Case Based Polishing Process Planning with Fuzzy Set Theory

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Abstract - **It is difficult to make optimal process planning for polishing product because of the complex processes and the multi-criteria, attributes and vagueness of process parameters. To solve this problem, this paper combines the methodologies of Case Based Reasoning (CBR) and fuzzy Set Theory (FST) to support process planners in planning processes and making decisions effectively for polishing product. Moreover, various mathematical models are designed and integrated to the Web Based Portal System (WBPS) which supports the optimization computation of process parameter settings and case reasoning for polishing product. Finally, some cooker samples from the collaborating company have been collected to demonstrate the effectiveness of Case Based Process Planning (CBPP) model.**

Keywords –**Process Planning, Fuzzy Set Theory, Case Based Reasoning, Case Based Process Planning**

I. INTRODUCTION

Polishing product and process analysis (PPPA) for a new polished product involves complicated operations and process parameters which influence the quality of the polishing process greatly. In most polishing companies, the tasks of arranging and selecting polishing operations, identifying principal process parameters, as well as setting their values, is conducted manually by company engineers and technicians. However, the judgments and experiences of different process planner may lead to the differences in the process planning. Many factors such as product category, size, materials, tolerance, quality, and the available resources (machines, fixtures, and tools, etc.) affect process-planning tasks. And the task of process planning is complicated and time consuming. Maintaining the consistency of all process plans and keeping them optimized are usually difficult. This is one of the main reasons for the development of automatically process planning systems that attempt to support process planners in planning processes and making decisions effectively for polishing product.

Case based reasoning is an artificial technique proposed in the early 1980s. It means reasoning from old cases or experiences in an effort to solve new problems. Recently, Case Based Process Planning (CBPP) model is developed to implement automatic process planning, which emphasizes the findings of appropriate past experiences as a solution to new problem and makes effective results.

In this polishing product cases, the input parameters involving multi-criteria and attributes (most attributes are vague and ambiguous). These complex and un-ambiguity parameters result in the difficulty to define the mapping between inputs and outputs. And make the performance of Case Based Reasoning (CBR) system will descend if the input parameters are not effective enough to reflect the actual problem situation.

Therefore, we integrate the advantage of CBR and Fuzzy Set Theory to solve the above problems. The rest of the paper is arranged as follows. Section 2 reviews the methodologies of Case Based Reasoning and fuzzy Set Theory. Section 3 presents the overview model of CBPP and its work logic. Section 4 introduces the key methodologies and techniques for CBPP. In Section 5, a case is used to demonstrate the effectiveness of the approach. Conclusions are drawn with brief comments in Section 6.

II. LITERATURE REVIEW

A. Case Based Reasoning

Case-based reasoning (CBR) is a problem-solving paradigm in the field of Artificial Intelligence (AI) in which previous similar situations are retrieved and used to solve a new problem [1]. Instead of relying solely on general knowledge of a problem domain, CBR is a methodology for solving problems with the use of past experience [2]. Watson [3] described that CBR is a kind of analogical reasoning, which treats the target case and cases in the case library as instances of the same category. Aamodt and Plaza [4] proposed the reasoning framework of CBR shown in Figure.1. The reasoning framework comprises four stages, which are described as follows:

- Case Retrieval: the most similar case is retrieved from case libraries;
- Case Reuse: retrieved case is used as a potential candidate solution to solve the new problem;
- Case Revise: the old knowledge is revised to generate a proposed solution case that fit the problem;
- Case Retain: generated solution is stored in case libraries for future use.

CBR has been well researched and applied in the field of Manufacturing Process Planning for many years. Early CBR system for simple process planning in machining was reported by Yang et al. [5]. Takahashi et al. [6] combined the concept of CBR and knowledge reuse to

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solve real, large-scale manufacturing process design problems. Haque et al. [7] suggested that three phases, i.e. problem description, solution development and outcome should be comprised in CBR application of manufacturing processes planning.

B. Fuzzy Set Theory

Although the methodology of Case Based Reasoning has been proved effective to extract the "most similar" and "most useful" solutions to problem cases, it still has certain shortcomings to define the mapping between inputs and outputs. The input parameters of polishing cases in our research involve multi-criteria (that is, Product Category, Product Size and Product Material) so it is not easy to define decision making steps that lead to accurate, efficient and flexible case retrieval in case based reasoning.

The study of Fuzzy Sets helps the system to explore multi-criteria to input parameters. The approach advised by Dvir et al. [8] advocated the switching of parameters into linguistics in fuzzy theory. With reference to important definitions and notations of Fuzzy Set theory to case representation, Lee et al. [9] depicted a general structure of CBR system embedded with Fuzzy matching engine. Dubois et al. [10] proposed a fuzzy set-based formalization of case-based reasoning. The approach advised by Dvir et al. [11] advocated the switching of parameters into linguistics in fuzzy theory. With reference to important definitions and notations of Fuzzy Set theory to case representation, Lee et al. [12] depicted a general structure of CBR system embedded with Fuzzy matching engine. In case-based reasoning systems, some works have focused on the handling of fuzzy descriptions in the retrieval step [13].

III. OVERVIEW OF THE CBPP Model

Figure 1 shows the overview of the CBPP system proposed in this research. The system is built upon a CBR model commonly available in the literature as reviewed in the preceding section. It integrates the advantages of the generative approaches of CBR mechanism for generative planning. Such reasoning analysis of the whole product is of product-oriented in explicit form of design specification and parameter level settings. Different from general knowledge-based solutions, the CBPP demonstrates a superior capacity to incorporate the recognizable successful knowledge in the past to derive the optimal solutions. It involves four major stages, namely case presentation, case retrieval, case reasoning and case adaptation. Each stage serves particular purposes. They are discussed in more detail in the rest of this section.

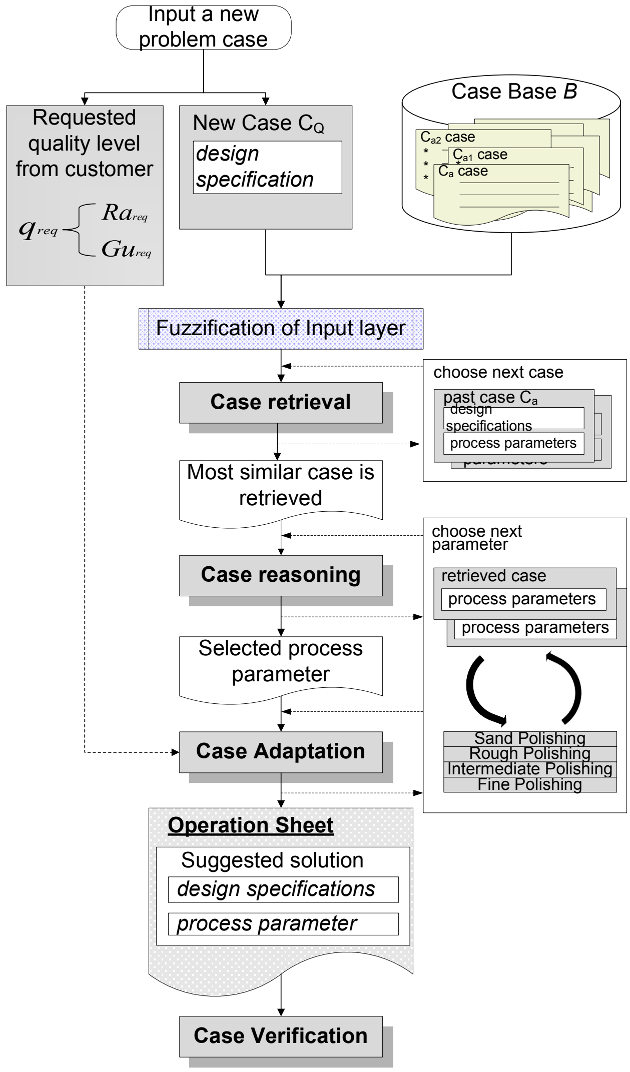

Fig. 1. Decision logic of Case Based Process Planning model

IV. CBPP MODEL FOR PPPA DETERMINATION

A. Input Parameters: defining attributes for CBPP Model

The most important knowledge asset in CBR is a casebase that contains a reasonable number of past cases for solving real-life problems. The construction of a polishing casebase includes two steps. One is to define relevant attributes that adequately describe polishing cases. The other is how to represent polishing cases.

The polishing product process depends mainly on its parameters and relevant attributes. Therefore, the input parameters and attributes should be firstly defined to describe polishing case. Figure.2 shows the structure of parameters and their attributes of polishing product. There are four input parameters defined in polishing product process planning, namely, "Product Category", "Product Size", "Product Material" and "Quality Level Specification".

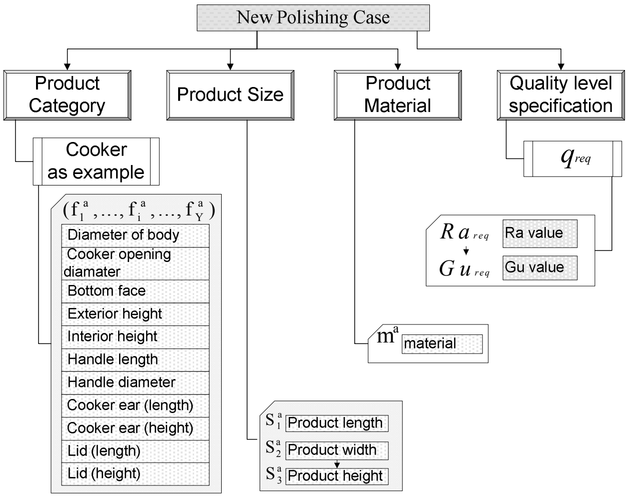

Fig. 2. Four discriminating input parameters for new problem case

B. Case Representation

CBPP model describes each problem case as cQ through its interface in WBPS. The approach is to standardize it to a structured problem case description cQ . Solution case is represented by cS. Then CBPP model uses algorithm of nearest neighbor searching computation (the CBPP engine built in the system) to compute and retrieve cases in the case-base B , each of which is denoted as ca , where ca is the ath past case in the base:

$$B = \{c_a \mid a = 1, \ldots, X\}$$

Where

- X is the total number of past cases in B.
- a = 1, 2, …, X are all cases with their case description ca similar to the problem case cQ .

Following the representation style, specification of polishing feature for ca in case-base B as $(f_1^a, \ldots, f_i^a, \ldots, f_Y^a)$, where f_i^a is the ith feature attribute value of ca and Y is the total number of feature specification.

C. Fuzzification on Input Parameter

The stage of solution generation is in a large extent dependent on the input parameters of the problem case. However, the performance of CBR system will descend if the input parameters are not effective enough to reflect the actual problem situation. To solve this problem, a Fuzzy Membership Function is introduced. Its major contribution is to present vagueness in any terms of variables. Upon such introduction, input variables can be transformed with combination of fuzzy membership functions in the linguistic property sets.

The following symbols and hypothesis are defined to build the Fuzzy Membership Function.

Let F be the universe of discourse for product feature under Product Category (one of the Input Parameters), so $F = \{f_1^Q, \ldots, f_i^Q, \ldots f_Y^Q\}$. A fuzzy set $\tilde{A}$ of F is a set of order pairs $\{(f_1^Q, \mu_{\tilde{A}}(f_1^Q)), \ldots, (f_i^Q, \mu_{\tilde{A}}(f_i^Q))\}$, where $\mu_{\tilde{A}}(f_1^Q) : F \to [0,1]$ is the membership function of $\tilde{A}$, and $\mu_{\tilde{A}}(f_i^Q)$ presents the membership degree of f_i^Q in $\tilde{A}$.

It is assumed that the membership functions $\mu_{\tilde{A}}(f_i^Q)$ follows $\max_f \mu_{\tilde{A}}(f_i^Q) = 1$, so the fuzzy set $\tilde{A}$ of the universe of discourse F is normal.

Assume the fuzzy terms of each input parameter are three, and there are different membership functions for each variable. Fuzzy terms of f_i^Q are defined as Low (L), Medium (M) and High (H):

Their membership function $\mu_{\tilde{A}}(f_i^Q)$ is presented by a triangular fuzzy number.

To compute the membership value of each variable, the term with highest membership value is selected:

$$\mu_{\tilde{A}}(f_i^a) = \text{maximize}(\mu_{\tilde{L}}(f_i^a), \mu_{\tilde{M}}(f_i^a), \mu_{\tilde{H}}(f_i^a)) \quad (1)$$

Under such transformation with fuzzy concept, product feature of Product Category can be represented in terms of fuzzy set. Same procedures are applied to other input parameters (Product Size and Quality Level). Fuzzy set theory allows polishing cases with vague and imprecise input parameters to be transformed to membership function first, so the transformed attributes can bear useful and significant references in later stages.

D. Case Reasoning

A Mutual Correlation Parameter Selection (MCPS) is proposed as a reasoning strategy. By utilizing MCPS, the adoption of some of variables has been modified in the formulae to fit the polishing case, aimed at selecting principal process parameters. After that, the correlation coefficient between principal process parameters and polishing quality is calculated one by one and considered as determinants of selection criteria. One principal process parameter can have a stronger influence on the polishing quality than others, so the correlation value between this parameter and the polishing quality should be relatively higher. The procedures of the proposed MCPS method are described as follows:

(1.) Two variables pi and q, which stands for ith parameter and polishing quality respectively, are set:

$p_i = (p_{i1}, \ldots\ldots, p_{in})$: ith process parameter setting

$q = (q_1, \ldots\ldots, q_n)$: quality level where n is the total number of selected-to-be-significant features for the product.

(2.) Correlation coefficient between pi and q is:

$$\rho(p_i,q)^2 = \left(\frac{\sum_{t=1}^{n}(p_{it}-\bar{p}_i)(q_t-\bar{q})}{\sqrt{\sum_{t=1}^{n}(p_{it}-\bar{p}_i)^2} \times \sqrt{\sum_{t=1}^{n}(q_t-\bar{q})^2}} \right)^2$$

(3.) Mutual correlation measure between pi and q is defined as $\rho(pi,q)^2$, with the range $0 \le \rho(pi,q)^2 \le 1$. If $\rho(pi,q)^2$ is close to 1, pi and q are strongly correlated; If $\rho(pi,q)^2$ is close to 0, pi and q are independent or totally uncorrelated.

(4.) Repeat step 2 and step 3 for next process parameters, until all process parameters of the project case are analyzed.

(5.) Repeat the above steps for next polishing operations until all operation sequences are conducted. With an estimation of value range, company technicians can conduct further research on value settings to determine the optimal values for the principal process parameter.

E. Case Adaptation

Case Adaptation approach consists of two phases. The first phase adopts Linear Extrapolation Size Adjustment (LESA) to produce a data set of adaptation pattern based on reasoned process parameter settings. Then, a mathematical variable called Correlation Significance Proportion (α_i) is used to automatically generate process parameters based on the data set in the second phase, Parameter Fulfillment Adjustment (PFA).

The main phases are described as follows:

(1.) The first phase constructs adaptations on reasoned process parameters according to Linear Extrapolation Size Adjustment (LESA). LESA works to take into account the difference in size between retrieved case and target case. A linear extrapolation is applied in term of one-dimensional feature size.

(2.) Second phase is called Parameter Fulfillment Adjustment (PFA). It can further generalize parameter settings to a level that is believed to be more realistic and applicable to resolve the problem case.

(3.) Finally the solution of process parameter $P^{i.est}$ is calculated.

(4.) Repeat step 1 to step 3 for other process parameter until a complete set of estimated parameter settings for this polishing is calculated.

(5.) After a list of process parameters is completed for this particular polishing operation, repeat step 1 to step 4 for other polishing operations until all operations are evaluated and analyzed.

Ⅴ. CASE STUDY

According to the methodologies and algorithms proposed in this paper, we use the actual polishing data derived from real polishing company to verify the CBPP's possibility and applicability. Nine cases are collected from collaborating polishing company for model demonstration. Eight cases are used to form a case-base, while one case is drawn as a problem case. Among the eight cases, the most similar one is found according to similarity measures from the model. It is then is conducted via reasoning and adaptation strategies to derive an optimal solution to the problem. To verify the effective of our system, we contrast the actual process parameters from the engineering to the recommended one from our CBPP system. The relationship of the percentage of absolute error between actual operation sheet and recommended solution generated by CBPP model is shown in Figure 3.

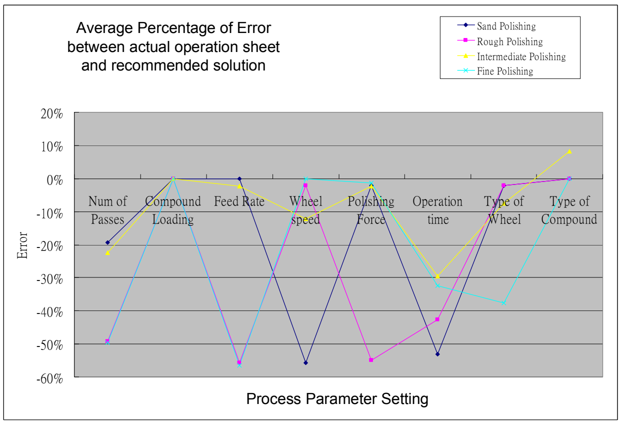

Fig. 3. The relationship of the percentage of absolute error between actual operation sheet and recommended solution generated by CBPP model

Result of the research showed that the proposed CBPP model could successfully be used to implement the automatic product and process analysis on cooker sample. The average percentage of absolute error, which is estimated by comparison between recommended operation sheet generated by CBPP model and the actual sheet conducted by polishing experiment. The average absolute error of practical process parameters taken from nine samples is -24%. There exists a considerable larger error trend in num of passes, feed rate, polishing force and operation time, which is up to 50%, meaning the standards of these process parameters from the retrieved case may not be too good to match the surface requirement of problem case. On the other hand, compound loading, operation time, type of wheel and type of compound rather keep at a low error percentage (around 10%), which means in the study of similar case analysis, the operations of retrieved case have similar settings of these process parameters with the problem case.

Ⅵ. CONCLUSION

This paper proposes a Case Based Process Planning (CBPP) model for automatically generating process planning. The underlying principle of CBPP model is oriented towards Case Retrieval, Case Reasoning, Case Adaptation and Case Verification. A capable matching mechanism is designed, based on the structure of polishing case, to characterize the three input parameters and their respective settings. It manipulates the computational determination of which case is believed to be the most suitable as a recommended solution. This function generates automatic programming packages to reason and adjust the operational process parameters in a capability chain. Preliminary evaluation findings suggest that CBPP model in AutoPlanner Module of WBPS is efficient and effective in terms of shortening process-planning time, coupling analysis with scientific computations, providing more time-effective solutions and helping improve the decision-making quality

Similarity measures were built with pre-set importance weights on input parameters in discussion of methodology of CBPP model. The three input parameters of CBPP model in this research are assumed equally important. However, in actual situation, different users may have different sensitivity to the input parameters when judging the criteria on product appearance, so importance weights are in fact vulnerable to subjective determination of system users. A suggested direction to further improve this research is to identify the optimum combination of importance weights to different input parameters, giving a more robust and reliable performance to retrieval mechanism.

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