http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet

Asian Network for Scientific Information

308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (3): 530-533, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.530.533

Type Selection of Gating System Based on Bayesian Reasoning

[1,2]Wang Bin, [3]Tan Gui-Qin, [1]Liu De-Fang and [2]Chen Xin-Bo
[1]UGS School, Yancheng Institute of Technology, Yancheng, Jiangsu, 224051, People's Republic of China
[2]School of Automotive Studies, Tongji University, Shanghai, 201804, People's Republic of China
[3]School of Mechanical Engineering, Nantong University, Nantong, Jiangsu, 226019, People's Republic of China

Abstract: To improve the design efficiency of casting die, a Bayesian-based reasoning theory was introduced. The framework of the reasoning mechanism of gating system was established based on the comparison of Bayesian reasoning and other traditional reasoning methods. Some key techniques such as the establishment of standard type model set and posterior information processing were described in detail. Finally, an application case was employed to testify the efficiency of the Bayesian reasoning mechanism of intelligent design system for gating system design of casting dies.

Key words: Bayesian reasoning, type selection, intelligent design, gating system

INTRODUCTION

In nonferrous metal casting, pressure casting is one of the most important methods of production (Yang and Oh, 2008). Gating system is a channel through which molten metal can fill the cavity of the die under outside pressure. Since all liquid melt required filling up the casting cavity needs to be introduced through the gating system, it has been long recognized that gating system design plays one of the key elements in casting quality (Sun *et al.*, 2008). Therefore, designing a reasonable gating system is an important link of die casting die design.

Gating system design is a process of reusing past design experience and knowledge. CBR (case-based reasoning) is widely used in the process of product design which can select a reasonable design from the case base of old design cases (Liu *et al.*, 2011). But CBR technique is primarily used for accurate reasoning of precise knowledge; however, for imprecise information it is difficult for intelligent design system to understand (Guo *et al.*, 2012). There exist a large amount of imprecise design information and design process information in the process of casting die design. For example, if the structure of casting die is complex, then aluminum magnesium alloy should be chosen and the average thickness of the wall of casting die should be between 0.6 to 1.5 mm and the inside gate thickness should be between 0.6 to 1.0 mm. When the information that the average thickness of the wall of casting die should be between 0.6 to 1.5 mm, this is an example of imprecise design information; the information that the inside gate thickness should be between 0.6 to 1.0 mm is an example of imprecise design process information.

This study introduces a knowledge reasoning-based design process which contains four steps (Fig. 1):

Step 1: Establish standard type model for each gate
Step 2: Classify design information into precise and imprecise groups and preprocess imprecise information by fuzzy math method
Step 3: Retrieve the satisfying gate type base by applying Bayesian reasoning mechanism
Step 4: Select the best gate model by applying CBR reasoning mechanism

THEORY OF PRODUCT TYPE SELECTION

Product type selection principle: Product selection is defined as a process of selecting a suitable product design method from a series of existing product designs based on analyzing existing design requirements which is the basis of precise design which is the next step. Therefore, model type design can make the best use of product feature model that has been established to meet customer's requirements of higher speed. The foundation of model type design is introduced as follows:

Corresponding Author: Chen Xin-Bo, School of Automotive Studies, Tongji University, 201804, Shanghai, People's Republic of China

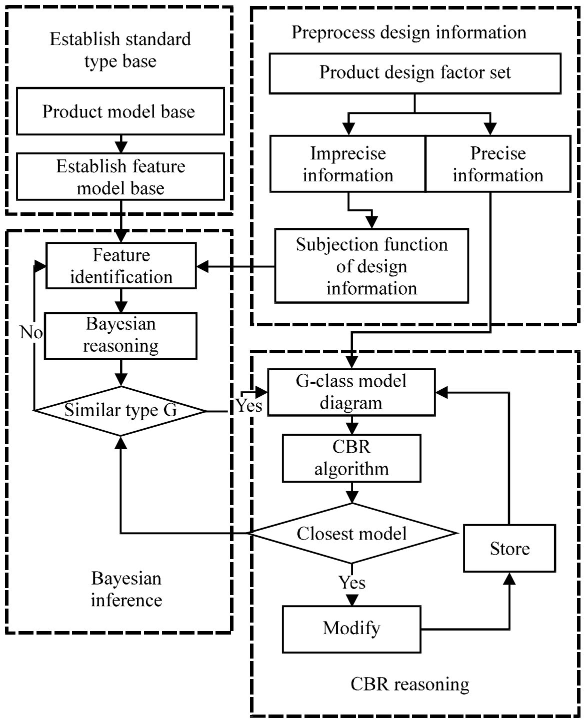

Fig. 1: Framework of Bayesian reasoning-based design process

Modularization of design features: Feature modularization is defined as marking out a series of feature modules to meet market needs through selecting and combining different modular structures. With the development of advanced design and manufacturing techniques, modularization design can reduce the time of product design and meet the dynamic market requirements which has a important impact on product design, upgrade and reuse.

For example, gating system design is comprised of sprue gate, the way, gating, remaining material and other related parts. In addition, each part also contains different types of modules, where each module has a variety of ways to combine. The way of combination can be changed in accordance with different design requirements.

The following conditions should be considered in module partition process:

- **Suitable granularity:** being convenient for combination and not increasing the difficulty of parts management
- Practicality and convenience in product design cycle
- **High reusability:** which is suitable for batch production and reducing cost

Standardization design: The standard design is an easy way to get a unified solution. The application of standard parts can reduce the cost of design.

Parametric design: On the condition that the shape and structure of design object has been chosen, a group of parameters are used to determine the relationship between dimension and type. Parametric design has a positive effect on casting overflow system type design. For example, $W = C\sqrt{A_r}$ can be used as constraint information for design type rapid selection, where W is the width of gating and Ar is the sectional area.

Product type design method comparison:

- **Rule-based method:** Rule-based method refers to applying production rules to solve design problems. This method has strong reasoning ability and simple expression form which is easy to be realized. But the knowledge base is difficult to maintain and for complex problems it is difficult to handle
- **Case-based method:** Case-based reasoning is a type of similar analogy reasoning method. The case base of CBR system has stored a large number of related cases which were organized in particular way and could be retrieved for modification and reuse during the reasoning process
- **Bayesian-based method:** Both of the above metioned methods belong to precise reasoning. However, the product type selection information of gating system design is of greater fuzziness. Bayesian reasoning method is a type of probability logic-based method which can represent fuzzy information of expert experience and historical information of expert knowledge by probability method. This method is more objective for product type design than other methods

Through the comparison of the above reasoning method, this paper selects bayesian-based method for the type selection design of gating system.

ESTABLISHMENT OF STANDARD TYPE MODEL SET

Gating system can be divided into multiple sub-classes and each sub-class can also be further divided, until a tree structure is established. For example, segment gating, aequilate gating and T-gating belong to the same parent class-the cross gating. These three gating subclasses of the standard type models compose a standard type model set which is expressed as F.

Assuming F is a set of a type of product cases. And this class of products can be divided into s sub-classes, expressed as $F = |F_h|_h = 1, 2, \ldots s|$. The jth sub-class has $f^{(j)}$ samples and each sample contains n attributes which constitute a attribute set $T = |t_i|i = 1,2,\ldots,n|$; The feature vector of kth sample is written as $C_k^{(j)} = (y_{k1}^{(j)}, y_{k2}^{(j)},\ldots,y_{kn}^{(j)})$, where $y_{ki}^{(j)}$ is the ith attribute value of $C_k^{(j)}$. $k = 1, 2,\ldots,f^{(j)}$; $i =1, 2,\ldots,n$. The ith sub-model of $F^{(j)}$ is defined as follows:

$$F_i^{(j)} = \mu_{F_i}^{(j)} = \exp\left\{-\frac{1}{2}\left[\frac{y - a_i^{(j)}}{\sigma_i^{(j)}}\right]^2\right\} \tag{1}$$

Where:

$$a_i^{(j)} = \frac{1}{f^{(j)}}\sum_{k=1}^{f^{(j)}} y_{ki}^{(j)} \quad \sigma_i^{(j)} = \sqrt{\frac{1}{f^{(j)}-1}\sum_{k=1}^{f^{(j)}}(y_{ki}^{(j)} - a_i^{(j)})^2}$$

$\mu_{Fi}^{(j)}$ is a subordinate function of fuzzy set $F_i^{(j)}$. $F_i^{(j)}$ can be represented as $(a_i^{(j)}, \sigma_i^{(j)})$.

$$F^{(j)} = (F_1^{(j)}, F_2^{(j)},\ldots,F_n^{(j)}) = [(a_1^{(j)}, \sigma_1^{(j)}), (a_2^{(j)}, \sigma_2^{(j)}), \ldots, (a_n^{(j)}, \sigma_n^{(j)})] = [(a_i^{(j)},\sigma_i^{(j)})]_{1\times n}$$

Similarly, standard model base F can be represented by following matrix:

$$F = (F_1, F_2, \ldots, F_s)^T = [(a_i^{(j)}, \sigma_i^{(j)})_{ji}]_{s\times n}$$

where, $F_i^{(j)}$ represents a piece of domain knowledge and it can be written in the form of a rule which is as follows:

IF the feature value of x_i is close to $F_i^{(j)}$ (premise condition).

THEN type $F^{(j)}$ should be chosen which delegates j subclasses (conclusion).

BAYESIAN-BASED TYPE SELECTION

Bayesian theory: Bayesian reasoning is a math theory of transforming prior probability into posteriori probability. Asuming y has k kinds of natural states, y1, y2,..., yk. P(yi) is the prior probability distribution of state yi; P(x/yi) is the probability of incident y on the condition of state yi; P(yi/x) is the posteriori probability of yi. P(x) is the comprehensive probability value of x in different states. Therefore, P(x) and P(y/x) can be expressed by the following equations:

$$P(x) = \sum_{i=1}^{k} P(yi)\, P(x/yi) \tag{2}$$

$$P(y/x) = \frac{P(y)P(x/y)}{\sum_{i=1}^{k} P(x/y_i)P(y_i)} \tag{3}$$

In the equation, P(y/x) is the posterior probability density function of y which represents the distribution regulation of parameter y in accordance to the observation value x; P (y) is the prior probability density function of y which represents the distribution regulation of parameter y without data observation. The parameters are typically from handbooks, expert experience and subjective judgment, etc. P (x/y) is named as likelihood function which indicates the similar degree between models and data observed. The greater the value, the higher the similar degree, otherwise, the lower the similar degree. The reasoning process is shown in Fig. 2:

- **Prior information:** Information of statistics before sampling which is typical from handbooks and experience. x is a random variable which can be described by probability distribution. As each variable has its uncertainty, probability is a good tool to express this degree of uncertainty
- **Likelihood function:** A function of parameters of statistical models used to express the degree of likelihood. Likelihood is used for parameter estimation on the base of observation
- **Posterior information:** Which is gained from Bayesian or other equations on the base of modification of prior information. Compared with prior information, posterior information meets the reality better

In this study, the type of gating system is selected according to the information of castings which is described as solving problem S. To solve S, a mapping from S to standard type model set F should be established. The product types of the models of F that are mapped by S are reasoning results.

Dealing with imprecise design information: S can be described as a vector $S = (S_1, S_2,\ldots S_n)$, where S_i ($i = 1, 2,\ldots, n$) is a random type among precise number, imprecise number or imprecise interval. The constraint of imprecise interval is expressed as follows:

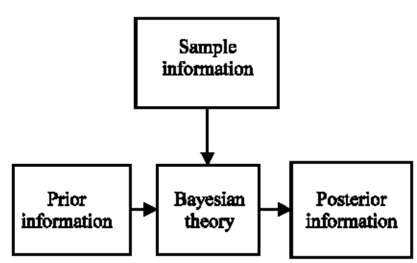

Fig. 2: Bayesian-based reasoning

$$S_j(x) = \exp\left[-\frac{1}{2}\left[\frac{x - 0.5\,(x_j^{(S)_{(R)}} + x_j^{(S)_{(L)}})}{\theta^{-1}\,(x_j^{(S)_{(R)}} + x_j^{(S)_{(L)}})}\right]^2\right] \quad (4)$$

where, θ is a constant which is among the range of 2.0~4.0. Prior probability of each incident can be calculated by Eq. 5:

$$P(S) = \sum_{i=1}^{\infty} S(x_i)P(x_i) \quad (5)$$

where, P (xi) is the probability of variable X having value xi and X∈R, S∈R.

Expression of imprecise information: The uncertainty of F can be expressed by probability P (F) or by odds O (F). The relationship between P (F) and O (F) can be expressed by following equation:

$$O(F) = P(F)/(1-P(F)) \quad (6)$$

The value of Eq. 6 has following situations:

- IF F is true, THEN P (F) = 1, O (F) = ∞
- IF F is false, THEN P (F) = 0, O (F) = 0
- IF F is an uncertain number, THEN the values of P (F) and O (F) are equal to prior probability and odds, respectively

APPLICATION CASE

Assume aluminum is selected for casting. When selecting the type of inner gate, central gate, wheel gate and pin gate are three choices. The design information includes: wall thickness is 1.5 mm, filling time is between [0.01, 0.03](s), filling speed is a fuzzy number and the reference function is expressed as exp [-0.5 $(x-40)^2$]. Therefore, the attributes set is expressed by F = $|f_i|_{i=1,2,3}$ |average wall thickness, filling time, filling speed|.

We have weight set: W = $|w_j|_{j=1,2,3}|$ = [0.4, 0.3, 0.3] which is attained from expert experience. And the data of the type model set can retrieved from knowledge base which is expressed as follows:

$$\begin{aligned} F &= \{\text{central gate, wheel gate, pin gate}\} \\ &= \left|F_{m|_{m=1,2,3}}\right| = [(a_i^{(j)}, \sigma_i^{(j)})_{m_i}]_{3\times 3} \\ &= \begin{pmatrix} (10.54, 2.45) & (7.12, 2.5) & (20.5, 10.25) \\ (5.42, 1.51) & (20.15, 10.15) & (9.14, 4.41) \\ (2.11, 0.45) & (12.35, 6.15) & (7.55, 3.15) \end{pmatrix} \end{aligned} \quad (7)$$

According to the above equations, we have following results:

$$\begin{aligned} [P(F/S)] &= \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \begin{bmatrix} P(F_1/S_1) & P(F_1/S_2) & P(F_1/S_3) \\ P(F_2/S_1) & P(F_2/S_2) & P(F_2/S_3) \\ P(F_3/S_2) & P(F_3/S_2) & P(F_3/S_3) \end{bmatrix} \\ &= \begin{bmatrix} 0.248 \\ 0.477 \\ 0.718 \end{bmatrix} \end{aligned} \quad (8)$$

Therefore, P(F/S) = 0.718 and pin gate should be selected.

CONCLUSION

Compared with traditional reasoning models, bayesian-based intelligent design reasoning makes a better use of imprecise information and draws a design conclusion which meets the requirement of the designers well.

REFERENCES

Guo, Y., J. Hu and Y. Peng, 2012. A CBR system for injection mould design based on ontology: A case study. Comput.-Aided Des., 44: 496-508.

Liu, D.F., G.Q. Tan, B. Wang and H.P. Wu, 2011. Research on model selection method for gating system based on bayesian inference. Mach. Des. Manuf., 6: 46-48.

Sun, Z., H. Hu and X. Chen, 2008. Numerical optimization of gating system parameters for a magnesium alloy casting with multiple performance characteristics. J. Mater. Process. Technol., 199: 256-264.

Yang, H.D. and Y.K. Oh, 2008. A study on cooling characteristics of tire mold during a manufacturing process of Al-Mg system alloy casting mold. J. Mater. Process. Technol., 201: 64-67.