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Decision-making analysis of scheme selection under different preferences

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Abstract

In the conceptual design stage of new product development, one of the major challenges is how to effectively determine the single best scheme from multiple alternatives. Based on the Axiomatic Design Theory, this paper proposes a new method to analyze and compare alternative schemes, and the Markov function is then used to calculate cost and determine the optimization direction of the chosen scheme. The cost of the optimal solution is estimated through calculations with utility functions. To add more details to the final design, it is necessary to consider both the working environment and user preferences, then to further analyze the schemes via fuzzy intuitions in order to determine the best prototyping and optimization strategy. This paper employs the design process of a library robot, which is designed in the context of university campus environment, as an illustrate example to showcase how to use the proposed method.

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Keywords: Robot; Markov-utility function analysis; Intuition fuzzy analysis.

1. Introduction

Alongside rapid advancements in technology, the demand for personalized products has increased substantially in recent years. To create a successful product scheme, the designer must consider both customer preferences and discrepancies in product usage. Traditionally, the design scheme is transformed into fuzzy set-theory for decision-making analysis [1]. Suggested by the Axiomatic Design Theory, there are a variety of different design decisions, which should be categorized into different domains. Furthermore, design decisions of the same kind should be organized into a hierarchy to accommodate their different abstraction levels. Despite many obvious advantages of such a two-dimensional design structure (i.e., domain and hierarchy), the design decision making process inevitably becomes more complicated, because design decisions are oftentimes fuzzy, in particular, during the early design phases. In the past, many researchers have attempted to address the fuzziness in axiomatic design [2]. For example, Hu et al. used a Markov model to predict the design direction of the discrete optimization design scheme [3]. By using a Markov model, Girard J. et al. proposed a set of optimized control logic, which controls the robot by mimic-learning [4]. Although these methods can only solve decision-making problems within a single domain, however. Due to the different preferences among decision-makers, several decision-making methods should be comprehensively applied and effectively integrated throughout the overall design process [5,6]. He et al. used the fuzzy intuition method to solve multi-program decision-making problem sunder a variety of circumstances [7]. Through this method, the designer transforms the index of several schemes into a compound matrix and then selects the best scheme by analyzing the matrix priority [8]. In the robot design field, Wallace et al. successfully improves the reliability of the robot design through an axiomatic design method [9].

Based on the existing axiomatic design theory, related works, and a combination of subjective and objective models, we quantitatively analyzed the decision-making process of a complex design scheme, and then comprehensively analyzed the possible problems of a partial or overall decision-making process during the design stage. We utilize the "I moving" robot, which works in the university campus environment, as an example to prove the effectiveness of this method.

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2. Theoretical framework

During the axiomatic design process, this paper established three designs on different research levels: conceptual design, product design, and technical design. The relationships among the three design stages are progressive but also iterative. It is obtained several conceptual design schemes, product design schemes, and function design schemes applicable throughout the process. The decision-making analysis was then applied to select the optimal scheme of the three different designs. The Markov model is used to predict the cost transition matrix of the product scheme in the conceptual design stage. In the product design stage, the utility function is used to discover the relationships between the risk, profit, and cost of a product. In the technical design process, the fuzzy intuition method is used to select the optimal scheme among several design schemes.

Axiomatic design serves as the theoretical foundation of the proposed framework. As shown in Fig. 1, cost estimation of the next stage can be obtained through the cost probability matrix. By doing so, we can preliminarily determine the cost of each function module of the next stage.

Next, three sets of prototype machines were proposed, and the one best suited to the operating environment. Due to the subjective influence of many factors, after obtaining several design schemes of the prototype machine, we analyzed the schemes through a subjective decision-making method, the fuzzy intuition method.

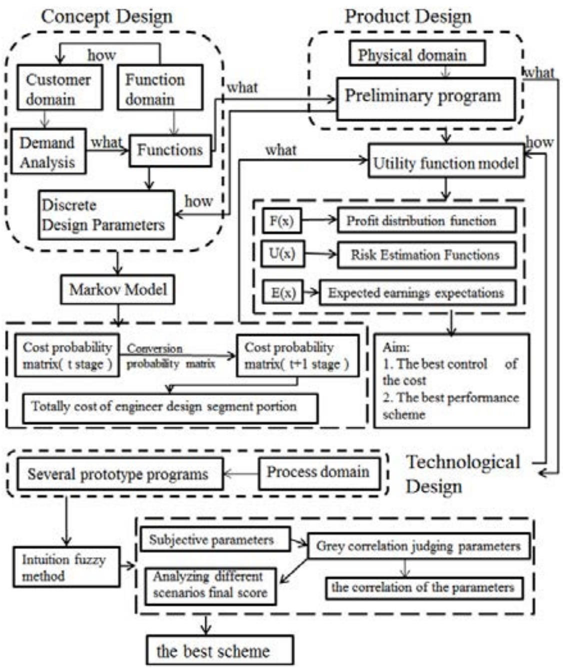

Fig.1. Framework of the proposed method

3. Preliminary scheme design

3.1. Markov function analysis

According to the independence axiom, the matrix of product design is determined by the mapping relationships between functional requirement (FR) and design parameters (DP) during the conceptual design stage [10]. A design matrix is used to represent the FR-DP relationships:

$$[FR]_{m\times1} = [A]_{m\times n}\times[DP]_{n\times1} \tag{1}$$

Where the parameter matrix of A is determined by

$$A_{ij} = \frac{\partial FR_i}{\partial DP_i} \tag{2}$$

If matrix A is a purely diagonal matrix, the scheme is uncoupled, meaning that all its functional requirements can be satisfied independent of each other.

This paper establishes a conversion probability function for the parameter matrix of the product via the Markov function. Under the conditions of discrete-time and finite-state, the first order Markov function forms a state sequence composed of random variables that are dependent only on the random variables of the previous stage. By using the transfer function, we can deduce the probability matrix of the next state from the probability matrix of the current state.

Let δ_i be the risk of cost fluctuation under the current state, and $i=1,2,3,\ldots,n$.

The cost probability matrix for designing a certain function of the robot is:

$\mu=\{\mu_i,\mu_j,\mu_k\}$;

The converted cost probability matrix for adding a new function or changing the original function on the robot is

$$\mu' = \left\{ \frac{\mu_i}{\sum_{i=1}^{n}\mu_i}, \frac{\mu_j}{\sum_{j=1}^{n}\mu_j}, \frac{\mu_k}{\sum_{k=1}^{n}\mu_k} \right\} \tag{3}$$

$i,j,k\in C$.

Adding or changing a function on the robot will lead to an expected profit change (x), where:

$x=\{x_i,x_j,x_k\}$, $i, j, k\in C$.

The transition probability matrix is P. After analyzing the conceptual scheme, we can obtain the parameters of the basic functional system cost, the risk of cost fluctuation in the current state, and the estimated profit. The above parameters construct matrix P, which is the conversion probability matrix that converts the current cost probability into the cost probability matrix of the next stage. So,

$$P = \frac{\mu_{i,j,k}}{\mu'_{i,j,k}\cdot\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\mu_{i,j,k}} \tag{4}$$

The state transition matrix of the next stage is

$$\mu_{i,j,k}^{t+1'} = \mu_{i,j,k}^{t'}\cdot P \text{ , } t\in C . \tag{5}$$

3.2. Dividing cost-utility stages

Because the Markov model can only predict the variation tendency of the design cost for the next stage, modular design should be adopted to realize the basic functions for moving, steering, and bearing during the design process. These functions are designed so that all functions meet the requirements of axiomatic design. While making an axiomatic decision, the following two axioms must be complied with.

Axiom 1: The Independence Axiom, which maintains the independence of functional requirements.

Axiom 2: The Information Axiom, which minimizes information content.

Based on the above, it is found a relationship in matrix A: m=n.

The cost of the movement system is determined by three factors: The turning radius, the control difficulty, and the hardware selection. These three factors should all meet the Independence Axiom, so the cost distribution matrixes of the three factors must meet the requirements of the diagonal matrix. Therefore, m=n=3.

The utility function can help explain the relationships between risk, cost and profit.

Assuming the cost (μ) and the net profit distribution function f(x) follow the linear plus exponential utility function, we have:

$$f(x)=\begin{cases}\delta_{ij}\cdot e^{-(x-\mu)^2}/\int_0^\infty e^{-(x-\mu)^2}\,dx & x\geq 0\\ 0 & x<0\end{cases} \tag{6}$$

i,j∈C.

The risk preference function is:

$$v(x)=\frac{\int_0^x \delta\cdot e^{-(x-\mu)^2}dx}{\int_0^\infty e^{-(x-\mu)^2}dx}\ . \tag{7}$$

Under the risk preference theory, we have:

$$U(x)=-\frac{v''(x)}{v'(x)}=\frac{-2(x-\mu)^2\cdot e^{-(x-\mu)^2}+e^{-(x-\mu)^2}}{\mu e^{-\mu^2}+(x-\mu)e^{-(x-\mu)^2}} \tag{8}$$

$$U(x)=\begin{cases}>0 & \text{Risk aversion}\\ =0 & \text{Risk neutral}\\ <0 & \text{Risk preference}\end{cases} \tag{9}$$

Taking the effectiveness function, the average expectancy of decision risk is given by:

$$E(x)=\delta\cdot\frac{2x\int_0^x e^{-(x-\mu)^2}dx}{\sqrt{\pi}}+\frac{\sqrt{\pi}}{2} \tag{10}$$

According to the risk preference theory, when x=μ, the scheme is a risk-neutral type; when x>μ, the scheme is a risk-seeking type; when x<μ, the scheme is a risk-aversion type. As the profit increases, the risk increases correspondingly.

4. Cost-utility preference analysis of the second generation robot

4.1. *"I moving" robot*

Taking the initial design of the library robot at Beijing University of Civil Engineering and Architecture (BUCEA), as an example, we discussed three key factors which influence the movement system through the Markov-utility function model. The cost is mostly related to the turning radius, control difficulty, and hardware selection. Assuming that all three design schemes are fit for the library's operational demands, there are still other factors that affect the design scheme such as comfort level, service target and usage cost.

Previous studies indicated that the influencing factors of the robot's production cost include: turning radius, control difficulty and hardware selection [12]. The detailed classifications of different cost schemes affected by various influencing factors are shown in Fig.2.

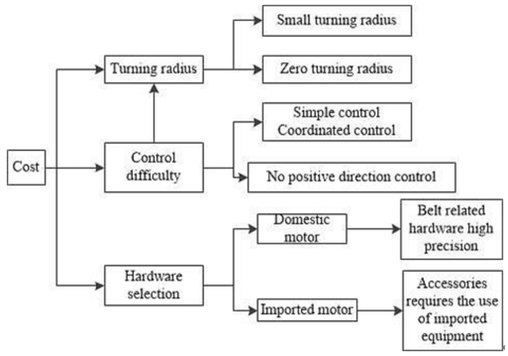

Fig. 2. Influencing factors of the robot's movement system.

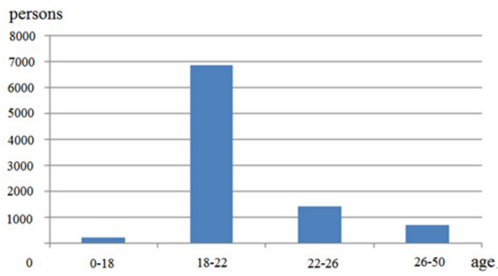

Fig. 3. Age distribution of the library user in BUCEA.

4.2. *Cost-function parametric index of the robot*

Figure 3 shows the age distribution of library users in BUCEA. As illustrated, college students are the primary target customers of the library robot. Therefore, during the fuzzy intuition analysis, we preferentially selected the scheme most suited to young people.

The relevant parameters determined through market research are shown in Table 1.

Based on the complete data of the completed basic movement system, we can obtain the cost of design and construct μ_1= [2300, 1400, 1500]. Therefore, we can calculate the cost distribution probability as μ_1=[0.442, 0.269, 0.289].

Table 1. Cost distribution of walking robot system.

	Cost μ (RMB)
Turning radius	2300
	3300
Control difficulty	1600
	1400
Hardware selection	3500
	1500

Due to Eq.(4), we have:

$$P=\begin{bmatrix} 1.032 & 0 & 0 \\ 0 & 0.878 & 0 \\ 0 & 0 & 1.066 \end{bmatrix}.$$

Substituting the result P into Eq.(5), we get the estimated cost distribution probability in $\mu_1=\mu_1'\cdot P=[0.457, 0.236, 0.307]$.

Thus, without adding additional cost, choosing the right hardware and truncating the turning radius can further improve the robot's performance.

The estimated profit of this first generation engineering prototype machine is RMB(means China monetary unit) 5,000 and the cost is RMB 8,000. Through Eq.(8) and Eq.(9), we have $U(x)>0$, which shows the scheme of this first generation is a risk aversion type.

Based on Markov function calculations, we found that the robot's performance can improve the cost distribution probability, where $\mu_1=[0.457, 0.236, 0.307]$. Through Eq. (8) and Eq.(9), we found: Let $U(x)=0$, so $x=u$. With Eq.(10), we have:

$$E(\mu)=5932\delta+\frac{\sqrt{\pi}}{2}-\varepsilon.$$

When ε is at a minimum, $E(\mu)=0$, which means the risk of cost fluctuation (δ) can be ignored.

Using the Markov function, it was found that the library robot design has a high demand for hardware selection and turning radius; demands for control precision and accuracy are low. Using the utility function, we discovered that when the total cost is RMB 5,932, the Markov-utility function is at its best decision point. Thus, controlling the cost of the robot at RMB 5,932 allows us to obtain the maximal return probability. To secure a higher profit, it should consider not only the robot's functional parameters but also the adapt ability of its appearance in a service group using fuzzy intuition analysis.

4.3. Three design schemes

The optimized cost was subdivided into three parts and three sets of movement system schemes were designed accordingly. The objective calculation shows that in addition to the movement demands, the designers should consider subjective factors like the robot's appearance, service target and unique environmental factors at BUCEA. Table 2 shows the three basic library robot schemes. Three sets of prototype robots are shown in the Fig. 4.

4.4. Expert valuation indicators of the fuzzy schemes

Table 3 facilitates analysis the schemes through the subjective evaluation of the movement system, appearance and service target. However, it is difficult to find subjective factors relative to an objective analysis of the schemes through factors such as research cost, service life and operative difficulty index. Figures 3-5 show three sets of scheme evaluations given by three experts who analyzed the schemes by a multi-attribute fuzzy preference decision-making method. This paper distributed the weight of the three decision-makers as (μ_k,v_k,π_k), as shown in table 6.

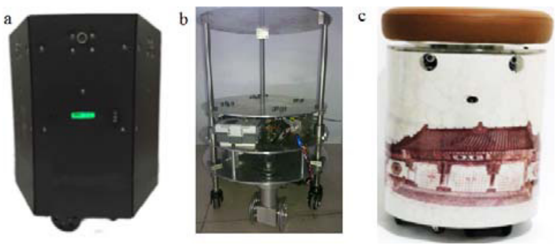

Fig. 4. (a) A_1; (b) A_2; (c) A_3.

Table 2. Features profiles of three schemes.

	Wheel	Steering System	Bearing and Movement System	Product Future	Service Target
A_1	Normal train wheel (small), Elastic, with brake, easily causes a side skid.	Turning radius stays at zero, inflexible direction turning, the wheel has an off-center problem.	Separate bearing and movement systems.	Equipped with battery indicator. Easy installation. Small in appearance.	18-26 years old
A_2	Compound wheels.	Wheel steering system.	Integrated bearing and movement systems.	Small in appearance. Fixed- height. Hard installation.	10-36 years old
A_3	Normal train wheel (large), steady running.	Turning radius stays at zero.	Separate bearing and movement systems, but cannot move when a load is being applied.	Adjustable-height. Large in appearance, heavy weight, ergonomic design, rides comfortably.	14-26 years old

Table 3. Evaluation by Expert D_1.

	Movement System	Appearance	Target User
A_1	C_{11}(0.7,0.1,0.2)	C_{12} (0.6,0.2,0.2)	C_{13} (0.5,0.4,0.1)
A_2	C_{21}(0.3,0.6,0.1)	C_{22}(0.1,0.6,0.3)	C_{23}(0.5,0.2,0.3)
A_3	C_{31}(0.3,0.6,0.1)	C_{32}(0.1,0.5,0.4)	C_{33}(0.4,0.1,0.5)

Table 4. Evaluation by Expert D_2.

	Movement System	Appearance	Target User
A_1	C_{11}(0.5,0.2,0.3)	C_{12}(0.5,0.3,0.2)	C_{13}(0.6,0.3,0.1)
A_2	C_{21}(0.2,0.7,0.1)	C_{22}(0.1,0.8,0.1)	C_{23}(0.7,0.2,0.1)
A_3	C_{31}(0.3,0.5,0.2)	C_{32}(0.1,0.7,0.2)	C_{33}(0.2,0.2,0.6)

Table 5. Evaluation by Expert D_3.

	Movement System	Appearance	Target User
A_1	C_{11}(0.6,0.1,0.3)	C_{12}(0.7,0.2,0.3)	C_{13}(0.3,0.6,0.1)
A_2	C_{21}(0.5,0.2,0.3)	C_{22}(0.2,0.6,0.2)	C_{23}(0.8,0.1,0.1)
A_3	C_{31}(0.2,0.7,0.1)	C_{32}(0.1,0.6,0.3)	C_{33}(0.3,0.3,0.4)

Table 6. Policymaker's weight distribution.

Expert	Weight	Numerically Value
D_1	I(important)	(0.75,0.20,0.05)
D_2	VI(very important)	(0.90,0.05,0.05)
D_3	M(medium)	(0.50,0.40,0.10)

Table 7. Complex multi-attribute matrix.

	Travel System	Shape	Suitable Crowd
A_1	C_{11} (0.5936,0.1420,0.2654)	C_{12} (0.5820,0.2421,0.2235)	C_{13} (0.4958,0.4051,0.1001)
A_2	C_{21} (0.3050,0.5493,0.4212)	C_{22} (0.1234,0.6844,0.1932)	C_{23} (0.6542,0.1769,0.1699)
A_3	C_{31} (0.2770,0.5820,0.1420)	C_{32} (0.1001,0.6076,0.2933)	C_{33} (0.2933,0.1886,0.5191)

4.5. Analysis of the characteristic environmental suitability by using fuzzy intuition analysis method

Changing the weights of the policymakers into weight coefficients, we have:

$$\lambda=\frac{\Delta min+\rho\cdot\Delta max}{\Delta_{ij}+\rho\cdot\Delta max} \tag{11}$$

Where kϵ(1,3) is substituted k into Eq.(11) as follows:

λ_1=0.349, λ_2=0.419, λ_3=0.233.

With the above values we obtained the complex multi-attribute fuzzy intuition matrix shown in Table 7. The fuzzy intuition entropies of the three attributions can be obtained by

$$H_j=-\frac{1}{n\cdot ln2}\sum_{i=1}^{3}[\mu_{ij}\cdot ln\mu_{ij}+v_{ij}\cdot lnv_{ij}-(1-\pi_{ij})ln(1-\pi_{ij})] \tag{12}$$

So we have: H_1=0.613, H_2=0.526, H_3=0.659. The entropy weight of the above values can be obtained by

$$\omega_j=\frac{1-H_j}{n-\sum_{j=1}^{n}H_j}. \tag{13}$$

And thus: ω_1=0.322, ω_2=0.394, ω_3=0.284.

After setting the corresponding grey correlation coefficient corresponding to different attributes, this paper obtained the value difference between the minimum and maximum. The fuzzy intuition entropy values of the three properties in Eq. (12) are: H_1=0.613, H_2=0.526, H_3=0.659. The weights of the corresponding attribute entropy are: ω_1=0.322, ω_2=0.394, ω_3=0.284. So each attribute's corresponding gray correlation coefficient value between the minimum and maximum can be determined.

It can substitute the value into $\varepsilon_{ij}=\frac{\Delta min+\rho\cdot\Delta max}{\Delta_{ij}+\rho\cdot\Delta max}$

Where ρ is a resolution ratio, in normal circumstances, ρ= 0.5. The Δij value shows the difference in value between the single-line maximum and the single-line minimum.

The corresponding gray relational degree γ_i is given by:

$$\gamma_i=\sum_{j=1}^{3}\omega_j\cdot\varepsilon_{ij} \tag{14}$$

Through the above equation, we have:

γ_1=0.7412, γ_2=0.8298, γ_3=0.7135.

Therefore, using the library environment, shape is more important than suitable crowd, while suitable crowd is more important than travel system. It is assigned different weight coefficients to different characters: The coefficient of travel system is 0.35, of shape is 0.45, and of suitable crowd is 0.20. The results are shown in Table 9.

Therefore, in the college environment where the floor is smooth and the running speed is high, it found A_1 preferential to A_2 and A_3 preferential to A_2.

Table 8. Grey correlation coefficient of each attribute.

	C_1	C_2	C_3	Min.	Max.
δ_1	0.4064	0.4180	0.5042	0.4064	0.5042
δ_2	0.6950	0.8766	0.3458	0.3458	0.8766
δ_3	0.7230	0.8999	0.7067	0.7067	0.8999
Δmin				0.3609	
Δmax					0.3957

Table 9. Overall merit of the programs.

A_1	A_2	A_3
0.5123	0.3472	0.4176

4. Conclusion

By using the Markov function, it is found that hardware selection and turning radius are the two driving forces that affect the robot's performance. By analyzing the utility functions, it was concluded that the risk of increasing cost is low. Above all, it came to the conclusion that the second-generation robot design will satisfy basic demands when operating in the library environment. It is also found that the cost-profit distribution conforms to the basic investment principle where profit increases with risk.

It was found that individuals pay the most attentions to the robot's appearance among all the factors it explored. Therefore, the first consideration when establishing the basic design scheme is that the appearance should satisfy the usage demand and ergonomic demand of the target users.

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