A Smart Knowledge Deployment Method for the Conceptual Design of Low-carbon Products

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Abstract

As the consciousness of the global environment and sustainability has increased, low-carbon products have played a vital role in the transformation to a circular economy. Advanced smart design technology has enabled product designers to fulfill customer requirements by offering tailor-made functions and low-carbon solutions. However, although the existing approaches used in the conceptual design process can help in functional reasoning, knowledge modelling, and scheme evaluation, the smart reuse of knowledge, such as in design model improvement and concept scheme iteration for lower carbon emission, the corresponding process evaluation concerning carbon footprint has not been given sufficient attention. To resolve this, in this work, a smart knowledge deployment method is proposed for reasoning, configuring, and optimizing the conceptual scheme (CS) based on carbon emission evaluation and interaction. First, to match discretized knowledge, sub-function requirements after function decomposition are mapped with granular clustered knowledge into a matrix based on a requirement function knowledge deployment (RFKD) model. Second, the derived candidate concept schemes (CCSs) are selected in three steps: conflict-based primaries, configuration, and carbon footprint ranking. Finally, the initial conceptual scheme (ICS) with the lowest carbon emission is used as input for the interactive genetic algorithm (IGA) to better capture a comprehensive set of user feedback on potential candidate schemes through interactions. Accordingly, improvements are completed as intended. The prototype design and an experimental study of a brand-new friction-wear testing machine are conducted. The results suggest that the proposed approach could effectively reduce the carbon emissions of products obtained through CS and improve the convergence of the schemes produced via genetic operation.

Keywords: Smart Knowledge Deployment; Conceptual Design; Low-carbon Products; Interactive Genetic Algorithm

1. Introduction

Excessive carbon emissions have become a global concern in manufacturing (He et al., 2015). Serious environmental problems are caused by carbon emissions generated during the production and use of high-energy-using products (O'Connell and Stutz, 2010). Since the implementation of the Paris Agreement, there has been a dramatic increase in the demand for low-carbon products, and product design with a low-carbon footprint has become a focus in research on industrial manufacturing. Low-carbon product design has been recognized as the most effective way to reduce product carbon emissions at the source (He and Hua, 2017), especially in the conceptual design stage, which includes the development of CS that can meet the user’s low-carbon requirements.

Concept design is based on the construction of a system's functional structure. It is a critical step in generating a conceptual scheme for a product. The solution process, which is innovative, complex and cognitive, includes the analysis of user’s requirements in order to generate product schemes,(Zheng et al., 2018). However, when low-carbon requirements need to be considered, most design frameworks lack sufficient tools to influence the design results based on knowledge. This conceptual design is challenging for two reasons. First, fuzzy design requirements increase the uncertainty of the design results, and the lack of smart knowledge deployment often prevents the CS from matching the design requirements quickly and efficiently. Second, conceptual design, especially of complex products, is typical transdisciplinary, involving multiple and diverse ranges of methods and knowledge (Sobolewski, 2017). Although the efficiency of design knowledge application has improved, no previous study has explored how to derive carbon emission values, retrieve knowledge by stage and type, and combine granular knowledge to include sub-functions in CCSs. Therefore, the conceptual design of low-carbon products has two basic challenges: to match and rank the knowledge required for low-carbon products using a general conceptual design framework based on knowledge deployment; and to configure this knowledge using an interactive optimization method. Specifically, functional requirements (FRs), as manifestations of functional goals, demand a functional knowledge deployment method and a smart method for optimizing CS. A tool based on this theory could help designers reduce design redundancy and conflicts while achieving low-carbon and innovative schemes.

The study is organized as follows. A review of related studies is presented in Section 2. A framework that supports functional schemes for low-carbon products is presented in Section 3, which demonstrates a new iterative design process, and introduces the knowledge assistance method derived from the knowledge deployment and smart optimization solution. Section 4 introduces the framework and describes its steps. The RFKD model and IGA method are also introduced in this section. Section 5 describes the application of the proposed framework and methodology in the design of a friction and wear testing machine. This case study is conducted to clarify meeting the design requirements to the greatest extent, reduce the carbon emission level of products, and shorten the design cycle based on the proposed framework. Finally, the conclusion is presented in Section 6.

2. Related Work

2.1 Overview of Conceptual Design of Low-carbon Products

In the conceptual design, various FRs are realized by choosing the appropriate functional knowledge (FK). FK is the body of knowledge associated with conceptual design functional decoupling. Under the guidance of design methods and processes, a CS that meets FRs is formed through a reasonable combination of FK and design principles (Ma et al., 2017). Among them, the decomposition and analysis of FRs and the establishment of functional structures have been the focus of previous studies in the literature (Pahl and Beitz, 2013). Yuan et al. (2016) established a design framework based on design processes, methods, knowledge, and tools that help designers identify and resolve product requirements and conflicts. FRs was defined as product behaviour, which is the process of transformation that system components perform on input to produce output (Zheng et al., 2019). In considering low-carbon performance, demand was characterized by uncertainties, fuzziness, and hesitancy (Zarte et al., 2019), which challenge the function-solving process.

Several previous studies have been conducted on the conceptual design solving process. Huang et al. (2017) described a process model to realize a theoretical interaction based on the theory of constraints. This method has been commonly used to construct a conceptual design framework based on an iterative process of applying various design methods to improve and optimize it. Fiorineschi et al. (2018) and Kroll (2012) proposed frameworks based on a parameter analysis methodology and functional decomposition and morphology, which they used to solve the problems of functional decomposition, element configuration, and innovative design. However, this type of framework does not consider the formation of CCSs. The “black box” process has often been criticized concerning whether it could meet FRs in the completed design, which would inevitably increase design time and modification costs.

Research worldwide has been committed to developing an increasing number of green products. Chu et al. (2009) used the genetic algorithm (GA) technique to produce an optimal product structure from the conceptual design alternatives generated by the approach. Smith and Yen (2010) presented a method based on atomic theory to solve design modularization problems in conceptual design. This method can be used to modularize products based on given green constraints. Bai et al. (2020) developed a BioTRIZ multi-contradiction resolution method targeting a conceptual design, finding the crucial contradictions and achieving the necessary inventive principles. Ren et al. (2017) provided a novel model for accelerating the preliminary low-carbon design by integrating the Theory of Inventive Problem Solving (TRIZ) and extension methods. Ai et al. (2020) proposed an improvement conceptual design strategy from the perspectives of technical systems and human usage to help establish a low-carbon function structure. These previous solutions have been proven effective although their applications are independent, and they need to be integrated within a suitable logical framework. Because information about the product is uncertain in the conceptual design stage, it is often difficult to assess its carbon emissions. Some methods used to calculate the carbon footprint, which supports other stages in product design, can be used as references in the conceptual design stage. For example, Peng et al. (2019) proposed a design method based on a qualitative/semi-quantitative carbon footprint calculation of low-carbon products. He (2017) and Zhang et al. (2018) integrated material selection, lightweight technology, and carbon footprint calculation to reduce carbon emission. The conceptual design of low-carbon products is a complex system decision-making process involving multi-disciplinary and multi-domain knowledge, and the applicability of these methods in the conceptual design stage needs further demonstration.

2.2 Knowledge-based Reasoning in Conceptual Design

Knowledge-based reasoning in conceptual design matches and operates data by using knowledge-based rules and deriving conclusions by applying certain reasoning methods. Several previous studies have been conducted on knowledge-based reasoning in conceptual design. Yu et al. (2020) decomposed a model into a series of memory-based reasoning steps using a control module(GRUC) that conducts parallel reasoning in both visual and semantic information. Han et al. (2019) constructed an assertive reasoning selection methodology by improving acquisition in the balance coefficient in the C4.5 algorithm. A two-level model selection method, based on a top model construction process and an underlying model selection process, was proposed through hierarchical representation. Malak Jr et al. (2009) proposed a set-based approach to concept design, which enabled the systematic arrival at a solution, despite imprecise characterizations of design concepts. These previous studies were based on the knowledge source of ontology and provided designers with the relevant knowledge needed to construct the model. However, in different frameworks, the method of constructing the ontology varies, especially in low-carbon products. In addition to matching FRs, the carbon footprint levels, according to the current knowledge, need to be considered.

If some knowledge were connected to the sub-functions of decomposition, it would help to obtain further insights into the conceptual design stage. In this study, we define this kind of knowledge as granular functional knowledge. Granular knowledge is the genuine generalization of information or knowledge (Pedrycz and Song, 2012). Hence, granular knowledge offers a way of quantifying a diversity of knowledge sources for use in low-carbon conceptual design and expressing them in the form of granularity (i.e., specificity). It can also be considered the basic elements of the CS of low carbon products. The concept-knowledge theory (C-K) proposed by Hatchuel and Weil (2008) the traditional methodology used to describe the design thinking process. It has had a significant influence in guiding the study of knowledge flow in the solution process used to design low-carbon products. When a low-carbon footprint became a design requirement, configuring and sorting scattered FK was challenging. Although some researchers, such as Yusr et al. (2017) and Breznik (2018), have highlighted the importance of knowledge management with respect to general innovation and product design, little attention has been paid to the role of knowledge reuse and its transfer from low-carbon design to embodiment design.

Some previous studies promoted the development of knowledge reasoning in conceptual design. For example, He and Hua (2017) proposed a low-carbon conceptual design catalogue based on a carbon footprint representation method. Zhang et al. (2020) proposed a smart knowledge application method based on a design matrix throughout the product life cycle. They discussed the model selection and reasoning process in the preliminary theoretical analysis stage. Therefore, further research is required to explore the knowledge reasoning process and mapping method in the conceptual stage of designing low-carbon products.

2.3 Functional Solution and Intelligent Optimization

Previous studies have proposed a design methodology that contributes to requirements analysis, functional decomposition, concept solving and evaluation decision-making in the conceptual design process (Li et al., 2010). Umeda et al. (1990) defined product function as a description of behaviour abstracted by a human through recognition of the behaviour required to utilize the behaviour, Yuan et al. (2016) proposed a hybrid approach based on qualitative processing reasoning, and a formal interpretation of the integration logic between axiomatic design (AD) and the design structure matrix (DSM) to automate the process of functional decomposition, respectively. These methods have provided an effective logical decomposition strategy for FRs. However, mapping and combining the decomposed sub-functions and knowledge quickly and optimally requires further research. Methods for solving the scheme have been proposed in several previous studies. Jenab et al. (2013) proposed a multi-layer graph model based on decision criteria. Klashner and Sabet (2007) reported a decision support system

(DSS) design model for mission-critical situations. These methods find directions for solving obvious design conflicts, but specific problem-solving strategies are often very different. At present, case knowledge is vital. The TRIZ has been proven effective, and it has been widely used in the conceptual design of industrial equipment and customized products (Guo et al., 2016; Guo et al., 2021; Li et al., 2018). Scheme evaluation and decision-making are important in judging the degree of consistency between FRs and CSs. Sabaghi et al. (2016) introduced a fuzzy-inference system to evaluate product/process sustainability based on a morphological matrix of design objectives, customer requirements, and functional constraints. The Analytic Hierarchy Process (AHP) is a qualitative and quantitative decision method (Saaty and Hu, 1998) used to support conceptual design. These methods are relatively independent and are used mainly in the final stage of conceptual design; moreover, they lack support for the design process. Hence, it is necessary to integrate evaluation methods while constructing an iterative design process.

Low cost, high quality, personalization, and timeliness have gradually become themes of corporate competition. Shortening the design cycle is conducive to improving product competitiveness. The current product configuration of design methods includes methods based on structure, model, constraint, rule, extension, ontology, and cases (Zeng et al., 2007). Johnson and Kirchain (2009) proposed a process-based product family cost model to evaluate the economic benefits of sharing product raw materials and components. Liu (2010) and Yang (2012) introduced the application of the constraint satisfaction problem (CSP) and a fuzzy multi-objective optimization algorithm in configuration optimization design, respectively. The methodology of configuration design has been proven to reduce design time effectively. However, the configuration of structures and materials is based on CSs in the detailed design stage. In the conceptual design stage, we need to learn from the idea of configuration design and extend the FK combination plan to realize FRs for the designer. In this process, the coordination of FK and FRs is a key issue.

In new product development and decision-making, collaborative design needs effective support for product innovation through the combination of collaborative work and advanced manufacturing technology. Previous studies have shown that IGA can be useful in assisting in collaborative design (Dou et al., 2016). IGA is a method of optimization and evolution that treats a human's subjective evaluation as individual fitness. IGA typically integrates human intelligence and obtains individual fitness designated by users based on their preferences. In this method, evaluation data are integrated into the genetic algorithm by replacing the objective function of optimization and participating in the evolutionary process. This method differs from traditional GA in three points:1) the participation of humans; 2) the fitness value of IGA can be given by the user directly, instead of being obtained by function solution; 3) the objective function of IGA can be both explicit and implicit. Previous studies have generated and optimized conceptual design schemes through random combination and genetic operation. If the input value were standardized as ICS, it would help produce a CS that was more consistent with FRs, reduce carbon emissions, and improve design efficiency.

2.4 A Brief Summary

Although the conceptual design of products has advanced recently, determining ways to design a low-carbon conceptual design product structure to accommodate more FRs remains challenging. Several factors have hindered its development and adoption:

1. In an unstructured conceptual design process of the low-carbon product, each stage is uncertain, especially when the FRs are complex. Both the designer and the user need targeted

knowledge and intelligent function solutions. It is necessary to build a connection, that helps to realize knowledge reuse between FRs and case knowledge characteristics to guide design activities through knowledge and its inherent originality.

2. Based on knowledge representation and clustering research, granular knowledge needs to be configured based on green factors and FRs and then sorted by carbon emission to help designers broaden their design ideas.

3. Traditional ontology-based knowledge retrieval usually only meets specific FR. Therefore, it is necessary to integrate and optimize sub-function-oriented discrete knowledge through the application of intelligent methods that provide designers with strong overall CCSs for selection.

Although some previous studies have investigated the effects of design knowledge on the conceptual design of low-carbon products, low intelligence and non-staged operations still challenge design activities. Thus, a smart knowledge deployment method for the conceptual design of low-carbon products based on an interactive optimization method is needed to solve these challenges.

3. Supporting Functional Solution: A Framework Based on RFKD and IGA

The focus of the present study is to propose a generic framework to support the conceptual design of low-carbon products, which includes four parts, as shown in Figure 1. This executable and iterative conceptual design process begins with both user and low-carbon requirements and ends with the development of conceptual schemes. A requirement function knowledge deployment (RFKD) model is proposed, which provides granular FK in response to sub-FRs after functional decomposition. A carbon emission model is used to organize the deployed granular knowledge based on green attributes and then to generate CCSs. an interactive optimization method is based on the IGA model, which optimizes the CS through interactions and genetic operations based on ICS.

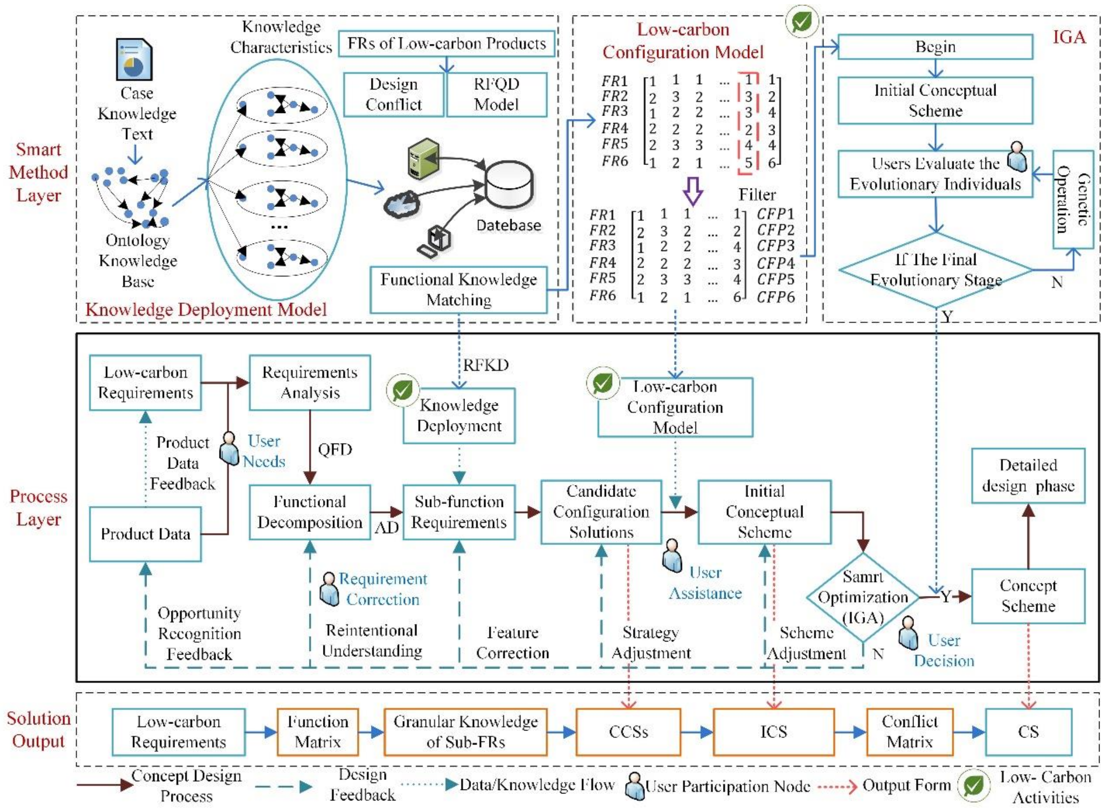

Figure 1. The framework supporting the smart conceptual design of low-carbon products

An iterative process for the conceptual design is developed constructed to enhance function solution ability and reduce uncertain judgments caused by a lack of knowledge. A knowledge reasoning model (RFKD) and a conceptual scheme optimization method (IGA) are two key steps in the development of the conceptual design of low-carbon products. The methodological framework comprises low-carbon requirements analysis, functional decomposition, sub-function solving, CCSs generations, low-carbon ranking, and scheme optimization. The design attributes are revised and improved in stages through evaluation and feedback methods, including opportunity recognition, knowledge retention, feature correction, strategy adjustment, and scheme adjustment. Smart knowledge deployment is divided into two parts: granular knowledge deployment and concept scheme optimization and reorganization. Granular FK is configured and deployed based on various sub- FRs to broaden the design horizon. Sorting and reorganizing this knowledge by low-carbon evaluation effectively ensures that the CS is designed with low carbon emission values. The IGA combines user preferences and product FRs based on subjective human evaluations and then, optimizes, and generates a CS based on ICS. This process removes environmentally harmful knowledge through RFKD and combines the optimal CS through carbon emission evaluation, which are the two main means to meet low-carbon requirements.

4. Methodology

4.1 The Conceptual Design Process of Low-carbon Products Based on Smart Knowledge Deployment Method

The conceptual design process begins by analyzing FRs. In this process, a satisfactory conceptual solution from user requirements is derived and green demand is met based on design methods and knowledge. By implementing the requirement analysis and functional decomposition, the requirement set R is expanded and integrated into a functional requirement set FR, and the knowledge set FK is mapped to FR through the function set F based on RFKD. The CCSs set and ICS are obtained through the evaluation and combination of a low-carbon configuration model, followed by the iterative generation of CS through user feedback and a genetic algorithm:

$$CS = F(R \rightarrow FR \rightarrow \mathrm{FK}) \rightarrow \mathrm{CCSs} \rightarrow \mathrm{ICS} \tag{1}$$

Where R is derived from various requirement clues r_i, which can be converted to FR based on quality function deployment (QFD). AD decomposes FR into conceptual design sub-functions $f(i,j)$, where i represents the ordinal number of the sub-function and j is the sequence number of the sub-function i. This process can be expressed as follows:

$$\forall f_i, f(i,j) = FR(r_i \rightarrow f) \tag{2}$$

If FK represents the functional element base, CCSs can be expressed as:

$$\forall f(i,j), \exists \mathrm{FK}, \overline{CCS'} = \psi(f(i,j), \mathrm{FK}) \tag{3}$$

where $\overline{CCS'}$ is configured by FK representing different FRs. ψ stands for the configuration method of low-carbon FK. To judge whether FK meets FRs, feasibility for describing $\overline{CCS}$ is proposed as follows:

$$\emptyset\big(FR, f(i,j)\big) = \sum_{i=1}^{n} \sigma\big(\mathrm{verb}_i, \mathrm{verb}'_i\big)\sigma'\big(\mathrm{noun}_i, \mathrm{noun}'_i\big) \tag{4}$$

where σ and σ' are the degrees of relevance between f and the verbs and nouns of FK_i. If $\emptyset\big(FR, f(i,j)\big)$ is greater than the threshold Φ, the principal solution can be considered by the designer to meet the FRs. If $I = (\mathrm{I}_1, \mathrm{I}_2, \dots, \mathrm{I}_n)$ represents the evaluation index set, its corresponding index weight set is $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_n)$, and the correlation function of the conceptual scheme performance index is $T = (T_1, T_2, \dots, T_n)$. Then the degree of satisfaction $C(CS)$ with the CS is expressed as follows:

$$C(CS) = \sum_{i=1}^{m} \alpha_j T_{ij} I_j \quad (j = 1,2, \dots, n) \tag{5}$$

The most satisfactory design scheme is chosen as the best CS, and the process data are recorded in the knowledge base. If the evaluation result does not meet the FRs after being iterated and optimized, the designer should determine whether the functional requirements are accurate.

4.2 An RFKD Model for the Conceptual Design of Low-carbon Products

In designing and analyzing complex systems, it is necessary to decompose FRs using a logical tool. Based on the review of the relevant literature, the investigators considered that AD is an effective traditional tool. The underlying hypothesis of AD is that the existing fundamental principles govern good design practice (Tang et al., 2009). It avoids the traditional “design-build-test-redesign” cycle. Customer attributes (CAs), FRs, design parameters (DPs) and process variants (PVs) are used to describe the entire design world. The “Z” mapping between the CAs and FRs domains provides a top-down functional decomposition process. The functional requirement analysis involves the mapping from the user domain to the functional domain. The FRs are decomposed level-by-level to form a hierarchical topological structure, which helps realize knowledge mapping. A QFD-based method and a similarity calculation method are used in the RFKD model to realize mapping from low-carbon requirements to FRs and mapping from FRs to functional knowledge, as shown in Figure 2.

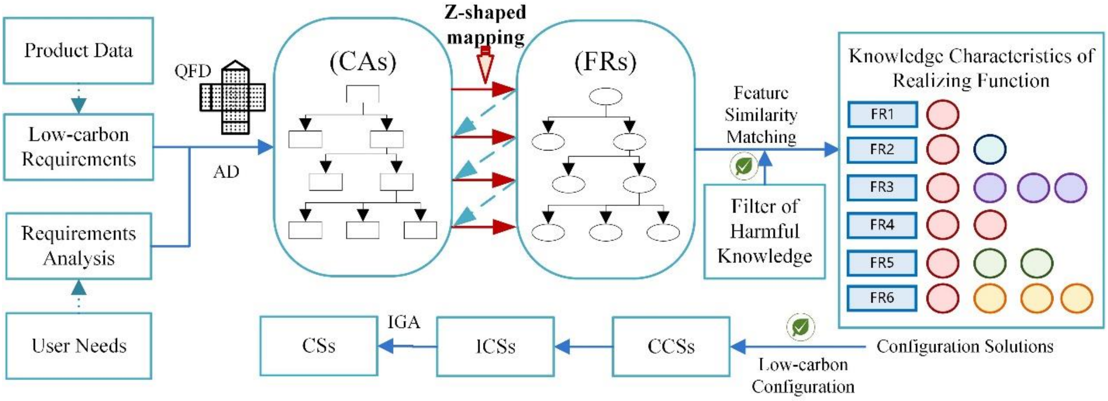

Figure 2. An RFKD model for designing low-carbon products

FK is a class of discretized clustering knowledge that is used to map sub-FRs. In this study, the author established a knowledge clustering model of RFKD based on the Constrained Functional Knowledge Model (CFKM) (Hu et al., 2012). The model was organized by function and structure, as follows:

$$FK_i = f(i,j) \oplus S_i(i \in N) \tag{6}$$

where S_i represents the structural knowledge required to realize function $f(i,j)$. The expression of this function adopts the method of semantic constraint (C_f) and single-function predicate. Semantic constraints are supplementary descriptions of the scope, object or mode of action of a functional predicate. The structure is represented by nouns and their constraints (C_S). After decomposition based on axiom design, the functions are independent, and FK and the constrained functional knowledge model (C_{FK}) have the following relationship:

$$\begin{cases} FK_1 \cap FK_2 \cap \ldots \cap FK_n = \emptyset \\ FK_1 \cup FK_2 \cup \ldots \cup FK_n = \sum FK \\ C_{Fk} = f_i\{\exists C_f\} \oplus S_j\{\exists C_S\} \ (i,j \in N) \end{cases} \tag{7}$$

Based on the authors' previous research, the model realized knowledge reasoning through the similarity comparison method (Guo et al., 2016; Guo et al., 2017; Li et al., 2018). If M represents the similarity between f(i,j) and FK, then

$$Sim(f(i,j),FK) = \frac{p}{m+n+p}\sum_{i=1}^{p}\left(\omega_i \times S(f,FK_i)\right) \tag{8}$$

where m and n, respectively represent the number of sub-functions and knowledge, p represents the number of sub-functions used in the similarity calculation, ω_i represents the weight of the i-th sub-functions, and $\sum_{i=1}^{n}\omega_i = 1$. $S\left(f,FK_{(i,j)}\right)$ represents the similarity between the knowledge and the (i, j)-th sub-function to be matched and $S\left(f,FK_{(i,j)}\right) \in [0,1]$, which is calculated by cosine similarity (Zhu et al., 2011). Variable-length encoding was adopted in the proposed RFKD. In the conceptual design of low-carbon products, its four parts were respectively encoded using binary code, and they were stored in the general conceptual design database after decoding. The coding format included a feature category code, a feature principle code, a feature degree code, and a green identification bit, such as $\{11010|1001011010|1010111010|00\}$. Based on the classic coding method, the green identification bit was defined in the coding format to increase the priority of green FK; 11, 01, and 00 were defined as knowledge that is beneficial to the environment, neutral or harmful to the environment, respectively. If the code for (a,b)-th knowledge $FK_{(a,b)}$ is $v_{FK_{(a,b)}}$, and its green identification bit $B_{FK_{(a,b)}}$ was set to 00, the code of a certain sub-function f(a,b) was $v_{\mathrm{f(a,b)}}$, and the green identification bit was indicated by $B_{\mathrm{f(a,b)}}$. Then the similarity calculation formula of the two was as follows:

$$Sim\left(\mathrm{f(a,b)},FK_{(a,b)}\right) = \frac{\sum_{a=1,b=1}^{n}\left(v_{\mathrm{f(a,b)}} \times v_{FK_{(a,b)}}\right)}{\sqrt{\sum_{a=1,b=1}^{n}\left(v_{\mathrm{f(a,b)}}\right)^2} \times \sqrt{\sum_{a=1,b=1}^{n}\left(v_{FK_{(a,b)}}\right)^2}}$$

$$\text{s.t. } B_{FK_{(a,b)}} \vee B_{\mathrm{f(a,b)}} \neq 0; a = 1,2,\dots,n; b = 1,2,\dots,n, \tag{9}$$

The restriction given to the model by the author was as follows. If the logical OR operation of the green identification bits between the knowledge and the sub-function was 0, it indicated that the knowledge would harm the environment, and it was not pushed. For example, it was reported that a sulphur-based extreme pressure additive might induce less serious effects on environments, such as health, disposal, air, and soil pollution compared with pressure additives contained in, for example, antimony, iodine, or chlorine (Kuram et al., 2013). Therefore, the green identification bit of the semi-synthetic cutting fluid ($FK_{(41,1)}$) and antimony-synthetic cutting fluid ($FK_{(41,2)}$) were 11 and 00. If the green identification bit of $f_{(4,1)}$ was 11, according to Equation 9, s.t. $B_{FK_{(41,2)}} \wedge B_{f_{(4,1)}} = 0$, $FK_{(41,2)}$ did not meet the constraint conditions and were not be pushed. $FK_{(41,1)}$ similarity matching was successful, and the output was an alternative solution.

4.3 Low-carbon Configuration Model

The low-carbon conceptual design sub-function includes main functions and secondary functions. For any $f(i,j)$, one or more FK will match, which may lead to multiple CCSs. If the p-th FK corresponding to the m-th FR was $FK_m(p)$, the author defined the decision variables of FK in conceptual design $x_p^{m(n)}$ as follows:

$$x_p^{m(n)} = \begin{cases} 1 & \begin{matrix} If\ FK_m(p) is\ used\ to\ configure \\ the\ n\text{-}th\ conceptual\ scheme \end{matrix} \\ 0 & If\ not \end{cases} \quad (p = 1,2,\dots,P; m = 1,2,\dots,M) \tag{10}$$

The FK expressed by clustering met the FRs, but the selection of the best design elements for each $f(i,j,k)$ and realize their configuration and display required a key technology. For the conceptual design of low-carbon products, the author proposed a low-carbon configuration model based on carbon emission levels and constraints.

PAS2050, which was issued by the British Standards Institute (BSI), is a method used for quantifying the carbon footprint of goods and services based on LCA evaluation (BSI, 2008). The carbon footprint (CFP) source in the life cycle can be divided into five stages: raw material acquisition, manufacturing and assembly, distribution, use, and the end of the life cycle. If CFP_{Raw}, CFP_{Manuf}, CFP_{Dist}, CFP_{Use}, and CFP_{Eol} respectively represent this carbon footprint levels of these five stages, CFP is expressed based on PAS2050 as follows:

$$CFP = CFP_{Raw} + CFP_{Manuf} + CFP_{Del} + CFP_{Use} + CFP_{Eol} \tag{11}$$

The CPF at each stage can be calculated as shown in Table 1 (Ren et al., 2017; Wang et al., 2016).

Table 1 Carbon Footprint Quantitative Model of $FK_{(i,j)}$ and Abbreviations List

$CFP_{Raw} = \sum_{r=1}^{s} Em_r + \sum_{j=1}^{m} EAD_j^{Manuf} + CFP_{Raw_{Dist}}$ *	(12)
**Em_r is the CFP of the r-th material, s is the number of materials, EAD_j^{Manuf} is the CFP of the jth operation of the blank manufacturing process, m is the number of operations, $CFP_{Raw_{Dist}}$ is the CFP by the transportation of materials and blanks.*	
$CFP_{Manuf} = \sum_{j=1}^{m_1} EAD_j^{Mach} + \sum_{j=1}^{m_2} EAD_j^{Assem} + \sum_{k=1}^{p} ES_k$ **	(13)
***EAD_j^{Mach} is the CFP of the j-th operation during the processing, m_1 is the number of operations. EAD_j^{Assem} is the CFP of the j-th operation in the assembly process, m_2 is the number of operations. ES_k is the CFP when the equipment consumes the k-th energy.*	
$CFP_{Dist} = \sum_{t=1}^{z} ED_t + \sum_{k=1}^{p} ES_k$ ***	(14)
****** ED_t is the CFP of the t-th distribution method during transportation. ES_k is the CFP produced when the k-th energy is consumed in the storage process. p is the amount of energy.*	
$CFP_{Use} = \sum_{k=1}^{p_1} ES_k^{Use} + \sum_{j=1}^{m} EAD_j^{Maint} + \sum_{k=1}^{p_2} ES_k^{Auxi}$ ****	(15)
***** ES_k^{Use} is the CFP when the k-th energy is consumed during use, and p_1 is the number of energy consumed. EAD_j^{Maint} is the CFP of the j-th operation in the maintenance process. ES_k^{Auxi}a is the CFP of the k-th energy consumed by infrastructure and equipment.*	

$$CFP_{Eol} = \sum_{j=1}^{m_1} EAD_j^{Dassem} + \sum_{j=1}^{m_2} EAD_j^{Remanf} + \sum_{k=1}^{s}(1-\varphi_r)Em_r^{Recy} \quad {}^{**}_{***} \tag{16}$$

${}^{**}_{***}$ *EAD_j^{Dassem} is the CFP of the jth operation during the disassembly process. EAD_j^{Remanf} is the CFP of the j-th operation during the remanufacturing process. Em_r^{Recy} is the CFP of the r-th material recovery, φ_r is the reusability rate of the r-th material.*

Some conceptual design constraints also need to be considered, such as performance level constraints, compatibility constraints, and so on (Wang et al., 2018). If any FR has an initial scheme, the newly recommended FK should have a better performance level. The FKs in the knowledge base were based on past product design cases, network data or other design resources. If $P_{j(k)}$ is the performance level of the $FK_{(i,j)}$ configured by the j-th FR, then $P_{\mathrm{j(initial)}}$ is the performance level of the corresponding element in the initial scheme, as follows:

$$P_{j(k)} \geq P_{j(initial)} \tag{17}$$

There may be a mismatch between different FKs. It is necessary to ensure the feasibility of the FK configuration scheme through compatibility constraints. A triangular symmetric matrix [COMP] can be used to express the compatibility between FKs, as follows:

$$[COMP] = \begin{bmatrix} C_{11} & \cdots & C_{1j} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & C_{ij} \end{bmatrix}, C_{ij} = \begin{cases} 1 \; if\ FE_i\ and\ FE_j\ are\ compatible \\ 0 \qquad\qquad if\ not \end{cases} \tag{18}$$

Based on the above analysis, a low-carbon configuration model was constructed:

$$\begin{cases} \text{Object: } \alpha = \min \text{CFP} \ \ (Table\ 1) \\ \quad \text{Subject } \beta\text{: } \ (Eq.17{,}18) \end{cases} \tag{19}$$

To implement the low-carbon configuration of the FK obtained by the RFKD model, the following three steps were completed: 1) filtering, 2) configuration and 3) carbon footprint ranking. Based on the exhaustive method, a set of CCSs was established, which would allow designers to stimulate design thinking and input their ideas into the IGA model for further concept scheme optimization. A schematic case is shown in Figure 3.

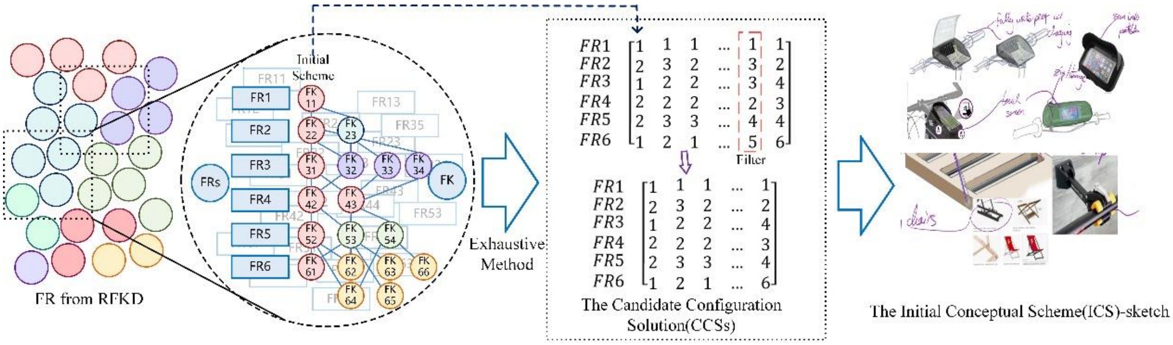

Figure 3. Example of generation and filtering of low-carbon configuration sets

4.4 IGA Method for Concept Scheme Optimization

Based on the above model, the configured and sorted CCSs showed various carbon emission levels while meeting product FRs. The configuration schemes selected by the designer could be intelligently integrated and optimized through IGA. Finally, an ICS was generated for users and designers to evaluate. IGA assigned fitness to randomly generated programs based on users' and designers' subjective evaluations. In the iteration of the evolution process, users and designers would be closer to achieving the ideal solution. The deviation between the evaluation fitness and the true fitness then will become smaller.

Based on previous research such as Dou et al. (2016), an IGA method for concept scheme optimization, which compares similarities in human recognition and design schemes, was proposed and used to generate CS.

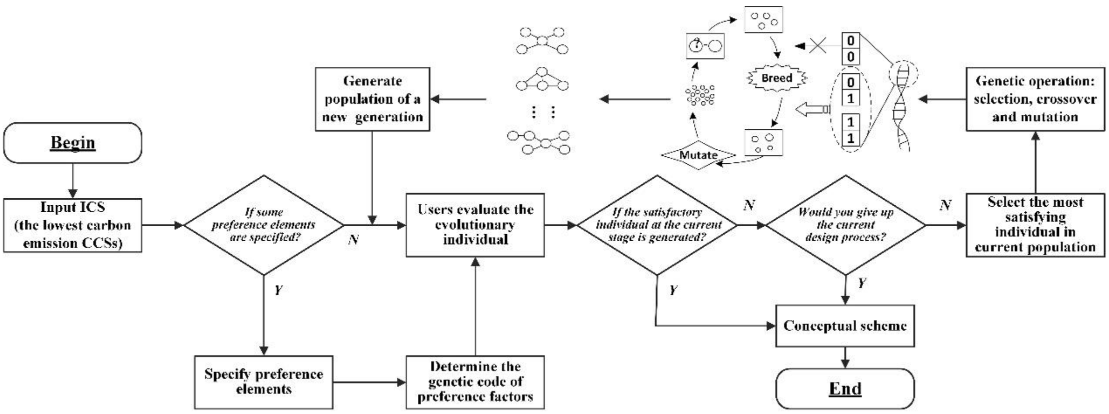

Figure 4. The process of the IGA method for *concept scheme* optimization

This method includes the following steps: 1) the top-ranked CCSs (ICS) were prioritized the input value for generating the conceptual scheme; 2) before the random population is generated, if the user or designer has a clear preference for certain design elements, the relevant gene types are locked to accelerate the convergence of the algorithm; 3) randomly generate the ICS population; 4) the user or designer evaluates the fitness of the generated scheme and calculates the awareness of the evaluation process, and if the awareness is not enough, then it is assigned the average fitness value of a highly similar case; 5) if a satisfactory solution has been generated or the end condition is met, the current better scheme is the output; otherwise, genetic selection, crossover and mutation operations are performed to generate a new population; 6) repeat steps 4 and 5 until the ideal scheme CS is the output.

Among them, the fitness of the i-th scheme for the t-th generation $CS_i(t)$ can be represented by $C_i(t)$, as follows:

$$C_i(t) = \left\{\mu \times \frac{\sum_{j=1}^{n_t} ReLU(T_i(t) - T_j(t))}{n_t} + \tau \times T_i(t) \times \left(\frac{T_i(t) - \overline{T(t)}}{\overline{T(t)}}\right)\right\}^{-1} \tag{20}$$

$$ReLU = \begin{cases} 0, x \le 0 \\ x, x > 0 \end{cases} \tag{21}$$

where n_t is the number of the t-th generation population, $T_i(t)$ represents the evaluation time of the user or the designer about the i-th scheme of the t-th generation and $T_j(t)$ is the evaluation time of the j-th scheme of the t-th generation. The function $ReLU\left(T_i(t) - T_j(t)\right)$ plays a filtering role. $\overline{T(t)}$ represents the average evaluation time of the t-th generation population. If the values of $T_i(t)$ and $T_i(t) - T_j(t)$ are smaller, the evaluator's awareness of the CS will be better, and its fitness value is higher; μ and τ are two weight values, which need to be set in advance. When the fitness value $C_i(t)$ is greater than the default value C_0, the awareness of the user or the designer can be considered sufficient, and the evaluation is credible. Otherwise, the evaluator has an incomplete and unclear understanding of the design scheme, and the evaluation results are prone to deviation.

Based on the similarity matching method, the IGA model assigns the average fitness value of high-similarity schemes to schemes with deviations in order to adjust the unreasonable scheme scores. In the IGA model, each generation of CS is composed of the FK corresponding to the sub-FR modules, and the gene fragments of each sub-function constitute the gene code of the overall scheme. The model calculates gene similarity between two different schemes based on the cosine similarity algorithm. For any individual $CS_i(t)$, if the gene code is represented by $g_i(t)$, and the evaluated individual gene code can be represented by g_j, then the similarity of the two schemes $S_i\left(g_i(t), g_j\right)$ can be shown as follows:

$$S_i\left(g_i(t), g_j\right) = \frac{\sum_{i=1}^{n}\left(g_i(t) \times g_j\right)}{\sqrt{\sum_{i=1}^{n}\left(g_i(t)\right)^2} \times \sqrt{\sum_{i=1}^{n}\left(g_j\right)^2}} \tag{22}$$

When this similarity is greater than the similarity critical value S_0, the scheme is put into the CS set. Through similarity calculation, a set of schemes similar to the individual deviation genes can be obtained, If the user or designer evaluates the fitness value of the scheme $CS_i(t)$

as $f\left(CS_i(t)\right)$, then the average fitness value $\bar{f}(CS)$ of the scheme evaluation in the set can be obtained. By assigning an approximate average fitness value to the deviation scheme, the evaluation deviation caused by insufficient awareness can be reduced.

5. Case Study

5.1 Introduction

The friction and wear testing machine is commonly used to verify the wear performance of materials. It is widely used in the study of the wear performance of metallic materials, non-metallic materials, and various coatings. Under a certain contact pressure, the testing machine can simulate rolling, sliding or sliding-rolling compound motions. It has a variety of friction pairs and can complete point, line and surface friction simulation tests. It can be used to evaluate the friction and wear performance of lubricants, metals, plastics, coatings, rubber, ceramics and other materials. Currently, the amount of lubricant used in the machine is considerable. In a previous study, Meier and Shi (2012) reduced the fluid consumption in traditional equipment by 0.6 L/min, and the average carbon emission was cut by 0.96 $kgCO_2$/min. The life cycle of this testing equipment is characterized by high energy consumption and high carbon emissions. Therefore, environmental pollution must be reduced by developing new conceptual design methods that meet design requirements. In using a conceptual design as a case study, the authors aimed to design a new conceptual scheme for a low-carbon friction-wear testing machine that meets functional needs and low-carbon requirements based on the proposed model and methodology. The basic user requirements of the machine are shown in Table 2.

Table 2 User Requirements of Friction and Wear Machine

Spindle speed range	Main motor output maximum torque	Maximum test force	Friction torque measurement range	Operating temperature	Friction arm distance
r/min	N·m	N	N·mm	℃	mm
1-2000	5	1000	0-2500	-10~60	50

5.2 Knowledge Retrieval Based on RFKD

To achieve the requirements shown in Table 2, it was necessary to conduct a requirements analysis and functional decomposition of the friction and wear machine through QFD and AD. As shown in Table 3, user needs were decomposed into four functional requirements (f_1-f_4). Among them, the author used f_4 as an example to perform a secondary decomposition ($f_{(4,1)}$-$f_{(4,6)}$).

Table 3 Function Decomposition and Design Matrix Judgement

Requirements	FRs	Description	Design matrix of FRs
Ability to supply electricity	f_1	Power supply system	$\begin{vmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{vmatrix}$
Ability to control friction/temperature	f_2	Control system	
Ability to drive the test metal block	f_3	Drive system	
Ability to realize friction and wear	f_4	Friction and wear system	Lower triangular matrix
Sub-Requirements description	**Sub-FRs**	**Sub-FRs description**	**Design matrix of $f_{(4,j)}$**
Ability to lubricate and cool	$f_{(4,1)}$	Lubrication and cooling	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Ability to spray lubricating fluid	$f_{(4,2)}$	Lubricant spray	
Ability to open and close pipelines	$f_{(4,3)}$	Open and close the pipeline	
Ability to rotate and rub	$f_{(4,4)}$	Rotating friction	
Ability to monitor friction	$f_{(4,5)}$	Friction monitoring	
Ability to raise temperature & pressure	$f_{(4,6)}$	Temperature / pressure rise	Diagonal matrix

The design matrices on various levels are lower triangular or diagonal matrices that satisfy the axiom of independence. These decomposed sub-functions were decoupled through the RFKD model. The tested material is usually difficult and requires high cutting force and high tool wear. These adverse effects need to be eliminated by the cutting fluid. Figure 5 shows a knowledge push system based on the RFKD model, which realizes mapping and pushing between the decomposed sub-FRs and FK. Using the friction and wear module as an example, the binary coding rules are shown in the figure.

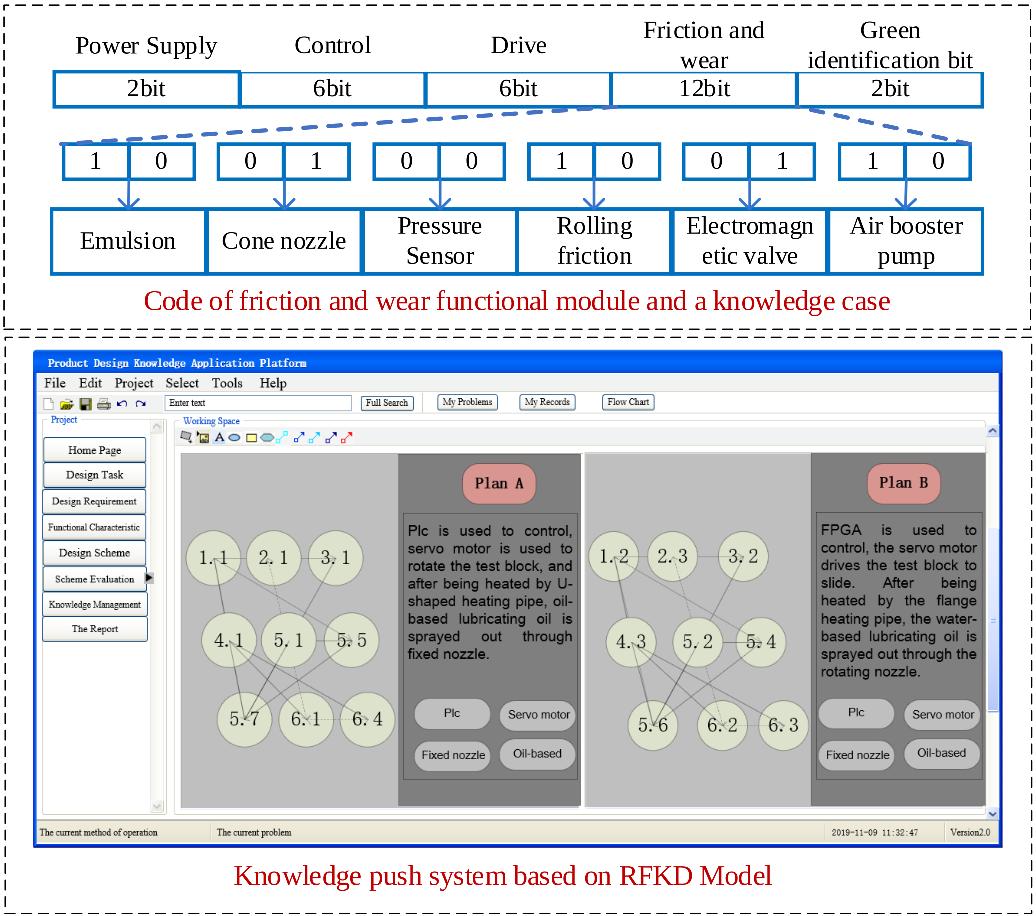

Figure 5. Functional requirement coding method and knowledge push interface

Based on the RFKD model, all sub-FRs and FK were matched and filtered through a similarity algorithm. For example, six sub-FRs of f_4 were mapped to the corresponding FK via the knowledge base system. For example, the temperature/pressure rise function $f_{(4,6)}$ was further broken down into two sub-functions: heating and pressurization. The related $FK_{(4,6)}$ set composition is shown in Figure 6. First, the top-ranked granular knowledge was obtained through similarity calculation. Secondly, the knowledge that was obviously harmful to the environment was filtered based on the green identification bit.

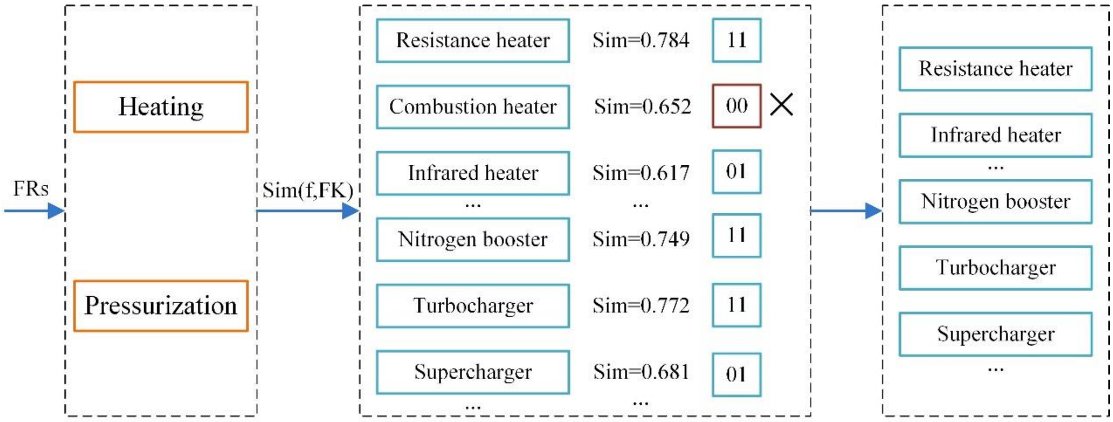

Figure 6. Example of the knowledge reasoning method based on RFKD

5.3 Low-carbon Configuration

The feasible granular knowledge of each sub-function requirement was firstly determined. Using an exhaustive algorithm and carbon footprint evaluation, the candidate configuration scheme was set, and the optimal candidate configuration was then obtained. In the example of f_4, as shown in Figure 7, the first column of $CSS_{(4)}$ set indicates that granular knowledge $FK_{(4,1,1)}$, $FK_{(4,2.1)}$, $FK_{(4,3.1)}$, $FK_{(4,4.1)}$, $FK_{(4,5.1)}$ was selected for $CSS_{(4.1)}$. By deploying a similar method, a set of candidate configuration schemes for other FRs was obtained. Assuming an obvious conflict between $FK_{(4,1,2)}$ and $FK_{(4,3,3)}$, the designer could eliminate these infeasible CSSs and obtain a new set of feasible CSSs.

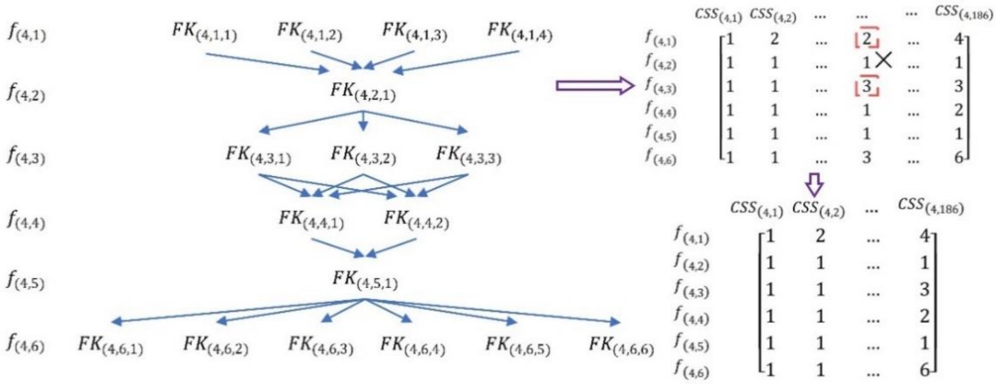

Figure 7. Knowledge configuration and filtering of f_4

After all CSS sets were obtained, these plans were calculated individually based on the low-carbon configuration model and then sorted according to the carbon emission value of each set of CSS. According to the CFP calculation procedure in PAS2050, each CCS was defined as a functional unit for calculating CFP, and the total CFP of all parts in each knowledge was calculated separately. As in the example of $CCS_{(4,22)}$, the material properties, quality parameters and main processing methods of each part are shown in Table 4.

Table 4 A list of CFP calculation parameters for the $CCS_{(4,22)}$ of lubricant spray ($f_{4.2}$)

Number	Name	Material properties	processing methods	Quality/kg
2	Pump body	Carbon steel	Casting, Milling, Drilling	87.74
4	Suction and exhaust disc	Aluminum alloy	Casting, Milling, Drilling	7.056
16	Impeller	Aluminum alloy	Casting, Milling, Drilling	50.254
53	Pump cover	Carbon steel	Casting, Milling, Drilling	203.542
36	Unicom pipeline	Carbon steel	Casting, Milling, Drilling	29.324
…	…	…	…	…

As shown in Table 1, the carbon footprint level of each component during the life cycle was calculated. In the example of the CFP_{Eol} of $CCS_{(4,22)}$ shown in Table 5, parts were reused through remanufacturing including the pump cover, the pump body, and the front and rear bearing housing glands.

Table 5 The $CFP_{Eol(4.22)}$ of the $CCS_{(4,22)}$ at the end of its life cycle

Num	Stage	AD_{jk}	EF_k	CFP_{Eol}
		kWh	$kgCO_2/kwh$	$kgCO_2$
Eol_1	Disassemble	2	0.627	1.254
Eol_2	Remanufacturing	12	0.789	9.468
Num	Stage	AD_{jk}	EF_k	CFP_{Eol}
		kg	$kgCO_2e/t$	$kgCO_2e$
Eol_3	Recycle	421.295	3.581	5.849
Total				16.571

The CFP of each stage of CCSs was calculated (Table 1). Table 6 shows the CFP of each stage of the full life cycle of $CCS_{(4,22)}$. Based on Eq. (11), the CFP estimates of $CCS_{(4,22)}$ can be summed to obtain.

Table 6. The $CFP_{(4,22)}$ of each stage of the full life cycle of $CCS_{(4,22)}$

	CFP_{Raw}	CFP_{Manuf}	CFP_{Dist}	CFP_{Use}	CFP_{Eol}	Total
$CFP/kgCO_2e$	2823.14	2154.28	42.8	257854.52	16.571	262,891.311

By adopting the proposed method and completing the CFP calculation of each CCS, the design system ordered the CFP value from large to small, and the CCS with the highest-ranking was used as the input value to generate the ICS.

5.4 Generating a Low-carbon Conceptual Scheme Based on IGA

In this study, based on friction and wear function f_4 as an example, the ICS with the lowest carbon emissions was randomly combined to form a genetic population based on IGA. The initial population size N_0 was set at 50, and the population number of each generation was set at 6, considering the fatigue degree evaluated by users. The cut-off evolution algebra was set at 30, the crossover probability was set at 0.7, and the mutation probability was set at 0.01. According to experts' experience, the weights μ and τ were set at 0.3 and 0.7, respectively. To ensure that the system running time was as short as possible, C_0 and S_0 were set at 7.2 and 0.8, respectively. To improve user evaluation efficiency and reduce the degree of fatigue, the human-computer interaction interface was used for the fitness evaluation, as shown in Figure 8. Each iteration user needed to evaluate six schemes.

It is worth mentioning that in addition to the input CSS of the IGA-based c*oncept scheme* optimization was the result of CFP screening, in the process of the new population iteration.

Some FKs beneficial to reducing carbon emissions were also used in the CS based on the feedback from the reviewers. For example, f_4 was the core of the testing machine, and it was also the structure with the most carbon emissions during the use phase. In the proposed model, low-carbon emission structures and materials were selected to generate ICS. However, the required use of large amounts of lubricating fluid in ICS still poses a huge threat to environmental pollution and recycling. Based on the premise of not affecting the realization of FRs, the need to resolve the conflict between lubrication and environmental pollution was proposed by the commenter and fed back into the IGA process. As shown in Figure 8, the pouring lubrication is replaced by a micro lubrication technology, which reduced the amount of lubricating fluid per unit time without affecting the friction and wear function.

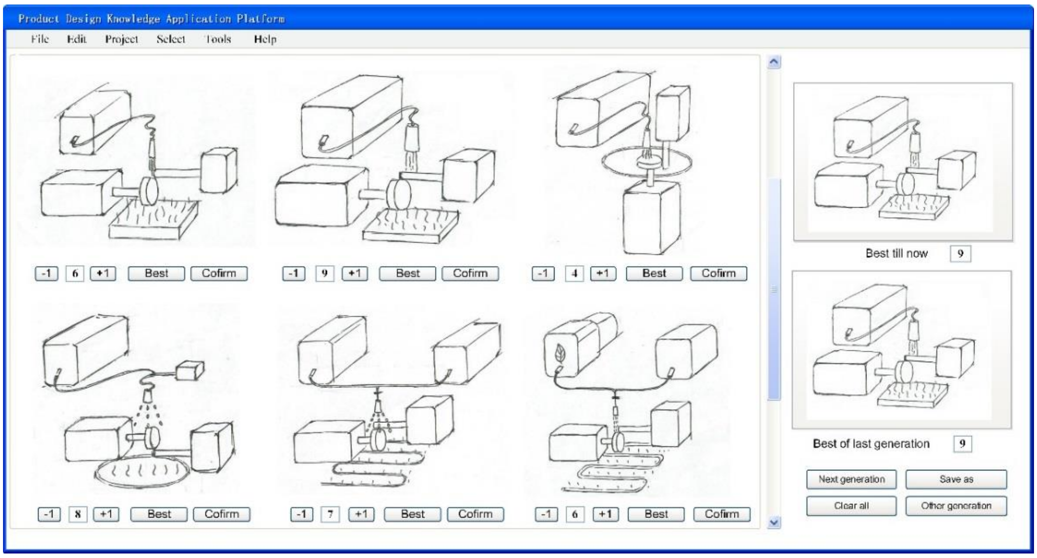

Figure 8. Interaction interface of the friction and wear module design system

As shown in Figure 9, the conceptual design process described was used to produce the CS of the proposed friction and wear testing machine, including switching power supply (36 V), servo motor, micro lubrication device (including fuel tank, air pump, oil-air mixer, pressure reducing valve, throttle valve, MQL nozzle, etc.), single-chip microcomputer, electric heating tube, pressure sensor and other structures.

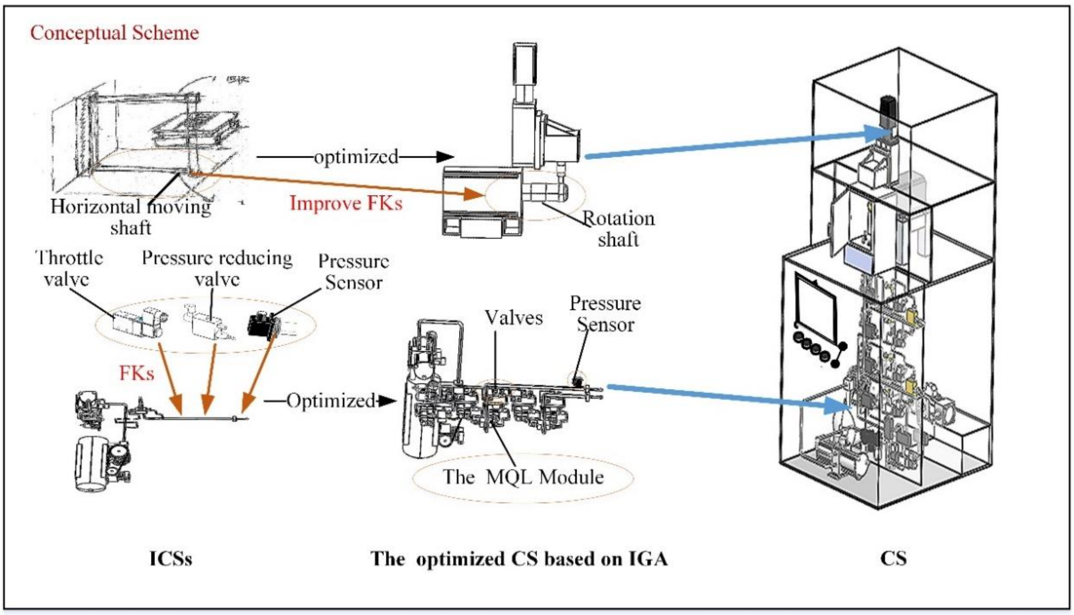

Figure 9. Conceptual scheme of friction and wear testing machine

5.5 Prototype and Micro-lubrication Test

According to the CS shown in Figure 10(a), a prototype of the testing machine was constructed after the detailed design and parameter adjustment, which indicated that the users' needs (Table 2) were met. The materials, lubricating fluids, motors, and so on used in the prototype were processed for low-carbon based on the FK processed by RFKD. To verify that the micro-lubrication device optimized by the IGA process could effectively reduce the carbon footprint while meeting FRs, we conducted the comparative evaluation shown in Figure 10.

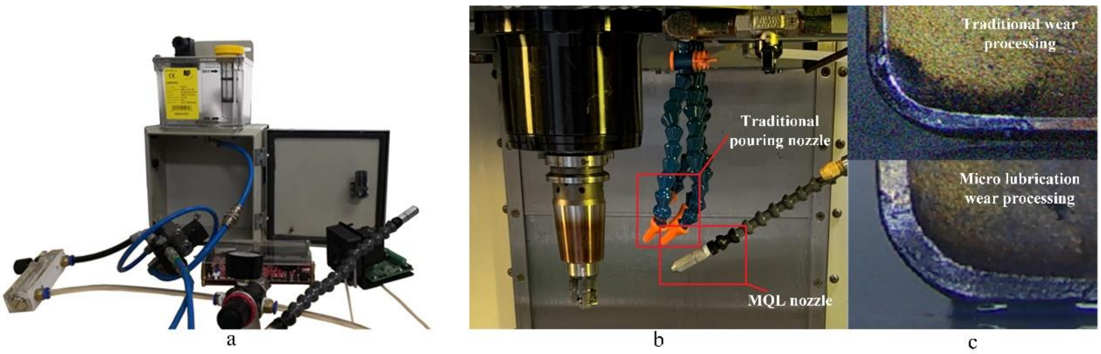

Figure 10. Prototype and comparative evaluation

In this experiment, the material of the cemented carbide blade produced by Kennametal Inc. (APKT1604PDTR KC725M) was used as the wear object, and the lubricant produced by Blaser Swisslube AG (Vascomill MMS FA2) was used as the wear fluid. As shown in Figure 10(b), the comparative test platform was built based on traditional pouring lubrication and micro lubrication technology. The basic parameters of the experiment are shown in Table 7.

Table 7. Experimental Parameters

Wear mode	Reciprocating Speed	Amplitude	Temperature	Humidity	Test Load	Wear Time
Spherical-Disk	10 mm/s	5 mm	20℃	40 N	30 N	25 min

The experiment measured the wear of the cemented carbide blade materials based on two lubrication methods. To reduce errors in the results, roughness was measured six times, and the average value was calculated. The author continuously monitored the roughness of the two worn surfaces to compare the amount of lubricant used during similar wearing. The wear surface of the test material is shown in Figure 10 (c), and the test results are shown in Table 8.

Table 8. Micro-lubrication Test Results

Lubrication method	Entry position	Middle position	Left position	Average	Lubricant dosage	Test time
Micro lubrication	0.324	0.299	0.313	0.315	60ml/min	25 min
Pouring lubrication	0.302	0.307	0.333	0.314	926ml/min	31 min
Pouring lubrication	0.203	0.206	0.260	0.223	600ml/min	25 min

The test results showed that the wear degree of the material with micro-lubrication met the user's FRs. The metal may have had a rapid cooling effect and affected the friction and wear. Compared with traditional pouring lubrication technology, micro-lubrication reduced the amount of lubricating fluid by 90%. For example, in the lubricating fluid used in the test, if the oil content was 63%, the amount of lubricating fluid reduced by each friction and wear testing machine was calculated at $540ml/min$. The number of reduced carbon emissions per minute during the use phase of the micro lubrication module was calculated as follows:

$$CFP_{Use\downarrow} = \frac{0.96kgCO_2e}{0.6L/min \times 70\%} \times 0.54l/min \times 63\% = 0.7776kgCO_2e \tag{23}$$

Therefore, the CCS proposed based on the RFKD model and low-carbon evaluation method ensured the solution of FRs, and the smart interaction method based on IGA further reduced the carbon emission level of products while improving the efficiency of the scheme combination. These results are in line with developmental needs in the green transformation of the manufacturing industry.

6. Conclusion

Conceptual design is the first step of the multiphase process involved in creating a new product, a preventive environmental protection process to meet user requirements, and minimizing invalid emissions. In this study, a knowledge application method was proposed to solve low-carbon product functions based on RFKD and IGA. The CS of products was configured and generated by granular knowledge of similar functional requirements. Compared with previous methods, the contributions of this study are as follow: 1) A new general process for the conceptual design of low-carbon products with low-carbon knowledge configuration and smart optimization was proposed; 2) A structured knowledge reasoning method that combines demand transformation, functional decomposition and low-carbon configuration was proposed to realize the intelligent matching of candidate concept schemes; 3) An RFKD-IGA was proposed to guide designers in completing mapping from CCSs to ICS and smart optimization design in stages. Based on the proposed method, we considered decisions and feedback on functional requirements and environmental protection regarding a low-carbon product functional solution. A low-carbon case study of the conceptual design of friction and wear in the testing machine was presented. Using the friction and wear system as an example, the process of similarity calculation and configuration of the proposed method was introduced. Micro-lubrication technology replaced traditional lubrication methods based on IGA, which effectively reduced carbon emissions and possible environmental pollution during the use phase. Based on the conceptual scheme, a prototype was built and evaluated to verify the fulfilment of FRs and the reduction of the carbon footprint. The results showed that a sustainable conceptual design scheme of low-carbon products was identified and discrete knowledge was used to realize cross-domain smart reasoning and configuration driven by functions.

The configuration and optimization of CS based on RFKD-IGA were better than the traditional stages in the conceptual design process, which was based on our understanding of design activity. In addition, the test results were further analyzed to verify the efficiency of generating the concept scheme and satisfying user requirements. However, the evolution of low-carbon CS in the collaboration between multiple design roles was not ideal. The authors recommend the following future research directions. First, the development of a collaborative low-carbon design between the customer and the designer, which could benefit product configuration, should be further explored. Second, a knowledge base and decision database should be established for the concept design of low-carbon products in diverse fields. Finally, an effective software tool should be developed to support the application of the proposed method in the conceptual design of low-carbon products.

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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