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A Knowledge-Based Method for Rapid Design Concept Evaluation

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ABSTRACT Concept generation is one of the most critical steps in product design process. Recently, several computational tools for automatically generating design concepts were developed, which can generate a big number of design concepts. This brings a new challenge to traditional expert-based design concept evaluation methods since experts are not capable of evaluating a large number of design concept in a short time. Therefore, this work develops a knowledge-based method to roughly evaluation design concepts and elect a small number of design concepts for expert-based evaluation. In the proposed method, a knowledge base containing 100 design concepts extracted from existing products is constructed, and four features, including Number of Function (#F), Function Compatibility Index (FCI), Function Component Mapping Index (FCMI) and Component Compatibility Index (CCI) are defined for building evaluation models. Based on the knowledge base and features, several computational evaluation models are developed including novelty evaluation model (NEM), feasibility discrimination model (FDM) and feasibility evaluation model (FEM). Empirical results show the proposed method is capable of evaluating design concepts. This work makes two-fold contributes to the research community, the first is a manually constructed knowledge base is published, while the second is four features are defined and used to define design concept evaluation models.

INDEX TERMS Concept evaluation, configuration flow graph, feasibility, Naïve Bayesian classifier, neural network, novelty.

I. INTRODUCTION

Concept generation is an indispensable step of innovation design [1], and there is a significant correlation between the quality of design concepts and the success of final products [2]. Traditionally, brainstorming is adopted in many scenarios. Following this paradigm, the 6-3-5 [3] and C-Sketch [4] were proposed to evaluate design concepts. In these methods, only a small number of design concepts can be generated, and the generated design concepts can be evaluated by expert-based methods.

Recently, several computational methods were developed to generate design concepts automatically. For examples, Kurtoglu *et al.* [5] extracted 45 rules from existing products, and a rule-based system was developed to computationally generate new design concepts. Bryant *et al.* [6] developed a design concept generation algorithm based on two matrices: function component matrix and design structure matrix, which are extracted from a web-based knowledge base. Huang *et al.* [7] adopted genetic algorithms and fuzzy neural networks to generate design concepts. The above methods can generate many design concepts in a short time, which makes the expert-based methods fail to evaluate the design concepts. Therefore, aided tools must be provided to help designers during the evaluation process.

In this work, we attempt to develop a method to filter the design concepts first and only leave a small number of design concepts for expert-based evaluation. Hence, the proposed method is not to replace the expert-based methods. Overall, we have the following goals in this work.

- First, to manually build a knowledge base by extracting design concepts from existing products;
- Second, to define informative features that can be used to define design concept evaluation models;
- Third, to develop design concept evaluation models based on the knowledge base and features.

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The rest of the paper is structured as follows. The next section provides related works to the current research. Section 3 explains the proposed method in detail. Section 4 conducts several experiments to verify the evaluation models. Section 5 discusses the results and Section 6 summarizes this work and outlines some potential future studies.

II. RELATED WORKS

This section makes a summary of the research efforts that paved the way for this study. Two aspects are addressed, including design concept representation and design concept evaluation.

A. DESIGN CONCEPT REPRESENTATION

Design concept representation is critical for design concept generation and evaluation. One structured representation of design concept was called function structure (FS) [9], which defines all functions and their relationships between them in a structure manner, and the relationships are defined by flow, such as material, signal and energy. Following this idea, several structured methods were developed, including Function-Behavior-Structure (FBS) [10], [11], Structure-Behavior-Function (SBF) and Function-Behavior-State [12], [13]. Recently, Kurtoglu proposed a structured method for representing design concepts, which is called "Configuration Flow Graph (CFG)" [14]. This method provides both structure representation of functions and the components. In this work, we use CFG to represent a design concept.

Standard function and component vocabulary are another issue to represent design concept. Many researchers have contributed to the development of standard vocabularies in recent decades. Most of the existing vocabularies have two important parts, including function and flow. For example, Pahl and Beitz listed five function terms (Channel, Connect, Change, Vary and Store) and three flow terms (Material, Signal, Energy) at a very abstract level [9]. Based on this work, Hundal further defined six function terms (Branch, Channel, Connect, Change magnitude, Convert and Store/Supply) with 44 specific sub-function terms [17]. Furthermore, Altshuller defined 30 function terms by analyzing massive patents [18]. Koch *et al.* introduced living systems theory into product design and used 20 subsystems (function terms) to describe a mechanical product [19].

Currently, a set of function terms called Function Basis (FB) has been formed [20], which is built based on the database proposed by Wood and Little [21]. The FB also includes function part and flow part, and the function part includes 8 categories and 24 sub-classes, while the flow part includes 3 categories and 18 sub-classes. Further, Hirtz *et al.* formed the RFB (Reconciled FB) [22] by integrating the terminology built up by NIST (National Institute of Standards and Technology) [23] and FB. The function part of RFB includes 8 categories and 22 sub-classes, while the flow part includes 3 categories and 20 sub-classes. Excepting the above vocabularies about function, Kurtoglu *et al.* [24] developed a vocabulary called component basis (CB) to represent the configuration of design concepts. The details of the above vocabularies are listed chronologically in TABLE 5 at the Appendix.

B. DESIGN CONCEPT EVALUATION

To evaluate design concepts, two issues must be addressed, including evaluation metrics and evaluation method.

1) EVALUATION METRICS

During the last two decades, different metrics have been proposed for evaluating design concepts. In 2000, Shah *et al.* [25] used novelty, variety, quality and quantity to evaluate design concepts, and further defined the formula to calculate these four metrics in 2003 [26]. Novelty means the degree to which a given design concept is unusual. Variety means the degree of dissimilarity of a group of design concepts. Quality means the degree of a given design concept satisfying requirements. Quantity means the total number of a group of design concepts.

Since then, these metrics were acknowledged by the research community, although different terminologies were adopted [1]. In this work, we make a brief summarization of the metrics, the result is shown in TABLE 1. In this table, the metrics that have similar meanings are grouped by the four metrics proposed by Shah. However, this classification does not imply that the metrics in the same group can be replaced by each other. This is because even metrics in the same group have different meanings. For example, the "Need Satisfaction" and "Completeness" refer to the degree that the requirements are met, while the "Feasibility" and "Utility" refer to the degree a given design concept can be implemented.

2) EVALUATION METHOD

From a technical perspective, two dimensions can be used to classify the evaluation methods. The first dimension is what method is used to deal with different criteria values. In the research community, it was well acknowledged that design concept evaluation inherently involves uncertainty and fuzziness [34]–[36]. To handle the uncertainty, fuzzy set [34], [37]–[41] and vague set [42] are adopted. However, these methods require the setting of membership functions, which will bring new subjectivity. Therefore, rough set [35], [36], [43]–[47] is adopted in the last decade to deal with the uncertainty, and this method does not require the setting of membership.

The second dimension is what method is used to rank design concepts. Corresponding to the methods of dealing criteria values, many traditional multi-criteria decision-making (MCDM) approaches, such as AHP, ANP, TOPSIS, VIKOR and so on, are extended by fuzzy set, vague set and rough set. For example, AHP is extended to formulate several new methods including fuzzy-AHP [40], [48] or FAHP [49], rough-AHP [36], [43]. Similarly, TOPSIS and VIKOR are

TABLE 1. The metrics proposed to evaluate design concepts.

Literatures	Novelty			Variety			Quality							Quantity	
	Novelty	Creativity	Originality	Variety	Differentiability	Diversity	Quality	Usefulness	Utility	Effectiveness	Need Satisfaction	Feasibility	Completeness	Quantity	Efficiency
[27]	○		○				○				○				
[25]	○			○			○							○	
[26]	○			○			○								
[28]	○						○							○	
[2]	○			○									○		
[29]		○			○			○			○				
[30]	○	○						○							
[31]									○	○					○
[32]	○		○												
[33]	○	○						○							
[1]	○					○						○			

also extended and used in many previous research works [34], [36], [42], [43], [46], [49]. Another tendency of the recent researches is to combine the advantages of different methods to develop new methodologies, such as TOPSIS, fuzzy set and AHP are combined in [49]; AHP, rough set and VIKOR are combined in [36] and so on. Besides these traditional methods, some advanced methods adopting data mining and machine learning also proposed by researchers. The second dimension is what method is used to rank design concepts. Corresponding to the methods of dealing criteria values, many traditional multi-criteria decision-making (MCDM) approaches, such as AHP, ANP, TOPSIS, VIKOR and so on, are extended by fuzzy set, vague set and rough set. For example, AHP is extended to formulate several new methods including fuzzy-AHP [40], [48] or FAHP [49], rough-AHP [36], [43]. Similarly, TOPSIS and VIKOR are also extended and used in many previous research works [34], [36], [42], [43], [46], [49]. Another tendency of the recent researches is to combine the advantages of different methods to develop new methodologies, such as TOPSIS, fuzzy set and AHP are combined in [49]; AHP, rough set and VIKOR are combined in [36] and so on. Besides these traditional methods, some advanced methods adopting data mining and machine learning also proposed by researchers [50], [51].

C. RESEARCH GAP

While the above evaluation methods are effective when evaluating a small number of design concepts, when an automatic design concept generation system is launched, which can generate many design concepts in a short time, the above evaluation methods tend to fail since all existing methods rely on experts' ratings. Therefore, there is a research gap between the requirement of rapid evaluation of many design concepts and the existing expert-based evaluation methods.

III. THE PROPOSED METHOD

This work is an attempt to fill the research gap illustrated in section II by building a knowledge-based method for rapid design concept evaluation. This method takes a number of design concepts as input and outputs the evaluation results instantly. To implement this method, three steps are conducted in this work.

STEP 1: Knowledge Base Construction. A group of design concepts are extracted from existing products and represented in a structural manner.

STEP 2: Features Definition. Several numerical features are defined based on the knowledge base. Then, all the design concepts are converted into numerical representation.

STEP 3: Evaluation Models Construction. Three evaluation models are constructed by machine-learning algorithms to evaluate the novelty and feasibility of given design concepts.

The following subsections illustrate the above three steps in detail.

A. KNOWLEDGE BASE CONSTRUCTION

Knowledge base is an indispensable part of the whole method since the underlying idea is to evaluate new design concepts

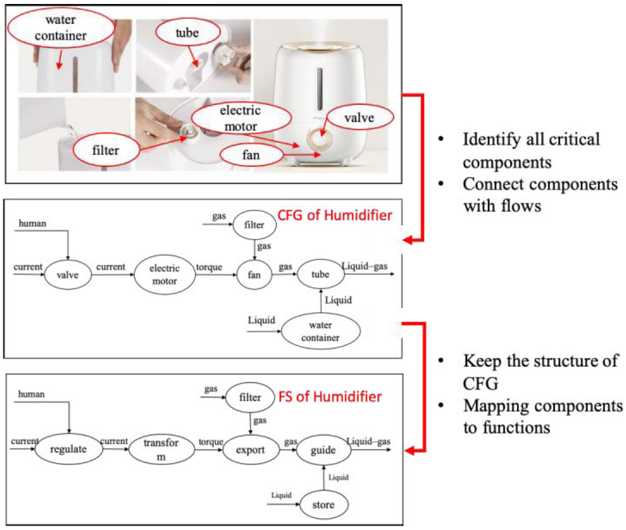

FIGURE 1. **The process of extracting design concepts from existing product.**

based on previous knowledge. In this work, we assume every existing product contains a design concept. Therefore, building knowledge base is to extract design concept from existing products. To implement design concept extraction, we first build CFG and FS of an existing product, which are illustrated in section II. Then a matrix-based representation is designed to contain all information stored in CFG and FS. Based on this idea, each existing product can be represented by a matrix. We build a knowledge base containing 100 design concepts (100 matrices) of 100 electromechanical products obtained from two e-commerce websites (JD[1] and Taobao),[2] which are two largest e-commerce websites in China. To illustrated how the knowledge base is constructed, we take the humidifier as an example.

As shown in FIGURE 1, a specific humidifier is shown in the top layer and the critical components are identified first. Then, these components are connected by flows to form the corresponding CFG of the humidifier (the middle layer). The terms of components are from standard vocabulary CB and RFB (see section II). Each component implements one or more different functions. Therefore, the FS of humidifier (the bottom layer) is constructed by simply mapping each component to its main function.

To process design concepts by computer language, we further develop a matrix-based method to represent a design concept. All the terms of functions, components and flows are assigned an identical integer first. Then, a design concept with N functions is represented by a $(N+3) \times (N+1)$ matrix. This matrix has two main parts: the $N \times N$ core matrix and the $2 \times N$ additional matrix. In the core matrix, each value is the flow that connects a pair of functions. In the additional matrix, the first row stores the N components, while the second stores the functions that implement the N components. Besides,

[1]www.jd.com
[2]www.taobao.com

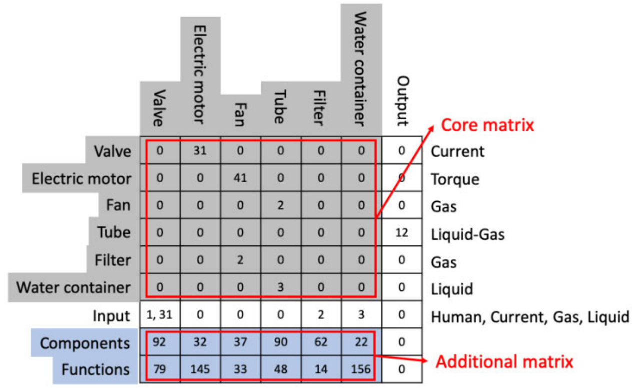

FIGURE 2. **The matrix-based method for design concept representation.**

the input row and output column are the input flow and output flow.

For the humidifier, a 9×7 matrix is built, as shown in FIGURE 2. The 6×6 core matrix records the relationships between the six components, which are marked in the top and left side in FIGURE 2. On the right sides the term of flows that connect the six components are also marked. The 2×6 additional matrix records the six functions corresponding to the six components. This 9×7 matrix can be processed easily by computer programs, and it holds all information in CFG and FS.

Besides, the 100 existing products are shown to three users to rate their novelty, and all users majored in mechanical design, and they are familiar with these products. Each user was asked to assign a novelty score (from 1 to 10) to each product. The final novelty score is the average of all three users.

B. FEATUERS DEFINITION

Based on the knowledge base, several features are defined to represent each design concept in a numerical manner, including number of functions (#F), function compatibility index (FCI), function component mapping index (FCMI) and component compatibility index (CCI). With these features, a design concept can be represented by a vector $\{\#F, FCI, FCMI, CCI\}$.

To clearly explain the meaning of these features, we assume a design concept with N functions $\{F_1, F_2, \ldots, F_N\}$ which are implemented by N components $\{C_1, C_2, \ldots, C_N\}$.

- ➢ #F means the total number of functions N of the design concept.
- ➢ FCI indicates how often the functions $\{F_1, F_2, \ldots, F_N\}$ appear together.
- ➢ FCMI indicates how often the functions $\{F_1, F_2, \ldots, F_N\}$ are implemented by the components $\{C_1, C_2, \ldots, C_N\}$.
- ➢ CCI indicates how often the components $\{C_1, C_2, \ldots, C_N\}$ appear together.

To calculate the value of these features, three matrices are extracted from the knowledge base, including function compatibility matrix (FCM), function component mapping matrix (FCMM) and component compatibility matrix (CCM).

FCM records the compatibility value between each pair of functions. The compatibility is measured by the frequency of co-occurrence in the 100 design concepts. If a pair of functions always appears together in various products, the compatibility will be high, and vice versa. The value of compatibility is calculated simply by normalizing the co-occurrence frequency so that the value is between [0, 1].

Similarly, FCMM records the relevancies between functions and components, and by this matrix we can ask the question like which component is capable of implementing a function. The relevancies are measured by the frequency that a component implements a specific function. If a function is always implemented by a component in various products, the relevancy is high, and vice versa. The relevancy is calculated simply by normalizing the co-occurrence frequency of functions and components so that the value is between [0, 1].

CCM records the compatibility between each pair of components. The compatibility is also measured by the frequency of co-occurrence, if two components always appear together in various products, the compatibility will be high, and vice versa. Similar with FCM, the compatibility is also calculated simply by normalizing the co-occurrence of components.

Given a design concept with N functions $\{F_1, F_2, \ldots, F_N\}$ which are implemented by N components $\{C_1, C_2, \ldots, C_N\}$, the FCI is the average compatibility values between every pairs of functions in $\{F_1, F_2, \ldots, F_N\}$; the FCMI is the average relevancy value of all mappings between functions $\{F_1, F_2, \ldots, F_N\}$ and components $\{C_1, C_2, \ldots, C_N\}$; and the CCI is the average compatibility value between every pair of components $\{C_1, C_2, \ldots, C_N\}$.

C. EVALUATION MODELS CONSTRUCTION

Considering the fact that novelty and feasibility are two critical metrics for design concept evaluation at the very beginning of design process, three evaluation models are developed here: novelty evaluation model (NEM), feasibility discrimination model (FDM) and feasibility evaluation model (FEM), the following subsections detail these models.

1) NOVELTY EVALUATION MODEL (NEM)

NEM is used to predict the novelty of a given design concept represented by the four features. Since it is very hard to give a computational definition of novelty, this work directly learns a mapping between the four features and the novelty.

To learn the mapping, artificial neural network (ANN) is adopted as the machine learning model since its capability for design concept evaluation has been proved [52]. This work uses a neural network with only one hidden layer. This model is simple since not too much data is available. In the future, with the increased data volume the NEM can be expanded to a deep structure.

2) FEASIBILITY DISCRIMINATION MODEL (FDM)

FDM is used to judge whether a design concept is feasible or not, and it is used to roughly filter a big number of design concepts. It takes a design concept as input and output 0 (infeasible) or 1 (feasible). The design concept is represented by FCI, FCMI and CCI. We try to train a model to discriminate the existing design concepts (Group A) and randomly generated design concepts (Group B). Group A contains design concepts stored in the knowledge base, and we assume all design concepts are feasible since they are extracted from existing products. Group B contains a group of randomly generated design concepts, and we assume all design concepts are infeasible. The design concepts are generated according to the following steps:

- To randomly select a number of functions from RFB. The number of functions follow the same distribution with number of functions of the existing design concepts;
- To randomly select a component from CB corresponding to each function;
- To repeat the two steps until the required number of design concepts are generated.

To train the model, this work adopts naïve Bayes classifier as the machine learning model because of its simplification and performance in many different tasks.

3) FEASIBILITY EVALUATION MODEL (FEM)

FEM is used to predict a value to measure the feasibility of a given design concept. It takes a design concept as input and outputs a value of feasibility. The design concept is represented by FCI, FCMI and CCI. To train FEM, we assume all design concepts in the knowledge base are feasible but have various degrees of feasibility. Intuitively, design concepts that are close to existing design concepts are more feasible. We further assume the value of feasibility decreases exponentially with the increase of distance. Therefore, this work calculates the value of feasibility as the following equation.

$$Fv = e^{-\left\| \frac{DC-C}{\Sigma} \right\|} \tag{1}$$

where Fv indicates the value of feasibility; DC indicates a design concept, which is represented by a vector $[FCI, CCI, FCMI]$; C is the cluster center of all existing design concepts in the three-dimensional space; Σ is a 3×3 matrix, which can be used to set preferences about the measurement of feasibility.

IV. EXPERIMENTS

A. EXPERIMENTS ON NEM

We first visually investigate whether it's possible to evaluate the novelty of the existing design concepts using FCI, CCI and FCMI. As shown in FIGURE 3, the top and last 10 design concepts in terms of their novelty are scattered in the three-dimensional space defined by FCI, CCI and FCMI. In this figure, the last 10 design concepts are indicated by blue diamonds. We can see that FCI, CCI and FCMI are obviously

TABLE 2. The Performance Of FDM Based On 10 Times 10-Fold Cross-Validation.

Folds \ Runs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	0	0	0.05	0.1	0.05	0.05	0.05	0	0.05	0
2	0	0	0	0	0.1	0	0.05	0.05	0.05	0
3	0	0	0.1	0.05	0	0.1	0	0	0.05	0.05
4	0.1	0	0	0	0	0	0	0.05	0	0
5	0	0.05	0.05	0	0	0.05	0	0	0	0
6	0.05	0	0.05	0.05	0	0	0	0.1	0.05	0.05
7	0	0.05	0	0	0.05	0.05	0.1	0	0	0
8	0.05	0.1	0.05	0.05	0.1	0	0	0	0	0.05
9	0	0	0	0	0	0	0.05	0.05	0.05	0.05
10	0.05	0.05	0	0	0	0	0.05	0	0	0.05
AVG	**0.025**	**0.025**	**0.03**	**0.025**	**0.03**	**0.025**	**0.03**	**0.025**	**0.025**	**0.025**

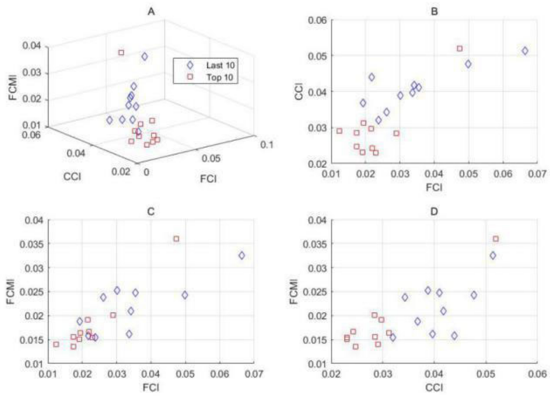

FIGURE 3. **The distribution of the top 10 and last 10 design concepts in terms of the novelty value. The subplot A shows the design concepts in the three-dimensional space (FCI, CCI, FCMI), and subplot B, C and D show the projection view from the three directions.**

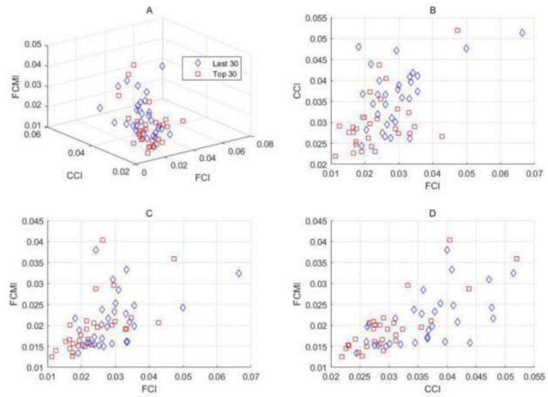

FIGURE 4. **The distribution of the top 30 and last 30 design concepts in terms of the novelty value. The subplot A shows the design concepts in the three-dimensional space (FCI, CCI, FCMI), and subplot B, C and D show the projection view from the three directions.**

bigger than that of the top 10 design concepts indicated by red rectangles. As shown in FIGURE 4, when the top and last 30 design concepts are drawn in the three-dimensional space, we still can observe the top 30 (red rectangles) located on the lower left while the last 30 (blue diamonds) are scattered on the upper right. From this result, we know that FCI, CCI and FCMI are capable of measuring the novelty of design concept.

To evaluate NEM, the learning and testing are conducted 30 times. For each run, all datasets (100 design concepts) are divided randomly into three groups, including training data (70%), validation data (15%) and test data (15%). This work takes the Mean Square Error (MSE) as an indicator to measure the performance. The average MSE of the 30 runs is 0.3709. We think this is acceptable since the mean of all novelty value is about 5.7 and the ratio of the error is about 6.51%.

B. EXPERIMENTS ON FDM

As shown in FIGURE 5, the number of functions of all the 100 design concepts follow a Gaussian distribution

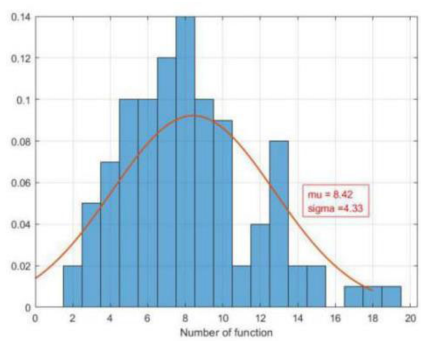

FIGURE 5. **The histogram and estimated Gaussian distribution of the number of functions.**

($\mu = 8.42$ and $\sigma = 4.33$). Based on this, 100 design concepts are randomly generated, and they are scattered in FIGURE 6 together with the existing design concepts. From this figure, we can find that (1) the distribution of randomly generated design concepts is obviously different with existing design concepts. Specifically, the generated design

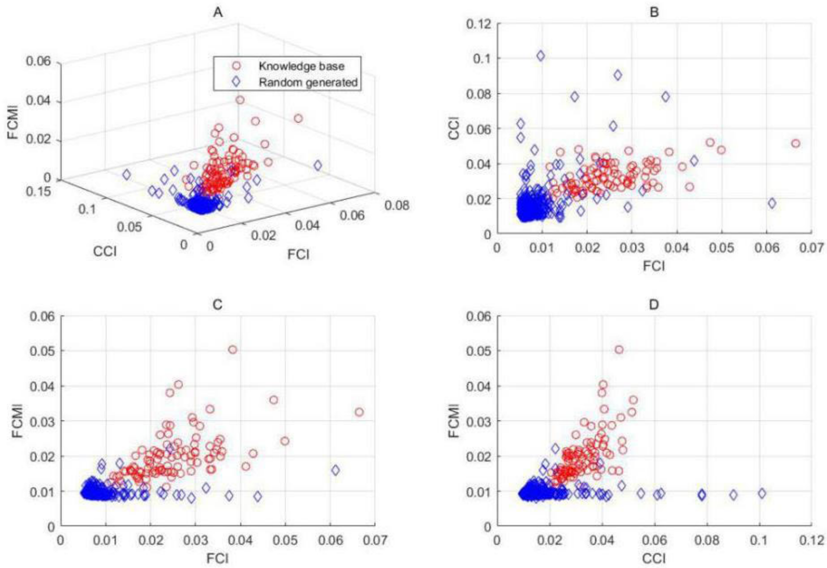

FIGURE 6. The distribution of the 100 existing design concepts (circle) and 100 random generated design concepts (diamond). The subplot A shows the design concepts in the three-dimensional space (FCI, CCI, FCMI), and subplot B, C and D show the projection view from the three directions.

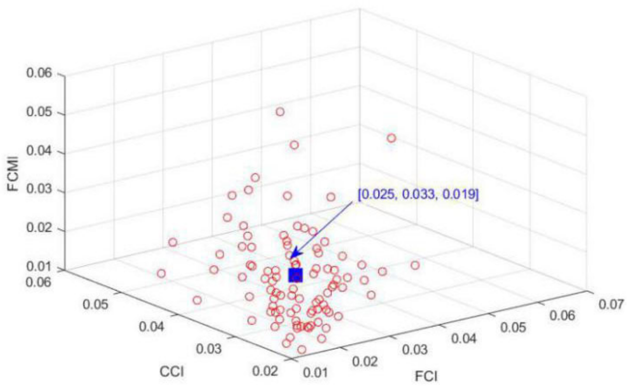

FIGURE 7. The cluster center (the blue rectangle) of all design concepts in the knowledge base.

concepts are clustered in the lower left, while the existing design concepts are clustered in the upper right. (2) There are no obvious correlations between the FCI, CCI and FCMI of generated design concepts, and this is quite different from existing design concepts.

The above analysis shows that FCI, CCI and FCMI are capable of distinguishing the generated design concepts and the existing design concepts. Therefore, this work trains a naïve Bayesian classifier with the two groups of design concepts. The model is validated by 10 times 10-fold cross-validation. As shown in TABLE 2, the average error is 2.65%, i.e. the prediction accuracy is 97.35%.

C. EXPERIMENTS ON FEM

As shown in FIGURE 7, the cluster center of all design concepts is indicated by a blue rectangle and its coordinate is $\begin{bmatrix} 0.025 & 0.033 & 0.019 \end{bmatrix}$. FIGURE 8 shows the feasibility

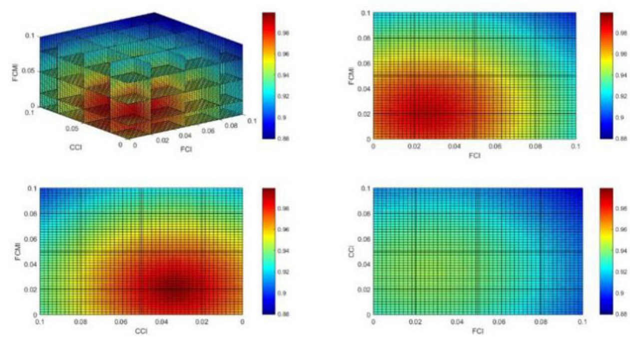

FIGURE 8. The distribution of feasibility value in the three-dimensional space when Σ is an identity matrix. The three two dimensional subplots show the projection view from the three directions.

value in the three-dimensional space when Σ is a 3×3 identity matrix. We can see that the space close to the cluster center has higher feasibility value, and the feasibility decreases with the increase in distance. Another thing that should be noticed is the trends of feasibility value are the same in all directions since Σ is an identity matrix. This result can also be clearly seen when comparing FIGURE 8 with FIGURE 9, which shows the distribution of feasibility value when Σ is set as below.

$$\Sigma = \begin{bmatrix} 1 & 0.3 & 0.5 \\ 0.3 & 1 & 0.5 \\ 0.5 & 0.5 & 1 \end{bmatrix}$$

Unlike FIGURE 8, different directions have various trends in FIGURE 9. From the upper right subplot in FIGURE 9, we know that the feasibility value in the diagonal direction decreases slower than other directions, and this is determined by Σ. In this work, the setting of matrix Σ is left to the developer of the design concept evaluation model. However,

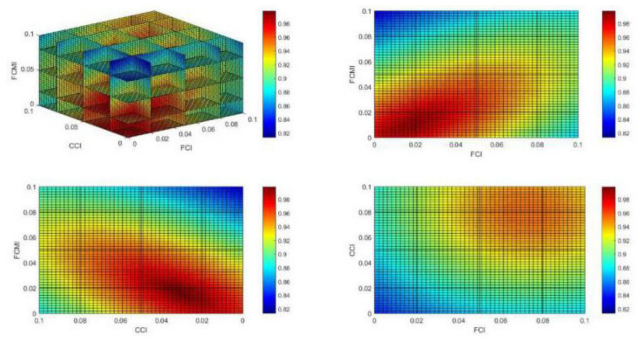

FIGURE 9. The distribution of feasibility value in the three-dimensional space when Σ is a predefined matrix. The three two dimensional subplots show the projection view from the three directions.

FIGURE 10. Mountain bicycle.

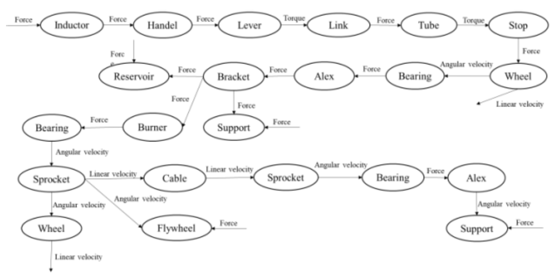

FIGURE 11. The CFG of mountain bicycle.

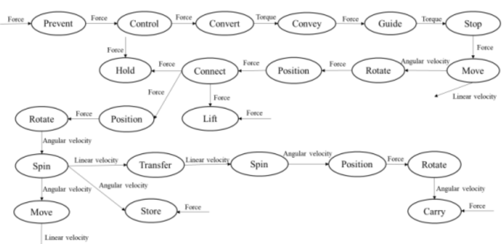

FIGURE 12. The FS of mountain bicycle.

FIGURE 13. Scooter.

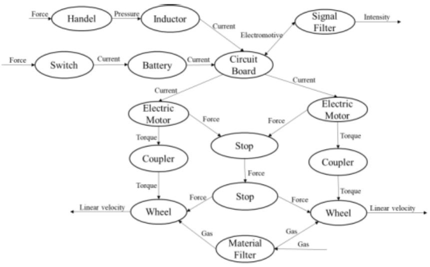

FIGURE 14. The CFG of scooter.

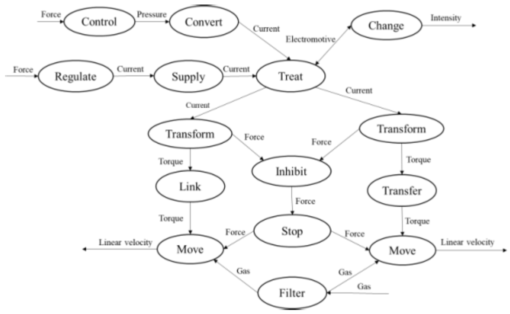

FIGURE 15. The FS of scooter.

FIGURE 16. Bicycle with fan.

in scenarios where some prior information about feasibility is known, this matrix can also be determined by machine learning methods.

To validate FEM, we collect 5 variants of two products respectively. All variants have several distinctive functions which are implemented by different components. The variants are listed in with their feasibility value computed by FEM.

As shown in TABLE 3, all product variants get very high feasibility values (indicated by Fv). This result is reasonable since all variants are already in the market. Further analysis finds that the number of functions influences feasibility value significantly. Therefore, we divide Fv by the number of functions to get Fv', and the last column of TABLE 3 shows the order in terms of Fv'. Generally speaking, the order is in line

TABLE 3. The feasibility value of real product calculated by FEM.

Products	Variants	Function (Id)	Component (Id)	Fv	Fv'	Order
Toothbrush	Variant-1 (Regular)	Supply(156) Actuate(78) Transform(145) Remove(38)	Battery(5) Switch(87) Electric Motor(32) Comb(20)	**0.9767**	**0.2442**	**2**
	Variant-2 (Pressure sensing)	Supply(156) Actuate(78) Transform(145) Remove(38) Sense(159) Regulate(79)	Battery(5) Switch(87) Electric Motor(32) Comb(20) Inductor(51) Chip(16)	**0.9925**	**0.1654**	**3**
	Variant-3 (Spray)	Supply(156) Actuate(78) Transform(145) Remove(38) Eject(35) Guide(59) Supply(156)	Battery(5) Switch(87) Electric Motor(32) Comb(20) Valve(91) Tube(90) Housing(47)	**0.9885**	**0.1412**	**5**
	Variant-4 (Bluetooth control)	Supply(156) Actuate(78) Transform(145) Remove(38) Regulate(79) Convert(132)	Battery(5) Switch(87) Electric Motor(32) Comb(20) Chip(16) Bluetooth(97)	**0.9845**	**0.1641**	**4**
	Variant-5 (Plug-in type)	Import(29) Actuate(78) Transform(145) Remove(38)	Electric Cord(30) Switch(87) Electric Motor(32) Comb(20)	**0.9837**	**0.2459**	**1**
Air blower	Variant-1 (Portable)	Import(29) Actuate(78) Transform(145) Import(29)	Electric Cord(30) Switch(87) Electric Motor(32) Fan(37)	**0.9780**	**0.2445**	**1**
	Variant-2 (Regular)	Import(29) Actuate(78) Transform(145) Import(29) Convert(132)	Electric Cord(30) Switch(87) Electric Motor(32) Fan(37) Heating Element(45)	**0.9856**	**0.1971**	**2**
	Variant-3 (Anion)	Import(29) Actuate(78) Transform(145) Import(29) Convert(132) Transform(145)	Electric Cord(30) Switch(87) Electric Motor(32) Fan(37) Heating Element(45) Signal Receiver(105)	**0.9806**	**0.1634**	**4**
	Variant-4 (Automatic temperature)	Import(29) Actuate(78) Transform(145) Import(29) Convert(132) Sense(159) Regulate(79)	Electric Cord(30) Switch(87) Electric Motor(32) Fan(37) Heating Element(45) Inductor(51) Chip(16)	**0.9893**	**0.1413**	**5**
	Variant-5 (Fixed)	Import(29) Actuate(78) Transform(145) Import(29) Convert(132) Stabilize(182)	Electric Cord(30) Switch(87) Electric Motor(32) Fan(37) Heating Element(45) Handle(43)	**0.9914**	**0.1652**	**3**

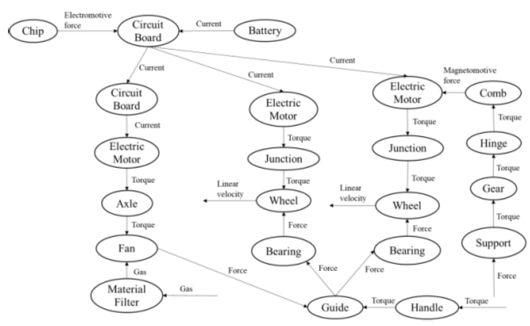

FIGURE 17. The CFG of bicycle with fan.

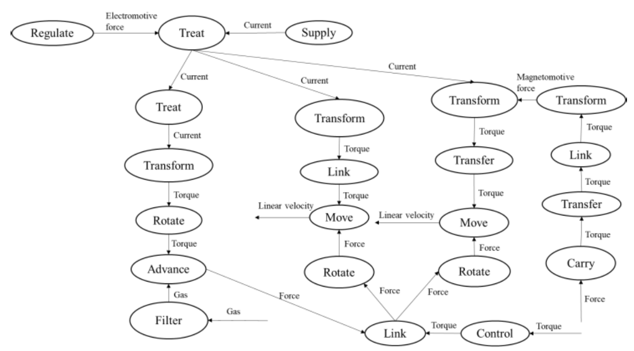

FIGURE 18. The FS of bicycle with fan.

TABLE 4. The evaluation results of the three products.

	Features	NEM	FDM	FEM
Bicycle	[22, 0.0066, 0.0119]	0.659	1	0.9816
Scooter	[15, 0.0010, 0.0223, 0.0143]	0.808	1	0.9921
Bicycle with fan	[22, 0.0086, 0.02, 0.0135]	0.831	1	0.953

with our intuition. For example, variant-1 and variant 5 of toothbrush have higher Fv' since they only have simple functions and components, while variant-3 has lower Fv' since it has very unusual functions.

V. CASE STUDY

To verify the proposed method, which incudes a knowledge base, four defined features and three evaluation models, this work adopts three transpotation products, including mountain bicycle (FIGURE 10), scooter (FIGURE 13) and bicycle with fan (FIGURE 16). Accoding to the method illustrated in existring literature, the CFG and FS are constructed which involves the main components and functions, as shown in FIGURE 11, FIGURE 12, FIGURE 14, FIGURE 15, FIGURE 17 and FIGURE 18.

The CFGs and FSs of the three products are transformed in to a numerical vector based on the method illustrated

TABLE 5. The detail of the vocabularies.

Function			**Flow**		
1984 Pahl & Beitz					
Channel, Connect, Change, Vary, Store			Material, Signal, Energy		
1984 Altshuller					
Separate, Transfer, Change, Control, Form, Initiate, Intensify, Lower, Modulate, Raise, Create, Destroy, Generate, Accumulate, Check, Indicate, Inspect, Measure, Set-up, Stabilize			Movement, Aerosol Flow, High Pressure, Friction, Mechanical & Heat Energy, Energy, Electromagnetic Radiation, Electromagnetic Radiation, Light, Chemical changes, Mixture, Object, Structure, Field, Temperature, Position, Interaction, Dimension, State & properties, Surface properties, Volume		
1990 Hundal					
Branch	Cut, Branch, Separate, Count, Display		**Material**		
Channel	Transmit, Transport				
Connect	Compare, Divide, Subtract, Switch, Connect, Mix, Pack, Add, Multiply, Valve, Mark		**Signal**		
Change Magnitude	Crush, Process, Form, Coalesce, Change		**Energy**	Mechanical	
Convert	Condense, Convert, Differentiate, Evaporate, Integrate, Liquefy, Solidify, Sense			Electrical	
				Thermal/Fluid	
Store/Supply	Release, Store, Supply, Stop, Hold			Miscellaneous	
1994 Koch					
INFORMATI-ON	Input Transducer, Decider, Internal transducer, Channel and Net, Decoder, Timer, Memory, Output Encoder, Transducer, Associator,		**MATTER/E NERGY**	Ingestor, Distributor, Converter, producer, Matter/Energy Storage, Extruder, Motor, Supporter	
1997 Little & Wood					
Channel	Import, Export, Transport, Transmit, Guide, Stop		**Material**	(Solids, Human hand, Product, Product part, Liquid, Air, Corrosive materials)	
Store/Supply	Store, Supply				
Connect	Couple, Mix		**Signals**	(Human signal, Status, Pressure, Temperature, Noise, Visual effect)	
Branch	Branch, Filter, Separate, Remove, Distribute, Dissipate				
Control Magnitude	Actuate, Regulate, Change, Form		**Energy**	Rotational Energy, Electricity, Human Energy, Linear Energy, Pneumatics, Heat, Magnetism Sound/Acoustic, Light, Vibration, Friction Energy, Oscillating, Linear Force, Hydraulics, Solar Energy	
Convert	Convert				
Support	Stabilize, Secure, Position, Translate, Rotate, Allow DOF				
Signal	Sense, Indicate, Display, Measure				
2000 Robert FB					
Branch	Separate	Remove	**Material**	Human	
	Refine				
	Distribute			Gas	
Channel	Import				
	Export			Liquid	
	Transfer	Transport, Transmit,			
	Guide	Translate, Rotate, Allow DOF		Solid	
Connect	Couple		**Signals**	Status	Auditory, Olfactory, Tactile, Taste, Visual
	Mix				
Control Magnitude	Actuate			Control	
	Regulate		**Energy**	Human	
	Change	Form, Condition		Acoustic	
Convert	Convert			Biological	
Provision	Store			Chemical	
	Supply			Electrical	
	Extract			Electromagnetic	Optical, Solar
Signal	Sense				
	Indicate			Hydraulic	
	Display			Magnetic	
	Measure			Mechanical	Rotational, Vibrational
Support	Stop				Translational,
	Stabilize			Pneumatic	
	Secure			Radioactive	
	Position			Thermal	

TABLE 5. *(Continued.)* **The detail of the vocabularies.**

2002 Julie & Robert RFB					
Branch	Separate	Divide, Extract, Remove,	**Material**	Solid	Object, Particulate, Composite,
	Distribute			Gas	
Channel	Import			Liquid	
	Export			plasma	
	Transfer	Transport, Transmit		Human	
	Guide	Translate, Rotate, Allow DOF		Mixture	Gas-gas, Liquid-liquid, Solid-solid, Colloidal Solid-liquid, Liquid-gas, Solid-gas, Solid-liquid-gas,
Connect	Couple	Join, Link			
	Mix				
Control Magnitude	Actuate		**Energy**	Electromagnetic	Optical, Solar
	Regulate	Increase, Decrease		Acoustic	
	Change	Increment, Condition, Decrement, Shape		Mechanical	Rotational, Translational
				Biological	
	Stop	Prevent, Inhibit		Chemical	
Convert	Convert			Electrical	
				Human	
Provision	Store	Contain, Collect		Hydraulic	
	Supply			Magnetic	
				Pneumatic	
Signal	Sense	Detect, Measure		Thermal	
	Indicate	Track, Display		Radioactive/Nuclear	
	Process				
Support	Stabilize		**Signals**	Status	Auditory, Olfactory, Tactile, Taste, Visual,
	Secure				
	Position			Control	Analog, Discrete

2016 Jeremy's function terms	
Branch	Divide, Extract, Clean, Distribute, Penetrate, Remove, Dilute, Split, Disperse, Break, Machine
Channel	Import, Export, Transport, Transmit, Translate, Move, Rotate, Transfer, Oscillate, Arrange, Direct
Convert	Convert, Substitute, Transform, Produce, Condition, Treat, Modify
Connect	Connect, Couple, Mix, Mount, Apply, Add, Combine, Encounter, Bond
Control	Increase, Decrease, Increment, Decrement, Shape, Control, Form, Change, Adjust, Actuate
Provision	Store, Supply, Prevent, Collect, Protect, Stop, Contain, Inhibit
Signal	Indicate, Process, Display, Detect, Measure, Compare, Select, Define, Determine, Monitor, Output, Calculate
Support	Place, Secure, Support, Align, Anchor, Hold, Maintain

2007 Kurtoglu's component terms	
Branchers	Separators, Distributors
Channelers	Importers/Exporters, Transferors, Guiders
Connectors	Couplers, Mixers
Magbitude Controllers	Actuators, Regulators, Changers, Stoppers
Converters	Output gas material, Output liquid material, Output acoustic energy, Output electrical energy, Output electromagnetic energy, Output hydraulic energy, Output magnetic energy, Output mechanical energy, Output pneumatic energy, Output thermal energy, Output control signal
Provisioners	Material Suppliers, Energy Suppliers
Signalers	Sensors, Indicators, Processors
Supporters	Stabilizers, Securers, Positioners

in section III.B, which are shown in TABLE 4. The evaluation results of the NEM, FDM and FEM are also calculated and shown in TABLE 4.

The results show that bicycle has the lowest novelty and bicycle with fan has the highest novelty. This result is consistent with our intuition. The FDM shows that the three products are all feasible and can be implemented. The feasibility values of these three products are also onsistent with our intuition. The three product are all have a very high feasibility value and the values of bicycle and scooter are higher than that of the bicycle with fan.

VI. CONCLUSION

A knowledge-based method for computational design concept evaluation is developed in this work. This method contains a knowledge base and four numberical features. With this method, this work implements three evaluation models, including NEM, FDM and FEM.

The empirical results show that the NEM can predict the novelty value of design concepts with a low MSE. Since this model is a three-layer neural network, the calculation process is efficient. Therefore, it can be used to roughly predict the novelty value of a big number of design concept.

We also find that the FDM can distinguish existing design concepts and randomly generated design concepts with high accuracy. This model can act as an in-loop function to filter infeasible design concepts in real time.

The empirical results show that the FEM is generally in line with our intuition. We also believe that the parameter Σ leaves a space to train and develop different feasibility evaluation models for different domains.

The empirical results show that the proposed method and its knowledge base and feature space have the potential to support the development of computational design concept evaluation models. However, the proposed method also has its own limtations. The main limitation is that the method heavily relies on the quality of the knowledge base, which is time-consuing to construct. However, in the big data era some advanced methods can be applied to build the knowledge base, such as knowledge graph. By this way, the quality of the knowledge base can be improved. On the whole, this work contributes to the research community by manually building and publishing a knowledge base, and defining four featurest that are used to develop design concept evaluation models.

APPENDIX

See Table 5.

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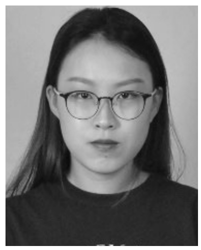

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