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REVIEW ARTICLE

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Intelligent methods for the process parameter determination of plastic injection molding

Abstract Injection molding is one of the most widely used material processing methods in producing plastic products with complex geometries and high precision. The determination of process parameters is important in obtaining qualified products and maintaining product quality. This article reviews the recent studies and developments of the intelligent methods applied in the process parameter determination of injection molding. These intelligent methods are classified into three categories: Case-based reasoning methods, expert system-based methods, and data fitting and optimization methods. A framework of process parameter determination is proposed after comprehensive discussions. Finally, the conclusions and future research topics are discussed.

Keywords injection molding, intelligent methods, process parameters, optimization

1 Introduction

Injection molding is an important method used in processing plastic products, which are widely used in packaging, automobiles, electronics, and other applications. Once an injection mold is constructed, the most important task is to find a set of appropriate process parameters to produce qualified products. Dozens of process parameters should be set up based on information from material suppliers, mold designers, and machine manufacturers. Traditionally, the molding process parameters are determined by trial-and-error method. For this method, shots are taken during the start-up process, and the product quality attributes are measured after each shot to evaluate the quality of the produced products. The molding personnel then uses his/her knowledge on the process to adjust the process parameters and to improve the quality of the product from shot to shot. This tuning exercise is repeated until the specifications of product quality are satisfied [1]. Such a procedure not only requires significant amounts of time and money but also depends on the proficiency of the molding personnel, who must undergo years of practice to be an expert. However, the growing demand for molding experts in the industry far exceeds the supply. Moreover, in some circumstances, the injection molding process can be extremely complicated that it is beyond the range of personal experience.

Therefore, when determining the optimal process parameters, many shortcomings have been encountered in the traditional trial-and-error method, especially with the rapid development of requirements for high product quality and low production cost. In the last two decades, many researchers have proposed various intelligent methods to automatically determine the process parameters. In the present work, the current activities of the intelligent methods for injection molding are reviewed. These methods are classified into three categories: Case-based reasoning (CBR) methods, expert system-based methods, and data fitting and optimization methods.

The rest of this paper is organized as follows. In Sections 2–4, the existing results of intelligent methods for determining the process parameters in plastic injection molding based on the three methods are respectively presented. In Section 5, the relevant discussions and a proposed framework are presented. Finally, a brief conclusion and some suggestions for future trends are presented by referring to experiences from previous works by the State Key Laboratory of Material Processing and Die & Mould Technology.

2 Case-based reasoning

CBR refers to the use of old solutions to meet new demands, explanation of new situations according to old

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cases, and evaluation of new solutions through the applications of old cases [2]. The basic idea of CBR is to use a case-based reasoner to solve a new problem by adapting the solutions used to solve the old problems [3]. The new problem is matched against the cases in the case library, after which one or more similar cases are retrieved. The case that is most similar to the new problem is then used to yield a solution. A typical CBR includes the following processes: 1) Case representation and organization: Organizing the case in pre-defined structure; 2) case retrieval and matching: Retrieving the most similar case or cases; 3) case reuse: Reusing the information and knowledge in the case to solve the new problem; 4) case revision: Revising the proposed solution; and 5) case retention: Retaining the useful parts of the experience and using it for future problem solving.

CBR has been found to be extremely helpful in determining the initial process parameters for injection molding. Kwong et al. [4,5] first developed a CBR system to obtain proper process parameters. This method was subsequently adopted in the studies of Mok et al. [6,7], Shelesh-Nezhad and Siores [8], and Zhou et al. [9]. The flowchart for setting initial process parameters based on CBR is shown in Fig. 1. The geometric characteristics and the material physical properties are selected as the features in an injection molding case. The optimal process parameters are adopted as part of the solution. To facilitate the case retrieval, all cases are indexed by defining similarity metrics, such as the type of material, product geometry, and configuration of the mold cavity. The process parameters of the similar cases are then adapted to fit the new problem by using several adaptation strategies.

CBR can quickly determine a set of process parameters for injection molding based on previous successful cases. The application of CBR has several benefits in terms of determining the initial process parameters for injection molding. First, solutions can be obtained quickly by the reasoner, thus reducing the reasoning time. Second, remembering previous experiences is particularly useful in avoiding the repetition of past mistakes. Third, by increasing the memory of old solutions and adapting them, the CBR system makes the learning process more efficient. Nevertheless, the effectiveness of CBR is mainly dependent on the relevance of old cases, size of the case library, and case retrieval algorithm [3].

3 Expert system

Expert system-based methods emulate the decision-making process of a human expert. The basic idea of these methods is that massive task-specific knowledge is transferred from a human to a computer and then stored in that computer. When users call upon the computer for specific advice, the computer can make inferences, give advice, and explain the logic behind the advice.

A variety of techniques have been used to develop an expert system for the defect correction of injection molding. In general, the expert system-based methods can be divided into the following closely associated steps. First, the user input information about the molding material, the process parameters of the current setting, and the product defects is observed. Then, the knowledge base is deduced. Finally, the optimized process parameters

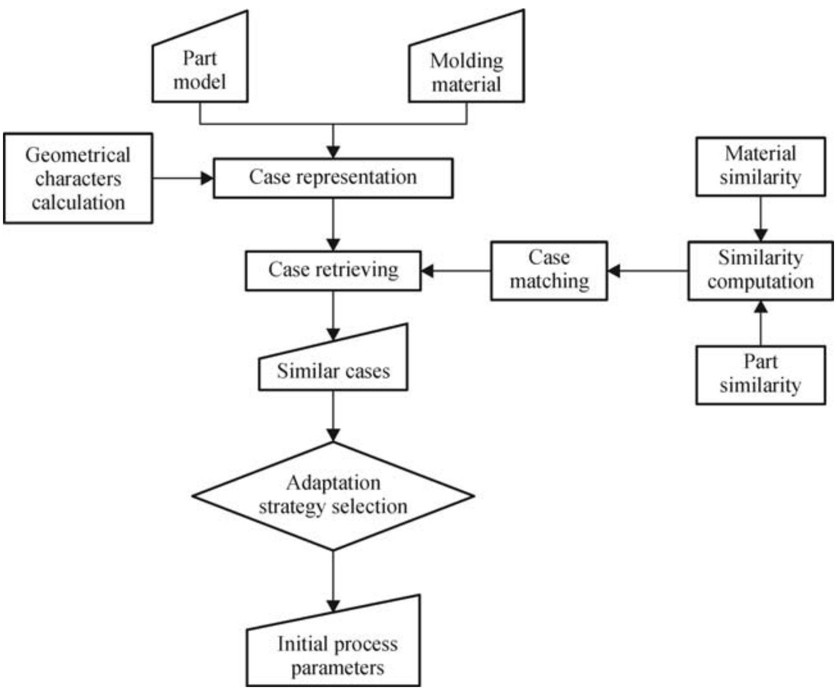

Fig. 1 Flowchart of the initial process parameters setting based on CBR

are recommended. According to the different forms of knowledge representation, the expert system-based methods can be divided into knowledge-based reasoning (KBR), rule-based reasoning (RBR), and fuzzy reasoning (FR), etc. A survey on the expert system-based methods and their applications in injection molding is listed in Table 1.

3.1 Knowledge-based reasoning

KBR attempts to understand and initiate human knowledge in computer systems. The KBR is mainly composed of four components: User interface, inference engine, knowledge database, and knowledge engineering tool [19]. The development of a KBR system can be divided into the following tightly linked substeps [11]. First, the form for representing and constructing knowledge base should be determined. Then, the inference mechanism is developed based on the available knowledge database. Finally, the facility programs are designed for experts, which can be used to update the knowledge database and improve the inference mechanism.

The KBR can reduce the demand for experimentation by taking advantage of the a priori knowledge of injection molding. For example, Pandelidis and Kao [11] presented a knowledge-based system to diagnose multiple defects in injection molding. Inaba et al. [20] proposed a knowledge-based expert system that uses on-line measured process parameters from the molding machine to make decisions for eliminating molding defects. Yang et al. [1] developed a knowledge-based tuning method to obtain the suitable process parameters. The method provides an estimate of the process window (process feasible region) and updates its knowledge base during tuning.

3.2 Rule-based reasoning

RBR is a protocol that represents the information acquired from a human expert in a defined form of a rule, such as if-then. The rule can, in turn, be applied for the operations on data to reach appropriate conclusions, and the inferences can be provided with a computer program by reasoning about information in the rule base and formulating conclusions [21].

When setting the process parameter of injection molding, RBR can provide useful guidance for the molding personnel. Thus, RBR can greatly reduce the requirements for the experience of molding personnel. Shelesh-Nezhad and Siores [8] proposed the idea of using RBR to eliminate part defects. However, due to its incomplete integration of qualitative and quantitative reasoning, a typical symbolic RBR system output contains only the parameter types and associated correction direction. No range of correction or crisp value is given.

3.3 Fuzzy reasoning

Based on the theory of fuzzy logic, the FR can efficiently model the qualitative aspects of human knowledge and reasoning processes via the fuzzy if-then rules, obtaining less precise and logical computation by the computer than the conventional ones. The decision-making process is not always a matter of black and white or true or false; hence, the approach can be used to deal with gray areas and the terms. For instance, process parameters must be carried out on the injection machine, and mold trial is indispensable. Generally, many molding defects can be encountered during mold trials. The defects can be defined as D_i ($i = 1, 2, \ldots, m$). To eliminate each defect D_i, a number of process parameters, such as P_j ($j = 1, 2, \ldots, n$), should be adjusted. Here, ΔP_{ji} is written as the adjustment of one of the relative process parameters P_j, which results from a certain defect D_i. ΔP_{ji} consists of two parts: Adjustment range and adjustment direction. The adjustment range is determined by the seriousness of the defect and the current value of process parameters and can be acquired through the fuzzy inference. The adjustment direction is determined by the type of defect and the process parameter and can be acquired easily by the traditional RBR. The defects are handled one by one, and each defect results in adjustments

Table 1 Expert system-based methods and their applications in injection molding

Methods	References	Applications
KBR	Kim and Suh [10]	Weld line
	Pandelidis and Kao [11]	Bubbles, cracking, shrinkage
	Jan and O'Brien [12]	Pit marks, surface ripples, flashing
	Kameoka et al. [13]	Short shot, sink mark, warpage
	Yang et al. [1]	Short shot, flash, dimension
RBR	Shelesh-Nezhad and Siores [8]	Burn streaks, weld line, jetting
FR	He et al. [14,15]	Short shot, sink mark, flash, flow mark, warpage
	Tan and Yuen [16]	Flash, short shot, black streak
	Zhou et al. [9]	Short shot, flash
	Chen et al. [17]	Weld line
	Li et al. [18]	Short shot, flash

to its related process parameters. Finally, the adjustments for the same parameter are integrated into its final adjustment through the composition method. The framework of a typical FR system is shown in Fig. 2 [9].

FR is an efficient method in eliminating product aesthetic defects. It can obtain the correction direction of process parameters and the adjustment range of process parameters. However, the adjustment range of process parameters are determined by the seriousness of defects, which involves two potential problems. The first problem is how to diagnose the degree of defects accurately. The second problem is how to eliminate operator bias and ensure the consistency of the diagnostic results.

4 Data fitting and optimization

Data fitting and optimization methods evaluate the comprehensiveness of a variety of methods. These methods mainly include three steps: Sampling, model fitting, and optimization, as shown in Fig. 3. In the sampling method, the initial molding parameters are randomly selected in the feasible search space. The quantitative relationship model between product quality and process parameters is established by a fitting model. The process iterates until the process parameters are found to be capable of producing qualified products.

4.1 Sampling

Sampling is the process of obtaining sample data by employing various experimental design methods. An experimental design indicates a series of experiments, which are expressed as the factors of specified levels. Classical experimental designs originated from the theory of design of experiments when physical experiments were conducted. These methods focus on planning experiments, and thus the random error in physical experiments has minimal influence on the approval or disapproval of a hypothesis. Fractional factorial design [22] and central composite design (CCD) [23] are widely used classical experimental design methods. These methods obtain a sample at the boundaries of the design space. Compared with random error in physical experiments, computer experiments mainly involve systematic error. Thus, a good experimental design tends to fill the design space rather than focus on boundaries. The Taguchi method [24], various Latin hypercube designs (LHDs) [25], and uniform designs (UDs) [26] are three common types of space-filling sampling methods.

By using the experimental design methods, good results with less experiment times, short experimental period, and low experimental cost can be obtained. Thus, experimental design methods are widely used in injection molding. A survey of experimental design methods for injection molding from 2005 to 2016 is shown in Table 2. Among these experimental design methods, the Taguchi method is the most widely used. By integrating range analysis, variance analysis, and signal-to-noise analysis, the Taguchi method can be used to produce sample data, identify the influence of different process parameters on product quality, and determine the optimal process parameters for specific product quality indicator. Chen et al. [27] conducted experiments using the Taguchi method to determine the significant factors. Zhao and Cheng [28] utilized the Taguchi method to determine the effect of process parameters on warpage. However, this method can only find the best combinations of specified process parameter level but not the global optimal solution.

4.2 Model fitting

Model fitting establishes the relationship model between the process parameters and the product quality indexes. Model fitting involves three main steps: Model choosing, model fitting, and model validation.

Model choosing refers to the process of choosing the appropriate surrogate model to establish the relationship between the process parameters and product quality indexes. The common surrogate model includes polynomial regression (PR), Kriging, response surface methodology (RSM), artificial neural network (ANN), support

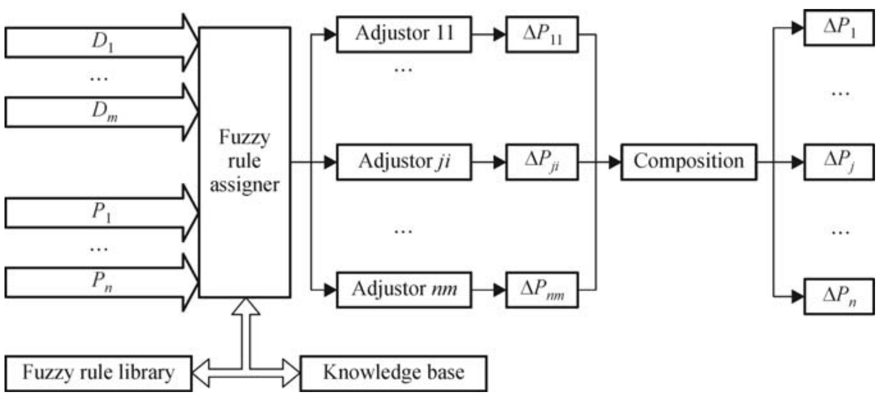

Fig. 2 Framework of a typical FR system

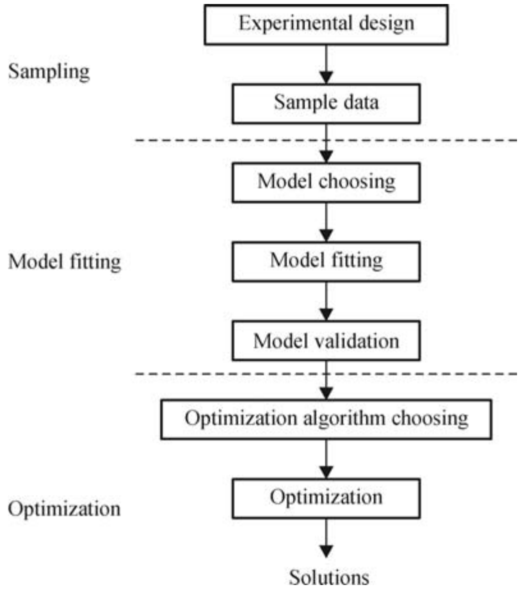

Fig. 3 The main framework for the data fitting and optimization methods

Table 2 Survey of experimental design methods for injection molding

Method classification	References
Space filling	Taguchi method [27–59]
	LHD [60–68]
	UD [69,70]
Classical	CCD [71–73]
Others	Full factorial experimental design [74,75]

vector regression (SVR), and hybrid models, etc. A survey of surrogate models used in injection molding is listed in Table 3. The characteristics of the abovementioned surrogate models are given in Table 4.

Table 3 Survey of surrogate models used in injection molding

Fitting model	Applications
RSM [27,30,35,36,40,72]	Warpage, shrinkage
Kriging [28,64,67,76]	Warpage, cycle time, deflection, and max injection pressure
PR [46,71]	Sink mark, waviness, weight
ANN [32,33,37,38,61,77–86]	Warpage, shrinkage, runner volume, weight, cycle time, strength
SVR [87,88]	Weight, cycle time, max injection pressure, shrinkage

After the surrogate model is selected, the next step is model fitting. The common model fitting methods include least square regression, best linear predictor, best linear unbiased predictor (BLUP), back propagation, and multi-point approximation, etc. Each surrogate model has its associated fitting method. For example, polynomial functions are usually fitted by the weighted least square method, and the kriging method applies the BLUP for model fitting [89]. Simpson et al. [90] have already given a detailed review with respect to the equations and fitting methods for common surrogate models.

Once the meta-model is fitted, the model must be validated before acting as a "surrogate" model. Model validation is thought to be a challenge, and it shares common challenges with the verification and validation of other computational models [91]. Cross-validation is the most commonly used validation method.

4.3 Optimization

Optimization works to search the optimal process parameter setting to produce the best-qualified product through various optimization approaches. Optimization approaches can be classified into three categories according to the methods of improving the optimal point within each iteration. These categories include the deterministic, stochastic, and hybrid optimization approaches.

For the deterministic approaches, the adjustment direction for each trial is determined. The commonly used deterministic approaches include the Newton method or the quasi-Newton method [51] and sequential quadratic programming [52], etc. Deterministic approaches take advantage of the analytical properties of the problem to obtain a sequence of points, which can quickly converge to the optimal solution. However, deterministic approaches easily fall into a local optimum, rather than a global one.

For the stochastic approaches, the random variables are generated and used. The widely used stochastic approaches include genetic algorithm (GA) [92], particle swarm optimization [86], artificial bee colony [78], and simulated annealing [93], and so on. Compared with the deterministic approaches, the stochastic approaches are more flexible and efficient. However, stochastic approaches are inefficient. Sometimes, they probably cannot reach the optimum because of their non-deterministic characteristic. Moreover, the probability of finding the global solution decreases when the problem size increases [94].

Hybrid optimization approaches are combinations of the deterministic and stochastic approaches. These approaches maximize the single optimization technique while avoiding its disadvantages [95]. Lam et al. [96] conducted GA/gradient hybrid approach to search the optimal injection molding process parameters and claimed that the optimization results of hybrid is stable.

5 Discussions and framework

Based on previous successful cases, CBR can quickly determine a set of feasible process parameters for injection molding. CBR is especially suitable for determining a set of initial process parameters, which would be further

Table 4 Advantages and disadvantages of several surrogate models

Approaches	Advantages	Disadvantages
PR	Can be easily constructed, has clear rules on parameter sensitivity, allows quick convergence of noisy functions	Instabilities that may arise for high-order polynomials; difficulty in obtaining sufficient sample data for high-order polynomials; cannot interpolate new sample points and be restricted by the selected function type
Kriging	Does not need to construct a specific mathematics model, is extremely flexible in capturing nonlinear behavior, is accurate for nonlinear problems under small sample with moderate scale of variables	More complex compared with RSM
RSM	Requires less manual intervention, does not need the trial-and-error method to achieve a suitable model because of the benefit of data driven	Falls easily into the local minimum value
ANN	Has learning capability, is best for repeated application, has a highly nonlinear mapping capability, can approximate any function	High computational expense, lack of a complete and mature theoretical system and high dependence on experience, overfitting; it is a "black box" method and cannot obtain explicit and meaningful models for further analysis
SVR	Has solid theoretical foundation, is suitable for small sample data, has good generalization ability	Not suitable for large sample data

modified or optimized. The major difficulty in CBR refers to the features in a case that are used to describe the problem and define similarity metrics. Material, product geometry, mold design, and injection machine are consistently regarded as indispensable information that should be considered. The manual definition of the strict features of the information, especially for the product geometry and mold design, seems to be impossible. This finding also results in the lack of a case library with a consistent structure and leads to difficulties in gathering sufficient cases. Consequently, some transformation models should be designed to compensate for the deviations between the theoretical solution and the actual solution, including case imbibition, case matrix, RBR, etc., according to the number of similar cases and the corresponding similarities.

Owing to the large amount of works relying on experience and empirical knowledge, the expert systems are thought to be suitable for process parameter optimization. For example, expert systems have been successful in emending initial process parameters to avoid aesthetic defects (e.g., short shot, flash, sink marks, and burn), which are difficult to measure quantitatively by regular instrumentation methods. However, implementing an all-encompassing expert system for the injection molding is difficult because human experts are not a rule system. The nature of the human experience is fragile and cannot be acquired easily or readily transferred into a simple rule format. In addition, to build an expert system, a knowledgeable engineer must interview the molding personnel and try to elicit appropriate knowledge from them. Indeed, the knowledge acquisition bottleneck hinders the construction of expert systems.

The data fitting and optimization methods have been widely applied to determine the process parameters in plastic injection molding. Many researchers have achieved great success in optimizing the process parameters for injection molding by combining different sampling, fitting, and optimization methods. However, they are mainly used to obtain optimal process parameters for quantitative product quality (e.g., warpage, dimensions, and weight), whose quality indexes need to be quantified. Furthermore, in an actual production process, the quality indexes hardly undergo online feedback. The lack of corresponding sensing equipment or measurement process is particularly complex. Thus, data fitting and optimization methods are mainly used for offline optimization.

Many existent methods that have been applied to process parameter determination demonstrated that no perfect method can solve all process parameter determination problems. CBR has mainly been used for initial process parameter setting, whereas the expert system-based methods have been successfully adopted to eliminate qualitative defects. Data fitting and optimization methods have been widely utilized to determine the optimal process parameters for quantitative product quality. A complete injection molding process consists of initial process parameter setting, qualitative defect correction, and quantitative defect optimization. Thus, a hybrid intelligent system that covers all these aspects should be established. The framework of the hybrid intelligent system is shown in Fig. 4. Moreover, some aspects need to be emphasized in a practical system.

1) The defect correction rules for qualitative defects correction are mainly organized and collected by human. However, human knowledge is limited and can easily be affected by other factors.

2) The aesthetic quality is usually detected by machine operator visual inspection, which can lead to two issues. One issue is the complexity of establishing a precise diagnosis of the defect degree. The other issue is the elimination of operator bias and ensuring that the

inspection independent from the operator conduct.

3) The direct and online measurement of quantitative product quality remains a challenging task, due to the lack of corresponding sensors or the particularly complex and time-consuming measurement process.

4) Data fitting and optimization methods still require sample data to fit and validate the model, which has a high demand for the number of sample data. In an actual mold trial process, the mold trial data is limited for a particular mold, material, and injection molding machine.

5) The effects of the data fitting and optimization methods are easily affected by various parameters. However, the setting of these parameters lacks theoretical basis and mainly depends on experience. Thus, the effectiveness of the method cannot be guaranteed.

6 Conclusions and future trends

This study reviews the advanced intelligent methods for injection molding process parameter determination. Based on the literature survey, great advancements have been made in the modeling of intelligent methods for process parameter determination. However, no commercial application and systematic solution have been reported. Apart from conducting fundamental studies, the following suggestions on future research directions are proposed.

1) Sensor and sensing technologies

With the traditional technologies, obtaining direct and online feedback of the product quality within the cycle time in practical applications remains a challenge. In addition, the diversity of product quality requirements makes obtaining quality feedback difficult. Thus, the sensor and the sensing technology should be taken into consideration to provide more feedbacks for process parameter determination.

2) Feature extraction technologies

The features in a case, which are used to define the problem and describe similarity metrics, are mainly determined by human. The commonly used features include flow length, maximum thickness, projected area, part volume, runner type, and size, etc. However, whether these features are sufficient to characterize the case is unknown. Thus, more sophisticated feature extraction technologies should be developed to extract useful features from molding material, part, and mold geometric information.

3) Multi-objective optimization technologies

The injection molding process involves multiple-input multiple-output (MIMO) features. Thus, many processing parameters (e.g., injection pressure, injection velocity, packing pressure, packing time), product qualities (e.g., aesthetic, dimensional, and performance), and requirements (e.g., efficiency, cost, and energy) should be considered simultaneously. In recent years, some researchers have conducted various multi-objective optimization

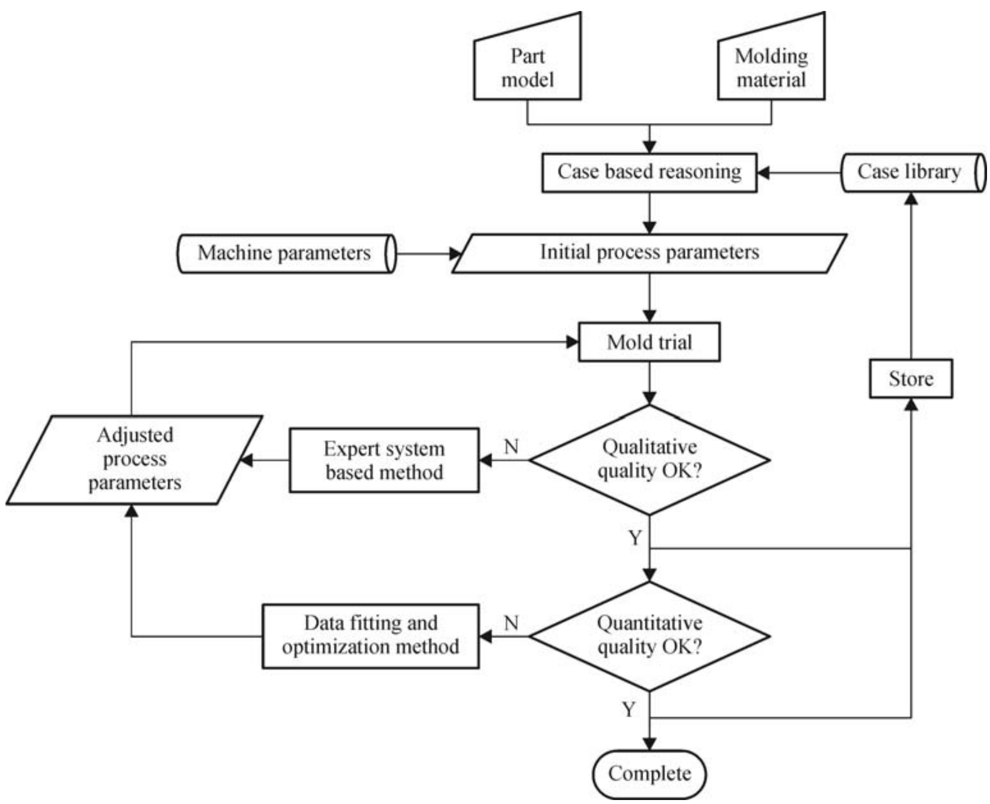

Fig. 4 The framework of the hybrid intelligent system

studies in injection molding [77,97]. However, most of the researchers only considered a handful assorted process parameters independently, along with the desired product quality indices to simplify the problem. Injection molding is a complex process with MIMO features [98]; hence, the development of multi-objective optimization technologies for injection molding is essential.

4) Knowledge discovery technologies

Many successful and failed mold trial cases in the process parameter determination of plastic injection molding have been conducted. More knowledge should be automatically extracted from these cases, rather than organized by experts or developers from the existing CBR systems and expert systems. Hence, dedicated knowledge discovery technologies need to be developed to extract useful information from mold trial cases.

5) Online compensation technologies

In an actual production process, even the process parameters are properly set up, and the product quality might fluctuate. The injection molding process is a time-varying process with various perturbations (e.g., material property variations, machine wear, and manufacturing circumstance change). Conventionally, unscheduled manual interferers with process parameters are indispensable in dealing with the aforementioned perturbations. However, an unscheduled manual interferer could potentially be costly and time consuming. Therefore, establishing automatic compensation technologies for process parameters is very important in ensuring the stability of product quality.

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