Product-service system engineering characteristics design for life cycle cost based on constraint satisfaction problem and Bayesian network

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Abstract A product-service system (PSS) has many engineering characteristics (ECs), their design is a critical work in PSS planning, which has an important influence on the cost and quality of PSS. How to design a reasonable PSS-ECs scheme, and evaluate its life cycle cost (LCC) is a challenging task. Aiming at the PSS-ECs design for LCC, this paper proposes a new PSS design method, it first treats and models the design of PSS-ECs as a customer requirements-based constraint satisfaction problem (CSP) for finding an initial set of satisfied PSS-ECs schemes, and then it evaluates these schemes based on Bayesian network (BN)-based LCC estimation model for finding an optimal scheme as a solution. Constructing a BN describing the uncertain relationships between PSS-ECs and LCC is the core of this research. By combining existing R&D data and expert experience, Bayesian estimation and arithmetic averaging are used to estimate the conditional probability in BN. Take a subway bogie and its maintenance service in a Chinese company as an example to verify the proposed method. The results show that the proposed method can effectively solve the problem of PSS-ECs design for LCC, it also shows that this method has positive significance in realizing engineering knowledge consolidation, assisting designers in exploring design space, and improving the rationality of design decisions.

Keywords Product-service system; Engineering characteristics; Design evaluation; Life cycle costing; Bayesian network

1. Introduction

Product-service system (PSS) integrates tangible products with intangible services and provides customers as a complete solution [1, 2]. From providing customers with products to providing PSS, the company's value chain can be extended. Nowadays, with severe product homogeneity, the PSS strategy gives companies more opportunities to implement differentiated competition and win customers and profits [3]. PSS's engineering characteristics (PSS-ECs) design is a critical work at the conceptual design stage, which greatly affects the success of PSS development [4, 5]. Therefore, it is necessary to research the design and evaluation methods of PSS-ECs. However, because it is still in the early design stage and lack of detailed product and service information, how to design reasonable PSS-ECs schemes, and evaluate them for cost, performance, quality, etc. is a challenging task.

The design of engineering characteristics (ECs) of products or PSS has attracted the attention of many scholars, and a large number of papers have been published in the importance calculation and the target values setting of ECs. For example, considering the ambiguity, randomness and subjectivity in quality function deployment (QFD) process, methods such as fuzzy linguistic sets, probabilistic language, cloud model and grey relational analysis are combined with QFD to study the importance of ECs [6-8]. Geng et al.[4, 9] calculate the importance of ECs under the consideration of both customer requirements and manufacturer requirements will affect ECs, and took utility measure as goal to optimize the ECs target values of PSS. Ji et al. [10] quantified Kano's model and integrated it with QFD, and then developed an optimization model with customer satisfaction as the goal, the budget and ECs range as constraints to optimize the value of ECs. He et al. [11] proposed an

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importance-frequency Kano model and integrated it into QFD, to determine Kano categories of customer requirements and target values of ECs under the best balance between enterprise satisfaction and customer satisfaction. Miao et al. [12] formulated two uncertain chance-constrained programming models to setting target levels of design attributes with consumer satisfaction and design cost as goal, respectively. Mi et al. [13] integrated QFD and failure modes and effects analysis to consider customers' needs and product's risk priority number simultaneously for evaluate ECs values before product redesign. Summarizing the existing literature, we found that the research of ECs design mainly adopts the QFD method, and the design goal was mostly customer satisfaction, but these literatures usually ignore the constraint relationships within ECs, which do exist in product or PSS design. For example, in the case study of [14], when "horsepower of the engine", "space of the seat", and "controlling force of braking system" are selected to be larger values, "amount of fuel per mile" is impossible to choose a smaller value due to technical constraints. In addition, the existing research simplifies the consideration of costs. It is usually assumed that a specific value of ECs corresponds to a specific cost, but such cost data is difficult to quantify in practice.

Compared with pure physical products, PSS emphasizes the use value of its full life cycle[15], especially for complex PSS with complex products and long service life, such as rail transit equipment, aircraft engines and related technical services. Life cycle cost (LCC) is the sum of the costs incurred during the entire life cycle from acquiring customer requirements to product scrapping and recycling [16]. It is an important indicator to measure the use value of PSS. Therefore, the PSS-ECs design method studied in this paper treats LCC as the design goal, while considering the constraints of customer requirements and the constraints within PSS-ECs. The macro logic of this design method is shown in Fig.1.

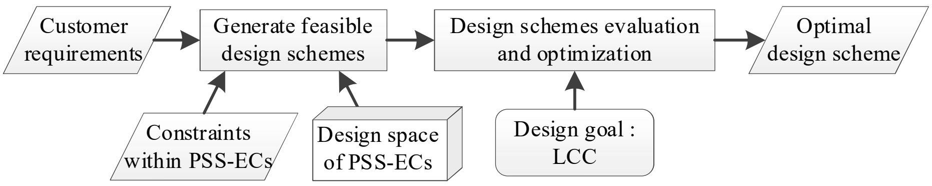

Fig.1 The macro logic of this design method

How to design, evaluate and optimize PSS-ECs for LCC in the conceptual design stage is an important issue that both companies and academia are concerned about, but research in this area is rarely carried out at present. According to the aforementioned analysis, this research needs to solve two key issues: (1) The solution of feasible design schemes of PSS-ECs considering the customer requirements and the constraints within PSS-ECs; (2) LCC evaluation and optimization of PSS-ECs design schemes. The first issue can be modeled and solved by the constraint satisfaction problem (CSP), which has been applied in product configuration to describe the constraint relationships between module attributes [17, 18]. Based on this, this paper uses CSP to describe the constraints within PSS-ECs, including constraints within product ECs, service ECs, and between the two types of ECs. To solve the second issue, it is necessary to establish an LCC estimation model with PSS-ECs as variables. According to literature research, cost estimation methods in the early design stage mainly include regression analysis (RA), artificial neural network (ANN), etc. [19]. These methods use machine learning to simulate the relationships between design variables and cost based on a large number of data samples to build a cost estimation model. In the early design stage, due to the lack of detailed design information, the relationships between PSS-ECs and LCC has great uncertainty, but methods such as RA and ANN express the estimation result with unique value, which cannot reflect the estimation uncertainty. In addition, complex PSS are usually difficult to establish cost estimation models due to the small number of available data samples. Therefore, it is necessary to incorporate expert experience to make up for the lack of data samples, but expert experience cannot be incorporated into these methods. Bayesian network (BN) is a model that uses conditional probability to express the causal relationships between variables, which is suitable for modeling uncertain relationships. BN has the advantages of being easy to incorporate into expert experience, the model can also be updated with the accumulation of data, and the causal relationships between variables can be presented intuitively [20]. Thus, this paper adopts BN to model the uncertain relationships between PSS-ECs and LCC in order to realize the LCC evaluation and optimal design of PSS-ECs.

Therefore, in view of the design, evaluation and optimization of PSS-ECs for LCC, this paper proposes a method based on CSP and BN, which includes two phases of modeling and solving. In the modeling phase, the design space of PSS-ECs is firstly constructed according to the market requirements analysis and historical R&D data; then it analyzes the constraint relationships within PSS-ECs, and constructs a CSP model of PSS-ECs; A BN-based LCC model can be constructed by combining expert experience and existing data samples to describe the uncertain relationships between PSS-ECs and LCC, and then by applying sensitivity analysis to obtain the impact ranking of PSS-ECs on LCC. In the solving phase, by solving the CSP, the PSS-ECs design schemes that meets customer requirements and constraints are resulted; On top of the result, use BN to perform LCC evaluation to obtain the scheme with lowest LCC; Finally, according to the impact ranking of PSS-ECs on LCC, the better values of PSS-ECs of the chosen scheme are adjusted to form the final optimized design solution. The main contributions of this paper are:

1. A new PSS-ECs design problem frame is proposed. This frame takes LCC as the design goal and considers the constraints between PSS-ECs, the uncertain relationships between PSS-ECs and LCC, and the limited samples of cost estimates that have not been well-addressed in existing ECs design research. This frame can be extended to other design variables and goals for similar design problems.
2. A combined method based on CSP and BN is developed for the framed design problem, where CSP is used to solve feasible PSS-ECs design schemes, while BN is used to realize the LCC evaluation of PSS-ECs design schemes. Compared with the existing cost estimation methods, BN can reflect the uncertainty of cost estimation, and can easily incorporate expert experience with limited data samples to improve the quality of LCC estimation model.

The rest of this paper is structured as follows. Section 2 introduces relevant literature and analyzes the deficiencies of existing research. Section 3 elaborates the framework and specific steps of the proposed design method. Section 4 takes a subway bogie and its maintenance service as an example to verify the effectiveness of the proposed method. The discussion and conclusion remarks are presented in Section 5 and Section 6 respectively.

2. Literature review

2.1. Engineering characteristics design

From existing research, ECs usually refer to the key performances, dimensions, materials or other properties of a product [21-23]. For PSS, ECs also include service characteristics, such as service response time, technical support level, etc. [8, 9]. The terminology of ECs has not yet been unified, and there are other terms such as engineering requirements [24], engineering specifications [25], design specifications [26, 27]. Considering that the most commonly used term is ECs, so this paper also uses this term.

ECs design is a key task in product conceptual design. The rationality of its design has a great impact on cost, quality, and customer satisfaction of product. Many scholars have conducted research on the design of ECs, ranging from simple personal consumer products to complex electromechanical products. The typical tool used in the research is QFD. By analyzing the importance of customer requirements, the relationships between customer requirements and ECs, the relationships between ECs, etc., the target value setting and importance calculation of a new product's ECs are studied.

In view of different customer requirements preferences in different market segments, Luo et al. [5] proposed a fuzzy optimization model, which comprehensively considered the relationships between customer requirements and customer satisfaction in all market segments, and optimized the values of ECs with the goal of maximizing customer satisfaction in the whole market. Geng et al. [4] divided the ECs of PSS into product-related ECs and service-related ECs, taking utility measure as the optimization goal, a 4-stage method was proposed to optimize the ECs, and constraints such as budget, market competition and technical feasibility were considered. Ji et al. [10] quantified Kano's model to get the functional relationships between the fulfillment degree of customer requirements and customer satisfaction, and integrated it with QFD to form an optimization model with customer satisfaction as the goal and budget and ECs values range as constraints, to optimize the values of ECs. Due to the inevitable information ambiguity and uncertainty in QFD, some scholars integrate fuzzy set theory and uncertainty theory with QFD to study the ECs design under uncertain environments. Zhong et al. [28] proposed a fuzzy chance-constrained programming model to set the target value of ECs, and applied the method to automobile design. Miao et al. [14] proposed two uncertain programming models based on the expected value modelling to optimize the target value of ECs, and the optimization goals are to maximize customer satisfaction and minimize development costs respectively. Zhang et al. [29] used radial basis function neural network to model the importance conversion relationships between customer requirements and candidate ECs, and to identify the key ECs of electromechanical products by calculating the importance of ECs. Han et al. [30] used network analysis and grey relational analysis to identify the key design characteristics of complex products.

Summarizing the existing research can find that the ECs design goal in most existing work is the customer satisfaction, not the LCC. There are some shortcomings:

1. The constraints between the values of ECs are ignored. Although some existing work considers the influence relationships between ECs on the roof of house of quality (HOQ), but it does not quantify these relationships as constraints between the values of ECs. Actually, some values of ECs are dependent on or constrained by others. Ignoring these constraints is likely to result in an unfeasible design of the ECs.
2. Simplified cost consideration. Existing literature usually assumes that the specific value or specific fulfillment degree of ECs corresponds to a certain cost, and the cost of design scheme is obtained by accumulating the cost corresponding to each ECs value. However, in actual product development, such cost data is difficult to obtain, thus lacks operability.
3. The influence of ECs design on LCC is rarely considered. Existing research usually only considers manufacturing or development costs. LCC is an important indicator to measure the use value of PSS. Therefore, it is necessary to analyze the impact of ECs design on LCC from the perspective of entire life cycle.

Therefore, the design of PSS-ECs needs to consider the constraints within PSS-ECs and the impact of PSS-ECs on LCC, and it is necessary to construct a cost estimation model in a practical and operational way.

2.2. Design for life cycle cost

Many literatures indicate that 70% to 80% of LCC is determined in the design stage, so it is the most effective to study the method of reducing LCC in the design stage [19, 31]. Design for LCC needs to estimate the LCC of product, and evaluate and optimize the design scheme to reduce the LCC in design stage [32]. Cost estimation, optimization design for cost, etc. are the key tasks. Many related studies can be found from the existing literature.

In order to estimate the cost of shell and tube heat exchangers in the early design stage, Duran et al. [33] used ANN to develop a cost estimation model to achieve cost prediction. Yeh and Deng [34] applied least squares support vector machines (LS-SVMs) and back-propagation neural networks (BPNs) to estimate the cost of product life cycle, and proved that LS-SVMs and BPNs have higher accuracy than traditional regression analysis (RA) through two examples. Liu et al. [35] compared the performance of five non-parametric regression models for LCC estimation under different simulation environments, such as different numbers of cost drivers and training samples. Chakraborty et al. [36] used hybrid light gradient boosting and natural gradient boosting to predict construction cost. Chang et al. [37] integrated case-based reasoning (CBR) and ANN to predict the production cost of mobile phones. CBR was used to retrieve similar product instances to estimate unknown production variables. ANN was used to find the relationships between production variables and product unit cost. Above research proves that artificial intelligence-based cost estimation is an effective way in early design stage.

How to optimize design scheme with cost as the goal is also a problem where many scholars are concerned about. Ameli et al. [38] considered the environmental impact (expressed in carbon footprint) and LCC of different component alternatives in the configuration of automotive, and optimized the automotive configuration with the total LCC as the goal and environmental impact as the constraint. Similarly, Zhang et al. [39] proposed an optimal configuration method based on life cycle assessment and LCC for the module configuration of complex mechanical products, which evaluated and weighed the environmental impact and LCC of the configuration scheme to obtain the optimal configuration. Oesterle et al. [40] developed a product assembly line design method that integrates product design and process selection, and solved the problem with production cost as the goal.

Analyzing the ANN, SVM and RA methods for estimating LCC in early design stage, it is found that the following shortcomings still exist:

1. Early design information still lacks detailed design parameters, thus the LCC estimation has great uncertainty. But the current estimation methods all express the estimation result with unique value, and do not reflect the uncertainty of LCC estimation.
2. In addition, complex PSS usually have fewer available data samples, thus it is difficult to build a cost estimation model. Therefore, it is necessary to combine expert experience to make up for the lack of data samples, but ANN, SVM, RA, etc. cannot incorporate expert experience.

Therefore, in order to support the cost estimation of complex PSS in early design stage, it is necessary to explore a cost estimation method that can integrate expert experience and data samples and reflect the uncertainty of cost estimation.

2.3. Bayesian Network and its application

Bayesian network is a network model that describes the uncertain causality between variables. It is composed of nodes, directed links and conditional probability tables (CPT). BN is one of the most effective theoretical models in the field of uncertainty knowledge modeling and reasoning. Compared with other reasoning models, BN has significant advantages in visually displaying the causal relationships between variables, facilitating the incorporation of expert experience, and continuously updating the model with data accumulation [20]. Benefit from these advantages, BN has been widely used in many fields such as fault diagnosis, reliability analysis, medical diagnosis, and risk prediction [41-44].

In the field of product development, BN also plays an important role in uncertain knowledge modeling and reasoning in product design. For example, Moullec et al. [45] expressed product architecture design problem as BN, which considered the uncertainty of component characteristics and compatibility between components. Based on this BN, product architectures meeting performance requirements can be generated quickly, and the overall confidence of product architecture can be evaluated. In order to evaluate reliability of the system in the early design stage, Lee and Pan [46] proposed a nonparametric Bayesian network (NPBN) approach to predict and diagnose the reliability of the system design scheme. The NPBN model expressed the relationships between system reliability and its component functions in probability. Jiao et al. [47] suggested the causal relationships between affective states and user experience prospects can be model by Bayesian Network in the study of user experience design. Peng et al. [48] used Bayesian approach to recommend engineering design knowledge based on a knowledge hypernetwork model. For understand the influence of product, company context and regulatory environment factors on medical device development, Medina et al. [49] collected 2400 groups of orthopedic devices data, and the structure of Bayesian network was learned from these data, the key factors affecting medical device development were identified by the BN. Sayed and Lohse [50] integrated design domain ontologies with failure modes and effects analysis (FMEA) models, and proposed a method to generate Bayesian diagnostic models based on the integrative ontology, and the BN was used for fault diagnosis of assembly systems. For more details about BN, can refer to [51].

Conditional probability is used to describe the influence of cause on result in BN, that is, when the cause variables take a certain value, the result variables present a conditional probability distribution on multiple values. Description of uncertain relationships based on conditional probability is suitable for describing the relationships between PSS-ECs and costs in the early design stage, that is, when PSS-ECs take a certain value, the costs is a conditional probability distribution on multiple cost values, rather than a definite value. In this description, the conditional probability distribution of costs on multiple values is determined by PSS-ECs and other factors that are still uncertain. In this paper, we focus on the impact of PSS-ECs on the costs, taking PSS-ECs as the cause nodes in BN, and other uncertain factors are not directly included in BN, their impact on costs are reflected indirectly by conditional probability. Considering the applicability of BN to express the uncertain relationships between PSS-ECs and costs, and the advantages of BN being easy to integrate into expert experience, this paper uses BN to model the uncertain relationships between PSS-ECs and LCC to support LCC evaluation and optimization of PSS-ECs design schemes.

3. Proposed methodology

3.1. Framework

The framework of PSS-ECs design for LCC based on CSP and BN is shown in Fig.2, which includes two phases: modeling and solving, with a total of six steps. The modeling phase is to construct the design space, CSP model and BN, which are stable within a certain period of time. The solving phase is to use the built design space and models to generate an optimized PSS-ECs design scheme according to the individual customer requirements.

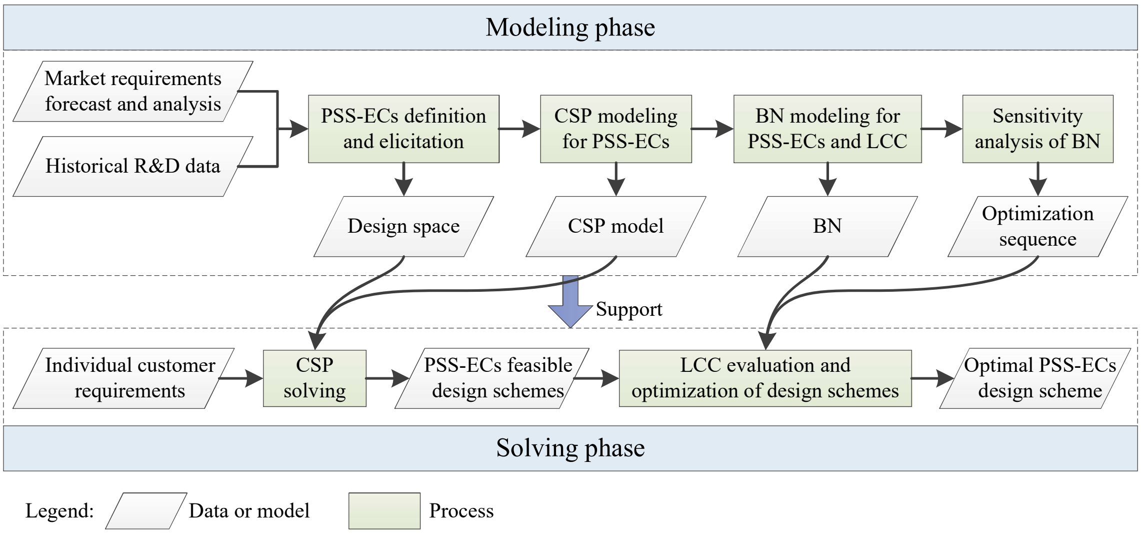

Fig.2 Framework of the proposed method

1. Modeling phase

Step1: PSS-ECs definition and elicitation. Through market requirements forecasting and analysis, combined with the historical R&D data of company, design experts determine the items and optional status of PSS-ECs to form the design space (Since PSS-ECs may be strings, discrete values or continuous values, the term “status” is used in this paper to express these design options of PSS-ECs).

Step2: CSP modeling. Analyze the constraints between the optional status of PSS-ECs, and use CSP method to model these constraints among PSS-ECs.

Step3: BN modeling. Decompose LCC into some cost items, analyze and establish the relationships between PSS-ECs and decomposed cost items, and combine with the decomposition structure of LCC to build BN’s structure; Combine expert experience and existing data samples, and use Bayesian estimation and arithmetic averaging to estimate the conditional probability of each cost node; Construct BN based on the determined structure and conditional probability.

Step4: Sensitivity analysis of BN. On the constructed BN, calculate the sensitivity of LCC node to all PSS-ECs nodes, and provide guidance for the subsequent adjustment of PSS-ECs.

2. Solving phase

Step5: CSP solving. According to the individual customer requirements and the CSP model, the backtracking method is used to solve the feasible PSS-ECs design schemes that meet the requirements and constraints. A design scheme referred to in this paper is a status combination of PSS-ECs, and there are usually multiple feasible design schemes.

Step6: LCC evaluation and optimization of design schemes. Use BN predictive reasoning to evaluate feasible PSS-ECs design schemes, and select the design scheme with the lowest expected value of LCC as the best scheme; According to the sensitivity ranking of LCC to PSS-ECs, adjust the values of PSS-ECs in the best scheme to further optimize LCC of the scheme.

3.2. Modeling phase in detail

3.2.1. PSS-ECs definition and elicitation

Due to the important effect of PSS-ECs on the cost and quality of PSS, in actual development process, PSS-ECs are generally designed by engineers of various disciplines and financial experts after weighing various factors together, and as input to the subsequent design process. Refer to the classification of PSS-ECs in [4], and divide PSS-ECs into product-related ECs (P-ECs) and service-related ECs (S-ECs). According to the knowledge of products and services, P-ECs can be further divided into some sub-classifications, such as function setting, technical principle, geometry structure, material, performance parameters, size parameters, etc., and S-ECs can be divided into installation mode, commissioning mode, training mode, maintenance mode, spare parts, service quality, etc.

For an actual PSS, it is necessary to predict and analyze market requirements (including both product-related requirements and service-related requirements), and combined with historical R&D data of company, the available PSS-ECs and its optional status within a certain period of time are determined by design experts according to the above classification of PSS-ECs. Market requirements can be acquired and analyzed by methods such as customer interviews, data mining on user-generated data (such as mobile social networks) and product-sensed data [52, 53], and the historical R&D data can be acquired from company's PDM (Product Data Management) and MRO (Maintenance Repair and Overhaul) system. The optional status of PSS-ECs may be continuous values or discrete values. In order to facilitate the subsequent modeling and reasoning, this paper discretizes the PSS-ECs with continuous values according to design experience, that is, all PSS-ECs represent the design space with discrete values.

3.2.2. CSP modeling for PSS-ECs

In PSS design, there may be compatibility constraints between functions, technical principles, structures, maintenance modes, etc., that is, there are constraints between the status of different PSS-ECs, including dependency constraints and exclusive constraints. Dependency constraints means that when a certain PSS-EC takes a specific status, another PSS-EC needs to select one or some specific status; The exclusive constraints means that when a certain PSS-EC takes a specific status, another PSS-EC cannot choose one or some specific status. These constraints may exist within P-ECs or S-ECs or between P-ECs and S-ECs. The constraints within PSS-ECs can be schematically shown in Fig.3.

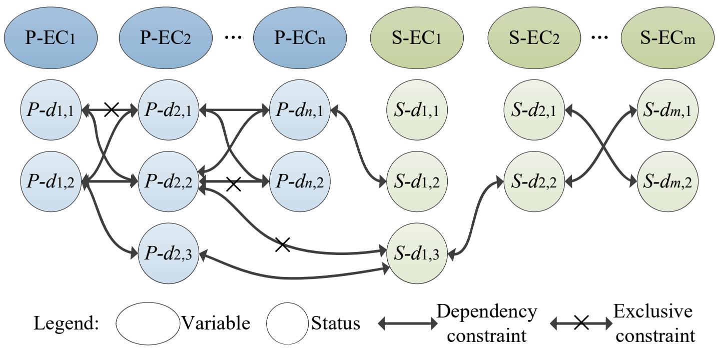

Fig.3 Constraints among the status of PSS-ECs

The CSP method is used to model the constraints within PSS-ECs. CSP method uses the triple CSP=(V, D, C) to describe the constraints between variables. Where V denotes the set of variables, that is, V={P-EC$_1$, P-EC$_2$, ..., P-EC$_n$, S-EC$_1$, S-EC$_2$, ..., S-EC$_m$}, n denotes the number of P-ECs, m denotes the number of S-ECs; D denotes the optional status field of all variables, for P-EC$_i$ or S-EC$_i$, $D_i=\{d_{i,1}, d_{i,2}, ..., d_{i,j}\}$, j is the number of status of P-EC$_i$ or S-EC$_i$; C denotes the set of constraints between the status of variables, $C=\{Cst_1, Cst_2,..., Cst_L\}$, Cst_L denotes the L-th constraint in set C, each constraint describes the dependency constraint or exclusive constraint between the status of PSS-ECs. For a certain PSS, the constraints between the PSS-ECs status can be obtained according to design principles and expert experience.

3.2.3. BN modeling for PSS-ECs and LCC

Bayesian network simulates the uncertainty of the causal relationships in the human reasoning process. It is a directed acyclic graph composed of two parts: the network structure and the conditional probability distribution. It can be expressed as BN= (G, P), G= (N, E). Where G denotes the structure of BN, N denotes the nodes set, which corresponds to the variables of problem, and a variable usually has multiple status; E denotes the set of directed edges, reflecting the causal relationships between variables, and the directed edge from node N_i to node N_j indicates that N_i has a direct causal influence on N_j; P denotes the conditional probability distribution of the nodes, which quantitatively describes the influence of the cause on the result, it is expressed in the form of conditional probability table (CPT). For directed edge (N_i, N_j), N_i is called the parent node of N_j, N_j is called the child node of N_i. A node without parent node is called a root node, and a node without children is called a leaf node. Use BN to model the uncertain relationships between PSS-ECs and LCC, it is first to construct the BN's structure, and then estimate the conditional probability in BN.

1. BN's structure

Constructing BN according to different variables order will result in completely different structure. According to [54], this paper builds BN's structure based on the causal relationships between variables. This method can make the network structure as simple as possible and easy to estimate the conditional probability distribution.

LCC is the sum of costs incurred at various stages in the life cycle. It can be decomposed into design cost, manufacturing cost, maintenance cost, and scrap cost by stage, and each cost can be further decomposed, for example, design cost can be decomposed into labor cost and knowledge acquisition cost, etc. Therefore, the composition of LCC can be regarded as a complex hierarchical structure, and the upper-level cost is affected by the lower-level cost. As design variables, PSS-ECs are the root cause affecting cost, and can undoubtedly serve as the root nodes of BN. If the causal relationships between PSS-ECs and LCC are directly established (LCC is a child node of all PSS-ECs), the status combination space formed by PSS-ECs will be too large, and the conditional probability estimation of BN will be cumbersome and difficult. Therefore, we decompose the LCC for a specific PSS to a certain level based on the principle of single cost item associated with as few PSS-ECs as possible, and then analyze and establish the causal relationships between PSS-ECs and the decomposed cost items, and combined with the decomposition structure of LCC, the structure of BN can be clarified.

Decompose LCC and establish the relationships between PSS-ECs and the decomposed cost items, instead of directly establish the relationships between PSS-ECs and LCC, the purpose is to divide the causal influences of many PSS-ECs on LCC into partial and simpler influences, to reduce the difficulty of conditional probability estimation, although it will increase the structural complexity of BN. Using the structural complexity of BN to replace the difficulty of estimation and reasoning of conditional probability is exactly the original intention of BN.

Before determining the conditional probability distribution in BN, the optional status of all nodes need to be determined. The optional status of PSS-ECs has been obtained in section 3.2.1. The optional status (possible cost level) of each cost node needs to be determined based on experience and existing cost data. This paper expresses the optional status of cost as interval numbers, such as (500 yuan, 550 yuan) and (550 yuan, 600 yuan) are two optional status. It is reasonable to express the status of cost in interval numbers, because it is impossible and unnecessary to obtain accurate cost values in the early design stage. The finer the interval is, the more accurate the inference result will be, but the more difficult it is to create a CPT. The structure of BN and the optional status of the nodes can be schematically shown in Fig.4. Each node is associated with a CPT that expresses the influence of its parent nodes on the node.

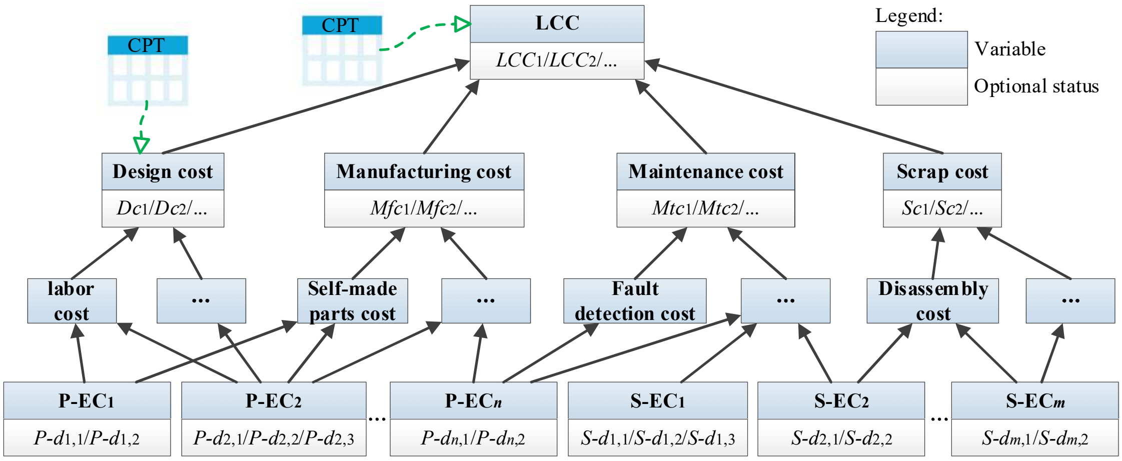

Fig.4 BN's structure of the proposed method

2. Conditional probability in BN

According to Fig.4, the prior probability of each status of PSS-ECs, the CPT of each cost, and the CPT of LCC need to be determined in BN. For all PSS-ECs in BN, the prior probability of each status of PSS-ECs is considered to be uniformly distributed, that is, each status of PSS-ECs has the same probability to be selected during design process.

The CPT of each cost and LCC reflect the quantitative influence of different statuses of PSS-ECs on various costs and LCC under a certain technical level and economic environment. For products with abundant data samples, using maximum likelihood estimation (MLE) to determine conditional probability is a reliable method. However, for complex PSS, usually fewer data samples are available, and the use of MLE to determine conditional probabilities will produce larger deviations. Therefore, in order to make up for the lack of data samples, this paper uses Bayesian estimation methods to combine expert experience with existing data samples to estimate the conditional probability in BN. The process is shown in Fig.5. The BN in Fig.5 is a simplification of BN in Fig.4, where node C_i represents any intermediate nodes in Fig.4.

Note that the BN in Fig.5 has constraints between the statuses of different PSS-ECs, and there may be parent node status combinations (i.e. PSS-ECs status combination) that do not meet the constraints in the CPT of node C_i, which means that there is no such PSS-ECs scheme (i.e. data sample) in the actual PSS, experts also lack the corresponding experience. Therefore, Bayesian estimation cannot be used directly to obtain the conditional probability distribution of node C_i under the corresponding status combination. Thus, before starting conditional probability estimation, it is necessary to distinguish all parent node status combinations in CPT of C_i into feasible status combinations and infeasible status combinations according to the CSP model of PSS-ECs, and then use different methods to estimate the conditional probabilities corresponding to these two situations. The conditional probability estimation of node C_i includes the following three steps (①②③in Fig.5).

For the CPT of nodes whose parent nodes are costs, such as the CPT of LCC, since there is no constraint between the status of different cost nodes, there is no need to judge the feasibility of the parent node status combination, and the Bayesian estimation in Step 2 can be used directly.

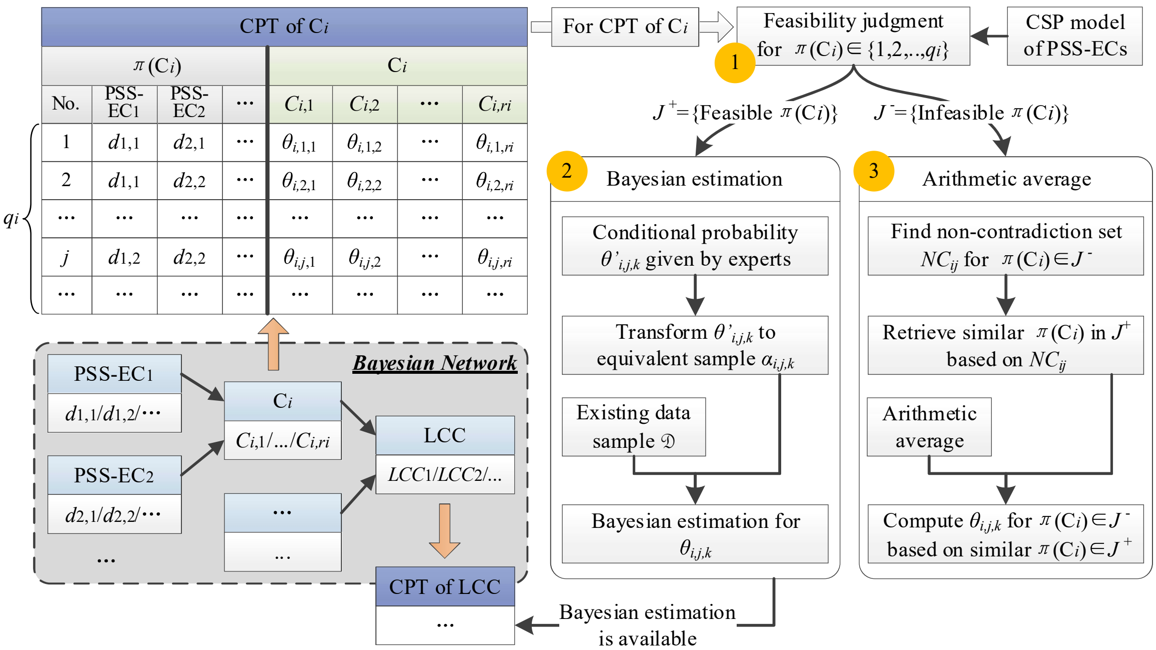

Fig.5 Conditional probability estimation process

Step1: Feasibility judgment for the parent node status combinations of node C$_i$

For BN in Fig.5, suppose node C$_i$ has n_i parent nodes, denoted as PN_i={PSS-EC$_1$, PSS-EC$_2$, ..., PSS-ECn_i}, and the parent node status combinations which denoted as π(C$_i$) has q_i in total. According to the constraints in CSP model, the feasibility of each status combination is judged, and the status combination is marked as feasible or infeasible. For infeasible status combinations, need to record the statuses that do not meet the constraints. This paper refers to the set of statuses that do not meet the constraints as contradiction, and denotes the contradiction as set $C_{i,j}$ for π(C$_i$)=j. The traversal method is used to determine the feasibility of the parent node status combinations of node C$_i$, the pseudo code of this algorithm is shown in Fig.6. According to the algorithm, the q_i status combinations are divided into two sets, which are expressed as $J^+=\{j \mid \pi(C_i)=j$ is feasible$\}$ and $J^-=\{j \mid \pi(C_i)=j$ is infeasible$\}$.

Input: π(C$_i$) as a matrix which size is $q_i{\times}n_i$, constraints that affect PN_i extracted from CSP, denotes as Cst={Cst_1, Cst_2,..., Cst_L}
Output: Set J^+, J^- and $C_{i,j}$

```
J+=Ø, J-=Ø, Ci,j=Ø
For j=1; j ≤ qi; j ++
    For l=1; l ≤ L; l ++
        If π(Ci)=j do not meet Cstl then
            add status that do not meet Cstl into Ci,j
        end If
    end For
    If Ci,j= Ø then add j into J+ // π(Ci)=j is feasible
                else add j into J- // π(Ci)=j is infeasible
    end If
end For
```

Fig.6 Feasibility judgment algorithm for π(C$_i$)

Step2: Conditional probability Bayesian estimation for feasible parent node status combinations

For feasible π(C$_i$)=j, that is $j\in J^+$, the Bayesian estimation method is used to determine the conditional probability distribution of node C_i. Suppose there are data samples $\mathfrak{D}$ for BN in Fig.5, the samples size is N, and there are r_i statuses of node C_i. Let $\theta_{i,j,k}$ denotes the conditional probability of node C_i being status k when $\pi(C_i)=j$, that is $\theta_{i,j,k}=P(C_i=k \mid \pi(C_i)=j)$, where $j\in\{1, 2,..., q_i\}$, $k\in\{1, 2,..., r_i\}$. According to the normality of probability, there is Eq. (1).

$$\sum_{k=1}^{r_i} \theta_{i,j,k} = 1 \tag{1}$$

Denotes the size of samples in $\mathfrak{D}$ that meet $\pi(C_i)=j$ as $N_{i,j}$, and the size of samples that meet $\pi(C_i)=j$ and $C_i= k$ as $N_{i,j,k}$. According to [55, 56], expert experience about $\theta_{i,j,\cdot}=\{\theta_{i,j,1}, \theta_{i,j,2},..., \theta_{i,j,ri}\}$ can be described by Dirichlet distribution $D(\alpha_{i,j,1}, \alpha_{i,j,2}, ..., \alpha_{i,j,ri})$, where $\alpha_{i,j,k}$ are hyperparameters. The meaning of this method is to equivalent expert experience about $\theta_{i,j,\cdot}$ to a certain amount of virtual data samples, and $\alpha_{i,j} =\alpha_{i,j,1}+\alpha_{i,j,2}+...+\alpha_{i,j,ri}$ represents the equivalent virtual sample size, $\alpha_{i,j,k}$ represents the virtual sample size corresponding to $\pi(C_i)=j$ and $C_i= k$. According to the Bayesian estimation method, combining the actual data sample with the virtual sample, $\theta_{i,j,k}$ can be estimated as:

$$\theta_{i,j,k} = \frac{N_{i,j,k} + \alpha_{i,j,k}}{N_{i,j} + \alpha_{i,j}} \tag{2}$$

Eq. (2) combines existing data samples and expert experience to estimate the conditional probability. The feature of Bayesian estimation is that when the data samples size is small, the estimation result mainly depends on the expert experience, but as the data samples gradually increases, the estimation result will depend more and more on the data, and the influence of the expert experience will gradually decrease. Therefore, as data samples increase, the estimation of conditional probability can be gradually updated and become more objective.

It can be seen from Eq. (2) that the equivalent sample size $\alpha_{i,j}$ has an important influence on the estimation of conditional probability, and the value of $\alpha_{i,j}$ reflects the confidence of expert experience (or the strength of prior knowledge). It is difficult to directly convert the expert experience about $\theta_{i,j,\cdot}$ into virtual samples, because it is difficult to directly judge how much sample size the expert experience can be equivalent to. However, it is possible for experts to judge the $\theta_{i,j,k}$ according to their experience, denotes conditional probability distribution obtained by expert judgment as $\theta'_{i,j,\cdot}=\{\theta'_{i,j,1}, \theta'_{i,j,2},..., \theta'_{i,j,ri}\}$. In fact, the confidence of the expert experience about $\theta_{i,j,\cdot}$ depends on the number of schemes that the expert has designed, that is, the number of samples $N_{i,j}$ that meets $\pi(C_i)=j$. When $N_{i,j}$ is larger, it means that the more expert experience about $\theta_{i,j,\cdot}$ is accumulated, the more reliable the judgment is. Therefore, it can be considered that there is a linear proportional relationship between $\alpha_{i,j}$ and $N_{i,j}$ which represents expert experience confidence and the number of actual samples respectively. The relationship is expressed as Eq. (3), where h is the proportional coefficient.

$$\alpha_{i,j} = N_{i,j} \times h \tag{3}$$

Therefore, Eq. (2) can be rewritten as Eq. (4). It shows that the Bayesian estimation of the conditional probability $\theta_{i,j,k}$ is equal to the weighted average of the conditional probability estimated by the actual samples and the conditional probability estimated by expert.

$$\theta_{i,j,k} = \frac{N_{i,j,k} + h \times N_{i,j} \times \theta'_{i,j,k}}{(1+h) \times N_{i,j}} = \frac{1}{1+h} \times \frac{N_{i,j,k}}{N_{i,j}} + \frac{h}{1+h} \times \theta'_{i,j,k} \tag{4}$$

Step3: Conditional probability estimation for infeasible parent node status combinations

For infeasible $\pi(C_i)=j$, that is $j\in J^-$, on the basis that all the conditional probabilities corresponding to $j\in J^+$ have been determined, the arithmetic average method is used to determine the conditional probability distribution of node C_i when $j \in J^-$. The estimation process is shown in Fig.7.

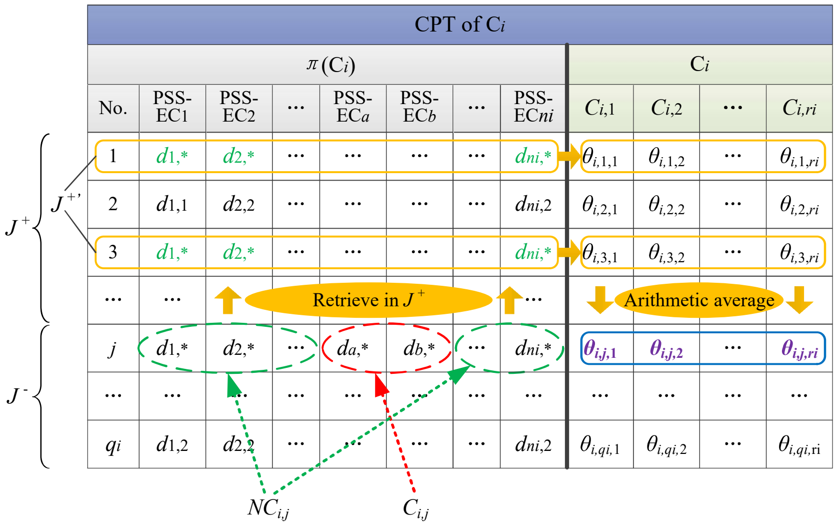

Fig.7 Conditional probability estimation for $\pi(C_i)=j$ and $j \in J^-$

Denotes the status combination corresponding to $\pi(C_i)=j$ as $PN_{i,j}$={PSS-EC$_1$=$d_{1,*}$, PSS-EC$_2$=$d_{2,*}$,..., PSS-ECn_i=$d_{n_i,*}$}[1]. According to the result of Step1, the contradiction of $PN_{i,j}$ is $C_{i,j}$={PSS-EC$_a$=$d_{a,*}$, PSS-EC$_b$=$d_{b,*}$,...}, then non-contradiction can be expressed as $NC_{i,j}=PN_{i,j}-C_{i,j}$. Status combinations with the same status as $NC_{i,j}$ are retrieved in J^+, and the set $J^{+'}=\{j \mid j \in J^+$ and $\pi(C_i)=j$ has the same status as $NC_{i,j}\}$ is formed. $J^{+'}$ represents a series of feasible status combinations similar to the target status combination, and the arithmetic average of the conditional probability corresponding to $J^{+'}$ is used as the conditional probability estimation for $\pi(C_i)=j$ and $j \in J^-$, as Eq. (5). It is easy to prove by Eq. (6) that the $\theta_{i,j,k}$ calculated by arithmetic average still meets the normality of probability.

$$\theta_{ijk} = \frac{\sum_{j \in J^{+'}} \theta_{ijk}}{|J^{+'}|} \tag{5}$$

$$\begin{aligned}
\sum_{k=1}^{r_i} \theta_{ijk} &= \frac{\sum_{j \in J^{+'}} \theta_{ij,1} + \sum_{j \in J^{+'}} \theta_{ij,2} + \ldots + \sum_{j \in J^{+'}} \theta_{ij,r_i}}{|J^{+'}|} \\
&= \frac{\sum_{j=J_1^{+'},k=1}^{r_i} \theta_{ijk} + \sum_{j=J_2^{+'},k=1}^{r_i} \theta_{ijk} + \ldots + \sum_{j=|J^{+'}|,k=1}^{r_i} \theta_{ijk}}{|J^{+'}|} \\
&= \frac{|J^{+'}|}{|J^{+'}|} = 1
\end{aligned} \tag{6}$$

3.2.4. Sensitivity analysis of BN

The conditional probability in BN implies the influence degree of different cause variables on the result variable, which can be quantified through the sensitivity analysis of BN. The mutual information method [57] is used to calculate the sensitivity of LCC to all PSS-ECs (i.e. the influence degree of PSS-ECs on LCC), and the calculation method is as shown in Eq. (7). Where $P(LCC_j, d_{i,k})$ denotes the joint probability distribution of LCC=LCC_j and PSS-EC$_i$=$d_{i,k}$, $P(LCC_j)$ and $P(d_{i,k})$ denotes the marginal probability distribution of LCC=LCC_j and

[1] This paper uses the symbol "*" to indicate that PSS-ECs take a specific status in its status domain, such as PSS-EC$_1$=$d_{1,*}$, PSS-EC$_2$=$d_{2,*}$.

PSS-EC$_i$=$d_{i,k}$ respectively, r_{LCC} denotes the number of status of LCC, and r_i denotes the number of status of PSS-EC$_i$.

$$S(LCC, PSS\text{-}EC_i) = \sum_{j=1}^{r_{LCC}} \sum_{k=1}^{r_i} P(LCC_j, d_{i,k}) \cdot \log_2 \frac{P(LCC_j, d_{i,k})}{P(LCC_j) \cdot P(d_{i,k})} \tag{7}$$

A greater sensitivity indicates that a slight change in PSS-ECs will result in a greater change in LCC. Conversely, smaller sensitivity means that a large change in PSS-ECs will not cause large changes in LCC. Obtaining the sensitivity ranking of LCC to PSS-ECs has the following effects: (1) In solving phase, for the PSS-ECs design scheme selected through LCC evaluation , the values of PSS-ECs can be adjusted according to the sensitivity ranking to further optimize LCC; (2) For PSS-ECs that take continuous values and have a greater impact on LCC, a smaller step size can be selected during discretization to guide the reconstruction of BN; (3) When updating the design space with the goal of reducing LCC, the sensitivity ranking can be used to guide the exploration and innovation of new status of PSS-ECs, that is, PSS-ECs that have a greater impact on LCC should be selected first, and design alternatives that can make LCC lower should be explored. This paper only discusses the first effect of sensitivity ranking, two others are beyond the scope of this paper, so no further explanation.

3.3. Solving phase in detail

3.3.1. Generate feasible design schemes by CSP solving

After receiving the individual customer requirements, the PSS-ECs design schemes that meet the requirements and constraints are solved according to the CSP model of PSS-ECs. Express customer requirements as $CR=\{R_1, R_2, ...R_t\}$， CR reflect the design goals and constraints. Through the mapping and conversion of CR, the status or status ranges of some PSS-ECs can be determined, and used as input to solve the design schemes, expressed as $Input$={PSS-EC$_{x1}$=$d_{x1,*}$, PSS-EC$_{x2}$≥$d_{x2,*}$,...}. Thus, the CSP model is solved in the PSS-ECs design space which is reduced by $Input$, and the PSS-ECs design schemes that meet CR and constraints are obtained. Backtracking (BT) method is a common algorithm for solving CSP. It uses a depth-first backtracking search strategy to solve the problem. That is to assign a value to a variable according to a given sequence. When a variable does not have a legal assignment, it will backtrack to the previous variable and change its assignment, and then continue to assign the next variable. This paper uses the BT method to solve the CSP model, and the specific process can be referred to [58].

Feasible design schemes of PSS-ECs obtained by CSP solving are expressed as $FDS=\{FDS_1, FDS_2, FDS_3, ...\}$, each design scheme is a status combination of PSS-ECs, namely FDS_i={P-EC$_1$=P-$d_{1,*}$, P-EC$_2$=P-$d_{2,*}$,... , P-EC$_n$=P-$d_{n,*}$, S-EC$_1$=S-$d_{1,*}$, S-EC$_2$=S-$d_{2,*}$,... , S-EC$_m$=S-$d_{m,*}$}.

3.3.2. LCC evaluation and optimization of design schemes

BN can perform predictive reasoning and diagnostic reasoning. Predictive reasoning means that the status of the cause variables is known as evidence, and the posterior probability distribution of the result variables is inferred. Diagnostic reasoning refers to that the status of the result variables is known as evidence, and the posterior probability distribution of the cause variables is inferred. LCC evaluation of PSS-ECs feasible design schemes belong to the predictive reasoning of BN, that is, according to the status combination of PSS-ECs, the LCC posterior probability distribution of each design scheme is predicted, and then the best PSS-ECs design scheme can be selected based on LCC ranking.

According to the PSS-ECs status combination of each FDS_i, the probability of the corresponding status of P-ECs and S-ECs in BN is set to 1. The conditional probability calculation method is used to calculate the LCC posterior probability distribution of each FDS_i, with Eqs. (8) and (9). Where $P(\text{LCC}=LCC_i)$ denotes the probability that LCC status is LCC_i, q_{LCC} denotes the number of parent node status combinations of LCC, and Z denotes the number of parent nodes of LCC. $P(\text{C}_k=C_{k,*})$ denotes the probability that C_k status is $C_{k,*}$ (the symbol "*" represents a specific status of C_k), and its calculation method is the same as $P(\text{LCC}=LCC_i)$.

$$P(LCC = LCC_i) = \sum_{j=1}^{q_{LCC}} P(\pi(LCC) = j) \cdot P(LCC = LCC_i \mid \pi(LCC) = j) \tag{8}$$

$$P(\pi(LCC) = j) = \prod_{k=1}^{Z} P(C_k = C_{k,*}) \tag{9}$$

The LCC expected value of FDS_i can be calculated using the posterior probability distribution of LCC, as shown in Eq. (10), where r_{LCC} denotes the number of status of LCC. It should be noted that LCC in this paper is an interval number, so the upper boundary, lower boundary and median of LCC expected value can be calculated according to Eq. (10), and the best design scheme can be selected according to the median of LCC expected value. For the selected best design scheme, according to the sequence of influence degree of PSS-ECs on LCC, the interval-valued PSS-ECs in the scheme are adjusted one by one in the direction of reducing costs under the consideration of other design indicators, to obtain the final design scheme.

$$LCC_E = \sum_{i=1}^{r_{LCC}} LCC_i \cdot P(LCC = LCC_i) \tag{10}$$

4. Case study

Subway bogie is a key subsystem of subway vehicles, which has important impact on the carrying capacity, operational safety, and comfort of the vehicle. It is composed of frame, wheel set, drive and transmission device, brake device, primary and secondary suspension device, etc. It is a typical complex product system, and its structure is shown in Fig.8. The service life of the main components in subway bogie are generally not less than 30 years. During the operation cycle, a lot of maintenance is required. For better control maintenance costs and ensure maintenance quality, subway operators in China are currently trying to transfer the maintenance work to the manufacturers of subway vehicles. In this context, subway vehicles manufacturers not only need to provide products to operators, but also need to provide all maintenance services during the product operation cycle. Therefore, it is necessary to design subway bogie and maintenance services simultaneously in design stage, and it is a typical product-oriented PSS [59]. This paper takes a subway bogie and its maintenance service of a subway vehicle manufacturer in china as the case PSS, and studies its PSS-ECs design, LCC evaluation and optimization to verify the proposed method.

It should be noted that subway bogie and its maintenance services are a kind of complex PSS, expert experience is mostly tacit and difficult to express in a structured way. Also, due to the limited data samples available, it is difficult to use methods such as data mining to automatically or semi-automatically extract experience knowledge. Therefore, in order to realize this case, we worked with the company's engineers for 4 weeks to consult the required expert experience and obtain historical R&D data related to the case PSS.

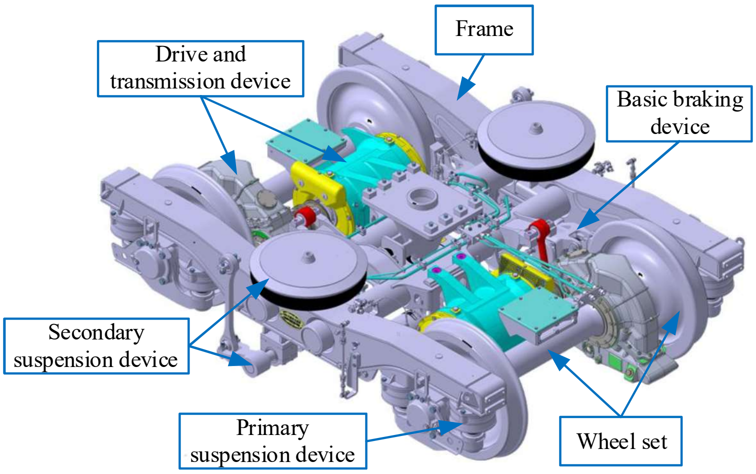

Fig.8 Subway bogie's composition

4.1. Modeling phase practice

4.1.1. PSS-ECs elicitation

Some ECs of the subway bogie and its maintenance services are determined by standards (such as GB and UIC standards) and operating line conditions, and usually take fixed values, such as safety indicators, stability indicators, and gauges. In addition, some ECs have been standardized, such as wheel diameter, tread shape, etc., also take fixed values. After excluding the above-mentioned fixed-value ECs, according to the company's market requirements forecast and analysis, as well as the existing subway bogie and maintenance service data, the PSS-ECs to be designed and their optional status are sorted out as shown in Table 1.

Table 1 PSS-ECs item and its optional status

Classification	Sub-classification	PSS-ECs	Optional status
Product-related ECs	Function setting	P-EC$_1$: Intelligent monitoring	$P\text{-}d_{1,1}$: YES; $P\text{-}d_{1,2}$: NO
	Technical principle	P-EC$_2$: Drive device type	$P\text{-}d_{2,1}$: Permanent magnet synchronous motor; $P\text{-}d_{2,2}$: Three-phase asynchronous motor
		P-EC$_3$: Primary suspension device type	$P\text{-}d_{3,1}$: Rotary arm type; $P\text{-}d_{3,2}$: Taper laminated rubber spring
	Geometry structure	P-EC$_4$: Braking device structure	$P\text{-}d_{4,1}$: Tread brake; $P\text{-}d_{4,2}$: Disc brake
		P-EC$_5$: Traction device structure	$P\text{-}d_{5,1}$: Single traction rod; $P\text{-}d_{5,2}$: Double traction rod
	Material	P-EC$_6$: Frame material	$P\text{-}d_{6,1}$: Low-alloy steel; $P\text{-}d_{6,2}$: carbon fiber
	Performance parameters	P-EC$_7$: Average acceleration	$P\text{-}d_{7,1}$: 0.6~0.7m/s^2; $P\text{-}d_{7,2}$: 0.7~0.8m/s^2
		P-EC$_8$: Emergency braking deceleration	$P\text{-}d_{8,1}$: 1.2~1.3m/s^2; $P\text{-}d_{8,2}$: 1.3~1.4m/s^2
		P-EC$_9$: Axle load	$P\text{-}d_{9,1}$: 14~15t; $P\text{-}d_{9,2}$: 15~16t
		P-EC$_{10}$: Bogie weight	$P\text{-}d_{10,1}$: 7~7.5t; $P\text{-}d_{10,2}$: 7.5~8t
		P-EC$_{11}$: Maximum Speed	$P\text{-}d_{11,1}$: 80km/h; $P\text{-}d_{11,2}$: 100km/h; $P\text{-}d_{11,3}$: 120km/h
	Size parameters	P-EC$_{12}$: Wheelbase	$P\text{-}d_{12,1}$: 2200mm; $P\text{-}d_{12,2}$: 2300mm; $P\text{-}d_{12,3}$: 2500mm
Service-related ECs	Maintenance mode	S-EC$_1$: Fault detection mode	$S\text{-}d_{1,1}$: Manual detection; $S\text{-}d_{1,2}$: Intelligent detection
		S-EC$_2$: Maintenance schedule	$S\text{-}d_{2,1}$: MS1; $S\text{-}d_{2,2}$: MS2
	Spare parts	S-EC$_3$: Spare parts inventory level	$S\text{-}d_{3,1}$: Level1; $S\text{-}d_{3,2}$: Level2

	Service quality	S-EC$_4$: Service response time	S-$d_{4,1}$: 4h; S-$d_{4,2}$: 8h
		S-EC$_5$: Fault detection time	S-$d_{5,1}$: FDT1; S-$d_{5,2}$: FDT2
		S-EC$_6$: Fault repair time	S-$d_{6,1}$: FRT1; S-$d_{6,2}$: FRT2

Note: MS1 denotes the traditional maintenance schedules including daily detection, bi-weekly detection, three-month detection, annual detection, 5 years detection, and overhaul; MS2 denotes the balanced schedules that separates bi-weekly detection, three-month detection, and annual detection into each month; Level1 denotes the stock of conventional spare parts; Level2 denotes the stock of redundant spare parts, and the shortage probability is lower than Level1; FDT1 denotes the detection time corresponding to manual detection; FDT2 denotes the detection time corresponding to intelligent detection; FRT1 denotes the repair time corresponding to MS1; FRT2 denotes the repair time corresponding to MS2.

4.1.2. CSP modeling

According to the design principles and expert experience, the constraints among the PSS-ECs status of the subway bogie and its maintenance service are analyzed, and the obtained constraints are shown in Table 2.

Table 2 Constraints among the status of PSS-ECs

NO.	PSS-ECs	Constraints
Cst_1	P-EC$_1$: Intelligent monitoring	(P-$d_{1,1}$: YES, S-$d_{1,2}$: Intelligent detection);
	S-EC$_1$: Fault detection mode	(P-$d_{1,2}$:NO, S-$d_{1,1}$: Manual detection)
Cst_2	P-EC$_{11}$: Maximum Speed	(P-$d_{11,1}$:80km/h, P-$d_{4,1}$: Tread brake)
	P-EC$_4$: Braking device structure	($\neg P$-$d_{11,1}$:80km/h, P-$d_{4,2}$: Disc brake)
Cst_3	P-EC$_6$: Frame material	(P-$d_{6,2}$: carbon fiber, P-$d_{10,1}$:7~7.5t)
	P-EC$_{10}$: Bogie weight	(P-$d_{6,1}$: Low-alloy steel, P-$d_{10,2}$:7.5~8t)
Cst_4	P-EC$_{11}$: Maximum Speed	(P-$d_{11,2}$:100km/h, P-$d_{7,1}$: 0.6~0.7m/s^2)
	P-EC$_7$: Average acceleration	(P-$d_{11,3}$:120km/h, P-$d_{7,1}$: 0.6~0.7m/s^2)
Cst_5	P-EC$_{11}$: Maximum Speed	(P-$d_{11,2}$:100km/h, P-$d_{8,1}$: 1.2~1.3m/s^2)
	P-EC$_8$: Emergency braking deceleration	(P-$d_{11,3}$:120km/h, P-$d_{8,1}$: 1.2~1.3m/s^2)
Cst_6	P-EC$_{11}$: Maximum Speed	(P-$d_{11,1}$:80km/h, $\neg P$-$d_{12,3}$:2500mm)
	P-EC$_{12}$: Wheelbase	(P-$d_{11,2}$:100km/h, $\neg P$-$d_{12,1}$:2200mm)
		(P-$d_{11,3}$:120km/h, $\neg P$-$d_{12,1}$:2200mm)
Cst_7	S-EC$_1$: Fault detection mode	(S-$d_{1,1}$: Manual detection, S-$d_{5,1}$: FDT1)
	S-EC$_5$: Fault detection time	(S-$d_{1,2}$: Intelligent detection, S-$d_{5,2}$: FDT2)
Cst_8	S-EC$_2$: Maintenance schedule	(S-$d_{2,1}$: MS1, S-$d_{6,1}$: FRT1)
	S-EC$_6$: Fault repair time	(S-$d_{2,2}$: MS2, S-$d_{6,2}$: FRT2)

Note: (a, b) denotes dependency constraint, (a, ¬b) denotes exclusive constraint.

4.1.3. BN modeling

1. BN's structure

Construct the BN of this case according to Fig.4. In general, the manufacturing cost and maintenance cost in LCC account for a relatively large proportion, while the proportion of design cost and scrap cost is relatively small [60]. In our case PSS, according to the collected cost data, the sum of design cost and scrap cost accounts for less than 10% of LCC, and it is mainly affected by the enterprise's informatization level, management factors, etc., and less affected by design factors. Therefore, in order to simplify the case BN, only the manufacturing cost and maintenance cost that account for a large portion of LCC and strongly affected by design factors are considered, while the design cost and scrap cost are ignored. In order to avoid too many parent nodes for manufacturing cost and maintenance cost, resulting in too many parent node status combinations and making the conditional probability estimation more complicated, the manufacturing cost is further decomposed into self-made parts cost, purchased parts cost and assembly cost, and the maintenance cost is decomposed into fault detection cost and fault repair cost. It should be noted that the subway bogie is produced according to order, adopting lean production strategy. The required raw materials and parts are purchased and used according to the production plan of the order. In general, the inventory time is very short. There will not be a large amount of materials occupying the inventory for a long time, thus the inventory cost is very low and is not considered in the manufacturing cost. Combining existing cost data and expert experience, determine the optional status of all considered cost items as shown in Table 3.

Table 3 Optional status of cost items[2]

Cost items	Optional status (unit:10^4 yuan)
Self-made parts cost	(36, 42), (42, 48), (48, 54)
Purchased parts cost	(126, 140), (140, 154), (154, 168)
Assembly cost	(18, 20), (20, 22), (22, 24)
Fault detection cost	(432, 480), (480, 528), (528, 576)
Fault repair cost	(288, 320), (320, 352), (352, 384)
Manufacturing cost	(190, 212), (212, 234), (234, 256)
Maintenance cost	(760, 840), (840, 920), (920, 1000)
LCC	(1000, 1100), (1100, 1200), (1200, 1300)

Through consulting experienced design experts, the causal relationships between PSS-ECs and cost items were analyzed, and the BN's structure was then determined as shown in Fig.9.

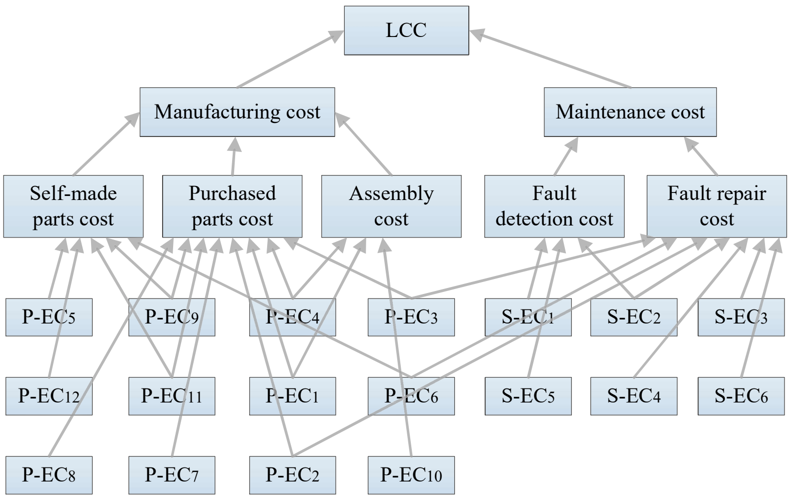

Fig.9 BN's structure of this case

It can be seen from Fig.9 that after decomposing the manufacturing cost and maintenance cost, the "Purchased parts cost" node has the largest number of parent nodes in BN, which has 8 parent nodes, and there are 384 parent node status combinations. Without cost decomposition, there are 12 parent nodes of the "Manufacturing cost" node, and there are 9216 parent node status combinations. Therefore, reasonable cost decomposition can avoid the explosion of parent node status combinations and reduce the difficulty of BN's conditional probability estimation.

2. Conditional probability in BN

[2] Considering the confidentiality requirements of real cost data, the data in the case is slightly adjusted, but its rationality is guaranteed.

The prior probability of each status of PSS-ECs is calculated according to a uniform distribution. The CPT of each cost and the CPT of LCC are estimated as described in section 3.2.3. The following takes the CPT of “Purchased parts cost” as an example to illustrate the estimation process of the conditional probability. The CPT is shown in Table 4.

Table 4 CPT of “Purchased parts cost”

π(Purchased parts cost)									Purchased parts cost (%)		
NO.	P-EC$_8$	P-EC$_9$	P-EC$_{11}$	P-EC$_7$	P-EC$_4$	P-EC$_1$	P-EC$_2$	P-EC$_3$	*Ppc*1	*Ppc*2	*Ppc*3
1	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,1}$	$P\text{-}d_{2,1}$	$P\text{-}d_{3,1}$	81	13	6
2	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,1}$	$P\text{-}d_{2,1}$	$P\text{-}d_{3,2}$	82	12	6
3	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,1}$	$P\text{-}d_{2,2}$	$P\text{-}d_{3,1}$	91	5	4
4	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,1}$	$P\text{-}d_{2,2}$	$P\text{-}d_{3,2}$	92	5	3
5	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,2}$	$P\text{-}d_{2,1}$	$P\text{-}d_{3,1}$	84	11	5
6	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,2}$	$P\text{-}d_{2,1}$	$P\text{-}d_{3,2}$	85	10	5
7	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,2}$	$P\text{-}d_{2,2}$	$P\text{-}d_{3,1}$	94	4	2
8	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,1}$	$P\text{-}d_{1,2}$	$P\text{-}d_{2,2}$	$P\text{-}d_{3,2}$	95	3	2
9	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,2}$	$P\text{-}d_{1,1}$	$P\text{-}d_{2,1}$	$P\text{-}d_{3,1}$	30.3	46	23.7
10	$P\text{-}d_{8,1}$	$P\text{-}d_{9,1}$	$P\text{-}d_{11,1}$	$P\text{-}d_{7,1}$	$P\text{-}d_{4,2}$	$P\text{-}d_{1,1}$	$P\text{-}d_{2,1}$	$P\text{-}d_{3,2}$	31.7	45.7	22.6
……	……	……	……	……	……	……	……	……	……	……	……
384	$P\text{-}d_{8,2}$	$P\text{-}d_{9,2}$	$P\text{-}d_{11,3}$	$P\text{-}d_{7,2}$	$P\text{-}d_{4,2}$	$P\text{-}d_{1,2}$	$P\text{-}d_{2,2}$	$P\text{-}d_{3,2}$	6.5	55	38.5

Note: *Ppc1*=(126, 140)×10^4yuan, *Ppc2*=(140, 154)×10^4yuan, *Ppc3*=(154, 168)×10^4yuan.

Step1: Based on the CSP model and the feasibility judgment method described in Fig.6, we use MATLAB programming to judge the feasibility of the 384 parent node status combinations in Table 4, and the result is 96 feasible status combinations and 288 infeasible status combinations. Infeasible status combinations and their contradiction have been shaded in Table 4.

Step2: For feasible parent node status combinations, Bayesian estimation is used to determine the conditional probability. Taking the 3th parent node status combination in Table 4 as an example, which is a common design scheme. Through the collection of the company’s existing R&D data, we have obtained 47 data samples, each of which consists of 12 P-ECs, 6 S-ECs, and 8 cost items (corresponding to the variables in the BN). Among these data samples, there are 14 samples that satisfy π(Purchased parts cost)=3, and there are 12, 1 and 1 data samples that satisfy π(Purchased parts cost)=3 and “Purchased parts cost”= *Ppc1*, *Ppc2*, *Ppc3* respectively. According to expert experience, the conditional probability of “Purchased parts cost” taking three states when π(Purchased parts cost)=3 is judged, and $\theta'_{P,3,\cdot}$={0.96, 0.03, 0.01} is obtained.

Eq. (4) is used to calculate the conditional probability distribution for π(Purchased parts cost)=3. This paper sets h=1, which means that the number of virtual samples and actual samples are the same in conditional probability estimation. According to Eq. (4), the result of conditional probability estimation is $\theta_{P,3,\cdot}$={0.91, 0.05, 0.04}. In the same way, Bayesian estimation is performed on the conditional probabilities corresponding to other feasible parent node status combinations.

Step3: After the conditional probability estimation corresponding to all feasible parent node status combinations are completed, the arithmetic average method is used to estimate the conditional probability for infeasible parent node status combinations, taking the 9th parent node status combination in Table 4 as an example. The contradiction in π(Purchased parts cost)=9 is $C_{P,9}$={P-EC$_{11}$=$P\text{-}d_{11,1}$, P-EC$_4$=$P\text{-}d_{4,2}$}, and the non-contradiction is $NC_{P,9}$={P-EC$_8$=$P\text{-}d_{8,1}$, P-EC$_9$=$P\text{-}d_{9,1}$, P-EC$_7$=$P\text{-}d_{7,1}$, P-EC$_1$=$P\text{-}d_{1,1}$, P-EC$_2$=$P\text{-}d_{2,1}$, P-EC$_3$=$P\text{-}d_{3,1}$}. Retrieve the parent node status combinations that have the same status as $NC_{P,9}$ from all feasible parent node status combinations in Table 4, and the result is the 1th, 41th, 73th status combinations, and $\theta_{P,1,\cdot}$={0.81, 0.13, 0.06}, $\theta_{P,41,\cdot}$={0.07, 0.88, 0.05}, $\theta_{P,73,\cdot}$={0.03, 0.37, 0.60}. According to Eq. (5), $\theta_{P,9,\cdot}$={0.303, 0.46, 0.237} is calculated. In the same way, estimate the conditional probability corresponding to other infeasible parent node status combinations.

The above three steps are also used to estimate the conditional probability in CPT of "Self-made parts cost" node, "Assembly cost" node, "Fault detection cost" node, and "Fault repair cost" node. The conditional probability in CPT of "Manufacturing cost" node, "Maintenance cost" node, and "LCC" node are directly estimated by Bayesian estimation (Step 2). According to the structure of BN and the estimated conditional probability, this paper uses NETICA[3] which is an easy-to-use BN development software to carry out BN modeling and reasoning. The BN constructed in NETICA is shown in Fig.10.

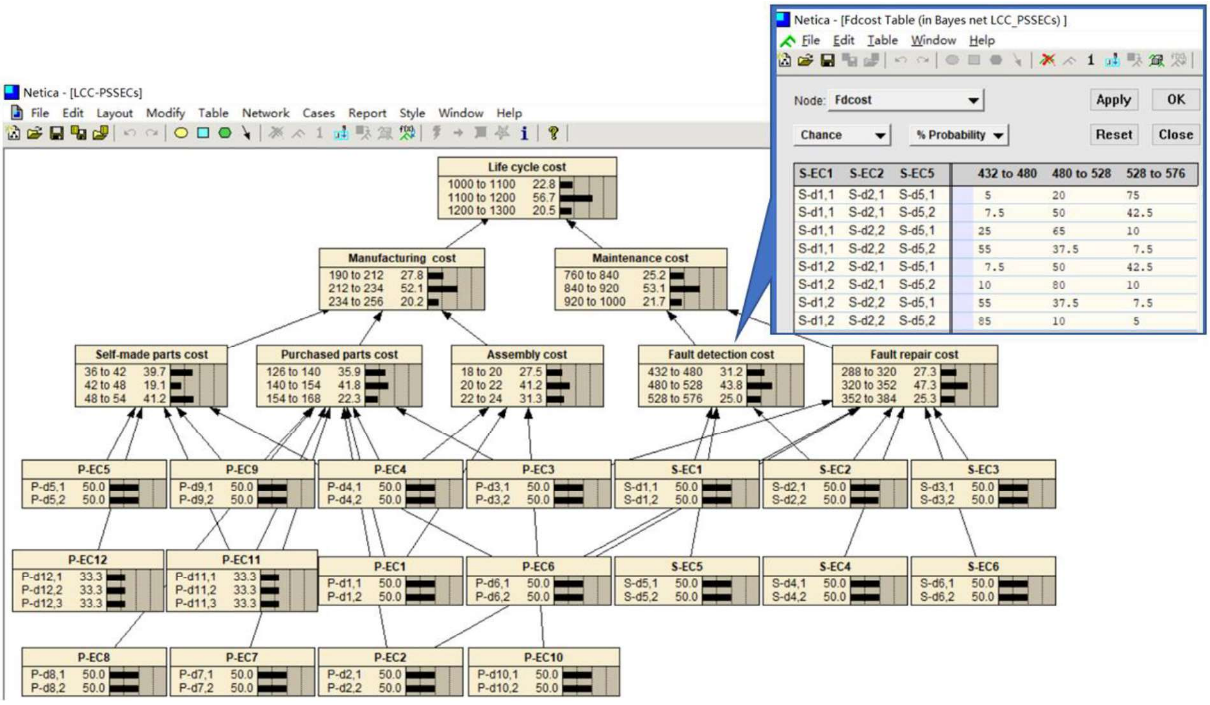

Fig.10 BN of this case

4.1.4. Sensitivity analysis of BN

Based on the BN in Fig.10 and Eq. (7) built in NETICA, the sensitivity of LCC to all PSS-ECs is calculated, and the result is shown in 11. It can be seen from 11 that the impact of S-ECs on LCC is obviously greater than that of P-ECs on LCC. This is because the maintenance cost of the subway bogie accounts for most of the LCC, which is almost 4 times the manufacturing cost, and maintenance cost is mainly affected by S-ECs, so S-ECs have a greater impact on LCC, and S-EC_2 (Maintenance schedule) has the greatest impact on LCC. Among P-ECs, P-EC_{11}(Maximum Speed), P-EC_6(Frame material), P-EC_4(Braking device structure), P-EC_9(Axle load) have a greater impact on LCC. The sensitivity ranking results are in line with engineering experience cognition.

[3] https://www.norsys.com/

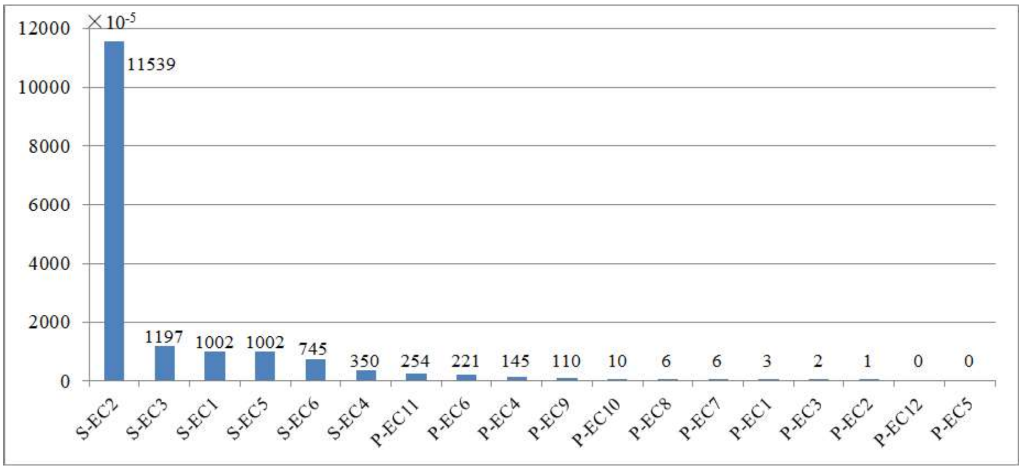

Fig.11 Sensitivity ranking of LCC to PSS-ECs

4.2. Solving phase practice

4.2.1. Generate feasible design schemes by CSP solving

The CSP solving of this case is implemented in MATLAB. A total of 6114 feasible design schemes that meet the constraints are obtained when there are no customer requirements input. Now suppose there are customer requirements CR_{test}, which puts forward requirements for speed, axle load, intelligent monitoring, maintenance schedule, service response speed, etc. for a subway bogie and its maintenance service. The design inputs are obtained by mapping and transforming these requirements, and $Input$={P-EC_1=P-$d_{1,1}$, P-EC_6=P-$d_{6,1}$, P-EC_9=P-$d_{9,1}$, P-EC_{11}=P-$d_{11,2}$, S-EC_2=S-$d_{2,2}$, S-EC_4=S-$d_{4,1}$}, solving CSP to obtain 32 design schemes that meet customer requirements and constraints, as shown in Table 5.

Table 5 Feasible design schemes corresponding to CR_{test}

	FDS_1	FDS_2	FDS_3	FDS_4	FDS_5	FDS_6	FDS_7	FDS_8	FDS_9	FDS_{10}	…	FDS_{32}
P-EC_1	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	P-$d_{1,1}$	…	P-$d_{1,1}$
P-EC_2	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	P-$d_{2,1}$	…	P-$d_{2,2}$
P-EC_3	P-$d_{3,1}$	P-$d_{3,1}$	P-$d_{3,1}$	P-$d_{3,1}$	P-$d_{3,1}$	P-$d_{3,1}$	P-$d_{3,1}$	P-$d_{3,1}$	P-$d_{3,2}$	P-$d_{3,2}$	…	P-$d_{3,2}$
P-EC_4	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	P-$d_{4,2}$	…	P-$d_{4,2}$
P-EC_5	P-$d_{5,1}$	P-$d_{5,1}$	P-$d_{5,1}$	P-$d_{5,1}$	P-$d_{5,2}$	P-$d_{5,2}$	P-$d_{5,2}$	P-$d_{5,2}$	P-$d_{5,1}$	P-$d_{5,1}$	…	P-$d_{5,2}$
P-EC_6	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	P-$d_{6,1}$	…	P-$d_{6,1}$
P-EC_7	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	P-$d_{7,1}$	…	P-$d_{7,1}$
P-EC_8	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	P-$d_{8,1}$	…	P-$d_{8,1}$
P-EC_9	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	P-$d_{9,1}$	…	P-$d_{9,1}$
P-EC_{10}	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	P-$d_{10,2}$	…	P-$d_{10,2}$
P-EC_{11}	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	P-$d_{11,2}$	…	P-$d_{11,2}$
P-EC_{12}	P-$d_{12,2}$	P-$d_{12,2}$	P-$d_{12,3}$	P-$d_{12,3}$	P-$d_{12,2}$	P-$d_{12,2}$	P-$d_{12,3}$	P-$d_{12,3}$	P-$d_{12,2}$	P-$d_{12,2}$	…	P-$d_{12,3}$
S-EC_1	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	S-$d_{1,2}$	…	S-$d_{1,2}$
S-EC_2	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	S-$d_{2,2}$	…	S-$d_{2,2}$
S-EC_3	S-$d_{3,1}$	S-$d_{3,2}$	S-$d_{3,1}$	S-$d_{3,2}$	S-$d_{3,1}$	S-$d_{3,2}$	S-$d_{3,1}$	S-$d_{3,2}$	S-$d_{3,1}$	S-$d_{3,2}$	…	S-$d_{3,2}$
S-EC_4	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	S-$d_{4,1}$	…	S-$d_{4,1}$
S-EC_5	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	S-$d_{5,2}$	…	S-$d_{5,2}$

S-EC6	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	$S\text{-}d_{6,2}$	…	$S\text{-}d_{6,2}$

With the increase of design inputs, the number of feasible design schemes will decrease. For example, when CR_{test} adds the requirement of wheelbase=2500mm (P-EC$_{12}$=$P\text{-}d_{12,3}$), the number of feasible design schemes will be reduced to 16. Using this method can assist designers to fully explore the design space when different customer requirements are input, and obtain feasible design schemes.

4.2.2. LCC evaluation and optimization of design schemes

BN in Fig.10 is used to evaluate the LCC of the above 32 design schemes. The status of P-ECs or S-ECs of each design scheme is input into BN as evidence. According to Eqs. (8) and (9) built in NETICA, BN automatically performs predictive reasoning and obtains the LCC posterior probability distribution of the design scheme. Fig.12 shows the LCC evaluation result of FDS_1.

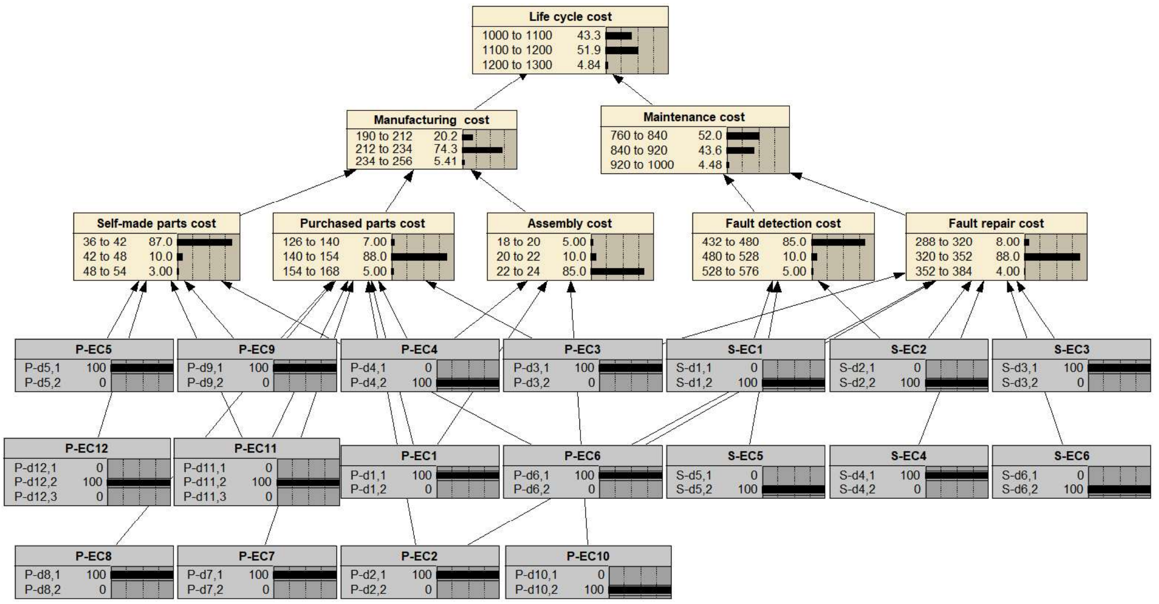

Fig.12 LCC evaluation result of FDS_1

According to the LCC evaluation results of 32 design schemes, calculate the LCC expected value of each scheme, which includes lower boundary value, upper boundary value and median value, and draw the LCC expected value comparison chart as shown in Fig.13. Observing Fig.13, we can see that the difference in LCC expected value of 32 design schemes is not too big. This is because the status of 13 PSS-ECs of these schemes are the same, including 6 PSS-ECs (P-EC$_1$, P-EC$_6$, P-EC$_9$, P-EC$_{11}$, S-EC$_2$, S-EC$_4$) determined by requirements and 7 PSS-ECs (P-EC$_4$, P-EC$_7$, P-EC$_8$, P-EC$_{10}$, S-EC$_1$, S-EC$_5$, S-EC$_6$) restricted by constraints, the remaining 5 PSS-ECs (P-EC$_2$, P-EC$_3$, P-EC$_5$, P-EC$_{12}$, S-EC$_3$) changed to form 32 design schemes. It can be seen from 11 that 4 P-ECs of the 5 changed PSS-ECs have little impact on LCC, so the LCC estimation results of 32 design schemes have a small difference.

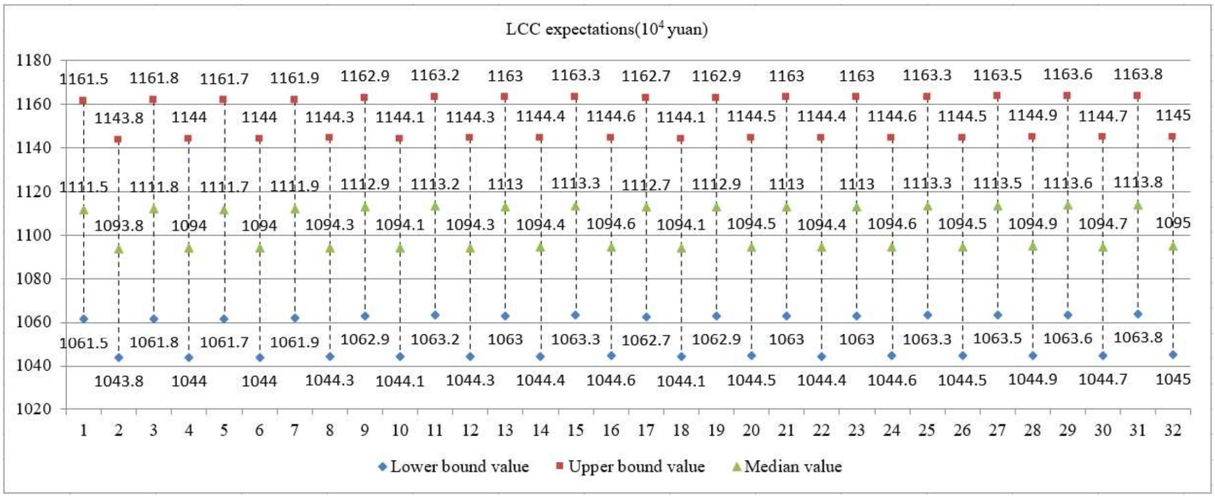

Fig.13 Comparison of LCC expectations for all *FDS*

A qualitative comparative analysis of 32 design schemes was carried out to prove the rationality of the LCC evaluation results. Among the 32 design schemes, for any design scheme, 5 design schemes that differ from the selected scheme by only one PSS-ECs status can be found. For example, for FDS_1, we can find FDS_2, FDS_3, FDS_5, FDS_9, FDS_{17}, and these schemes differ from FDS_1 by only one PSS-ECs status. In design schemes, when the status of other PSS-ECs is fixed, the qualitative influence of the status change of a certain PSS-ECs on LCC can be obtained based on empirical analysis. For example, FDS_1 and FDS_3 only have a different wheelbase (P-EC_{12}), while the rest of the PSS-ECs are in the same status. The wheelbase of FDS_1 is 2300mm ($P\text{-}d_{12,2}$), and the wheelbase of FDS_3 is 2500mm ($P\text{-}d_{12,3}$), because a larger wheelbase requires more raw materials, processing time, etc., it can be qualitatively judged that the LCC of FDS_3 is higher than that of FDS_1. Similarly, due to the higher manufacturing cost of the double traction rod (P-EC_5=$P\text{-}d_{5,2}$), it can also be qualitatively judged that the LCC of FDS_5 is higher than that of FDS_1. Based on this single-factor qualitative comparative analysis method, 32 schemes are compared one by one, each scheme can be compared with 5 schemes, a total of 160 comparisons were performed. The qualitative comparison of design schemes is shown in Table 6. Due to the large amount of data, only part of the comparison is listed in the table, and the 13 same PSS-ECs in design schemes are not listed.

Table 6 Qualitative comparative analysis of 32 design schemes

NO.	P-EC_2	P-EC_3	P-EC_5	P-EC_{12}	S-EC_3	Qualitative comparison of LCC
FDS_1	$P\text{-}d_{2,1}\downarrow^{17}$	$P\text{-}d_{3,1}\downarrow^{9}$	$P\text{-}d_{5,1}\downarrow^{5}$	$P\text{-}d_{12,2}\downarrow^{3}$	$S\text{-}d_{3,1}\uparrow^{2}$	$FDS_2<FDS_1<FDS_3, FDS_5, FDS_9, FDS_{17}$
FDS_2	$P\text{-}d_{2,1}\downarrow^{18}$	$P\text{-}d_{3,1}\downarrow^{10}$	$P\text{-}d_{5,1}\downarrow^{6}$	$P\text{-}d_{12,2}\downarrow^{4}$	$S\text{-}d_{3,2}\downarrow^{1}$	$FDS_2<FDS_1, FDS_4, FDS_6, FDS_{10}, FDS_{18}$
FDS_3	$P\text{-}d_{2,1}\downarrow^{19}$	$P\text{-}d_{3,1}\downarrow^{11}$	$P\text{-}d_{5,1}\downarrow^{7}$	$P\text{-}d_{12,3}\uparrow^{1}$	$S\text{-}d_{3,1}\uparrow^{4}$	$FDS_1, FDS_4<FDS_3<FDS_7, FDS_{11}, FDS_{19}$
FDS_4	$P\text{-}d_{2,1}\downarrow^{20}$	$P\text{-}d_{3,1}\downarrow^{12}$	$P\text{-}d_{5,1}\downarrow^{8}$	$P\text{-}d_{12,3}\uparrow^{2}$	$S\text{-}d_{3,2}\downarrow^{3}$	$FDS_2<FDS_4<FDS_3, FDS_8, FDS_{12}, FDS_{20}$
FDS_5	$P\text{-}d_{2,1}\downarrow^{21}$	$P\text{-}d_{3,1}\downarrow^{13}$	$P\text{-}d_{5,2}\uparrow^{1}$	$P\text{-}d_{12,2}\downarrow^{7}$	$S\text{-}d_{3,1}\uparrow^{6}$	$FDS_1, FDS_6<FDS_5<FDS_7, FDS_{13}, FDS_{21}$
FDS_6	$P\text{-}d_{2,1}\downarrow^{22}$	$P\text{-}d_{3,1}\downarrow^{14}$	$P\text{-}d_{5,2}\uparrow^{2}$	$P\text{-}d_{12,2}\downarrow^{8}$	$S\text{-}d_{3,2}\downarrow^{5}$	$FDS_2<FDS_6<FDS_5, FDS_8, FDS_{14}, FDS_{22}$
FDS_7	$P\text{-}d_{2,1}\downarrow^{23}$	$P\text{-}d_{3,1}\downarrow^{15}$	$P\text{-}d_{5,2}\uparrow^{3}$	$P\text{-}d_{12,3}\uparrow^{5}$	$S\text{-}d_{3,1}\uparrow^{8}$	$FDS_3, FDS_5, FDS_8<FDS_7<FDS_{15}, FDS_{23}$
FDS_8	$P\text{-}d_{2,1}\downarrow^{24}$	$P\text{-}d_{3,1}\downarrow^{16}$	$P\text{-}d_{5,2}\uparrow^{4}$	$P\text{-}d_{12,3}\uparrow^{6}$	$S\text{-}d_{3,2}\downarrow^{7}$	$FDS_4, FDS_6<FDS_8<FDS_7, FDS_{16}, FDS_{24}$
FDS_9	$P\text{-}d_{2,1}\downarrow^{25}$	$P\text{-}d_{3,2}\uparrow^{1}$	$P\text{-}d_{5,1}\downarrow^{13}$	$P\text{-}d_{12,2}\downarrow^{11}$	$S\text{-}d_{3,1}\uparrow^{10}$	$FDS_1, FDS_{10}<FDS_9<FDS_{11}, FDS_{13}, FDS_{25}$
FDS_{10}	$P\text{-}d_{2,1}\downarrow^{26}$	$P\text{-}d_{3,2}\uparrow^{2}$	$P\text{-}d_{5,1}\downarrow^{14}$	$P\text{-}d_{12,2}\downarrow^{12}$	$S\text{-}d_{3,2}\downarrow^{9}$	$FDS_2<FDS_{10}<FDS_9, FDS_{12}, FDS_{14}, FDS_{26}$
…	…	…	…	…	…	…
FDS_{32}	$P\text{-}d_{2,2}\uparrow^{16}$	$P\text{-}d_{3,2}\uparrow^{24}$	$P\text{-}d_{5,2}\uparrow^{28}$	$P\text{-}d_{12,3}\uparrow^{30}$	$S\text{-}d_{3,2}\downarrow^{31}$	$FDS_{16}, FDS_{24}, FDS_{28}, FDS_{30}<FDS_{32}<FDS_{31}$

Note: $\uparrow^{a}$ or $\downarrow^{a}$ denotes that FDS_a is used as the comparison benchmark, and the status of the corresponding PSS-ECs will cause the

LCC of the design scheme to be higher or lower than the benchmark.

Based on the qualitative comparison results in Table 6, part of the LCC ranking of design schemes can be obtained, such as $FDS_2 < FDS_1 < FDS_3 < FDS_7 < FDS_{15} < FDS_{31}$, $FDS_2 < FDS_4 < FDS_{12} < FDS_{28} < FDS_{32} < FDS_{31}$, $FDS_2 < FDS_{10} < FDS_{14} < FDS_{16} < FDS_{15} < FDS_{31}$. The rationality of the qualitative analysis results is approved by the engineers of the subway vehicles manufacturers, and the ranking of the LCC evaluation results in Fig.13 are consistent with the qualitative analysis results, so the LCC evaluation results of design schemes based on BN are reasonable. From the qualitative analysis results and Fig.13, it can be seen that FDS_2 has the lowest LCC expected value, with LCC as the design goal, FDS_2 is the best scheme for this case.

P-EC$_7$ (Average acceleration: 0.6~0.7m/s^2), P-EC$_8$ (Emergency braking deceleration: 1.2~1.3m/s^2), P-EC$_9$ (Axle load: 14~15t), P-EC$_{10}$ (Bogie weight:7.5~8t) in FDS_2 are interval numbers. According to the sensitivity ranking given in 11, namely S(LCC, P-EC$_9$) >S(LCC, P-EC$_{10}$) >S(LCC, P-EC$_8$) >S(LCC, P-EC$_7$), analyze the values of these P-ECs one by one, and adjust the values of P-ECs in the direction of reducing LCC as much as possible while ensuring proper performance margin and safety margin, such as setting axle load to 14.4t, emergency braking deceleration to 1.26m/s^2, etc. to determine the final design scheme.

5. Discussion

It can be seen from the case study that the proposed method based on CSP and BN can effectively solve the PSS-ECs design for LCC. Many steps in the implementation process need to rely on existing R&D data and expert experience, which are reflected in the design space determination, constraints analysis, BN's structure determination, and conditional probability estimation. Therefore, the prerequisite for implementing this method is to have the required data and experience. The proposed method can essentially integrate the data, knowledge and experience of actual product development into the problem description model, which includes CSP model and BN, to support the searching and evaluation of PSS-ECs design schemes.

It can be observed from the evaluation process of the 32 design schemes in the case study that it is more reasonable to take LCC as the design goal than to consider the manufacturing cost or maintenance cost alone. For example, the two design schemes of FDS_1 and FDS_{17} are only different in the selected motor (P-EC$_2$). FDS_1 has chosen permanent magnet synchronous motor ($P\text{-}d_{2,1}$), while FDS_{17} has chosen three-phase asynchronous motor ($P\text{-}d_{2,2}$). Since the manufacturing cost of three-phase asynchronous motor is cheaper, FDS_{17} is a better scheme if only the manufacturing cost is considered. However, due to the higher reliability of the permanent magnet synchronous motor, its maintenance cost is lower and the higher manufacturing cost is compensated, resulting in a lower LCC of FDS_1 than FDS_{17}. It shows that taking LCC as the design goal can make more reasonable design decisions. In addition, BN can be used not only to evaluate the LCC of each scheme, but also to guide the status change of PSS-ECs in NETICA, it is convenient to observe the impact of different PSS-ECs status on each cost, which helps designers to intuitively understand the relationships between PSS-ECs statuses and costs. With the accumulation of R&D data, BN can also learn new data samples and update its CPT according to Bayesian estimation to ensure the applicability of BN. From this case study we also found some limitations of the proposed method:

(1) The evaluation of PSS design schemes includes multiple aspects, such as evaluation indicators in economic, environmental, and social aspects. This paper chooses LCC as the goal to study the design and evaluation method of PSS-ECs, and the design solution obtained is the cost-optimal solution. In order to evaluate the PSS-ECs design schemes from multiple aspects and obtain a comprehensive optimal solution, it is necessary to integrate the evaluation indicators of environmental and social aspects into the BN-based evaluation model

mentioned in this paper, and analyze the influence of design factors on these evaluation indicators to support the multi-faceted evaluation of the PSS-ECs design schemes.

(2) LCC is affected by many complex and uncertain factors. This paper considers the influence of PSS-ECs on LCC to evaluate the PSS-ECs design schemes, and the influence of other uncertain factors on LCC is indirectly reflected by the conditional probability in BN. In order to estimate LCC more accurately, it is necessary to design or evaluate other factors affecting LCC at the same time when designing PSS-ECs in the future, such as operating conditions, changes in prices, product lifespan, etc., and include these factors in BN, to build a more comprehensive LCC estimation model.

(3) This paper uses MATLAB and NETICA to realize the design and LCC evaluation of PSS-ECs. During the implementation process, we had to switch between the two tools and part of the work requires manual operation. In order to improve efficiency and facilitate the designers' use, an integrated tool can be developed in future to realize the entire process.

6. Conclusion

PSS-ECs design is a critical work in PSS planning. How to design reasonable PSS-ECs schemes, and further evaluate and optimize the schemes is a very challenging task. This paper takes LCC as the design goal and proposes a PSS-ECs design method based on CSP and BN. This method first builds the CSP model and BN based on market requirements, existing R&D data and expert experience; When individual customer requirements are received, CSP is used to solve feasible design schemes that meet customer requirements and constraints, while BN is used to evaluate the LCC of design schemes to select the best scheme; Furthermore, the sensitivity analysis result of BN is used to guide the adjustment of PSS-ECs to form the final design scheme. The core of this research is the modeling of BN, which includes the structure and conditional probability. For the structure of BN, we take PSS-ECs as the root nodes, and decompose LCC into some cost items, and then determine the structure of BN by analyzing the relationships between PSS-ECs and these cost items. For the conditional probability in BN, we use Bayesian estimation and arithmetic average method to estimate the conditional probability reasonably, which comprehensively utilizes existing R&D data and expert experience.

The PSS-ECs design case of a subway bogie and its maintenance service proves the feasibility and effectiveness of the proposed method, and also shows that it has the following benefits: (1) Both R&D data and expert experience can be modeled into the CSP model and BN to realize the consolidation of engineering design knowledge. With the accumulation of R&D data, BN can be updated to ensure its applicability. (2) After individual customer requirements are input, the CSP model can assist the designer to fully explore the design space and ensure the feasibility of design schemes. (3) Based on the CSP model and BN, the optimal design scheme for LCC can be quickly obtained, the proposed method improves the design efficiency and the rationality of design decisions.

Through the above analysis and discussion, we found that the proposed method still has some limitations that need to be further explored and resolved in future work. For example, in addition to LCC, environmental and social evaluation indicators should also be considered in BN to achieve a comprehensive evaluation of the design schemes; many uncertain factors affecting LCC can be considered simultaneously with PSS-ECs for more accurate estimation LCC; and an integrated tool should be developed to support the entire design process.

Declaration of Competing Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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declaration Statement

Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: