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FUZZY PREFERENCE EVALUATION FOR HIERARCHICAL CO-EVOLUTIONARY DESIGN CONCEPT GENERATION

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ABSTRACT

Conceptual design is important but complex. Its success heavily depends on a designer's individual experience and intuition. Design support tools are in need to assist designers to improve design quality and efficiency. However, to date there are few computational tools that are mature enough to provide effective assistance for design concept generation. One of the major reasons is that design information is inherently incomplete and subjective at the early stage of design. No effective evaluation methods have been devised to assess the connectivity between means (i.e., sub-solutions or function carriers) although it has an impact effect on system performance. In this paper, we propose a fuzzy reference model for conceptual design evaluation as part of our hierarchical co-evolutionary design concept generation based on function-means connectivity. An example of designing a simple mechanical transporter is presented to demonstrate the proposed approach.

1 INTRODUCTION

Conceptual design is an important early stage activity of engineering design. It has been recognized that almost 60% of a product's functional features, performance, manufacturability and cost, are determined at this stage [1]. Despite its importance, our ability to provide computational support for conceptual design is relatively limited primarily due to the limited understanding of the design concept generation process and the lack of quantitative information at the early stage of design. While various design methods have been proposed [2][3][4][6], generating design concepts still largely depends on designers' experience. There is a need for effective design support tools that can help designers generate and evaluate design concepts at the conceptual design stage.

Efforts have been made with the intent of improving conceptual design. The design methods proposed thus far [2-7] attempt to prescribe how design should be represented and conducted. Using these methods as a foundation, automated design tools [8-13] have been devised to assist designers in design concept generation. However, few of these tools are mature to date. One of the major reasons is because the available information at the conceptual design stage is mostly imprecise or vague. As a result, evaluating the generated design concepts becomes difficult. Design evaluation is often heavily weighted by a designer's experience and intuition.

Conceptual design of mechanical systems is especially complex. It is usually impossible to directly find solutions or means to realize the abstract top-level functions. A practical approach to complex system design is to decompose higher-level functions into lower level ones and then identify implementable means to fulfill the higher-level functions. In either "zigzag" approach [2] or "function first" [3] method, making decisions on "what combination of means should be adopted" requires effective design concept evaluation. However, the available information is inevitably ambiguous and even inconsistent because of the qualitative nature of the information at the idea generation stage. In practice, the evaluation at the conceptual design stage is more focused on what concepts are acceptable rather than what concepts are the "best". Design concepts cannot be assessed effectively until they are transformed into more concrete forms. The poor evaluation can cause more redesign cycles to be undertaken when inconsistencies are identified at the later design stages, such as embodiment design or detail design [3].

Much research has been conducted for design concept evaluation. Wang and Jin [14] proposed an analytical approach to analyzing the consequence of a given function structure.

Two design axioms, namely the Independence Axiom and the Information Axiom, were introduced as a rational basis to evaluate solution candidates [2, 15, 16]. In the systematic approach [3], a *morphological matrix* is proposed to compose variants and a *schematic chart* of seven evaluation criteria is used to evaluate and select the mostly desired variant [17]. Evolutionary methods [9, 18-20] have been developed to support a range of design activities from conceptual exploration, decision making, to final product definition. Another approach to design evaluation is fuzzy set analysis. Wang [21] proposed a fuzzy outranking model for conceptual design evaluation, and Vanegas [22] employed a fuzzy-weighted average method in the multiple criteria evaluation of several design alternatives. Another application of fuzzy set theory includes imprecision representation and manipulation in engineering design [23][24]. However, these methods are effective only under the specific design conditions where the design performance can be determined by certain individual design properties, such as weight, cost, etc. They do not take into account the impact of means connectivity on design results.

It has long been recognized that means connectivity plays an important role in design performance [25]. Four structural interactions [24] have been identified in an effort to outline an assembly model method that is repeatable. Bryant [27, 28] presented an automated design tool that makes use of the repository of existing design knowledge for concept evaluation based on a function-component connectivity matrix. In his research, means connectivity is explicitly determined by the repository [29]. However, in reality, the resources may not be accessed by designers or designers may have a different understanding because the information is usually subjective or incomplete. Therefore, function-means connectivity is better treated as fuzzy variables rather than as crisp ones.

This paper proposes a fuzzy evaluation approach to conceptual design based on function-means connectivity. Our method considers the means connectivity as a linguistic term related to a fuzzy set. An algorithm is proposed to transform the fuzzy function-means connectivity into an imprecise preference. As a result, the alternatives are ranked based on the preference models. The most preferred candidates can then be used for further development.

The paper is organized as follows. Section 2 reviews the related work on the applications of fuzzy set theory in design evaluation and our previous work on hierarchical co-evolutionary approach to conceptual design (*HiCED*). Section 3 introduces our fuzzy preference models for the design evaluation in *HiCED*. An example illustrating the model is presented in section 4, and section 5 concludes the paper. Some concepts frequently used for design evaluation in fuzzy set theory are described in Appendix A.

2 RELATED WORK

The compatibility of means connection relations has a direct impact on design success. Incompatible connections introduced at the conceptual design stage can cause serious problems at the later stages of design. However, because of the imprecise or incomplete information at the early stage of design, the connection relations among means are vague. In this research, we aim to provide an evaluation method in our *HiCED* model based on *vague connections*. In this section, we first review the applications of fuzzy logic in design evaluation and then briefly introduce our *HiCED* model [13].

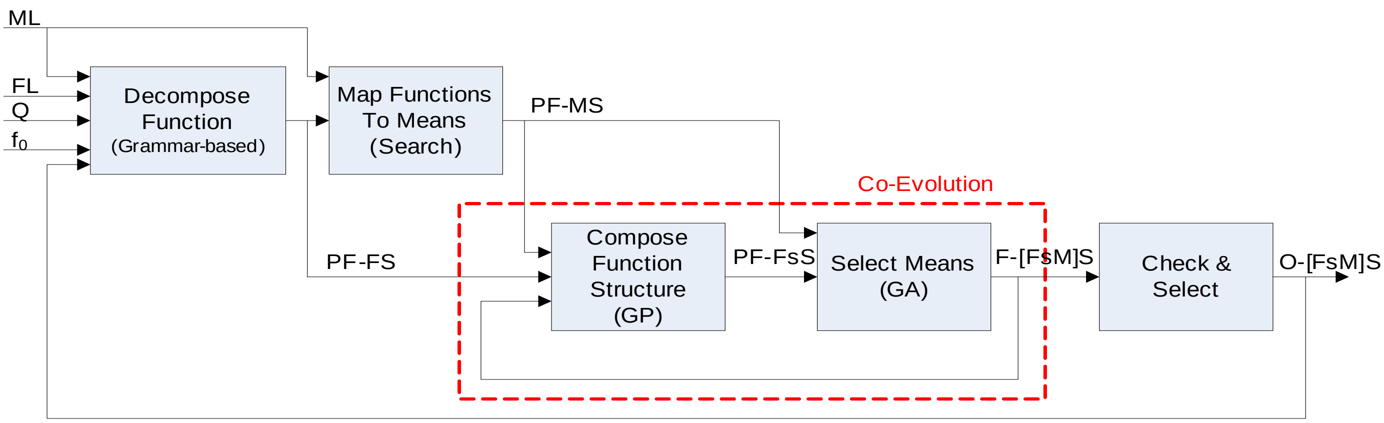
2.1 Application of Fuzzy Set Theory

Fuzzy set [30-32] is an extension of classic set theory and uses the grade of membership for all its members. It has been widely applied in the fields of design evaluation [21, 22, 33] and business decision-making [34, 35], where solutions must be derived from a substantial amount of imprecise or vague information.

As development progresses, engineering design becomes more and more complex. A design task usually involves multiple objectives to be optimized, whereas these objectives are often in conflict with each other. Fuzzy logic provides a more natural way to represent the various multi-objective optimization problems. That is, when we cannot select each criterion maximally due to the conflicts, we can optimize each of them to a certain extent. Thurston and Carnahan [36] proposed the usage of fuzzy set theory in multiple criteria engineering design evaluation. Fuzzy weighted average (*FWA*) was applied to find the overall desirability of the alternatives. Other similar applications can be found in bearing selection [37], bumper beam material selection [22], valve selection problem [21] and handle for closing a window [38].

Fuzzy weighted average (*FWA*) is commonly used to compute the overall desirability of the alternatives in a design evaluation in terms of fuzzy rating criteria and the weights of their corresponding importance. Dong and Wong [39] first proposed an algorithm to compute *FWA* based on the α-cut representation of fuzzy sets and interval analysis. Later, Liou and Wang [40] suggested an improved fuzzy weighted average algorithm to simplify the computational process. Lee and Park [41] improved the calculation process by reducing the number of comparisons and arithmetic operations to $O(n \log n)$. Nevertheless, operations on *FWA* tend to increase unnecessarily the imprecision. A new *FWA* (*NFWA*) [22][38] is proposed to obtain overall desirability levels less imprecise and more realistic than the conventional *FWA*.

One of the major challenges of conceptual design is to determine how to select the "best" design concepts against others for further development in the later design stages. Researchers have proposed different ranking methods for the selection of alternatives based on the design desirability, which is represented as a fuzzy number. Wang [21] suggested three preference modes based on the outranking approach to discriminate the alternatives. In [39], fuzzy preference relation is defined as a degree of outranking associated with each pair of alternatives *A* and *B*. While in the research [22][38], an



Legend : PF-: Partially Feasible; F-: Feasbile; O-: Optimal; ML: Means Library; FL: Function Library; Q: Requirements; f_0: Overall Function; FS: Function Set; FsS: Function Structure Set; MS: Means Set; [FsM]: Function Structure and Means Pair

Figure 1: Design Process of *HiCED*

equivalent crisp number for each fuzzy number is determined so that the fuzzy ranking problem becomes a simple ordering of real numbers.

2.2 Hierarchical Co-evolutionary design

Our long term research objective is to develop an effective support tool for design concept generation and evaluation. With this objective in mind, a hierarchical co-evolutionary approach to conceptual design (*HiCED*) has been proposed [13]. The basic idea underlying this approach is that *the conceptual design process can be seen as a process of co-evolution of both function structures and solution means across different levels of decomposition hierarchy*. At each decomposition level, functions and their structures serve as a basis for identifying desired means, and in turn, the means can help function structuring and decomposition until satisfactory design concepts are generated. In the *HiCED* model, a design concept is specified as a function structure together with a set of combined means to fulfill the functions in the function structure. Means (i.e., working principles in Pahl & Beitz's term or design parameters in Axiomatic Design) are defined as the possible technologies or solutions for the required functions.

The exploration process of conceptual design begins with a given overall function to be achieved and its associated requirements and constraints. The steps of this process are as follows (see Figure 1):

1. Based on the grammar rules, the overall function is decomposed into lower level sub-functions that are more specific and form a *partially feasible function set* (*PF-FS*).
2. At every level of the decomposition hierarchy, for every function in *PF-FS*, all its feasible means in the means library are identified and they form a *partially feasible means set* (*PF-MS*). Since the number of feasible means for each function can be so numerous for mechanical design problems, the *PF-MS* set can be very large.
3. A co-evolutionary algorithm is devised here to search for the optimal solutions from the means space (i.e., *PF-MS*) and the function space (i.e., PF-FS).
   - First, the genetic programming (*GP*) is employed to develop a set of *partially feasible function structures* (*PF-FsS*).
   - After the *PF-FsS* are developed, their information is used to identify *feasible combinations of the partially feasible means* by a genetic algorithm *(GA)*.
   - In light of the information of the identified *feasible combinations of the partially feasible means*, the system goes back to further evolve better *PF-FsS*.
   - The search focus switches between the function space and means space until a satisfactory *feasible function structure and means pair set* (*F-FsMS*) is found.
4. Select the best function structure and means pairs whose fitness values are higher than an allowable threshold. If the selected pairs contain means that need further implementation, then go to Step 1.

The design process of HiCED is shown in Figure 1. The details of the grammar-based function decomposition and GA-GP based design concept evolution can be found in [13][42].

3 FUZZY EVALUATION ON MEANS CONNECTIVITY

Means connectivity reflects the physical or logical relations between the two or more means needed for the fulfillment of the corresponding functional relations in a given function structure. For example in the function structure shown in Figure 2, the means to be selected to fulfill the functions <generate><ME> and <stop><ME> must satisfy the connection relation between the two functions both physically and logically.

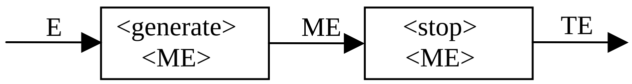


Figure 2: An Example of Function Structure

The connection relations among means have an important effect on the quality of the design. Research studies [23][24] have addressed the importance of this connection. However, few efforts have been made to evaluate how the connections affect final solutions because the relationship between the means connections and the system performance is very much unknown. Most evaluations about means connections are only experience-based or experiment-based. Especially at the early stage of design, the connectivity is vague or imprecise, which poses more difficulties for designers to make appropriate decisions.

In the *HiCED* model, means evolve in parallel with functions at the early stage of design [13]. The results of function evolution are function structures. The relationships among the functions in a function structure can provide logical and/or physical information for means selection. However, the connection relations of means are usually vague at conceptual design stage. For example in the function structure shown in Figure 2, we have the means “hand brake” to implement the function <stop> <ME>. If a designer selects “human” for the function <generate><ME>, then the connection between the two means is acceptable. But if he/she decides to use a motor as the energy source, the connection becomes unclear because the designer cannot determine how powerful the motor is at this stage.

The vagueness in means connections can usually be described with some linguistic terms, such as “*impossible*”, “*possible*”, “*very possible*,” etc. Those linguistic terms can be represented and manipulated with fuzzy set theory. In this section, we propose an approach to evaluating designs based on the fuzzy connectivity of means at the conceptual stage of design.

3.1 Weight of Means Connectivity

In *HiCED*, a functional connection between two functions is introduced in one of the three ways: inherited from the higher-level function structures, generated by executing functional grammar rules, or generated randomly through genetic operations. In a valid function structure, the lower level function structures must be consistent with the higher level ones. For example in the following function structure shown in Figure 3, the connection from f_1 to f_2 in the lower-level function structure (b) is directly inherited from its higher-level function structure (a), meaning that the connection has already been established at the higher level (i.e., level (a)) and thus needs to be maintained at the current level (i.e., level (b)). Therefore, it is more important for the means that implement function f_1 and f_2 to maintain the connectivity defined by f_1 and f_2.

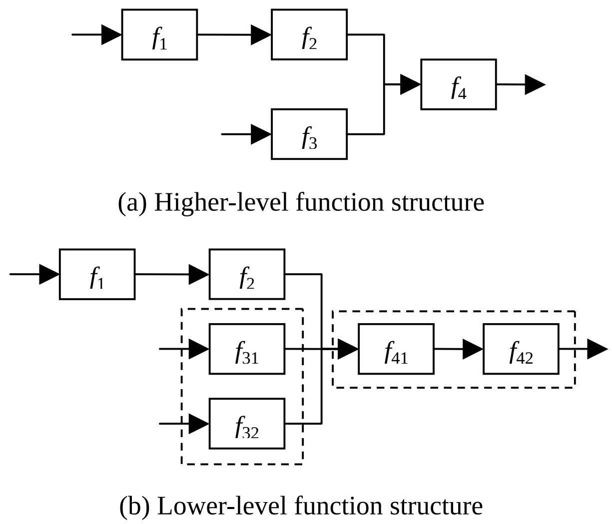


Figure 3: An Example of Function Decomposition

Second, when the grammar rules are applied in decomposing higher level functions, specific functional flow relations may be introduced. In *HiCED*, three sets of function grammar rules, namely *action-based function decomposition rules*, *action specific expansion rules* and *requirement-based function decomposition rules* [13] have been identified to facilitate function decomposition. Since these rules encode both formal and experiential knowledge, it is important for the implementing means to respect the corresponding function relations. For example, an action specific expansion rule is presented below. The means to be selected should satisfy the connection prescribed by the rule consequently.

$$\langle generate\rangle\langle ME\rangle \xrightarrow{ASE} \{\langle supply\rangle\langle E\rangle, \langle generate\rangle\langle ME\rangle\}$$

Compared to the connections produced by random generation by genetic operations in genetic programming, the connections generated from the higher-level function structure and the function grammar rules have more “knowledge” embedded. It is more important to make sure that the corresponding means connections respect these functional connections.

3.2 Preference Model for Design Evaluation

In terms of the fuzzy means connectivity and fuzzy weight of connections at the conceptual design stage, we propose a fuzzy preference model for design evaluation based on the means connectivity, which is inferred from the corresponding function structure.

From the topological point of view, there are two basic topological relationships in a function structure: serial and parallel. Serial is a configuration where two or more functions are connected one by one via functional flows, whereas parallel indicates that two or more functions (or sub function structures) have no direct interactions via functional flows (Figure 4).

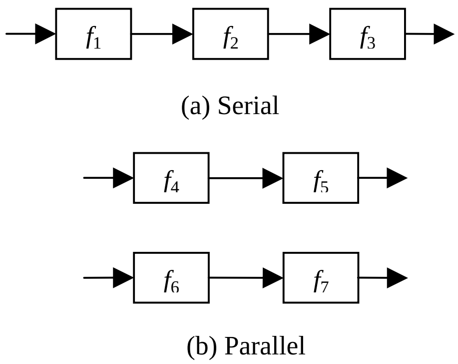


Figure 4: Topological Relationships in Function Structure

The relationships reflected in the physical domain are the means connections (Figure 5). In Figure 5, x is a fuzzy number for means connectivity and w is the corresponding importance of the connection.

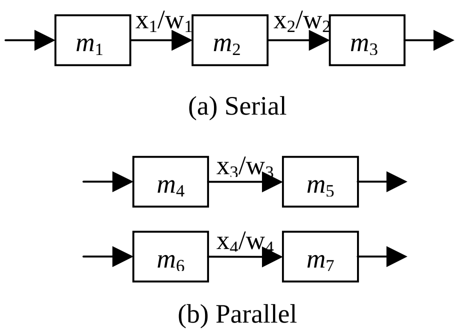


Figure 5: Means Connectivity Based on Function Structure

A design evaluation based on these relationships is conducted as follows.

<u>Step 1: Evaluate overall connectivity</u>

Designers want to select solutions with the most compatible connection. With this objective in mind, we apply fuzzy weighted average (*FWA*) to calculate the connectivity level for serial connection and fuzzy intersection operation for parallel relationship of means. For example, the total connectivity for Figure 5(a) is

$$c = \frac{x_1 w_1 + x_2 w_2}{w_1 + w_2} \qquad (1)$$

and the connectivity level for Figure 5(b) is:

$$c = x_3 \cap x_4 \qquad (2)$$

The detail of how to compute *FWA* is described in Appendix A.

The underlying idea of this approach is to evaluate how successful the design could be based on the means connectivity. For the serial connection of means, the *FWA* represents the average degree of success based on the designers' knowledge of the design. But for the parallel structure, design success is restricted by the poorest branches.

<u>Step 2: Determine fuzzy preference relation of alternatives</u>

In the area of mechanical engineering, the desired functions can be fulfilled by numerous *means*. Thus, the number of alternative solutions generated from *HiCED* is large.

After the first step, each alternative has a fuzzy number to represent its degree of success based on the connectivity, for example $s_1, s_2, ..., s_n$. Then we use a fuzzy preference relation [21][29] to determine their preference $P(s_i, s_j)$.

$$P(s_1, s_2) = \frac{D(s_1, s_2) + D(s_1 \cap s_2, 0)}{D(s_1, 0) + D(s_2, 0)} \qquad (3)$$

where $D(s_1, s_2)$ is the area where s_1 dominates s_2 (area 5 and 3 in Figure 6); $D(s_1, 0)$ is the area of s_1 (area 1, 4 and 5 in Figure 6); $D(s_2, 0)$ is the area of s_2 (area 2, 3, and 4 in Figure 6) and $D(s_1 \cap s_2, 0)$ is the area where s_1 and s_2 are indifferent (area 4 in Figure 6).

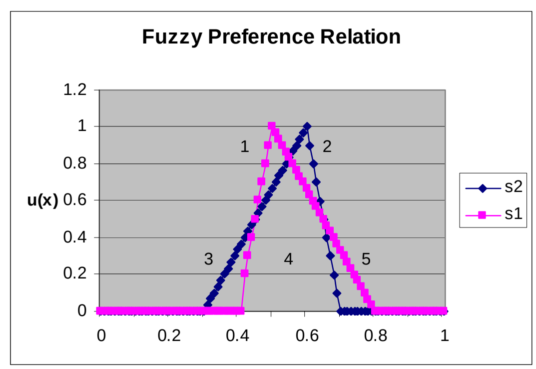


Figure 6: Example of Fuzzy Preference Relation

The detail of the fuzzy preference relation is introduced in Appendix A.

<u>Step 3: Select "best" alternatives</u>

One disadvantage of the fuzzy weighted average is that it unnecessarily increases the level of imprecision [22]. So it is not appropriate to rate the final solutions directly based on fuzzy preference relations from step 2. Two fuzzy preference models are used to discriminate the alternatives into preference and indifference sets. Assume a and b are connectivity levels, and the two models are:

Strict preference S

$$\forall a,b \in A,\ and\ \ \alpha > 0$$
$$a\,S\,b \Leftrightarrow p(a,b) > \alpha \qquad (4)$$

Indifference preference I

$$\forall a,b \in A,\ and\ \ \alpha > 0$$
$$a\,I\,b \Leftrightarrow p(a,b) \le \alpha \qquad (5)$$

The threshold α is used to discriminate two alternatives between strict preference and indifference. If the difference between *a* and *b* is greater than α, then it is convincing that candidate *a* is better than *b*. That is, designers have sufficient evidence to believe a, and *b* can be removed. But if the difference between *a* and *b* does not exceed α, then it is considered that solution *a* and *b* are of the same level of importance in terms of connectivity. If there are no other evaluation criteria available for further ranking, then both solution *a* and *b* must be kept until enough information is obtained.

The selection of threshold α expresses the degree of imprecision that a designer believes that solution *a* is preferable to *b*. If he (or she) is confident in the connectivity among the means he (or she) has selected, a lesser value is set. In our model, only the condition that alternative a is better than b is taken into account, that is, $p(a,b) \ge 0.5$. An interactive method in our preference model allows designers to provide their belief in means connection level for design concept evaluation.

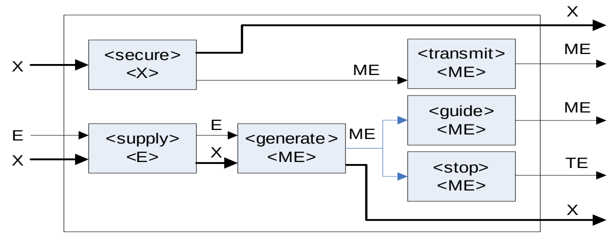
In the following section, a case of designing a simple mechanical transporter is presented to illustrate how the fuzzy preference model is applied for design concept evaluation in *HiCED* based on means connectivity.

4 CASE STUDY

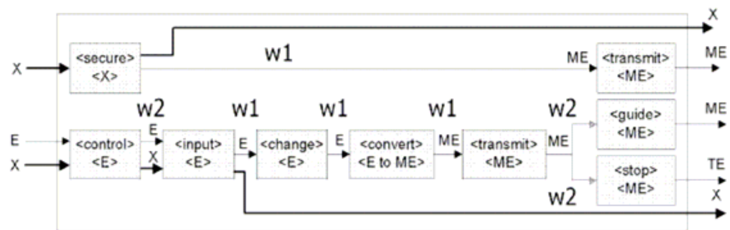
The case study presented in this section is based on the example of a simple mechanical transporter design [13]. In the model of *HiCED*, means evolve in parallel with functions at each level of the decomposition hierarchy. Function structures provide connection information for means evaluation. At the conceptual design stage, the means connectivity is fuzzy. The case study shows how means are assessed by fuzzy preference models based on their connectivity with respect to their corresponding functional connectivity introduced in the function structure.

4.1 Function Structure

Function structures are generated by *GP* after function decompositions. In this case, let us take a look at the function structures at decomposition level 5 (Figure 7b).



(a) Function structure at decomposition level 4



(b) Function structure at decomposition level 5

Figure 7: Function Structure Solution

The connection relation between $\langle control \rangle \langle E \rangle$ and $\langle input \rangle \langle E \rangle$ is prescribed by the action-based function decomposition rule (rule 4 in [13]). The connection relations between function $\langle transmit \rangle \langle ME \rangle$ and $\langle guide \rangle \langle ME \rangle$, and between $\langle transmit \rangle \langle ME \rangle$ and $\langle stop \rangle \langle ME \rangle$ are determined by the higher level function structure (Figure 7(a)). In the lower level of decomposition, these relations must be maintained when appropriate means are selected. They are more important than other connections produced by genetic programming. The weight (importance) of connections is expressed in the linguistic terms of "important" and "normal" (Figure 8).

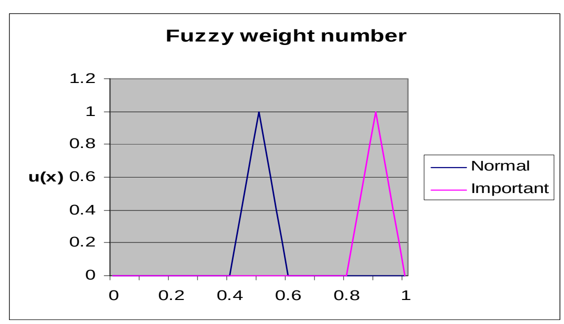


Figure 8: Linguistic Scale of Weight Value

4.2 Alternatives

In mechanical design, the number of applicable means for each function is numerous. Due to mental limitation or incomplete information, their connection relations can be vague. A finite set of fuzzy numbers is used to express these imprecision connection levels among means, namely, "very impossible", "impossible", "fairly impossible", "neutral", "fairly possible", "possible" and "very possible". The linguistic scale is used to transform a linguistic term into a fuzzy number (Figure 9).

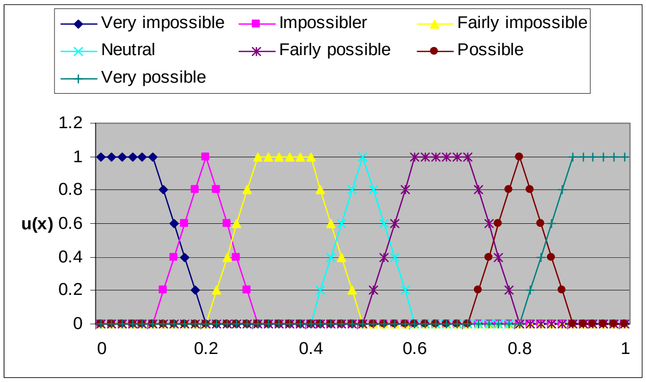


Figure 9: Linguistic scale of Fuzzy Connection

In *HiCED*, the means library provides a knowledge base of what can be specified as required function [13]. In this example, four candidate solutions are generated (Table 1) and the connection relations (7 means very possible, and 1 means very impossible) among means requires designers to input for fuzzy analysis later (Table 2).

Function	Solution (a)	Solution (b)	Solution (c)	Solution (d)
<secure><X>	Saddle	Board	Board	Seat
<transmit><ME>	Frame	Wheel	Frame	Wheel
<control><E>	Human	Human	Human	Hand
<input><E>	Pedal	Spring	Lever	Row
<change><E>	Pedal Arm	Lever	Gear	Level
<convert><E to ME>	Gear	Spring	Gear	Friction
<transmit><ME>	Chain	Spring	Gear	Body
<guide><ME>	Steering Wheel	Guide Wheel	Steering Wheel	Body
<stop><ME>	Pedal Brake	Cramp Brake	Friction	Friction

Table 1: Alternative Solutions

4.3 Evaluation Result

Given the function structure and means connectivity, the overall connection levels for solution *a*, *b*, *c* and *d* is shown in Figure 10. According to equation (3), we can obtain that

Saddle Frame	**7**	Board Wheel	**6**	Board Frame	**5**	Seat Wheel	**6**
Human Pedal	**7**	Human Spring	**7**	Human Lever	**7**	Hand Row	**7**
Pedal Arm	**7**	Spring Lever	**6**	Lever Gear	**4**	Row Level	**6**
Arm Gear	**6**	Lever Spring	**6**	Gear Gear	**7**	Level Friction	**4**
Gear Chain	**6**	Spring Spring	**7**	Gear Steering	**7**	Friction Body	**4**
Chain Steering wheel	**7**	Spring Guide Wheel	**2**	Gear Friction	**4**	Body Guide Wheel	**7**
Chain Pedal Brake	**4**	Spring Cramp Brake	**2**			Body Friction	**5**

(7: Very possible; 6: Possible; 5:Fairly possible, 4:Neutral; 3: Fairly Impossible; 2: Impossible; 1: Very Impossible)

Table 2: Fuzzy Connection Relations among Means

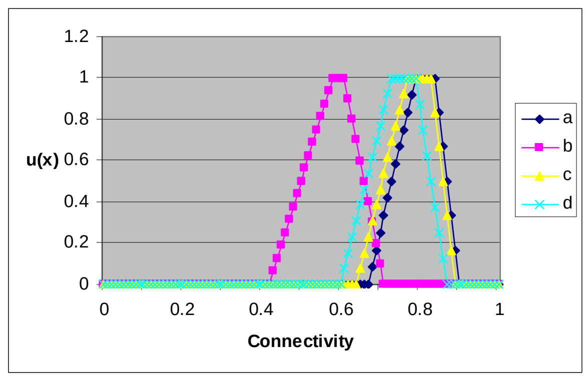


Figure 10: Overall Connectivity Level

$$\begin{aligned} &p(a,b)=0.97\\ &p(a,c)=0.55\\ &p(a,d)=0.7\\ &p(c,b)=0.92\\ &p(a,d)=0.59\\ &p(d,b)=0.85 \end{aligned} \quad (6)$$

The overall fuzzy preference relations can be determined as $a \succ c \succ d \succ b$ (expression $a \succ b$ indicates a is preferable to b). When the preference threshold $\alpha = 0.6$, it is observed that the preference for alternative *a* and *c* are indifferent, and both of them are preferable to alternative b. Although alternative *c* and *d* are indifferent, alternative *a* is preferable to *d*. Thus, candidate b and d can be removed, and *a* and *c* are kept for further refinement.

But if the designer is more confident in his (or her) knowledge on the means connectivity shown in Table 2, then he (or she) may choose a lower preference threshold, for example, $\alpha = 0.5$. Under such an assumption, alternative *a* is obviously preferable to all other alternatives *b*, *c*, and *d*. Therefore, only *a* is kept for further design consideration, and *b*, *c* and *d* are dropped.

4.4 Discussion

Unlike the traditional evaluation methods in means connection, which usually consider the connection relations as crisp variables, our fuzzy preference model uses fuzzy numbers to express the connectivity level among means to accommodate the incomplete and subjective information at the early stage of design. Based on the fuzzy values of the connectivity between the means, the designer can compare two alternatives, based on connectivity, by calculating the preference relation between the two alternative using Equation (3). The preference relations, e.g., those shown in Equation (6), provide a first-hand comparison information based on the given fuzzy connectivity knowledge.

In addition to the fuzziness of connectivity knowledge, there is another layer of subjectivity that makes the information at early stage of design imprecise, i.e., designers' confidence on their knowledge about the means connectivity. Making decisions based on Equation (3), for example, depends on how confident the decision-maker is about the connection knowledge of Table 2. In our approach the threshold α is introduced to handle the issue of subjective confidence. If a designer is not confident in his knowledge on means connectivity, a larger threshold can be set. In the above example, with a higher threshold $\alpha = 0.6$, solution *b* and *d* are discarded and both *a* and *c* are kept for further consideration. But if the designer is comfortable with means connectivity he or she assigned in Table 2, a lower threshold (α closer to 0.5) can be selected so that more alternatives are removed from further consideration. For example, given the threshold $\alpha = 0.5$, only alternative *a* is selected for further as the final design concept.

If two or more alternatives are kept for further consideration, i.e., they are *indifferent* given the current knowledge and the confidence on the knowledge, then further information is needed and the evaluation should go beyond means connectivity. For example, given the threshold $\alpha = 0.6$, alternative *a* and *c* are indifferent if only the means connectivity is taken into account. But if the weight of the transporter is also considered a major factor for design evaluation, the solution *a* is a better choice because gears are usually heavier.

5 CONCLUSION

Conceptual design can be characterized by the unclear process for design concept generation and the lack of quantitative information for design concept evaluation [13]. How to choose among alternative design concepts at the early stage of design is a major challenge for researchers. To develop computer tools for design concept generation, one must devise a concept generation process that can use incomplete, subjective, and qualitative information for concept evaluation. Among the existing methods, few considered means connectivity, although it has profound impact on the final design results. In our research, we treat means connectivity as an important source of information for evaluating design concepts. To deal with the qualitative nature and subjectiveness of the knowledge on means connectivity, we introduced a fuzzy evaluation approach that allows designers to code their qualitative knowledge about means connectivity into fuzzy relations among the means and make their selection decisions based on their confidence on the knowledge that they utilized. The case study has shown the mechanism and the effectiveness of our proposed approach.

It is worth mentioning that the reason why we could successfully use the means connectivity as an evaluation criterion for design concept selection was because *HiCED* allows function structures and means combinations to co-evolve such that the functional relations become basis to evaluate the means connections. Function structures provide logic and physical connection relationships for the means of a design concept. Our current research extends the means connectivity based fuzzy evaluation by including other evaluation criteria into the framework such as case-based function-means mapping.

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APPENDIX A: FUZZY SET THEORY

Fuzzy set theory is an extension of the mathematical concept of a set. Zadeh [28] proposed a grade of membership, which allows for the gradual assessment of the membership of elements in relation to a set. The grade of membership of all its elements is defined as a fuzzy set. A grade of membership is normally a real number between 0 and 1. In contrast, an element has a deterministic condition in relation to a classic set -- it either belongs or does not belong to a set.

A.1 Fuzzy weighted average

In conceptual design evaluation, the rating criteria and their corresponding weighting values are vague or can not be precisely determined. Fuzzy weighted average (*FWA*) is proposed to compute the weighted sum of the criteria. The fuzzy weighted average is frequently expressed as follows:

$$y = f(x_1, x_2, ..., x_n, w_1, w_2, ..., w_n) = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \quad (7)$$

Where $x_1, x_2, .., x_n$ are fuzzy numbers in fuzzy sets $A_1, A_2, ..., A_n$; $w_1, w_2, ..., w_n$ are fuzzy weights in fuzzy set $W_1, W_2, ..., W_n$.

Dong and Wong [37] described a computational algorithm based on the α-cut representation of fuzzy sets and interval analysis. However, this algorithm is very cumbersome with the increase of information. Liou and Wang [38] improved the algorithms by introducing the following notations:

$$f_L(w_1, w_2, ..., w_n) = \frac{\sum_{i=1}^{n} w_i a_i}{\sum_{i=1}^{n} w_i} \quad (8)$$

$$f_U(w_1, w_2, ..., w_n) = \frac{\sum_{i=1}^{n} w_i b_i}{\sum_{i=1}^{n} w_i} \quad (9)$$

and proving the following theorems:

$$\begin{aligned} \min: & f(x_1, x_2, ..., x_n, w_1, w_2, ..., w_n) \\ & = \min: f_L(w_1, w_2, ..., w_n) \end{aligned} \quad (10)$$

$$\begin{aligned} \max: & f(x_1, x_2, ..., x_n, w_1, w_2, ..., w_n) \\ & = \max: f_U(w_1, w_2, ..., w_n) \end{aligned} \quad (11)$$

where $[a_i, b_i]$ is the end point of the intervals of x_i .

Based on their work, Lee and Park [39] proposed a more efficient fuzzy weighted average (*EFWA*) by reducing the number of comparisons.

A.2 Fuzzy preference relations

A fuzzy preference relation *R* on a set *A* is a fuzzy set on the product $A \times A$, that is characterized by a membership function [21][29]:

$$\eta_R : A \times A \to [0,1] \quad (12)$$

Let $P(a,b) \in R$ be fuzzy preference relation between a and b, where $a, b \in A$, then $P(a,b)$ and $P(b,a)$ are reciprocal:

$$P(a,b) + P(b,a) = 1 \quad (13)$$

The fuzzy preference relations $P(a,b)$ and $P(b,a)$ are calculated as follows [21][33]:

$$P(a,b) = \frac{D(a,b) + D(a \cap b, 0)}{D(a,0) + D(b,0)} \quad (14)$$

$$P(b,a) = \frac{D(b,a) + D(a \cap b, 0)}{D(a,0) + D(b,0)} \quad (15)$$

where $D(a,b)$ is the area where a dominates b (area 5 and 3 in Figure A-1);

$D(b,a)$ is the area where b dominates a (area 1 and 2 in Figure A-1);

$D(a,0)$ is the area of a (area 1, 4 and 5 in Figure A-1);

$D(b,0)$ is the area of b (area 2, 3, and 4 in Figure A-1);

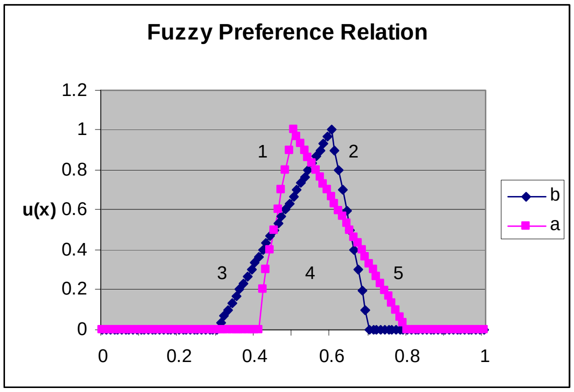

Figure A-1: Example of fuzzy preference relation

$D(a \cap b,0)$ is the area where a and b are indifferent (area 4 in Figure A-1).