Research on the Method of Reusing Injection Process Knowledge Based on CBR

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Abstract. The injection molding process is the most critical factor affecting the quality and efficiency of injection molded products. The traditional process setting mainly relies on the operator’s limited experience and simple calculation formulas to make repeated “Try”, which has the problems of long cycle, high cost, and difficulty in guaranteeing product quality. To this end, this article takes the injection molding process as the research object, and proposes a CBR-based injection process knowledge reusing method. This method models the historical cases of injection molding from seven dimensions to form an injection case library. Through the weighted calculation of the similarity algorithm, the parameters, context and auxiliary knowledge of the case with the highest similarity are pushed to the staff to provide references for the staff to determine the corresponding process parameters and improve work efficiency.

Keywords. Injection molding; CBR; reusing; model; weighted calculation.

1. Introduction
Injection molding technology has short molding cycle, high dimensional accuracy and easy automation, so it has been widely used in the manufacturing process of plastic products. Due to the obvious strong coupling and weak linear relationship between the various process parameters of injection molding and the quality of the final product, and the different degrees of coherence between different process parameters, it is difficult to rely on mathematical models to obtain the required process parameters. In the traditional injection molding production process, advanced mold trials are required. The craftsman firstly sets a set of initial process parameters and tries the mold based on past experience and relatively simple calculation formulas, and then continuously based on the product defects that appear during the mold trial. Adjust process parameters, eliminate product defects, and obtain qualified products [1]. As a result, the production cycle is long, the cost is high, and the product quality is difficult to guarantee, which in turn wastes time and resources [2]. These also show that injection molding production is a field of theory and strong experience. With the continuous development of the social economy, the speed of product update iterations has accelerated significantly, and there are more and more types of plastic products. The traditional trial mold technology can no longer meet the requirements of modern production. Therefore, the need for quick access to injection molding process methods is becoming more and more urgent.

Knowledge is the source of an enterprise’s vitality and innovation, as well as its core competitiveness. How to mine and reuse knowledge is a problem that many scholars care about. CBR (case-based reasoning) is a common method of knowledge reuse. It is a strategy in which the source case in historical memory is obtained from the prompt of the target example, and the source case guides the solution of the target case. It is a mode of reasoning and learning that is different from rule-based reasoning. It refers to borrowing old cases or experiences to solve problems, evaluate solutions, explain abnormal situations,
or understand new situations [3]. However, there are big differences between different scholars in how to use CBR, which is mainly reflected in the different modeling and push mechanisms, especially the success of historical case modeling determines whether CBR is effective. Zhang Jianhua et al. [4] took case knowledge as the research object and proposed a knowledge supply-demand matching method based on domain ontology and CBR. This method subdivides the supply and demand matching process of case knowledge into semantic matching and CBR matching, and determines the final matching result in the CBR matching stage. Ding [5] constructed a multi-dimensional steam turbine process knowledge context model and a process knowledge representation model, and mapped the process knowledge context and process knowledge to form a case database of steam turbine process knowledge context. Li [6] proposed a case retrieval model combining ontology and CBR, which improved the accuracy of case retrieval and the reuse rate of case knowledge. Yang [7] conducted a mixed case-based reasoning technology research for the design of self-propelled artillery variants, and determined the similarity calculation method in different situations in the process of self-propelled artillery case retrieval. Scholars have studied how to use CBR from different angles and methods, but there are generally problems such as less consideration dimensions, unclear weight determination methods, and single content. Therefore, this article models the injection history cases from seven dimensions to form an injection case library. After calculating the similarity of different dimensions, the entropy weight method is used to weight, and the injection parameters, context, and assistants in the three cases with the highest matching degree are calculated. Push the knowledge to the staff to improve production efficiency.

2. Injection Molding Example Modeling

2.1. Dimension Selection

2.1.1. Mold Characteristic Parameter Dimension, Material Performance Parameter Dimension and Injection Molding Parameter Dimension. At present, the common modeling of injection molding cases is mainly carried out from three dimensions, namely mold feature parameter collection, material performance parameter collection, and injection parameter collection. The similarity is calculated for mold feature parameters and material performance parameters, and then the similarity is calculated. The injection parameters of the highest case are pushed to the staff [2, 8]. These three dimensions are the three most directly related to injection molding. But only these three dimensions are far from enough. On this basis, this article adds four dimensions: type feature set, two-dimensional design drawing, production scenario, and auxiliary knowledge.

2.1.2. Type Feature Dimension. When injecting different types of products, the process parameters may be different, such as the number of gates, gate types, runner types, number of cavities, etc. The differences in these parameters will significantly affect the injection molding process. Therefore, type characteristics are an important dimension of the product model. Some scholars use type as a preliminary screening tool, but the number of cases may become very small after screening. And there may also be parameters and knowledge that can be referred to between different types of instances. So take the type feature as a dimension.

2.1.3. Two-Dimensional Design Drawing Dimensions. Design drawings are also an important dimension of product examples. Now there are two-dimensional design drawings in the product library, but the design drawings are rarely used. In view of the increasingly developed image processing technology. This article takes the design drawing as a dimension, and uses the histogram algorithm to process and utilize the pictures in the following text.

2.1.4. Production Context Dimension. Context are a neglected but very important part of the production process. To model a production instance in an all-round way, it is necessary to understand the production context, such as time and location, staff preferences, staff level, and so on. Some scholars have realized
the role of context in product design or production processes. Luo conducted research on knowledge push methods based on product design context [9]. Wang provides designers with knowledge push services by constructing a contextual interaction model [10]. Therefore, this article regards the production scenario as an indispensable dimension of the product case library.

2.1.5. Auxiliary Knowledge Dimension. There will be written records during the production process. These records may exist in voice or in paper text. The knowledge of the production process of the case can be extracted from it. It may be all the precautions in the production process, it may be the description of a phenomenon in the production process, or it may be the problems and solutions encountered in the production process at that time. This knowledge plays an important role in the future production of products. Therefore, these auxiliary knowledges are also regarded as an important dimension in the product instance model.

2.1.6. Summary. Therefore, this article models the examples from the above seven dimensions, where the type feature set, mold parameter set, material parameter set and two-dimensional design drawing are the matching layer, and the injection parameter set, production scenario set and auxiliary knowledge set are the push layer.

2.2. Model Building
The model constructed by the case of this article is shown in Figure 1, and the formula is as follows:

\[
\text{Case}(\{T, MO, MA, P\}, S, PS, AK) = \text{Case}(\{t_1, t_2, \ldots, t_n\}, (m_{o_1}, m_{o_2}, \ldots, m_{o_n}), (m_{a_1}, m_{a_2}, \ldots, m_{a_n}), P) \cup \{s_1, s_2, \ldots, s_k\}, \{p_{s_1}, p_{s_2}, \ldots, p_{s_k}\}, \{a_{k_1}, a_{k_2}, \ldots, a_{k_n}\}
\] (1)
Among them, \( T = (t_1, t_2, \cdots, t_m) \), \( T \) is a collection of type characteristic parameters, such as the number of gates, gate forms, and the number of cavities, which are composed of numerical data and text.

\( MO = (mo_1, mo_2, \cdots, mo_n) \), \( MO \) is a collection of mold characteristic parameters, including volume, flow length, average wall thickness, etc., which are all composed of numerical data.

\( MA = (ma_1, ma_2, \cdots, ma_k) \), \( MA \) is a collection of plastic material performance parameters, such as rheological performance parameters, PVT parameters, thermal performance parameters, etc., which are also composed of numerical data.

\( P \) is the two-dimensional design drawing of the example, archived in the form of electronic version.

\( S = (s_1, s_2, \cdots, s_l) \), \( S \) is a set of corresponding injection molding process parameters, such as injection parameters, VP switching parameters, pressure holding parameters, storage parameters, cooling parameters, etc., which are all composed of numerical data.

\( PC = (pc_1, pc_2, \cdots, pc_g) \), \( PC \) is the actual design and production of the instance set of context, such as time and location, personnel level, personnel preferences, etc., composed of structured text.

\( KL = (kl_1, kl_2, \cdots, kl_h) \), \( KL \) is the auxiliary knowledge generated in the actual production process of this example, such as precautions and how to solve the problems that arise. Most of this knowledge exists in the text in a semi-structured form. It is necessary to use the foundation of NLP natural language processing to extract knowledge from the text to form a triplet, and store the triplet in a set.

### 3. Similarity Calculation

#### 3.1. Local Similarity Calculation

After completing the modeling of the instance, it is necessary to retrieve which instance is the closest to the target instance. In this case, the similarity algorithm is used for matching. In this paper, local similarity calculations are performed on the four dimensions of \( T, MO, MA, \) and \( P \) respectively, and then the obtained local similarities are weighted to obtain the final instance similarity.

Different similarity algorithms need to be adopted for different feature types. Because \( MO \) and \( MA \) are both numerical parameters, the data is normalized first, and the processing method is as follows:

\[
X^* = \frac{x - \min}{\max - \min}
\]  

(2)

After the normalization is completed, it is necessary to calculate the similarity of these two dimensions. Because the Euclidean distance algorithm is simple to calculate, and there are no subjective factors in the data, it will not affect the calculation, so this method is used to calculate the similarity. The calculation formula is:

\[
S = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}
\]  

(3)

Because \( T \) contains both text and values, calculating similarity is actually calculating the coincidence degree between two vectors. The cosine similarity measures the consistency of the value directions between dimensions, and pays attention to the difference between the dimensions, and does not pay attention to the difference in the value. Therefore, the cosine similarity is used for calculation, and the calculation formula is:
\[
S = \frac{\sum_{i=1}^{m} A_i \times C_i}{\sqrt{\sum_{i=1}^{m} A_i^2} \times \sqrt{\sum_{i=1}^{m} C_i^2}}
\]  

(4)

\[P\] is a two-dimensional design drawing. There are algorithms such as histogram algorithm, hash algorithm, and Hamming distance to calculate the similarity of pictures. In this paper, the histogram algorithm is used to calculate the similarity of the design drawings. The algorithm steps can be divided into two steps. According to the pixel data of the source image and the candidate image, each histogram data is generated. The second step: using the histogram result output in the first step, use the Bhattacharyya coefficient algorithm to calculate the similarity value. Calculated as follows:

\[
\rho(p, p') = \sum_{i=1}^{N} \sqrt{p(i) p'(i)}
\]

(5)

Among them, \(p\) and \(p'\) represent the source and candidate image histogram data respectively. The result of adding the square root of the product of each data point with the same \(i\) is the image similarity value (Bap coefficient factor value), and the range is \(0\) to \(1\).

3.2. Weight Selection and Final Similarity Calculation

After obtaining the local similarities in the four dimensions, the four similarities are weighted to obtain the final similarity \(S\). The calculation formula is:

\[
S(A, C) = \sum_{i=1}^{n} \omega_i \times f(A_i, C_i)
\]

(6)

where is the weight of each attribute, and its sum is 1, that is: \(\sum_{i=1}^{n} \omega_i = 1\).

\(f(A_i, C_i)\) is the similarity between a single attribute \(A_i\) and \(C_i\) in the instance library, and its value range is \((0,1)\). Assigning different weights will result in different matching results. Common methods include principal component analysis, analytic hierarchy process, entropy method, subjective experience method, etc. This article uses entropy method to calculate similarity.

For \(n\) samples, 4 indicators \((T, MO, MA, P)\), then \(x_{ij}\) is the value of the \(j\)-th indicator of the \(i\)-th sample \((i = 1, \ldots, n; j = 1, 2, 3, 4)\). The indicators need to be normalized first. Then calculate the proportion of the \(i\)-th sample value under the \(j\)-th index in the index:

\[
p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{4} x_{ij}}, (i = 1, \ldots, n; j = 1, 2, 3, 4)
\]

(7)

Calculating the entropy value of the \(j\)-th index: \(e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij}), (j = 1, 2, 3, 4)\), among them \(k = \frac{1}{\ln(n)} > 0\). Need to meet condition \(e_j \geq 0\);

Calculating information entropy redundancy:

\[
d_j = 1 - e_j, (j = 1, 2, 3, 4)
\]

(8)
Calculating the weight of each indicator:

$$\omega_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, \quad (j = 1, 2, 3, 4)$$

(9)

After obtaining the weight $$\omega_j$$ of each index, the weight is brought into the formula for calculation, and the final similarity is obtained. The obtained similarity is a decimal between 0 and 1, and the cases are sorted according to the similarity value from high to low, and the case closest to the target can be obtained, and subsequent operations can be performed.

4. Reusing and Saving

After the similarity calculation is completed, the injection parameter set, production situation set and auxiliary knowledge set of the three cases with the highest similarity are recommended to the employees for reference. The employees use it after reference and correction to form a new instance, save the new instance to the instance set again, and expand the case set to facilitate the next round of knowledge reuse.

5. Conclusion

Aiming at the problem that the process parameters in the traditional injection molding production process mainly rely on the experience of employees, a CBR-based injection process knowledge reuse method is proposed. The historical case of injection molding is modeled from seven dimensions to form a case knowledge model and build an injection case library to match the process parameters, production context and auxiliary knowledge of the three highest-degree cases are pushed to the staff to provide a reference for the staff to determine the corresponding process parameters, reduce the number of mold trials and improve work efficiency. In future work, I will incorporate more artificial intelligence-related technologies into the injection molding process settings, and hoping to obtain the required injection molding parameters directly.

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