CHEMICAL ENGINEERING TRANSACTIONS

VOL. 46, 2015

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Peiyu Ren, Yancang Li, Huiping Song

ISBN 978-88-95608-37-2; **ISSN** 2283-9216

DOI: 10.3303/CET1546209

A Method of Product Extension Case Reasoning based on Region Semantic Correlation

Jian Lyu, Qingsheng Xie*, Haisong Huang, Weijie Pan

Key Laboratory of Advanced Manufacturing Technology,Ministry of Education Guizhou University, Guiyang, Gui-zhou, 550003, China.
305515940@qq.com

In view of the design scheme convergence in the process of product design, a method of product extension case rea-soning based on region semantic correlation is presented. In combination with product semantics and primitives theo-ry in extenics, the knowledge representation method in process of product design and convergence process of design cases were studied. In the convergence process, the semantic correlation function should be established first, and the evaluation method for convergence process of product family is presented. According to the semantic relevant web and partial correlation degree evaluation, the product extension case reasoning for product design can be achieved. This paper take a machine tool concept design as an example, and this method has a good effect in the design proses which can be a method reference for case reasoning in product design.

1. Introduction

CBR is a kind of important problem solving, and learning methond based on knowledge .Nowadays,CBR is a hot research topic in many areas. (ALTHUIZEN, N, et al., 2014) report: investigate the use of the case-based reasoning (CBR) technology, which is based on the principle of analogical reasoning, to aid individuals in solving business problems creatively.(YU, Y, et al., 2015) report: rule-based reasoning (RBR) and case-based reasoning (CBR) are applied into the boiler intelligent design.(HU, J, et al., 2015) report: employs weighted mean (WM) as a basic model, and presents a new CBR adaptation method for PMD by integrating with problem-solution (PS) relational information.(RASHEDI, E, et al., 2014) report: presents a long term learning method in CBIR systems adopting case based reasoning (CBR) which is called Case-based LTL (CB-LTL).(ROLDAN REYES, E, et al., 2015) report: presents a new interactive method for adaptation knowledge elicitation, acquisition and reuse, thanks to a modification of the traditional CBR cycle.(CHANG, S, et al., 2015) report: developed a system for CBR that can analyze the similarity through graph comparison and search for buildings.(TAKAI, S, et al., 2014) report: presents case-based reasoning methods for cost estimation and cost uncertainty modeling that may help designers select a new product concept at the early stage of product development.(ZHOU, P, et al., 2014) report: a data-driven soft-sensor using case-based reasoning (CBR) and fuzzy-similarity rough sets is proposed for product quality estima-tion.(BOUHANA, A, et al., 2015) report: present a novel information retrieval approach for personalized itinerary search in urban freight transport systems based on the integration of three techniques: Case Base Reasoning, Choquet integral and ontology.(ZHU, G, et al., 2015) report: proposes a hybrid CBR system by introducing reduction technique in feature selection and cluster analysis in case organization.(HONG, T, et al., 2015) report: developed an estimation methodology for the dynamic operational rating (DOR) of a new residential building using the advanced case-based reasoning (A-CBR) and stochastic approaches.(KOO, C, et al., 2015) report: develop a dynamic energy performance curve for evaluating the historical trends in the energy performance of existing buildings using a simplified case-based reasoning (S-CBR) approach.(HASHEMI, H, et al., 2014) report: propos a case-based reasoning (CBR) method, with improved indexing and retrieving approaches which are critical issues in machining fixture design systems.(MA, G, et al., 2015) report:propose an intelligent fault diagnosis model for power equipment based on case-based reasoning (IFDCBR).(MINOR, M, et al.,

Please cite this article as: Lyu J., Xie Q.S., Huang H.S., Pan W.J., 2015, A method of product extension case reasoning based on region semantic correlation, Chemical Engineering Transactions, 46, 1249-1254 DOI:10.3303/CET1546209

2014) report: present on a Case-based Reasoning approach for automated workflow adaptation by reuse of experience.
Here we focus on the convergence of product design schemes and put forward the extension case-based reasoning (ECBR) based on product semantic relevance. Through the semantic relevance function built, the method for goodness evaluation targeting the issue of convergence of product family comes into being. Finally, ECBR for the product function module is realized by relying on semantic relevance network and region relevance evaluation.

2. Basic element representation of design process knowledge

In extension theory, basic element unites quality and quantity and action and relation through a triplet consisting of object O, characteristic C and value V. By this means, the matters, affairs and relations are described in a formalized way. Basic element B is divided into matter element M, affair element A and relation element R, collectively expressed as Eq(1)

$$B=(O,\quad C,\quad V)=\begin{bmatrix} O & c_1 & v_1 \\ & c_2 & v_2 \\ & \cdots & \cdots \\ & c_n & v_n \end{bmatrix} \tag{1}$$

Basic element set $S=\{B\}$ of product design is established to represent the quantitative and qualitative issues during the design process. Thus the innovation method and product design evaluation method are described intuitively.

3. Convergence of design based on semantic relevance

3.1 Determination of evaluation indicators and weights

Design goodness evaluation is performed for the conceptual product set $S=\{B\}$. First, the evaluation objective characteristic set $c=(c_1,c_2,\cdots,c_m)$ is defined along with the corresponding value $v=(v_1,v_2,\cdots,v_m)$, where $v_i=x_i\subset V(c_i)$ and $V(c_i)$ is the value range of the evaluation objectives.Weight coefficient of the evaluation objective characteristic set $\alpha=(\alpha_1,\ \alpha_1,\cdots\alpha_m)$ is determined. The indicators that must be satisfied are denoted as Λ, i.e. $\alpha_r=\Lambda$, thus $\sum_{\substack{k=1\\k\neq r}}^{m}\alpha_k=1$. The evaluation indicator set is constructed as $H=\{H_1,H_2,\cdots,H_m\}$, where $H_i=(c_i,\ v_i),i=1,2,\cdots,\ m$.

3.2 Construction of semantic relevance function

For evaluation indicator set $H=\{H_1,H_2,\cdots,H_m\}$, where $H_i=(c_i,\ v_i),i=1,2,\cdots,\ m$, the corresponding weight coefficient $\alpha=(\alpha_1,\ \alpha_1,\cdots\alpha_m)$, and the relevance function is established as $K_1(x_1),K_2(x_2),\cdots K_m(x_m)$. Three situations may apply to the relevance function thus built:

If V_i is a finite interval or an infinite interval, the simple correlation function is $K_i(x_i)$; If V_i is the set of discrete data $b=\{b_1,\ b_2,\cdots,\ b_n\}$, then Eq(2)

$$K_i(x_i)=\begin{cases} a_1, & x_i=b_1 \\ a_2, & x_i=b_2 \\ \vdots & \\ a_n, & x_i=b_n \end{cases} \tag{2}$$

If V_i is the nested interval due to the mixing of the two situations above, the elementary dependent function is constructed. Consider the product family object S_p and its subobject O_{pj}. The correlation function of O_{pj} with respect to the evaluation indicator H_i is $K_i(O_{pj})$; the composite correlation function of product family object S_p with respect to the evaluation indicator set is $K_i(S_p)$.

The evaluation method for the product family taking S_p as object is then constructed. According to the connotation of correlation function in conceptual design, the correlation degree represents the distance between the conceptual scheme and the H_i value standard, which is divided into positive region $(0,+\infty)$, critical point 0 and negative region $(-\infty,0)$. The mean $E(K)$ denotes the value standard of the evaluation indicator. K_i is standardized as Eq(3):

$$k_{ij} = \frac{K_i(O_{pj})}{\max\limits_{o\in\{1,2,\cdots,n_p\}} \left|K_i(O_{po})\right|}, i=1,2,\cdots,m,\ j=1,2,\cdots,n_p, \tag{3}$$

and the standardized correlation degree of subobject $O_{p1},O_{p2},\cdots,O_{pn_p}$ in product family S_p with respect to the evaluation indicator H_i is $k_i=\left(k_{i1},k_{i2},\cdots k_{in_p}\right), i=1,2,\cdots m$.The standardized correlation degree of object O_{pj} with respect to evaluation indicator $H_1,H_2,\cdots,H_m$ is expressed as Eq(4)

$$K\left(O_{pj}\right)=\begin{bmatrix} k_{1j} \\ k_{2j} \\ \vdots \\ k_j \end{bmatrix}, j=1,2,\cdots,n_p \tag{4}$$

3.3 Goodness evaluation

Goodness of conceptual product object O_{pj} is denoted as $C\left(O_{pj}\right)$. Goodness is calculated in three different ways. First, goodness can be calculated with composite correlation function as Eq(5)

$$C\left(O_{pj}\right)=\alpha K\left(O_{pj}\right)=(\alpha_1,\ \alpha_1,\cdots\alpha_m)\begin{bmatrix} k_{1j} \\ k_{2j} \\ \vdots \\ k_j \end{bmatrix}=\sum_{i=1}^{m}\alpha_i k_{ij} \tag{5}$$

where $j=1,2,\cdots,n_p$. This method applies to multi-objective evaluation of most products.

Goodness is taken as the minimum of the correlation function, $C\left(O_{pj}\right)=\overset{m}{\underset{i=1}{\wedge}} k_{ij}, j=1,2,\cdots,n_p$, which means that all characteristics of products being evaluated must be satisfied for a product to be qualified, regardless of weight. This typifies the “short-board effect”. Goodness is taken as the maximum of the correlation function, $C\left(O_{pj}\right)=\overset{m}{\underset{i=1}{\vee}} k_{ij}, j=1,2,\cdots,n_p$, which means that only one characteristic need to be satisfied for a product to be qualified, regardless of weight.

Computation of the goodness of a product family consists of the computation of the goodness of individual products and the overall goodness. If $C\left(O_{p0}\right)=\max\limits_{j\in\{1,2,\cdots,n_p\}}\left\{C\left(O_{pj}\right)\right\}$, then individual object O_{p0} is superior. The individual products can be ranked in descending order of goodness.

Goodness $Y=C\left(O_{pj}\right)=\sum_{i=1}^{m}\alpha_i k_{ij}$ of individual products in the product family is a discrete random variable. The maximum goodness of individual in the product family is taken as the standard goodness, denoted as Eq(6)

$$E(Y)=C\left(O_{p0}\right)=\max_{j\in\{1,2,\cdots,n_p\}}\left\{C\left(O_{pj}\right)\right\}. \tag{6}$$

4. A case of ECBR

4.1 Knowledge acquisition and representation

We elaborate on the design of a machine tool as an application case.
First of all, the basic element model of objectives based on users' demand is constructed according to user knowledge:

$$B_0=(O,C,C(O))$$
$$=\begin{bmatrix} design\ parameters & workpiece\ diameter & 30\text{-}300mm \\ & distance\ between\ centers & \le 2000mm \\ & workpiece\ weight & \le 1000kg \\ & workpiece\ Rotational\ speed & V_4 \\ & grinding\ wheel\ Specification & V_5 \\ & Linear\ velocity\ of\ the\ grinding\ wheel & V_6 \\ & Convex\ amount\ of\ grinding & V_7 \\ & Concave\ amount\ of\ grinding & V_8 \\ & Precision & V_9 \end{bmatrix}$$

The set of key characteristics in roll grinding machine case base is given in Table 1.

Table 1: Grinding machine case characteristic set

Primary classify	Characteristic C	Characteristic value $C(O)$			
		MK8420	MK8440	MK8450	…
Range of processing 0.4	Grinding diameter mm	30-200	50-400	50-500	…
	Mass of the workpiece kg	≤500	≤2000	≤2000	…
	Distance between centers mm	≤2000	≤2000	≤2000	…
	Rotation speed of workpiece rpm	5-150	10-100	10-100	…
Grinding performance 0.2	Size of grinding wheel mm	(500,40,203)	(600,63,305)	(600,63,305)	…
	Linear velocity m/s	35	40	40	…
	Convex amount mm	≤ 1.0	≤ 1.3	≤ 1.3	…
	Concave amount mm	≤ 1.0	≤ 1.3	≤ 1.3	…
Grinding precision 0.4	Circularity mm	0.0015	0.002	0.002	…
	Cylindricity mm	0.0015	0.002-0.003	0.002-0.003	…
	Surface roughness μm	Ra0.1	Ra0.1	Ra0.1	…
	Cambering profile mm	0.002	0.002	0.002	…
	Surface roughness μm	Ra0.2	Ra0.2	Ra0.2	…

The evaluation indicator set $H=\{H_1,H_2,\cdots,H_m\}$ is established, where $H_i=(c_i,\ v_i), i=1,2,\cdots,\ m$ and the corresponding weight coefficient $\alpha=(\alpha_1,\ \alpha_1,\cdots\alpha_m)$. Since a diversity of indicators are involved, the cases can be hardly differentiated in terms of superiority based on simple evaluation. Therefore, multi-level evaluation is adopted, which is to cluster 13 evaluation indicators on the basis of secondary evaluation into 4 groups of primary evaluation indicators. This forms the standard for the final goodness evaluation.
The weights of each indicator are provided:

$$\alpha_0=(0.15,0.05,0,15,0.05,0.05,0.05,0.05,$$
$$0.05,0.05,0.05,0.1,0.1,0.1)^T$$

$$a=(0.4,0.2,0.4)^T$$

The parameter estimates of the conceptual product MK8430 (evaluation indicators) are also given as

$$H=(30-300,\le 1200,\le 2000,5-150,(500,40,203),35,\le 1.2,$$
$$\le 1.2,0.001-0.002,0.001-0.002,Ra0.1,0.002,Ra0.2)^T\ .$$

4.2 Relevance computation

The results of relevance computation for the above case are shown in Table 2.

Table 2: Standardized semantic relevance

Weight	Weight subdivision	Standardized semantic relevance						
		MK8420	MK8440	MK8450	MK8463	MK8463A	MK8480	…
0.4	0.15	0.847	0.954	0.883	0.435	0.374	0.296	…
	0.005	0.400	0.897	0.897	0.436	0.436	0.264	…
	0.15	1.000	1.000	1.000	0.258	0.258	0.175	…
	0.05	1.000	0.650	0.650	0.347	0.347	0.395	…
0.2	0.05	1.000	0.000	0.000	0.000	0.000	0.000	…
	0.05	1.000	0.500	0.500	0.300	0.200	0.200	…
	0.05	1.000	0.926	0.926	0.640	0.640	0.438	…
	0.05	1.000	0.926	0.926	0.640	0.640	0.438	…
0.4	0.05	1.000	1.000	1.000	0.595	0.463	0.347	…
	0.05	1.000	0.848	0.848	0.595	0.463	0.347	…
	0.1	1.000	1.000	1.000	0.800	0.800	0.800	…
	0.1	1.000	1.000	1.000	0.800	0.800	0.800	…
	0.1	1.000	1.000	1.000	0.800	0.800	0.800	…

The relevance of primary level evaluation is determined based on the standardized correlation of secondary level evaluation.

$$K_{R1} = \begin{bmatrix} 0.329 & 0.330 & 0.319 & 0.123 & 0.114 & 0.092 & \cdots \\ 0.200 & 0.118 & 0.118 & 0.079 & 0.074 & 0.054 & \cdots \\ 0.400 & 0.392 & 0.392 & 0.300 & 0.286 & 0.275 & \cdots \end{bmatrix}$$

The composite relevance of evaluation is $K = (0.929 \quad 0.840 \quad 0.829 \quad 0.502 \quad 0.475 \quad 0.420 \quad \cdots)$. Thus product family S_1 of roll grinding machine is selected for the extension case, i.e. workpiece moving-CNC roll grinding machine MK8420, MK8440 and MK8450. In product family S_1, MK8420 has the highest relevance.

As analyzed above, product family S_1 is chosen as the general module, and the machine tool module configuration scheme is formulated. Production family S_1 of workpiece moving-CNC roll grinding machine consists of products with mature modularization (see Figure. 1).

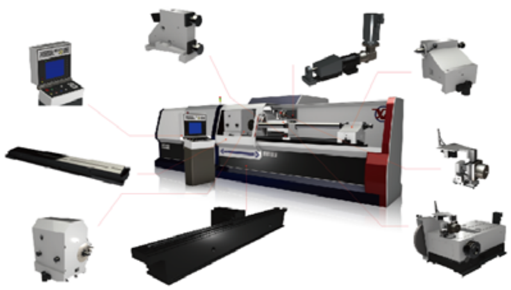

Figure 1: Workpiece moving-CNC roll grinding machine modules

5. Conclusions

We propose the method of semantic relevance-based convergence method aiming at CBR for product design. The empirical approach for product case selection in conventional product design process is adopted and integrated with the formalized and quantitative approach so as to achieve CBR. Starting from the perspectives of product semantics and basic element model in extension theory, the method for semantic relevance evaluation oriented towards the product family is established. For the design of machine tool, the design issue is formalized, and the user semantic is transformed into design semantic. The reference product or product family is selected by semantic relevance computation, and CBR is performed for the modules constituting the conceptual product using region relevance and semantic network. The case has verified the feasibility of the convergence method based on semantic relevance. Moreover, we present a method that integrates formalization and quantification of knowledge for the early stage of conceptual product design. Some further studies are required with respect to the application in the refined structural design, specifically, ECBR in refined structural design and in product appearance design.

Acknowledgement

This research is supported by the national natural science funds [51475097], [2014BAH05F01], GuiZhou natural science funds [2013]4005, [2013]2108, [2014]7644, [2012]2484, [2012]009.

References

Althuizen N., Wierenga B., 2014, Supporting Creative Problem Solving with a Case-Based Reasoning System [J]. JOURNAL OF MANAGEMENT INFORMATION SYSTEMS, 31(1): 309-340, DOI: 10.2753/MIS0742-1222310112

Bouhana A., Zidi A., Fekih A., Chabchoub H., Abed M., 2015, An ontology-based CBR approach for personalized itinerary search systems for sustainable urban freight transport [J]. EXPERT SYSTEMS WITH APPLICATIONS, 42(7): 3724-3741, DOI: 10.1016/j.eswa.2014.12.012

Chang S., Narangerel A., 함성일., 서동준., 2015, Exploratory Methodology for Acquiring Architectural Plans Based on Spatial Graph Similarity [J]. Architectural Research, 17(2): 57-64, DOI: 10.5659/AIKAR.2015.17.2.57.

Hashemi H., Shaharoun A.M., Sudin I., 2014, A case-based reasoning approach for design of machining fixture [J]. INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY, 74(1-4): 113-124, DOI: 10.1007/s00170-014-5930-4

Hong T., Koo C., Kim D., Lee M., Kim J., 2015, An estimation methodology for the dynamic operational rating of a new residential building using the advanced case-based reasoning and stochastic approaches [J]. APPLIED ENERGY, 150: 308-322, DOI: 10.1016/j.apenergy.2015.04.036

Hu J., Qi J., Peng Y., 2015, New CBR adaptation method combining with problem-solution relational analysis for mechanical design [J]. COMPUTERS IN INDUSTRY, 66: 41-51, DOI: 10.1016/j.compind.2014.08.004

Koo C., Hong T., 2015, A dynamic energy performance curve for evaluating the historical trends in the energy performance of existing buildings using a simplified case-based reasoning approach [J]. ENERGY AND BUILDINGS, 92: 338-350, DOI: 10.1016/j.enbuild.2015.02.004

Ma G., Jiang L., Xu G., Zheng J., 2015, A Model of Intelligent Fault Diagnosis of Power Equipment Based on CBR [J]. MATHEMATICAL PROBLEMS IN ENGINEERING, (203083), DOI: 10.1155/2015/203083

Minor M., Bergmann R., Goerg S., 2014, Case-based adaptation of workflows [J]. INFORMATION SYSTEMS, 40: 142-152. 10.1016/j.is.2012.11.011

Rashedi E., Nezamabadi-Pour H., Saryazdi S., 2014, Long term learning in image retrieval systems using case based reasoning [J]. ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE, 35: 26-37, DOI: 10.1016/j.engappai.2014.06.009

Reyes E.R., Negny S., Robles G.C., Le Lann J.M., 2015, Improvement of online adaptation knowledge acquisition and reuse in case-based reasoning: Application to process engineering design [J]. ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE, 41: 1-16, DOI: 10.1016/j.engappai.2015.01.015

Takai S., Banga K., 2014, Effects of Product Attributes in Case-Based Reasoning Methods for Cost Estimation and Cost Uncertainty Modeling [J]. JOURNAL OF MECHANICAL DESIGN, 136(0510055), DOI: 10.1115/1.4026869

Yu Y., Liao H., Zhou Y., Zhong W., 2015, Reasoning and fuzzy comprehensive assessment methods based CAD system for boiler intelligent design [J]. JOURNAL OF MECHANICAL SCIENCE AND TECHNOLOGY, 29(3): 1123-1130, DOI: 10.1007/s12206-015-0224-9

Zhou P., Lu S., Chai T., 2014, Data-Driven Soft-Sensor Modeling for Product Quality Estimation Using Case-Based Reasoning and Fuzzy-Similarity Rough Sets [J]. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, 11(4): 992-1003, DOI: 10.1109/TASE.2013.2288279

Zhu G., Hu J., Qi J., Ma J., Peng Y., 2015, An integrated feature selection and cluster analysis techniques for case-based reasoning [J]. ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE, 39: 14-22, DOI: 10.1016/j.engappai.2014.11.006