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# Combining rough set and case based reasoning for process conditions selection in camshaft grinding

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**Abstract** Case Based Reasoning (CBR) is a novel paradigm that uses previous cases to solve new, unseen and different problems. However, redundant features may not only dramatically increase the case memory, but also make the case retrieval more time-consuming. Furthermore, camshaft grinding process is controlled by a number of process parameters, and it is more complex comparing with the ordinary cylindrical grinding. The process conditions are achieved by skilled and professional workers. Therefore, this research combines Rough set (RS) and CBR for process conditions selection in camshaft grinding, and Genetic Algorithm (GA) is developed to discretize condition features. Through the approach an optimal subset of process conditions can be selected quickly and effectively from a large database with a lot of cases, and complexity of computation of the similarity testing is significantly reduced. Moreover, the validity of the proposed solution is verified by the application of practical experiments for the process conditions selection in camshaft grinding.

**Keywords** Rough set · Case based reasoning · Genetic algorithm · Case reclassify · Feature reduction · Case evaluation · Camshaft grinding

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## Introduction

Camshaft is one of the key components of vehicle engines. Its quality directly determines engine combustion and dynamic characteristics. The camshaft grinding process is a non-circular grinding, large grinding margin and high production. Hence, how to improve the grinding efficiency and the quality of processing is one of the key technologies needed to be solved. It becomes a critical task in camshaft grinding to identify the grinding process conditions from the overall process parameters.

Earlier Yang et al. (2003) proposed the Genetically Optimized Neural Network System (GONNS) for the selection of optimum composite material and operating conditions. It is proved that the GONNS is very promising for many complex optimization problems. A hybrid Artificial Neural Network (ANN) and Genetic Algorithm (GA) model was introduced to optimize the camshaft grinding process parameters (Deng et al. 2009). However, this model has some limitations: (1) It can only select some grinding process parameters and can not output a complete conditions of grinding process; (2) The configuration of the model is determined with $5 \times 12 \times 8$ and it is difficult to extend the model output for the entire grinding conditions.

To conquer this problem, a hybrid system combining Rough set (RS) and case based reasoning (CBR) is proposed to infer the grinding process conditions for a camshaft product. CBR is a novel paradigm that uses previous cases to solve new, unseen and different problems (Aamodt and Plaza 1994; Shin and Han 1999). The core idea of CBR is that 'similar problems have similar solutions' (Finnie and Sun 2003; Kwong et al. 1997). But traditional CBR is deficient for case reduction of information preserving data, representation of uncertain or imprecise knowledge, identification and

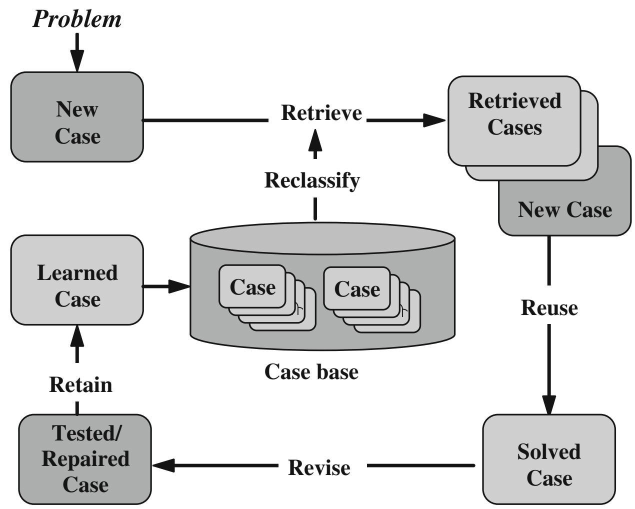



**Fig. 1** The $R^5$ model of CBR cycle

evaluation of data dependencies, reasoning with uncertainty and approximate pattern classification.

Some researchers such as Jiang et al. (2006), Huang and Tseng (2004), and Lin et al. (2009) and others have combined RS and CBR applying to some fields. Through the approach an optimal subset of process conditions can be selected quickly and effectively from a large database with a lot of cases, and the complexity of computation of the similarity testing is significantly reduced.

In the proposed system, a case consisted of the grinding processing environment, processing parameters and corresponding production qualities is stored in a case base. An algorithm based on RS and GA is proposed for feature reduction and feature weight calculation. By using those results a new set of some features is constructed to obtain high quality classifiers. According to weight value the features are classified into three grades. In the case retrieval stage of the CBR system, a Hierarchical Filtering Search (HFS) method is developed to retrieve past cases that have similar process condition to the new case in order to select the useful features from the database. By means of a method called 'Nearest Neighbor Matching (NNM)' the similarity between the new case and retrieved past cases is determined. After using a comprehensive evaluation method called 'Similarity-Confidence Level (SCL)' the most matching case will be presented to the user. At last, the system is used to practical application by collecting many cases of camshaft grinding. The results have verified the validity and dependability of the hybrid method integrating RS and CBR.

The rest of the paper is organized as follows. The related works about this research are surveyed in "Related work" section. "Framework of the proposed RS-CBR system" section introduces the framework of the proposed system combining RS and CBR in detail. "Application" section describes the effectiveness of the system by a practical application. Finally, in the fifth section some conclusions and suggestions have drawn for future study.

## Related work

### Case based reasoning

Case based reasoning (CBR) is an approach based on the reuse of the past experience in finding the solutions to new, similar problems. The classic definition of CBR was suggested by Riesbeck and Schank (1989): "A case based reasoner solves problems by using or adapting solutions to old problems."

Note that this definition points out "*what*" a case based reasoner does and not "*how*" it does what it does (Watson 1999). It can mirror the problem-solving approaches taken by human beings who solve current problems using past experiences (Chiu et al. 2003). Aamodt and Plaza (1994) introduced a process model of the CBR cycle [2]. The model is commonly called the $R^4$ model of CBR, because this cycle comprises four activities (the four-REs). Finnie and Sun (2003) proposed a $R^5$ model, in which *repartition, retrieve, reuse, revise* and *retain* are the main tasks for the CBR process. In fact the "finer" and "coarser" mentioned in the literature is the indiscernibility relation in the RS. RS can automatically calculate the weight of the features, so a new $R^5$ CBR model based on RS is proposed in Fig. 1. The model consists of five procedures: *reclassify, retrieve, reuse, revise* and *retain. Reclassify* means using the discrete and reduction algorithms to get the most classified set of features and reclassify the case base according to weight value.

The CBR which is a methodology not a technology has been widely used in the selection of process conditions. Kwong et al. (1997) developed a CBR system called CBRS for determining proper injection moulding parameters. Tsai and Chiu (2007) proposed a CBR system to infer the principal process parameters for a new printed circuit board product. Tong et al. (2001) introduced CBR in the process-parameters setting of transfer moulding in microchip encapsulation. Nagano et al. (2001) developed a system based on CBR to select high speed milling operation condition. The case retrieve of the CBR system depends on the similarity between tool shapes. But in grinding the shape and size of a grain is random and difficult to measure. Brian Rowe (1996) and Li et al. (1999) presented a CBR approach for the external cylindrical plunge grinding conditions selection.

### Rough set

Rough set (RS) is a new mathematical approach to intelligent data analysis and data mining (Pawlak 2002). The RS approach seems to be of fundamental importance to knowledge discovery from databases (Li et al. 2006b). Some researches have combined RS and CBR in Artificial Intelligence (AI) and cognitive sciences. Geng and Zhu (2009) proposed a hybrid mechanism based on RS integrating ANN (RS-ANN) for feature selection in pattern recognition to achieve fault diagnosis in industrial process. Moreover, the RS approach was used to analyze and induce rules by describing a case formulated with the Zachman framework (Huang and Tseng 2004). Jiang et al. (2006) presented a methodology to apply fuzzy similarity-based RS algorithm in feature weighting and reduction for CBR system. The methodology was used in tool selection for die and mold NC machining. The RS method and fuzzy sets Method were used for the adaptation study of the CBR of fluidized-Bed crystallization. The adaptation results showed that for average crystal size the RS method is better than the fuzzy sets method (Louhi-kultanen et al. 2009). More detailed information regarding features can be found in the works of Li et al. (2006b) and Gutiérrez Martínez and Bello Pérez (2003).

### Grinding process conditions selection

Grinding is a complex manufacturing process with a large number of interacting variables. Many investigations have been carried out to establish process models for grinding, including physical and empirical models (Chen et al. 1999; Gopal and Venkateswara Rao 2003; Gopala Krishna 2007). Since analytical models cannot be comprehensively defined and empirical models have a restricted range of validity with the aid of a number of grinding tests which are both time consuming and costly, the proposed models are not always reliable in practice. On the other hand, AI technology can describe the various non-linear relationships between grinding parameters (Sedighi and Afshari 2010). Choi and Shin (2007) described a Generalized Intelligent Grinding Advisory System (GIGAS), which employes the fuzzy basis

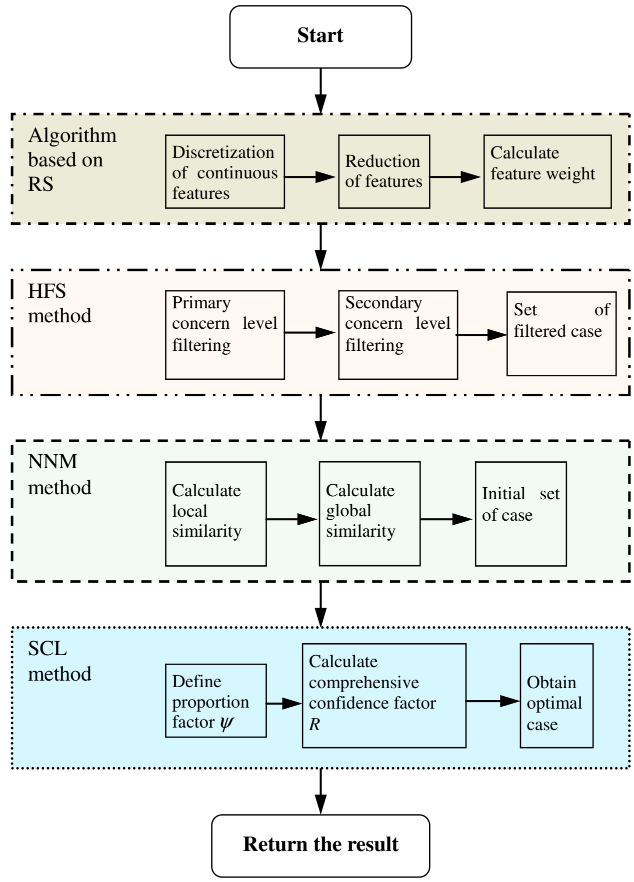



**Fig. 2** The flow chart of the proposed RS-CBR system

function network with an autonomous learning algorithm and the evolutionary strategy-based optimization algorithm. Cai et al. (2007) proposed an intelligent grinding database (IGA@) to provide only selective data to the operator based on CBR and rule based reasoning. However, a few studies conducted in camshaft grinding process conditions selection.

## Framework of the proposed RS-CBR system

Based on introducing RS theory and CBR theory, this section introduces how the proposed RS-CBR system achieves camshaft grinding process conditions selection. Four important parts of the system including case representation, reclassify, retrieval and evaluation are introduced in details. Its flow chart is shown in Fig. 2.

### Case representation

Camshaft grinding conditions that have been accumulated by the industry are regarded as past cases and stored in a case base $D$, where $D = \{d_a | a = 1, \ldots, X\}$, $d_a$ is the $a$th past case, and $X$ is the total number of past cases in $D$. Therefore,

**Table 1** The case base of the RS-CBR system

| Case | $c_1$ | ... | $c_p$ | ... | $c_s$ | $E^a$ |
|---|---|---|---|---|---|---|
| | | The problem | | The solution | | The evaluation |
| $d_1$ | $c_1 1$ | ... | $c_p 1$ | ... | $c_s 1$ | $E_1$ |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| $d_X$ | $c_1 X$ | ... | $c_p X$ | ... | $c_s X$ | $E_X$ |

the problem features of a past case $d_{\mathrm{a}}$ in $D$ can be represented as $\left(c_1^a, \ldots, c_i^a \ldots, c_p^a\right)$, where $c_i^a$ is the $i$th problem feature of $d_{\mathrm{a}}$ and $p$ is the total number of problem feature. The solution features of a past case $d_{\mathrm{a}}$ in $D$ can be represented as $\left(c_{p+1}^a, \ldots, c_j^a \ldots, c_s^a\right)$, where $c_j^a$ is the $j$th solution feature of $d_{\mathrm{a}}$ and the total number of solution feature is $s$-$p$. The evaluation features of a past case $d_{\mathrm{a}}$ in $D$ can be represented as $E^a$. In the proposed RS-CBR system, $p$, $s$ and $X$ are 14, 35 and 268, respectively. Table 1 shows an example of the case base.

Case reclassify

RS theory can deal with discrete data only, but many feature values in the camshaft grinding process conditions are both crisp and continuous. In the paper, GA is developed to discretize condition features $C$ (Chen 2007). Firstly, candidate breakpoints are encoded into binary code, in which a bit represents a breakpoint, and the value "1" and "0" denote "Adopted" and "Abandoned", respectively. Secondly, fitness function, reproduction, crossover and mutation operators are constructed, which fully assure that discernible relationship of decision table is not changed and the number of cut points is minimum. The principle of selecting breakpoints is that the number of breakpoints is least under the premise of the indiscernibility relation of the decision table not be changed. Therefore, the fitness function is defined as

$$\text{Fitness} = N_1 \times N_2 \tag{1}$$

where $N_1$ is the number of breakpoints, $N_2$ the degree of change of the indiscernibility relation. If the indiscernibility relation is not changed, $N_2$ is set to 1. On the contrary, $N_2$ is set to 0.

The flow chart of the discretization method based on GA is illustrated in Fig. 3.

The significance of condition feature $c_i$ is defined as:

$$W_D(c_i) = \frac{card(POS_C(D)) - card(POS_{C-|c_i|}(D))}{card(U)} \tag{2}$$

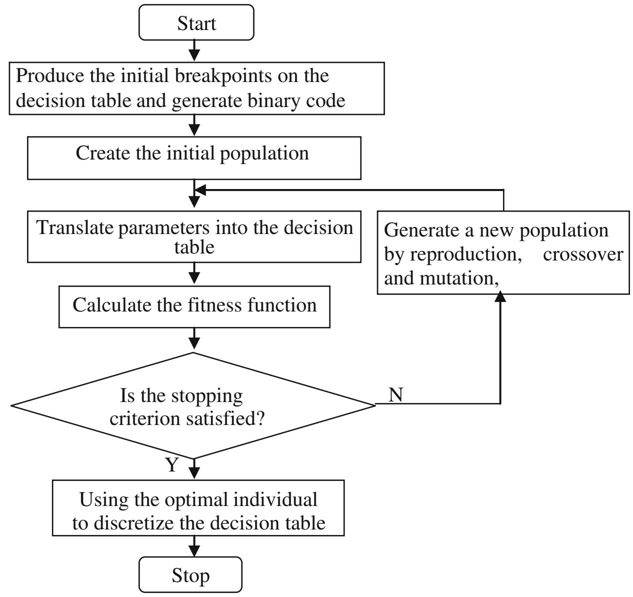



**Fig. 3** The flow chart of the discretization method based on GA

Clearly, the redundancy features have been deleted. So $W_D(c_i) \in (0, 1]$, and the greater the value of $W_D(c_i)$ the larger that the influence on the processing results. If the weight of a feature is equal to 0, the feature is redundant. Finally the feature weights can be calculated by Eq. (3).

$$\omega(c_i) = W_D(c_i) \Big/ \sum_{c_i \in C} W_D(c_i) \tag{3}$$

where $0 \le \omega(c_i) \le 1$, $\sum_{k=1}^{m} \omega(a_k) = 1$.

According to the weight a novel Hierarchical Filtering Search (HFS) is proposed and illustrated schematically in Fig. 4. In the method, primary concern level, secondary concern level and other concern levels have been divided. Each level contains some features whose weight is located in an interval. After normalization, the primary concern level contains the features whose normalized weights are located in (0.75, 1]. The Secondary concern level and the third concern level are located in (0.4, 0.75], (0, 0.4], respectively. The normalized weights can be calculated by Eq. (4).

$$\omega'(c_i) = \left(\omega(c_i) - \omega^{\min}(c)\right) / \left(\omega^{\max}(c) - \omega^{\min}(c)\right) \tag{4}$$

where $\omega^{\min}(c)$ is the minimum value of the feature weight, $\omega^{\max}(c)$ is the maximum value of the feature weight.

Case retrieval

The global similarity is determined by the local similarity of each feature. Some of the features are very important to case retrieval, but some other features may be redundant and only increase the complexity of retrieval process. It is necessary to decrease the search time and increase the effectiveness of the

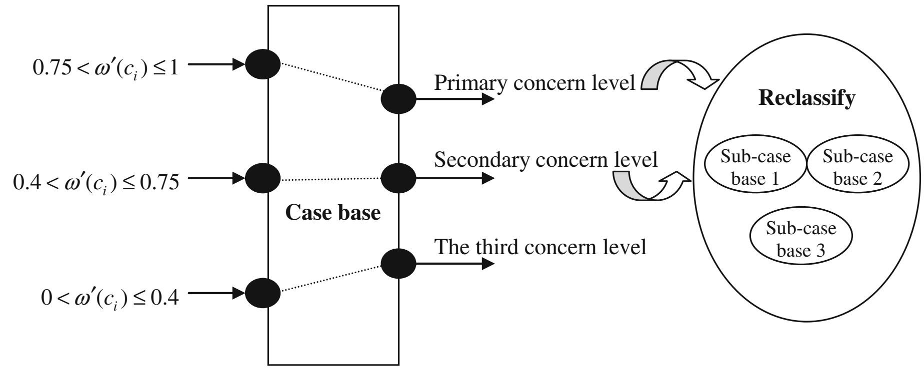



**Fig. 4** The schematic model of the HFS

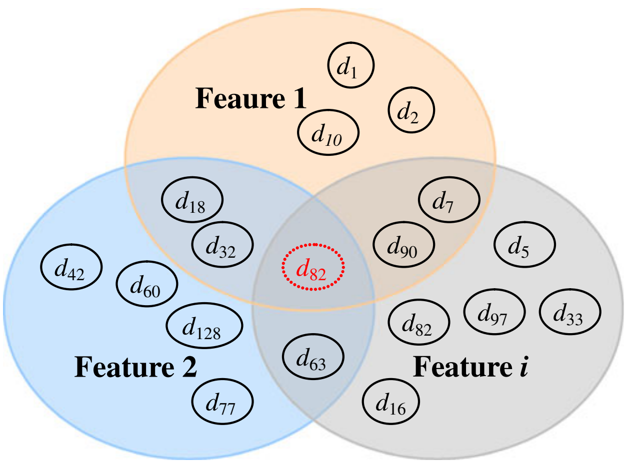



**Fig. 5** Description of the HFS method

retrieval. As mentioned before, by the HFS method the most classified set of features can be get and each feature of the set determines a subset of relevant source cases like sub-case base 1 shown in Fig. 4. Therefore, to select the subset of the more relevant cases for a new case, it is constrained for the search space to the sub-case base for the important feature and can quickly get the most appropriate case such as $d_{82}$ only by the intersection (Fig. 5).

After similar cases to the new case are obtained by the HFS method, the system tries to calculate the global similarity between the target problem and the source ones during the second step of retrieval. This crucial operation is realized with the local similarity. Though there are several types of techniques that could be employed in the process, i.e. nearest-neighbor retrieval, inductive approaches, knowledge-guided approaches, and validated retrieval, yet scope of application of the nearest-neighbor retrieval is the most widely. According to the descriptive features of the grinding processing environment, a method called'Nearest Neighbor Matching (NNM)' determines to the local similarity. Then all the local similarities are gathered to evaluate the global similarity. The NNM method can apply to different types of values: numeric, linguistic and enumeration for the presented example. The Euclidian and the Manhattan distances have been proposed to measure the distance between two values.

$$d(X, Y) = \left( \sum_{i=1}^{p} \omega(c_i) d(c_i^x, c_i^y)^l \right)^{1/l} \tag{5}$$

For $l = 1$ it is the Manhattan distance, $l = 2$ the Euclidian one. In formula (5), $c_i^x$ and $c_i^y$, respectively represent the $i$th features of $X$ and $Y$, and $\omega(c_i)$ the associated weight to this feature. According to the composition of the problem description features in the camshaft grinding, the features can be divided into the three types combined with the corresponding areas (metal cutting) knowledge. Each type corresponds to a calculation method for the local distance.

For numerical features, the calculation of the local distance is based on the following equation:

$$\mathrm{d}(c_i^x, c_i^y) = \frac{|c_i^x - c_i^x|}{\max(c_i) - \min(c_i)} \tag{6}$$

where, $\max(c_i)$ and $\min(c_i)$ are maximum value and minimum value of feature $c_i$ of all cases.

In camshaft grinding many of the features are numerical, such as hardness, maximum error of lift range, maximum adjacent error, surface roughness, total grinding allowance, number of cam, base diameter, maximum lift range and camshaft length.

For linguistic features, the different values are no connection and can be considered of independent. Its local distance can be calculated by the following equation:

$$\mathrm{d}(c_i^x, c_i^y) = \begin{cases} 0, & c_i^x = c_i^y \\ 1, & c_i^x \neq_i^y \end{cases} \tag{7}$$

In Eq. (7), the local distance is 0 while two features are identical, otherwise the local distance is 1. Cam type, material type and material brand are in the domain of the linguistic features.

For enumeration features, the calculation of the local distance is based on the following equation:

$$d(c_i^x, c_i^y) = \frac{|e(c_i^x) - e(c_i^x)|}{M} \quad (8)$$

where, $M$ is the maximum assignment value of the feature enumeration $c_i$, $e(c_i)$ the corresponding value. For example, degree of burn is classified into infrequent burn, moderate burn, severe burn, in turn defined as 1, 2 and 3. So for the degree of burn the maximum assignment value $M$ is equal to 3. Waviness is described by the ambiguous words as {infrequent, mild, moderate, severe}, and they are replaced by the set $\{1, 2, 3, 4\}$. Similarly, its maximum assignment value $M$ can be set to 4.

Therefore, by the values of the weights and the local distances, when determining the Euclidian distance the global similarity is based on the following equation:

$$\mathrm{sim}(X, Y) = 1 - d(X, Y) = 1 - \left( \sum_{i=1}^{p} \omega(c_i) d(c_i^x, c_i^y)^2 \right)^{1/2} \quad (9)$$

Case evaluation

It is necessary to firstly evaluate the output of the system to ensure that the data is fit-for-purpose. Similarity which derives from data expresses the match degree between the target problem and source cases. It is obtained with a certain degree of objectivity, but is vulnerable to the impact of noise data. Confidence is obtained through man-made judgment with a certain degree of subjective. In order to improve the accuracy and anti-jamming of case matching, a comprehensive evaluation method called 'Similarity-Confidence Level (SCL)' is presented. The SCL method defines a comprehensive confidence factor $E$ based on the similarity and the confidence.

$$E(X_j) = (1 - \psi)\varepsilon(X_j) + \psi \mathrm{sim}(X_j) \quad (10)$$

where, $\varepsilon(X_j)$ is the confidence of the $j$th case, $\psi$ the proportion factor.

The proportion factor $\psi$ determines the impact degree between the similarity and the confidence for the comprehensive confidence factor $E$. It is generally defined as $\psi = 0.7$. So in Eq. (10) the proportion of the similarity and the confidence are 30, 70%, respectively.

After the step of the HFS method and the retrieval, the system calculates the comprehensive confidence factor $E$ of the filtered cases. After carried out in ascending order, the most matching case whose $E$ value is the greatest will be presented to the user.

## Application

Case base establishment

*Experimental device*

Grinding experiments were performed upon a NC camshaft grinder (Type CNC8312A) developed by the National Engineering Research Center for High Efficiency Grinding in China. The numerical control (NC) system of the grinder is siemens 840D and it uses 611D digital servo motor to control the grinding carriage-axis(X axis), the working table-axis (Z axis) and the headstock-axis (C axis). NC cam grinding without master form can be achieved through the linkage of X axis and C axis. Furthermore, coarse grinding, precision grinding, finish grinding and no-spark grinding can be once finished after clamping the workpiece. The grinder is also equipped with an on-machine dynamic balancer (Type SBS4500) whose spindle bearing stiffness is not less than $100\,\mathrm{kg}/\mu\mathrm{m}$. The camshaft machined by the grinder has the high precision including the error of adjacent point less than 0.01 mm, the maximum error of lift range no more than 0.04 mm, surface roughness $Ra \leq 0.4\,\mu\mathrm{m}$.

Surface roughness was measured using a surface coarseness profiling instrument (Type Homel18000) made in Germany. Degree of burn was detected by a metallographic microscope (Type 5 XB-PC) and a magnetic detector. Cam waviness and error of lift range were observed by visual detection and a cam error measuring instrument (Type TL500), respectively.

*The samples of case base based on Uniform Design*

The condition of the grinding experiments was established on the choice of the following ways in CNC8312A camshaft grinder:

The grinding wheel whose specification is 14A1 500 × 24 × 160 × 5 CBN120A150 was dressed by an abrasive dresser (Type S-DC-C-110×12×28) in down dressing mode. The interval of dressing was also set to 120 min. A 3% solution of water-based coolant (Type W20) was applied. There are three types of the camshaft to be processed, namely, alloy steel 20CrNiMo, magnesium iron QT700 and chilled cast iron GCH1. The properties of the camshaft to be processed are shown in Table 2.

Establishing case base requires a series of process cases. A reasonable sample size and distribution can help the RS-CBR system to accurately express the relationship between the process features. There are two main ways of the establishment and expansion of the case base: (1) acquisition of existing camshaft grinding process plans; (2) using uniform test method to carry out testing process. Because the uniform design is an efficient factorial design method. More detail

**Table 2** The properties of the camshaft to be processed

| Material | 20CrNiMo | QT700 | GCH1 |
|---|---|---|---|
| Hardness | HRC30~HRC37 | HRC50~HRC55 | HRC55~HRC60 |
| Maximum lift range of inlet cam (mm) | 9.0882 | 9.4822 | 5.3454 |
| Number of inlet cam | 3 | 3 | 4 |
| Total length (mm) | 602.8 | 525 | 418 |
| Total grinding allowance(mm) | 2 | 1.2 | 1.4 |
| Base diameter (mm) | 28.4 | 26.8 | 30 |
| Maximum lift range of exhaust cam (mm) | 8.8823 | 8.4815 | 5.2823 |
| Number of exhaust cam | 6 | 6 | 4 |
| Total number of cam | 9 | 9 | 8 |

**Table 3** The values of six levels

| Factor | Levels | | | | | |
|---|---|---|---|---|---|---|
| Linear velocity of wheel $v_s$ (m/s) | 50 | 56 | 62 | 68 | 74 | 80 |
| Rotational velocity in the finish grinding stage $n_w3$ (rpm) | 60 | 84 | 108 | 132 | 156 | 180 |
| Feed rate in the coarse grinding stage $f_{r1}$ (mm/min) | 0.005 | 0.405 | 0.805 | 1.205 | 1.605 | 2 |
| precision grinding allowances $\triangle_{r2}$ (mm) | 0.1 | 0.18 | 0.26 | 0.34 | 0.42 | 0.5 |
| Feed rate in the precision grinding stage $f_{r2}$ (mm/min) | 0.005 | 0.325 | 0.645 | 0.965 | 1.285 | 1.6 |
| Finish grinding allowances $\triangle_{r3}$ (mm) | 0.01 | 0.05 | 0.09 | 0.12 | 0.16 | 0.2 |
| Feed rate in the finish grinding stage $f_{r3}$ (mm/min) | 0.005 | 0.205 | 0.405 | 0.605 | 0.805 | 1 |
| Turns of no-spark grinding $r$ | 0 | 2 | 4 | 6 | 8 | 10 |

introductions about applying it into the camshaft grinding have been introduced (Deng et al. 2009). Yet the type of the uniform design table for these experiments is $U_{60}(6^8)$. The table is 6 levels for each of the 8 factors and contains 60 samples. In order to improve the pertinence of the experiments, the spans of 8 experimental factors are appropriately enlarged on the basis of the earlier empirical data. Their spans and units are [50, 80] (m/s), [60,180] (rpm), [0.005, 2] (mm/min), [0.1, 0.5] (mm), [0.005, 1.6] (mm/min), [0.01, 0.2] (mm), [0.005, 1] (mm/min), [0, 10], respectively. The factors consist of: linear velocity of wheel, rotational velocity of the camshaft in the finish grinding stage, feed rates in the three stages (coarse grinding stage, precision grinding stage and finish grinding stage), grinding allowances in the precision grinding stage and finish grinding stage and turns of no-spark grinding. The Table 3 shows the values of six levels for each of the eight factors.

According to the uniform design table $U_{60}(6^8)$, the experiments for the camshaft to be processed shown in Table 2 have been completed, respectively. 60 group of case representation can be collected for each type of the camshaft. The experiments for alloy steel 20CrNiMo have been completed earlier. Using the same experimental scheme the experiments for the other materials can be carried out.

After collecting the initial cases, domain experts audit to obtain reasonable process cases by filtering out the unqualified. Based on actual processing conditions it will be set to the confidence of the reasonable cases, a detailed description of the processing location, the operator, the single chip processing time and the special circumstances. Through the acquisition of existing camshaft grinding process plans in Huda Haijie Manufacture Technology Co., Ltd, almost 100 cases can be gotten. Finally after deleting the copied cases, the case base including 268 cases based on three kinds of camshafts can be constructed. The detailed information of case $d_{109}$ is shown in Table 4.

## Application

Because the number of the decision features $D$ is greater than 1, that is, Card $(D) \geq 2$. When Card $(D) \geq 2$, the decision table is called multi-decision table. In general, in the discretization through coding and classification multi-decision table can be equivalently transformed into single decision table. Table 5 shows a small portion of the case base mentioned in the above. Rows of the table are labeled by cases and columns are labeled by the problem features of cases. The other features of cases are eliminated and converted to the decision feature $D$ in Table 5 by the method of coding and classification. The discretization from Table 5 are shown in Table 6. The population size was 30. Uniform cross-over and uniform mutation operators were used and the probability of cross-over and mutation operators are 0.75 (Pc) and 0.02 (Pm), respectively.

**Table 4** The detailed information of case $d_{109}$

| The problem | Value | The solution | Value | The evaluation | Value |
|---|---|---|---|---|---|
| Cam type | Ordinary camshaft | Camshaft grinder model | CNC8312A | Confidence $\varepsilon$ | 0.9 |
| Material type | Chilled cast iron | Wheel type | CBN | | |
| Material brand | GCH1 | Grain size | 120 | | |
| Hardness | HRC57 | Linear velocity of wheel ($m\,s^{-1}$) | 70 | | Processing Location: 3rd workshop, Huda Haijie Manufacture Technology Co., Ltd; |
| Maximum error of lift range (mm) | 0.03 | Rotational velocity in the coarse grinding stage (rpm) | 100 | | |
| Maximum adjacent error (mm) | 0.003 | Feed rate in the coarse grinding stage($mm\,s^{-1}$) | 0.08 | | |
| Waviness | Infrequent | Rotational velocity in the precision grinding stage (rpm) | 70 | | |
| Surface roughness ($\mu m$) | 0.32 | Precision grinding allowances (mm) | 0.12 | | Operator: H.Cao (T072213); |
| Degree of burn | Infrequent | Feed rate in the precision grinding stage ($mm\,s^{-1}$) | 0.023 | | |
| Total grinding allowance (mm) | 1.4 | Rotational velocity in the finish grinding stage (rpm) | 50 | Additional information | Single chip processing time: 35 s; The center frame is as an auxiliary support and no abnormal phenomena happens during processing. |
| Number of cam | 8 | Finish grinding allowances (mm) | 0.06 | | |
| Base diameter (mm) | 28.4 | Feed rate in the finish grinding stage ($mm\,s^{-1}$) | 0.008 | | |
| Maximum lift range (mm) | 9.0882 | Turns of no-spark grinding | 3 | | |
| Camshaft length (mm) | 602.8 | Dressing mode | Down dressing | | |
| | | Linear velocity of dressing ($m\,s^{-1}$) | 30 | | |
| | | Depth of dressing (mm) | 0.009 | | |
| | | Translational speed of dressing ($mm\,min^{-1}$) | 600 | | |
| | | Number of dressing | 3 | | |
| | | Coolant brand | W20 water-based | | |
| | | Fluid pressure of coolant (mpa) | 2.5 | | |
| | | Liquid flow of coolant ($L\,min^{-1}$) | 13 | | |

**Table 5** The list of the case base

| Case | Cam type | Material type | Material brand | Hardness | Maximum error of lift range (mm) | Maximum adjacent error (mm) | Surface roughness (μm) | Waviness | Degree of burn | Total grinding allowance (mm) | Number of cam | Base diameter (mm) | Maximum lift range (mm) | Camshaft length (mm) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $d_1$ | Ordinary camshaft | Alloy steel | 20CrNiMo | 32 | 0.025 | 0.005 | 0.27 | Mild | Infrequent | 2 | 9 | 28.4 | 9.0882 | 602.8 |
| $d_2$ | Pump camshaft | Magnesium iron | QT700 | 50 | 0.01 | 0.024 | 0.27 | Mild | Infrequent | 1.2 | 9 | 26.8 | 9.4822 | 525 |
| $d_3$ | Ordinary camshaft | Magnesium iron | QT700 | 52 | 0.035 | 0.005 | 0.38 | Infrequent | Infrequent | 2 | 9 | 26.8 | 9.4822 | 525 |
| $d_4$ | Ordinary camshaft | Alloy steel | 20CrNiMo | 35 | 0.042 | 0.007 | 0.35 | Infrequent | Infrequent | 1.8 | 9 | 28.4 | 9.0882 | 602.8 |
| $d_5$ | Ordinary camshaft | Magnesium iron | QT700 | 52 | 0.033 | 0.016 | 0.4 | Mild | Moderate | 1.2 | 9 | 26.8 | 9.4822 | 525 |
| $d_6$ | Pump camshaft | Magnesium iron | QT700 | 55 | 0.018 | 0.005 | 0.37 | Infrequent | Infrequent | 2 | 9 | 26.8 | 9.4822 | 525 |
| $d_7$ | Ordinary camshaft | Magnesium iron | QT700 | 50 | 0.049 | 0.006 | 0.20 | Infrequent | Infrequent | 1.2 | 9 | 26.8 | 9.4822 | 525 |
| $d_8$ | Ordinary camshaft | Alloy steel | 20CrNiMo | 34 | 0.032 | 0.004 | 0.25 | Infrequent | Infrequent | 2 | 9 | 28.4 | 9.0882 | 602.8 |
| $d_9$ | Pump camshaft | Alloy steel | 20CrNiMo | 37 | 0.04 | 0.01 | 0.32 | Infrequent | Infrequent | 2 | 9 | 28.4 | 9.0882 | 602.8 |
| $d_{10}$ | Ordinary camshaft | Alloy steel | 20CrNiMo | 33 | 0.106 | 0.022 | 0.5 | Mild | Moderate | 1.8 | 9 | 28.4 | 9.0882 | 602.8 |
| $d_{11}$ | Pump camshaft | Magnesium iron | QT700 | 55 | 0.038 | 0.003 | 0.6 | Infrequent | Moderate | 1.2 | 9 | 26.8 | 9.4822 | 525 |
| $d_{12}$ | Ordinary camshaft | Chilled cast iron | GCH1 | 60 | 0.022 | 0.004 | 0.8 | Moderate | Infrequent | 1.4 | 8 | 30 | 5.3454 | 418 |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| $d_{265}$ | Ordinary camshaft | Chilled cast iron | GCH1 | 55 | 0.036 | 0.009 | 0.20 | Infrequent | Infrequent | 1.4 | 8 | 30 | 5.3454 | 418 |
| $d_{266}$ | Pump camshaft | Magnesium iron | QT700 | 34 | 0.042 | 0.007 | 0.36 | Infrequent | Infrequent | 1.2 | 9 | 26.8 | 9.4822 | 525 |
| $d_{267}$ | Ordinary camshaft | Magnesium iron | QT700 | 55 | 0.028 | 0.008 | 0.28 | Infrequent | Infrequent | 1.2 | 9 | 26.8 | 9.4822 | 525 |
| $d_{268}$ | Pump camshaft | Alloy steel | 20CrNiMo | 35 | 0.026 | 0.006 | 0.28 | Mild | Infrequent | 2 | 9 | 28.4 | 9.0882 | 602.8 |

**Table 6** The discretization of the case base

| Case | Cam type | Material type | Material brand | Hardness | Maximum error of lift range (mm) | Maximum adjacent error (mm) | Surface roughness (μm) | Waviness | Degree of burn | Total grinding allowance (mm) | Number of cam | Base diameter (mm) | Maximum lift range (mm) | Camshaft length (mm) | Decision feature |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $c_1$ | $c_2$ | $c_3$ | $c_4$ | $c_5$ | $c_6$ | $c_7$ | $c_8$ | $c_9$ | $c_{10}$ | $c_{11}$ | $c_{12}$ | $c_{13}$ | $c_{14}$ | $D$ |
| $d_1$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 1 |
| $d_2$ | 2 | 2 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 2 |
| $d_3$ | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 |
| $d_4$ | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 3 |
| $d_5$ | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 |
| $d_6$ | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 |
| $d_7$ | 1 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 |
| $d_8$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 1 |
| $d_9$ | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 2 | 1 |
| $d_{10}$ | 1 | 1 | 1 | 1 | 3 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 1 |
| $d_{11}$ | 2 | 2 | 2 | 2 | 1 | 1 | 2 | 1 | 2 | 2 | 1 | 1 | 1 | 1 | 2 |
| $d_{12}$ | 1 | 3 | 3 | 2 | 1 | 1 | 3 | 3 | 1 | 1 | 1 | 1 | 2 | 1 | 2 |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| $d_{265}$ | 1 | 3 | 3 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 1 |
| $d_{266}$ | 2 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 |
| $d_{267}$ | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| $d_{268}$ | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 2 |

According to Table 6, the significance of the problem features of cases can be calculated.

$U/IND(D) = \{\{d_1, d_5, d_6, d_8, d_9, d_{10}, \ldots d_{265}, d_{267}\}, \{d_2, d_3, d_7, d_{11}, d_{12}, \ldots d_{266}, d_{268}\}, \ldots\}$

$U/IND(C - \{C_1\}) = \{\{d_1, d_{268}, \ldots\}, \{d_2, \ldots\}, \ldots\}$

$POS_C(D) = \{d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_9, d_{10}, d_{11}, d_{12}, \ldots d_{265}, d_{266}, d_{267}, d_{268}\}$

$POS_{C-\{C_1\}}(D) = \{d_2, d_3, d_4, d_5, d_6, d_7, d_9, d_{10}, d_{11}, d_{12}, \ldots d_{265}, d_{266}, d_{267}\}$

The significance of the first feature $c_1$ is

$$W_D(c_1) = \frac{card(POS_C(D)) - card(POS_{C-|c_i|}(D))}{card(U)} = 0.043$$

Also the significances of the other problem features is $W_D(c_2) = 0.232$, $W_D(c_3) = 0.232$, $W_D(c_4) = 0.21$, $W_D(c_5) = 0.196$, $W_D(c_6) = 0.096$, $W_D(c_7) = 0.112$, $W_D(c_8) = 0.091$, $W_D(c_9) = 0.083$, $W_D(c_{10}) = 0$, $W_D(c_{11}) = 0$, $W_D(c_{12}) = 0$, $W_D(c_{13}) = 0$, $W_D(c_{14}) = 0$.

The results show that the problem features $c_{10}, c_{11}, c_{12}, c_{13}$ and $c_{14}$ are dispensable in $D$. Note that the features are redundant and can be removed from the set of condition features. Therefore, the set of all the features indispensable in $D$ denoted $CORE(D)$ is $\{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9\}$.

Because any relative reduction of the decision table can keep the same classification ability and can not cause $D$ to be inconsistent. So the relative reduction must be inclusion to the core. It can be seen that the features $c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8$ and $c_9$ are absolutely necessary, while the features $c_{10}, c_{11}, c_{12}, c_{13}$ and $c_{14}$ are unnecessary, but may be not omitted at the same time. As $B$ is relatively independent in $D$ and $POS_B(D) = POS_C(D)$, the subset of features $B = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9\}$ constitutes a feature reduction of the decision table.

Thus the feature weights can also be obtained by Eq. (3): $\omega(c_1) = 0.033, \omega(c_2) = 0.179, \omega(c_3) = 0.179, \omega(c_4) = 0.162, \omega(c_5) = 0.151, \omega(c_6) = 0.074, \omega(c_7) = 0.086, \omega(c_8) = 0.07, \omega(c_9) = 0.064, \omega(c_{10}) = 0, \omega(c_{11}) = 0, \omega(c_{12}) = 0, \omega(c_{13}) = 0, \omega(c_{14}) = 0$.

The results show that material type, material brand, hardness, maximum error of lift range and surface roughness have a greater influence on process conditions selection in camshaft grinding. Maximum adjacent error, waviness and degree of burn have less influence. And total grinding allowance, number of cam, maximum lift range and camshaft length are the redundant features. The remaining results are basically consistent of experience criteria.

Thus the normalized weights can also be obtained by Eq. (4). Based on this study the HFS is framed. $\omega'(c_1) = 0.185, \omega'(c_2) = 1, \omega'(c_3) = 1, \omega'(c_4) = 0.905, \omega'(c_5) = 0.844, \omega'(c_6) = 0.414, \omega'(c_7) = 0.483, \omega'(c_8) = 0.392, \omega'(c_9) = 0.358, \omega'(c_{10}) = 0, \omega'(c_{11}) = 0, \omega'(c_{12}) = 0, \omega'(c_{13}) = 0, \omega'(c_{14}) = 0$.

For the levels the weight is decreasing along with the direction of the arrow.

*Primary concern level*: Material type (material brand) → Hardness → Maximum error of lift range

*Secondary concern level*: Surface roughness → Maximum adjacent error

*The third concern level*: Waviness → Degree of burn → Cam type

*An example*

A practical data provided by Huda Haijie Manufacture Technology Co., Ltd is used to verify the validity of the proposed RS-CBR system in camshaft grinding. If the camshaft grinder is stable, the maximum adjacent error can meet the requirements and generally do not need to be set. So the problem feature value can be filled by extracting from the current process description of the problem. The features whose values are empty or impossible to determine will be expressed by a question mark "?". Also its local similarity is equal to 0. The new case is given as following.

Cam type < Pump camshaft >

Material type < Alloy steel >

Material brand < 20CrNiMo >

Hardness < HRC32 >

Maximum error of lift range <0.02mm>

Maximum adjacent error < ?>

Waviness < Infrequent >

Surface roughness < 0.32µm >

Degree of burn < Infrequent >

Total grinding allowance < 2mm >

Number of cam < ? >

Base diameter < ? >

Maximum lift range < ? >

Camshaft length < ? >

After completing the feature weights and the case reclassify, using the HFS method the 16 retrieved cases are sent to the case reasoning stage. In the stage the global similarities

**Table 7** The detailed information of case $d_{42}$

| The problem | Value | The solution | Value | The evaluation | Value |
|---|---|---|---|---|---|
| Cam type | Pump camshaft | Camshaft grinder model | CNC8312A | Confidence$\varepsilon$ | 1.0 |
| Material type | Alloy steel | Wheel type | CBN | | |
| Material brand | 20CrNiMo | Grain size | 120 | | |
| Hardness | HRC34 | Linear velocity of wheel (m $s^{-1}$) | 80 | | |
| Maximum error of lift range (mm) | 0.02 | Rotational velocity in the coarse grinding stage (rpm) | 110 | | |
| Maximum adjacent error (mm) | 0.004 | Feed rate in the coarse grinding stage (mm $s^{-1}$) | 0.07 | | |
| Waviness | Infrequent | Rotational velocity in the precision grinding stage (rpm) | 75 | | |
| Surface roughness ($\mu$m) | 0.29 | Precision grinding allowances (mm) | 0.06 | | |
| Degree of burn | Infrequent | Feed rate in the precision grinding stage (mm $s^{-1}$) | 0.04 | | Processing Location: 3rd workshop, Huda Haijie Manufacture Technology Co., Ltd |
| Total grinding allowance (mm) | 2 | Rotational velocity in the finish grinding stage (rpm) | 55 | Additional information | Operator: H.Cao (T072213) |
| Number of cam | 8 | Finish grinding allowances (mm) | 0.03 | | |
| Base diameter (mm) | 40 | Feed rate in the finish grinding stage (mm $s^{-1}$) | 0.01 | | Single chip processing time: 38.8 s |
| Maximum lift range (mm) | 12.5 | Turns of no-spark grinding | 3 | | |
| Camshaft length (mm) | 480 | Dressing mode | Down dressing | | |
| | | Linear velocity of dressing (m $s^{-1}$) | 30 | | |
| | | Depth of dressing (mm) | 0.009 | | |
| | | Translational speed of dressing (mm $min^{-1}$) | 600 | | |
| | | Number of dressing | 3 | | |
| | | Coolant brand | W20 water-based | | |
| | | Fluid pressure of coolant (mpa) | 3 | | |
| | | Liquid flow of coolant (L $min^{-1}$) | 16 | | |

**Fig. 6** The picture of a camshaft manufactured by the solution of the case $d_{42}$

of the case set can be calculated using Eq. (9). The threshold is set as 0.9, when global similarity is greater than the threshold the case will be sent to the user.

It can be found that the global similarity between the case $d_{62}$ and the new case is the greatest and is equal to 0.924. Also the global similarity of the case $d_{42}$ equal to 0.915 meets the requirements of the threshold.

$\mathrm{Sim}(d_{42}) = 1 \times 0.033 + 1 \times 0.179 + 1 \times 0.179 + 0.96 \times 0.162 + 1 \times 0.151 + 1 \times 0.086 + 0.97 \times 0.07 + 1 \times 0.064 = 0.915$

The confidences of the case $d_{42}$ and the case $d_{62}$ are 1.0, 0.8, respectively. Using the SCL method when the proportion factor $\psi$ is defined as 0.7, the comprehensive confidence factors $E_{42}$ and $E_{62}$ are computed as Eq. (10): 0.94 and 0.899, respectively. Thus the case $d_{42}$ is the most similar with the new case. The detailed information of case $d_{42}$ is shown in Table 7.

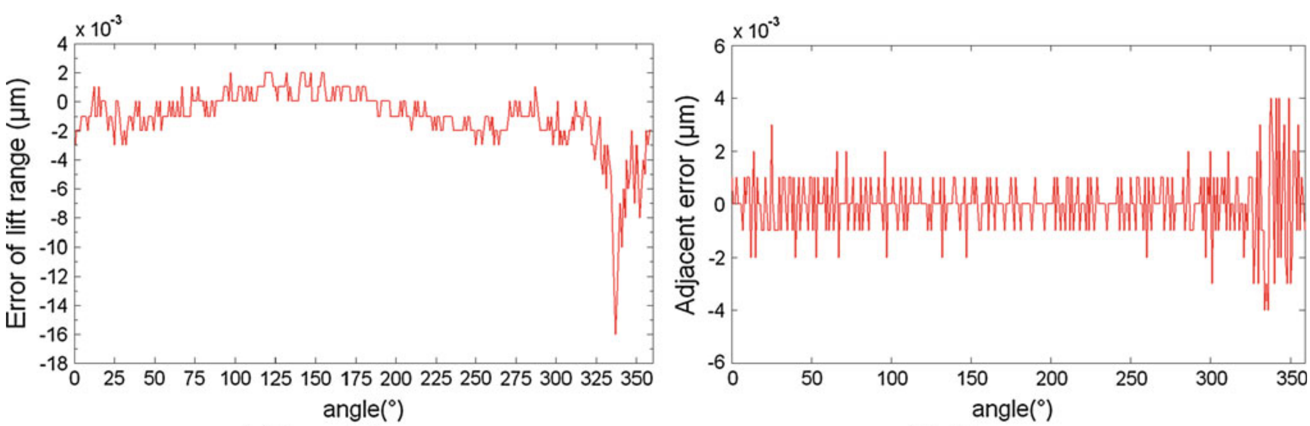
The solution of the case $d_{42}$ was applied to process 8 workpieces in CNC camshaft grinder. After random testing, it was found that maximum error of lift range is less than 0.018mm, maximum adjacent error is less than 0.004mm, surface roughness is less than 0.29μm, waviness and degree of burn are infrequent. The results showed that the solution of the case $d_{42}$ can meet the requirements of this batch of camshaft in NC grinding. A picture of the manufactured camshaft and the evaluation of the dimensional error are shown in Figs. 6 and 7, respectively.

Through the above analysis, it is obvious that application the RS-CBR system in process conditions Selection in Camshaft Grinding is correct and effective in this paper.

## Conclusions

In actual process industry camshaft quality and productivity depend to a large extent on the experience of the operator. The status quo is that the many camshaft grinding operations are run inefficiently and far from optimum. This research develops a hybrid method integrating Rough set (RS) and case based reasoning (CBR) to engineers selecting the optimal process conditions for a new camshaft product. An algorithm based on RS and Genetic Algorithm (GA) is proposed for feature selection and feature weight calculation. According to weight value the features from a classifier are classified into four grades. In the case retrieval stage of the CBR system, a Hierarchical Filtering Search (HFS) method is developed to retrieve past cases that have similar process condition to the new case in order to select the useful features from the database quickly and effectively. The similarity between the new case and retrieved past cases is determined by a method called'Nearest Neighbor Matching (NNM)'. After using a comprehensive evaluation method called 'Similarity-Confidence Level (SCL)', the most matching case is presented to the user.

The proposed system has been validated using a practical camshaft industry example. After random testing, it was




**(a)** Error of lift range **(b)** Adjacent error

**Fig. 7** The dimensional error of a cam manufactured by the solution of the case $d_{42}$

found that maximum error of lift range is less than 0.018 mm, maximum adjacent error is less than 0.004 mm, surface roughness is less than 0.29 $\mu$m, waviness and degree of burn are infrequent. The result shows that the RS-CBR system can help operations to select the optimal process conditions in camshaft grinding. The further work is finding the combination of RS and fuzzy theory to improve the quality of case retrieval and case similarity.

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