2}$, axle box device $M_{4,2}$, and rocker positioning node $M_{12,1}$ are acquired non-platform modules, thus it is required to contact the provider to acquire replacement physical modules that satisfy the technical specifications. When executing the configuration change actions, it is required to address the resulting change propagation and make any necessary adjustments to the impacted physical modules. After the configuration change has been finalized, the configuration rule verification and simulation verification processes are carried out until the final technical bid solution is produced.

5 Discussions

The major contribution of this research is the development of a two-stage and multi-objective optimization method for supporting the selection of the optimal technical bid solutions of a complex Engineering to Order (ETO) product under imprecise matching and other uncertainties. The proposed approach allows for a complete exploration of the problem domain for quickly developing an optimized product design for an ETO bidding. Even if the test case is focused on a subway's bogie, the method can be extended and used for the optimal configuration design of similar structures (products) such as cars.

In comparison with another two-stage model for ETO configuration design [19], the two-stage model in [19] enables design reuse while simultaneously maintaining flexibility to manage changes in customer requirements. In our two-stage framework, stage 1- product architecture configuration enables design for lifecycle cost (LCC) while taking into account some factors that are not fully considered in existing EC design studies, such as the constraint relationship between EC, the uncertain relationship between EC and LCC, and the limited sample of cost estimation data, which can also be extended to variables and objectives for other similar design problems. The first phase serves to reduce complex ETO product configuration space from the system level. The stage 2- product physical module configuration enables constructing and solving a multi-objective optimization model with uncertain cost and time estimation and customers' technical requirements for obtaining optimal configuration scheme. This framework covers the entire design process including the architecture configuration, module key parameters design, physical module multi-objective optimal configuration, and configuration change. Although its implementation does require a lot of design knowledge, its applicability has been demonstrated through the case study. Furthermore, NSGA-II was used to solve the Pareto solution set, and TOPSIS method was used to select the best solution from the candidate solutions as the recommended configuration scheme or configuration change scheme, which is helpful to gain the final configuration scheme.

The proposed method is intended for practical use in complex ETO product design, such as high-speed train, car, airplane, etc. However, there are some practical issues that need to be considered when applying above configuration modelling and solving method to solve real-world problems. Examples of such practical problems include how to validate cost estimation models and choose proper optimization algorithms. Further studies to address these issues are needed.

6 Conclusions and future work

In this article, we have studied the configuration method of a technical bid solution in a complex ETO product bidding process. In such a context, selecting the reasonable technical bid solution is complicated, a bidder faces the problem of the imprecise matching of technical requirements and uncertainty in production cost and delivery time. Therefore, in this paper, a new two-stage configuration design framework for complex ETO products is established to help the bidders make the right decision quickly for a complex ETO technical bid solution. For the physical module configuration problem of complex ETO products, considering the characteristics of similar and exact configurations of complex ETO products and the uncertainty of physical module cost and time data. The configuration object and the configuration space are defined. Both the production cost and delivery time estimation models and the technical demand matching degree calculation model are built. The uncertainty of cost and time data is characterized by the normal distribution and the 3σ

principle. A multi-objective optimal configuration model of physical modules is developed with the goals of minimum production cost, shortest delivery time, and maximum degree of matching technical requirements under imprecise matching and uncertainty. NSGA-II is utilized to solve the Pareto solution set, and the TOPSIS method is used to select the optimal solution as the recommended configuration scheme. The case of the design of a physical module configuration of a subway's bogie presented in Section 4 demonstrates the applicability and effectiveness of this method. This configuration framework and technique can aid the designer in a complex ETO bidding process or engineering design process, particularly in the early stages of the design process, which are highlighted by imprecision and uncertainty.

With the proposed approach, the person making the decision has to make changes to the existing product to gain the most interesting technical bid solutions. This may be time-consuming and uncertain in scenarios with a large number of ambiguous decision factors. Due to the influence of numerous complicated elements of design change, such as the availability of raw materials on the market, the scheduling of production workshops, the condition of processing equipment, and the state of the supply chain, the real cost and delivery time of change modules are uncertain. In order to obtain change module production cost and time more precisely, it is necessary to combine new technologies, such as cyber-physical systems and digital twins, to obtain all types of real-time dynamic factors and to simulate the physical module's production process in order to predict time and cost more precisely and to better support the change module's multi-objective optimization configuration. In the future research, we will do quantitative comparisons with other related methods by conducting some quantitative calculation analysis on the efficiency, accuracy and other performance aspects of this method.

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Declarations

Ethical approval and consent to participate Not applicable.

Consent for publication All the authors have given their consent for the publication of this manuscript.

Competing interests The authors declare no competing interests.

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