

A Method of Case Retrieval for Web-based Remote Customization Platform

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Abstract—A web-based remote customization platform is developed for hardware product in this paper. To realize the rapid product customization, a case-based reasoning approach based on fuzzy set is put forward. To retrieve the most similar case from the case base, a parabola membership function is constructed based on the fuzzy set, and synthesis weights are introduced by combining subjective weights with objective weights which are calculated based on the deviation information of similarity. Then the model for solving cases' global similarity is set up based on synthesis weights. To improve the accuracy of the similarity measurement, center distance revision method based on area is presented for the Bi-interval type which is one of fuzzy numeric attribute. Implementation example applying above methods is given in the area of electric drill customization. Results show that the presented approach helps to improve the accuracy of the similarity of the case product, and reduce the time and cost of product design process.

Index Terms—Individual Customization; Case-Based Reasoning; Membership Function; Similarity; Case Retrieval

I. INTRODUCTION

With the fast development of information technology, lots of manufacturing companies have set up remote online product customization system to meet user's need. Most of the systems could only provide product pictures, 3D product model information could not be demonstrated, all those limits the interactive communication between users and product designers, and this limitation will mostly increase the time and cost of product design process. To develop a web-based 3D product collaborative design system is an effective way to solve the problem.

Case-Based Reasoning is a good method in the fields of fast configuration design of mass customization. It has advantage in inducing and extracting the reasoning rules [1, 2]. Similar case indexing is the key of CBR [3]. Take impact drill as example, if product model with high similarity to the goal product could be found from the case base, then design period could be greatly shortened. As user's requirements are not clear enough in some circumstances, it is vital to calculate the similarity of

those unclear attributes such that the most similar case could be found.

Ref. [4] and Ref. [5] present a fuzzy logic approach which calculates the similarity and retrieves the best case based on the distance function and the fuzzy number converted from the exact number by the Gaussian function. However, cases' attributes could not be described by distance function which leads to the incomplete description of similarity and its inaccuracy. Ref. [6] and Ref. [7] propose the hybrid measure for comparing cases with a mixture of crisp and fuzzy features without considering the uncertainty for requirements. Similarity of fuzzy linguistic attribute and intervals could be calculated by applying the proposed measures. Accuracy of similarity is improved to some extent, and the measurement is used in the area of fault diagnosis, for example, abnormal tire wear. The limitations of the method are: (1) Hamming distance function is used for fuzzy attributes, (2) Overlapped area is repeated calculated of the similarity calculation of interval type. And this limitations set obstacle for obtaining the most accurate similarity and retrieving the best case. Ref. [8] and Ref. [9] solve the similarity to retrieve the case using the membership function constructed by using of the triangular, trapezoidal and Gaussian function. However, the membership functions are to some extent inaccuracy or complex [10]. Attributes of interval type are not considered in this method. And weights' average value is used as attribute weight. These could decrease the accuracy. On the other hand, triangular and trapezoidal function could not describe the characteristics of the cases' attribute correctly. And Gaussian function is too complicated for calculation.

To improve accuracy of similarity and to take cases' attributes into account, the paper puts forward a case-based reasoning approach based on fuzzy set (FSCBR). In this paper, first, the standard model set is defined. Then the parabola membership function of the model attribute is constructed, the similarity of the membership is calculated, the most matching case is searched and the rapid design platform based on the above approach is developed.

II. KEY TECHNOLOGIES OF CUSTOMIZATION PLATFORM

A. System Architecture

The proposed remote customization platform is composed of two parts which are server and client side. Customization design process could be described as following steps: first, user submit their demands to server from client side. Then, on server side, engineer from the company searching for the closest case from case base by applying the FSCBR method and the matched case with its 3D model are provided to user for 3D browsing and further processing. Fig. 1 shows the Model-View-Controller (MVC) architecture of the customization platform.

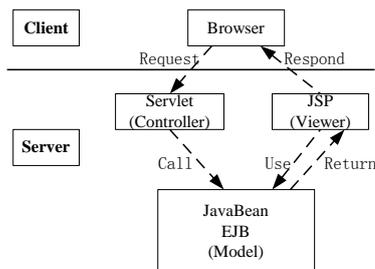


Figure 1. MVC architecture

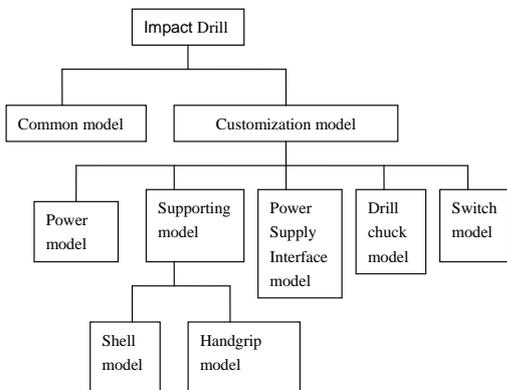


Figure 2. Components of impact drill model

B. 3D Interactive Browsing

AutoVue is used as 3D browser in the system. Functions like rotation, pan, zoom, sectioning and so on are provided. Geometrical and topological information could be extracted and enquired. 3D notation of design comments helps user better understands products. Part of the program codes is displayed here:

```

</tr>
<td width="15%">Product No.:</td>
<td width="15%" height="30"><%=project_code%></td>
<td rowspan="10">
<object id="AutoVueX" classid="clsid:B6FCC215-D303-11D1-
BC6C-0000C078797F" width="500" height="350">
<param name="src" value="<%=picture%>">
</object>
</td>
</tr>
    
```

C. Compact Drill Model

According to the structural analysis and the user requirements, components of compact drill are illustrated

as Fig. 2. The main attributes include: input power, body color, handle position, handle color, power supply voltage, maximum diameter of the drill, high idling speed, net weight, torque.

D. Proposed Approach

Case set is composed of product cases, it is written as M . Suppose there are n samples in M , and each sample has m attributes. Attribute set F is defined as

$$F = \{f_j \mid j = 1, 2, \dots, m\} \tag{1}$$

Attribute vector of i^{th} sample is defined as

$$\mathbf{c}_i = (z_{i1}, z_{i2}, \dots, z_{im}) \tag{2}$$

where: z_{ij} is the j^{th} attribute value of \mathbf{c}_i , $i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$. So M can be represented as

$$M = (\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_n)^T = (z_{ij})_{n \times m} \tag{3}$$

Because of the inaccurate of the input and output variables under fuzzy condition, trapezoidal membership function, triangular function and Gaussian function are normally used to calculate the similarity [11].

According to the characteristic, case attributes can be divided into four types as crisp symbolic attribute (CS), crisp numeric attribute (CN), fuzzy linguistic attribute (FL) and fuzzy numeric attribute (FN). A membership function illustrates the degree of membership for each possible crisp value of the fuzzy variables.

(1) CS attribute membership function

For CS attribute, there's no realistic quantity relation among all its possible values. We define crisp symbolic attribute membership function as

$$\mu_s(z) = \begin{cases} 1, & v = z \\ 0, & v \neq z \end{cases} \tag{4}$$

where: v is the value of the input attribute, z is the attribute value of the case base.

(2) CN attribute membership function

For CN attribute, its value represents a point in the attribute space. Distance between points describes the difference among case attributes. To define membership function based on distance is a good way for calculating the similarity among case attributes. CN attribute membership function is defined as following,

$$\mu_s(z) = 1 - \frac{|z - v|}{\max(z_i, v)} \quad ; i = 1, 2, \dots, n \tag{5}$$

(3) FN attribute membership function

In order to improve the accuracy and flexibility of problem description, an estimative figure v is always provided in practice. Fuzzy set theory is a suitable approach for assessing the similarity among these fuzzy attributes.

Assume fuzzy set S in the discourse domain D as following

$$S = \{(z, \mu_s(z)) \mid z \in D\} \tag{6}$$

TABLE I. PARAMETER VALUES FOR THE MEMBERSHIP FUNCTION EQ. (8)

	equal(=)	Not less than (> or ≥)	Not greater than (< or ≤)
c	v	max(f)	min(f)
di	min(λv; v - min(f))	min(max(f) - (v - λv); max(f) - min(f))	0
ds	min(λv; max(f) - v)	0	min((v + λv) - min(f); max(f) - min(f))

where: $\mu_s(\cdot)$ is the membership function of S , $\mu_s(z) \in [0,1]$ describes the grade of membership of z in S . The nearer the value of $\mu_s(\cdot)$ to unity, the higher the grade of membership of z in S .

Unlike scalars and intervals, fuzzy numbers are uncertain numbers for which, in addition to knowing a range of possible values, one can say that some values are more plausible, or ‘more possible’ than others. Triangular fuzzy number and trapezoidal fuzzy number are the most widely used fuzzy number types for decision making under the condition of fuzzy environment [12].

TABLE II. PARAMETER VALUES FOR THE MEMBERSHIP FUNCTION EQ. (9)

	Inside the range
c1	v1
c2	v2
di	min(λv1; v1 - min(f))
ds	min(λv2; max(f) - v2)

Fuzzy set based on parabola is applied here to simulate fuzzy numeric interval attribute, its function is defined as following,

$$L(z) = R(z) = z^2 \tag{7}$$

The membership function is denoted as,

$$\mu_s(z) = \begin{cases} 0 & , z \in [0, c1 - di] \\ \frac{1}{di^2} (z - c1 + di)^2 & , z \in [c1 - di, c1] \\ 1 & , z \in [c1, c2] \\ \frac{1}{ds^2} (z - c2 - ds)^2 & , z \in (c2, c2 + ds] \\ 0 & , z \in (c2 + ds, +\infty) \end{cases} \tag{8}$$

If $c1 = c2$, the membership function will be the same as that of FN, which is illustrated as following,

$$\mu_s(z) = \begin{cases} 0 & , z \in [0, c - di] \\ \frac{1}{di^2} (z - c + di)^2 & , z \in [c - di, c] \\ 1 & , z = c \\ \frac{1}{ds^2} (z - c - ds)^2 & , z \in (c, c + ds] \\ 0 & , z \in (c + ds, +\infty) \end{cases} \tag{9}$$

Suppose f as the membership, $d(f)$ as the domain, $\min(f)$ and $\max(f)$ are the minimum value and maximum value of $d(f)$, then its membership function

could be represented as $f(di, ds, c1, c2)$. Tab. 1 and Tab. 2 show the parameter values.

There exist six relationships, which are equal, less than, greater than, not less than, not greater than and within the range. And these six relationships could be grouped into three types: type I (Fig. 3) as equal, type II (Fig. 4 and 5) as less than, greater than, not less than, not greater than, type III (Fig. 6) as within the range.

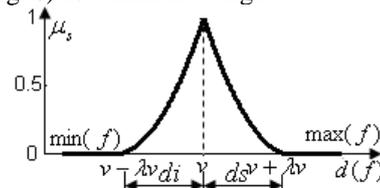


Figure 3. Type I

For fuzzy numerical interval attribute, if the input case attribute is also belong to type III, then there’s difficulty in calculating the attributes’ similarity by using above membership function. An approach based on overlapped area is put forward to revise the similarity for the Bi-interval type. Membership function is formulated based on Eq. (8), and the similarity of the fuzzy sets is calculated by computing the area overlapping rate of corresponding membership functions.

$$\begin{aligned} sim(x, y) &= A(x \cap y) / A(x \cup y) \\ &= A(x \cap y) / (A(x) + A(y) - A(x \cap y)) \end{aligned} \tag{10}$$

$$\begin{aligned} A(x) &= \int_{d(f)} \mu_s dz = \int_{c1-di}^{c2+ds} \mu_s(z) dz \\ &= \int_{c1-di}^{c1} \frac{(z - c1 + di)^2}{di^2} dz + \int_{c2}^{c2+ds} \frac{(z - c2 - ds)^2}{ds^2} dz + (c2 - c1) \times 1 \\ &= di / 3 + ds / 3 + c2 - c1 \end{aligned} \tag{11}$$

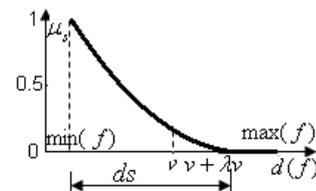


Figure 4. Type II (less than and not greater than)

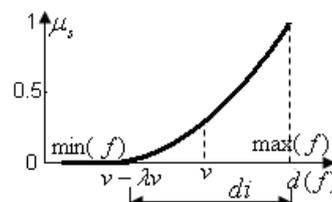


Figure 5. Type II (greater than and not less than)

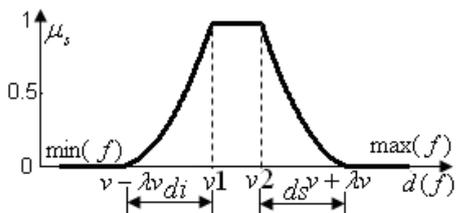


Figure 6. Type III

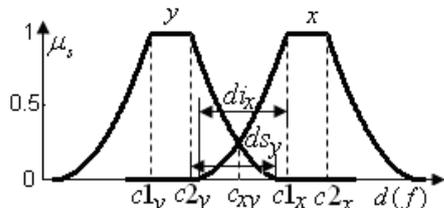


Figure 7. The representation of interval attribute and requirements

Take following Fig. 7 as example, the intersection area can be represented as

$$A(x \cap y) = \begin{cases} 0 & ; \quad x \cap y = \emptyset \\ \min(A(x); A(y)) & ; \quad x \subseteq y \quad \text{or} \quad y \subseteq x \\ \frac{(c_{xy} - c1_y + di_y)^3}{3di_y^2} + \frac{(c2_x + ds_x - c_{xy})^3}{3ds_x^2} & ; \quad x \cap y \neq \emptyset; c2_x \leq c1_y \\ \frac{di_y}{3} + \frac{ds_x}{3} + c2_x - c1_y & ; \quad x \cap y \neq \emptyset; c1_y < c2_x < c2_y \\ \frac{di_x}{3} + \frac{ds_y}{3} + c2_y - c1_x & ; \quad x \cap y \neq \emptyset; c1_x < c2_y < c2_x \\ \frac{(c_{xy} - c1_x + di_x)^3}{3di_x^2} + \frac{(c2_y + ds_y - c_{xy})^3}{3ds_y^2} & ; \quad x \cap y \neq \emptyset; c2_y \leq c1_x \end{cases} \quad (15)$$

For the Bi-interval type, if $x_i \subseteq y_i$, the coefficient k is introduced to revise the similarity based on the relative area.

Let $C_x = \frac{c1_x + c2_x}{2}$ and $C_y = \frac{c1_y + c2_y}{2}$, so

$$\varepsilon = |C_x - C_y| / (|c2_y - c1_y| / 2) \quad (16)$$

$$\overline{sim}(x, y) = ksim(x, y) \quad (17)$$

where:

$$k = \begin{cases} 1 & ; \varepsilon \geq 1 \\ 1 - \varepsilon & ; \varepsilon < 1 \end{cases} \quad (18)$$

(4) FL attribute membership function

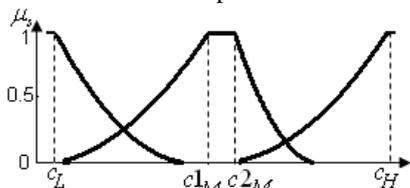


Figure 8. The representation of FL

FL attribute is a fuzzy concept which is associated with a certain fuzzy region. Because of the uncertainty of FL

$$A(x \cap y) = \int_{c1_x - di_x}^{c_{xy}} \frac{(z - c1_x + di_x)^2}{di_x^2} dz + \int_{c_{xy}}^{c2_y + ds_y} \frac{(z - c2_y - ds_y)^2}{ds_y^2} dz \quad (12)$$

$$= \frac{(c_{xy} - c1_x + di_x)^3}{3di_x^2} + \frac{(c2_y + ds_y - c_{xy})^3}{3ds_y^2}$$

where: c_{xy} is the value of the intersection point of fuzzy set border x, y .

Suppose $\mu_s(z_y) = \mu_s(z_x)$, and according to Eq. (8), we got

$$(z - c2_y - ds_y)^2 / ds_y^2 = (z - c1_x + di_x)^2 / di_x^2 \quad (13)$$

and

$$c_{xy} = (c2_y di_x + c1_x ds_y) / (di_x + ds_y) \quad (14)$$

The solution to intersection area could be written as:

attribute, the constructed membership function is shown in Fig. 8. The similarity can be measured by the FNI.

E. The Global Similarity

(1) Assess of hybrid weight

Hybrid weight is composed of two kinds of weights. For weight which illustrates the attributes from experts' subjective experience, it is defined as

$$\mathbf{w}^* = (w_1^*, w_2^*, \dots, w_m^*) \quad (19)$$

For objective weight which illustrates the attributes of the case product, it is defined as

$$\mathbf{w}^* = (w_1^*, w_2^*, \dots, w_n^*) \quad (20)$$

Suppose M_x as the case to be designed, s_{ij} is the similarity of the j^{th} attribute of M_x and M_i , similarity matrix of all the case attributes from M_x and M_i can be written as,

$$\mathbf{s} = \begin{pmatrix} s_{11} & s_{12} & \dots & s_{1m} \\ s_{21} & s_{22} & \dots & s_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \dots & s_{nm} \end{pmatrix} \quad (21)$$

Objective weight can be calculated by following formula.

TABLE III. REQUIREMENTS FOR RAPID DESIGN OF DRILL

Attribute	Input power/W	Body color	Handle position	Handle color	Power supply voltage/V	Maximum diameter of the drill/mm	High idling speed/rpm	Net weight /Kg	Torque /Nm
M_1	850	Black	bottom	Black	230	19	2800	2.7	5~15
M_2	1200	Black	middle	Grey	110	13	550	1.8	45~60
M_3	950	Red	bottom	Red	220	16	2000	2.5	25~35
...
M_s	900~1000	Red	bottom	Red	220	16	normal	≤ 3.0	10~40
Uncertainty degree	30%	0	0	0	0	40%	20%	20%	20%
Can be ignored?	No	No	No	Yes	No	No	No	No	No
Type	FN	CS	CS	CS	CN	FN	FL	FN	FN
Relationship	within	-	-	-	-	equal	mean	\leq	interval
Weight(w^*)	0.25	0.05	0.05	0	0.1	0.15	0.15	0.1	0.15

$$w_j^* = \frac{[\sum_{i=1}^{n-1} \sum_{k=i+1}^n (s_{ij} - s_{kj})^2]}{\sqrt{\sum_{j=1}^m [\sum_{i=1}^n \sum_{k=i+1}^n (s_{ij} - s_{kj})^2]}} \quad (22)$$

where $\sum_{i=1}^n \sum_{k=i+1}^n (s_{ij} - s_{kj})^2$ represents the sum of square of similarity deviations of the j^{th} attribute of each case.

The hybrid weight of case M_i can be given by following formula.

$$w = \left(\frac{w_1^* w_1^*}{\sum_{j=1}^m (w_j^* w_j^*)}, \frac{w_2^* w_2^*}{\sum_{j=1}^m (w_j^* w_j^*)}, \dots, \frac{w_m^* w_m^*}{\sum_{j=1}^m (w_j^* w_j^*)} \right) \quad (23)$$

(2) Global similarity

Solution model for global similarity can be denoted as following,

$$sim = s_{n \times m} w_{m \times 1}^T = (sim_1, sim_2, \dots, sim_n)^T \quad (24)$$

where:

$$sim_i = \frac{\sum_{j=1}^m w_j s(i,j)}{\sum_{j=1}^m w_j}, \quad i = 1, 2, \dots, n$$

$$\sum_{j=1}^m w_j = 1.$$

III. CASE STUDY AND SYSTEM IMPLEMENTATION

A. Case Study of Impact Drill

Tab. 3 shows the examples and requirements for the customized electric drill

(1) Similarity measurement for CS

Take attribute “handle position” for example, suppose the requirement of this attribute is “bottom”, if attribute value of the matching case is bottom, then the similarity equals 1, otherwise is 0.

(2) Similarity measurement for CN

Take “power supply voltage” for example, according to Eq. (5), following results could be attained

$$\mu_s(230) = 1 - |230 - 220| / 230 \approx 0.957,$$

$$\mu_s(110) \approx 0.522,$$

$$\mu_s(220) = 1.$$

(3) Similarity measurement for FN

(a) Type I

Take attribute ‘Maximum diameter of the drill’ as example, its specification is 4-49. According to Tab. 1, we got $c = v = 16$ and $di = ds = 0.4 \times 16 = 6.4$. Applying Eq. (9), we obtained

$$\mu_s(19) = (19 - 16 - 6.4) / 6.4^2 = 0.282,$$

$$\mu_s(13) = (13 - 16 + 6.4) / 6.4^2 = 0.282,$$

$$\mu_s(16) = 1.$$

(b) Type II

Take attribute ‘Net weight’ as example, the general weight range of drill is [1.5, 7.0]. Design requirement is less than or not greater than 3.0 kg. According to Tab. 1, we got $v = 3.0, \max(f) = 7.0, \min(f) = 1.5$, $\lambda v = 0.2 \times 3.0 = 0.6$ and $ds = 2.1$.

Applying Eq. (9), we obtained

$$\mu_s(z) = (z - 3.6)^2 / 2.1^2 \quad (25)$$

Then, $\mu_s(2.7) = 0.184, \mu_s(2.5) = 0.274, \mu_s(1.8) = 0.73$.

(c) Type III

Take attribute ‘Input power’ as example, design requirement is ‘900-1000’. According to Tab. 2, we got $c1 = v1 = 900, c2 = v2 = 1000, di = 0.3 \times 900 = 270$ and $ds = 0.3 \times 1000 = 300$.

Applying Eq. (9), we obtained

$$\mu_s(850) = (850 - 630)^2 / 270^2 = 0.664,$$

$$\mu_s(1200) = 0.111,$$

$$\mu_s(950) = 1.$$

(d) Bi-interval type

Take attribute ‘Torque’ as example, both requirement attribute and the case attribute are interval type. Suppose case1, case2, case3 and requirement attribute as $x1, x2, x3, y$. According to Eq. (11) and Tab. 2, we got

$$A(x1) = 11.333, A(x2) = 22,$$

$$A(x3) = 18.667, A(y) = 33.333$$

As there’s point of intersection between the torque curves of case 2 and the requirement, according to Eq. (14), we got

$$c_{x2y} = 42.353$$

Substituting it into Eq. (15) and Eq. (10), then we got

$$sim(x1, y) = 6.667 / (33.333 + 11.333 - 6.667) = 0.175,$$

$$sim(x2, y) = 1.993 / (33.333 + 22 - 1.993) = 0.037 ,$$

$$sim(x3, y) = 18.667 / 33.333 = 0.56 .$$

And, considering

$$c_{x3} = (20 + 35) / 2 = 27.5$$

$$c_y = (10 + 40) / 2 = 25$$

$$\epsilon = |27.5 - 25| / |(40 - 10) / 2| \approx 0.167$$

Then,

$$sim(x3, y) = (1 - 0.167) \times 0.56 = 0.466 .$$

(4) Similarity measurement for FL

Take attribute ‘High idling speed’ as example, design requirement is ‘normal’. The survey shows that the high, normal and low attributes of ‘High idling speed’ are [2500, 3200], [1000, 2500] and [500, 1000] respectively. So, the similarity can be measured by type II.

$$\mu_s(2800) = 0.160, \mu_s(550) = 0, \mu_s(2000) = 1$$

If the case attribute is also the fuzzy concept, the similarity can be measured according to Bi-interval type.

So, the similarity matrix can be given as following

$$s = \begin{pmatrix} 0.664 & 0 & 1 & 0.957 & 0.282 & 0.16 & 0.184 & 0.175 \\ 0.111 & 0 & 0 & 0.522 & 0.282 & 0 & 0.73 & 0.037 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0.274 & 0.466 \end{pmatrix}$$

According to Eq. (22), objective weight vector of similarity w^* can be given as

$$w^* = (0.32, 0.53, 0.53, 0.11, 0.28, 0.46, 0.14, 0.08)$$

Considering expert’s subjective weight

$$w^* = (0.25, 0.05, 0.05, 0.1, 0.15, 0.15, 0.1, 0.15) ,$$

hybrid weight vector w can be attained by applying formula (23)

$$w = (0.29, 0.09, 0.09, 0.04, 0.15, 0.25, 0.05, 0.04) .$$

Global similarity can be calculated as following by applying Eq. (24)

$$sim = s_{3 \times 8} w^T_{8 \times 1} = (0.421, 0.131, 0.943)^T .$$

Figure 9. Interface for inputting user requirements

B. System Implementation

Applying SQL Server and tomcat 6.0 together with the presented approaches, a Web-based remote customized

impact drill system is developed. Based on the parameters submitted by the user from client side shown in Fig. 9, the system finds the most suitable case from the existing case base by employing FSCBR algorithm. The corresponding 3D STEP model illustrated in Fig. 10 is given at the same time, which provides user the possibility to browse the product model and further interactive operation with product designer.

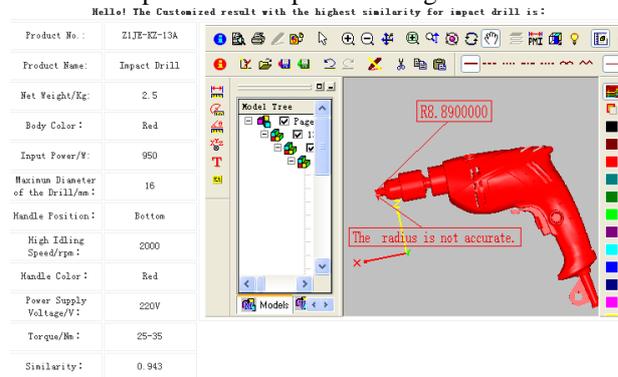


Figure 10. Illustration of the best case and its 3D model

C. FSCBR Retrieving Results

The similarity of all attributes shown in Tab. 3 is calculated by the nearest neighbor method, Hamming distance method and fuzzy similarity method (FSM) presented by Ref. [6], respectively.

The matrix of the attributes similarity with the nearest neighbor method is as following,

$$\begin{pmatrix} 0 & 0 & 1 & 0.917 & 0.5 & - & 0.75 & 0.091 \\ 0.286 & 0 & 0 & 0 & 0 & - & 0 & 0.455 \\ 1 & 1 & 1 & 1 & 1 & - & 0.583 & 1 \end{pmatrix} .$$

The matrix of the attributes similarity with Hamming distance method is as following,

$$\begin{pmatrix} 0.714 & 0 & 1 & 0.917 & 0.5 & - & 0.75 & 0.727 \\ 0.286 & 0 & 0 & 0.083 & 0.5 & - & 0 & 0.5 \\ 1 & 1 & 1 & 1 & 1 & - & 0.583 & 0.909 \end{pmatrix} .$$

The matrix of the attributes similarity with FSM is as following,

$$\begin{pmatrix} 0.664 & 0 & 1 & 0.957 & 0.282 & 0.16 & 0.184 & 0.175 \\ 0.111 & 0 & 0 & 0.522 & 0.282 & 0 & 0.73 & 0.037 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0.274 & 0.56 \end{pmatrix} .$$

The global similarity between M_x and M_i ($i=1, 2, 3$) listed in Tab. 3 is shown in Tab. 4.

Illustrated examples show that the final case found by FSCBR is the same as by Hamming Distance, Nearest Neighbor Method and FSM. M_3 is the closest case and M_2 is the least similar case. However, imilarity differences exist among those methods. The $sim(M_x, M_3)$ is almost the same while using FSCBR and Hamming Distance. And it’s larger than the similarity calculated by Nearest Neighbor Method and FSM. The $sim(M_x, M_1)$ is very close while using FSCBR and FSM. And it’s larger than the similarity calculated by Nearest Neighbor Method but smaller than that of Hamming Distance. The $sim(M_x, M_2)$ is almost the same while using FSCBR and Nearest

Neighbor Method. And it's smaller than the similarity calculated by Hamming Distance method and FSM.

TABLE IV. THE GLOBAL SIMILARITY CALCULATED BY FOUR METHODS

	Sim(M_1, M_2)	Sim(M_1, M_3)	Sim(M_2, M_3)	Time/s
the nearest neighbor method	0.305	0.140	0.808	0.62
Hamming distance method	0.729	0.380	0.945	0.54S
FSM presented by Ref. [6]	0.423	0.201	0.861	1.01S
FSCBR presented in this paper	0.421	0.131	0.943	1.09

The reasons caused the limitations of the traditional methods are analyzed as following, (1) The similarity of FL attribute 'High idling speed' is omitted, because requirement 'normal' can't be recognized. (2) For attribute of FN type, the medium value of the closed interval or the border value of the open interval is taken for calculating similarity which leads to inaccuracy of the final result. (3) For FSM, its similarity lacks high accuracy due to following reason: (a) Overlapped area is repeated calculated; (b) attribute weight is simply by using the weights' average. (4) Uncertainty factors are ignored in calculating similarity in traditional methods while FSCBR take it into accounts which result in better similarity accuracy.

IV. CONCLUSION

A case-based reasoning approach based on fuzzy set is presented for remote customization platform of hardware product and impact drill. This approach includes algorithm for generalized membership function, method for center distance correction based on relative area and calculation model for global similarity based on mixed weights. By applying the method, the limitation of the traditional similarity calculation methods which are mostly based on distance functions is to some extent solved, and the accuracy of the similarity is also improved. It provides a new solution to similarity measurement in the application of product customization.

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