Integrated fault diagnosis method for down-hole working conditions of the beam pumping unit

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Abstract: The Dynamometer card is commonly used to analyze down-hole working conditions of the beam pumping unit in the practical oil production. In order to improve the reliability and comprehensiveness of the computer diagnosis method, an integrated fault diagnosis method is proposed in this paper. First, the surface dynamometer card is transformed into the down-hole dynamometer card using the Fourier coefficient method by solving the one-dimensional wave equation; second, feature extraction of the dynamometer card is done using the Freeman chain code method; then, four different fault diagnosis methods are separately used to obtain different conclusions, that are, the curve moment and PSO-SVM based method, the curve moment and matter extension based method, the Freeman chain code and DCA based method, and the improved fuzzy ISODATA dynamic clustering based method; finally, a fusion decision method for multiple sources based on the weight optimization is proposed to integrate all conclusions, which can not only improve the focus ability but also decrease the conflict degree. Case study shows that the proposed integrated fault diagnosis method can obtain the reliable and comprehensive conclusion.

Key Words: Beam pumping unit, Dynamometer card, Down-hole working conditions, Integrated diagnosis, Fusion decision

1 INTRODUCTION

The beam pumping unit is the most common operation mode in the oil field at home and abroad, which belongs to the sucker-rod pumping. The key equipment is the pump, installed in the bottom of tubing string and sunk in the oil fluid underground. The fluid in the bottom of well is swabbed by the sucker rod which can deliver the power to the pump effectively. As the pump works thousands of meter underground, the failure rate is high due to the complex working conditions and bad working environment.

The dynamometer card is commonly used to analyze the down-hole working conditions of the oil well. The special data collection device is installed at the “horsehead” to collect the data of load and displacement. The closed curve of the displacement-load data is drawn, whose shape is used to analyze down-hole working conditions. There are some typical fault types, such as: “insufficient liquid supply”, “parted rod”, “oil of high viscidity”, “leaking travelling valve”, “leaking standing valve”, “pump bumping (upstroke)”, “pump bumping (downstroke)”, “sand production”, “piston goes outside of cylinder”, etc. Therefore, the shape of the dynamometer card can reflect the real working conditions of the oil wells, whose graph characteristics can be used as the fault feature.

In the traditional operation process, data acquisition, analysis and processing in oil production are mainly completed by the manual task. The dynamometer cards are collected by workers at a fixed time and then submitted to the production technology department to do further analysis, whose conclusions are used to judge whether stopping oil wells, repairing oil wells or adjusting operation parameters. However, this manual task can not only increase operation cost, but also be influenced by the personal subjective experience. When collecting the dynamometer cards, the oil well should be stopped, which brings negative influences to the operation and security problems to human. Besides, affected by the actual working schedule, down-hole working conditions of the oil wells cannot be grasped in time and the faults cannot be found in time as the frequent manual task is difficult to realize.

With the development of the computer and artificial intelligence technology, the requirement for advanced automation level in oil production is improving continuously. So, it has practical significance to use computer to replace human work to monitor down-hole conditions of wells in time. Oil production with safe, security and effective can be guaranteed by adjusting operation parameters and diagnosing faults according to the real-time down-hole condition. Many computer diagnosis methods have been applied, for instance, expert system, rough set theory, fuzzy theory, artificial neural networks, support vector machine, frequency spectrum analysis, filter techniques, grey theory, et al. However, the expert system and the rough set method have a single way of knowledge expression and reasoning strategy; determination of the membership function in the fuzzy theory has no unified methods or explicit theories; the artificial neural network needs a large number of training samples; although the support vector machine uses small training samples, the classification accuracy is affected by the choice of kernel function and its parameters; the physical interpretation of

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the identification standard in the frequency spectrum analysis method is not undefined; application of the filter technique have some limitations; and the computation when extracting grey matrix characteristics is large.

Using the computer based method to replace the manual work to diagnose down-hole conditions, is a transformation from the qualitative analysis to the quantitative analysis. Different methods may get different conclusions as their learning abilities and learning mechanisms are different. In some cases, these differences should not be evaluated by right or wrong, but by the reliability or the comprehensiveness. So, in order to avoid diagnosis errors by a single method, an integrated fault diagnosis method is proposed in this paper. First, for the diagnostic samples, several different methods are used to obtain their respective conclusions; then, a fusion decision method for multiple sources is used to combine these conclusions to obtain a final result.

2 INTEGRATED DIAGNOSTIC SYSTEM FOR DOWN-HOLE CONDITIONS OF BEAM PUMPING UNIT

The structure schematic of the system is shown in Fig.1.

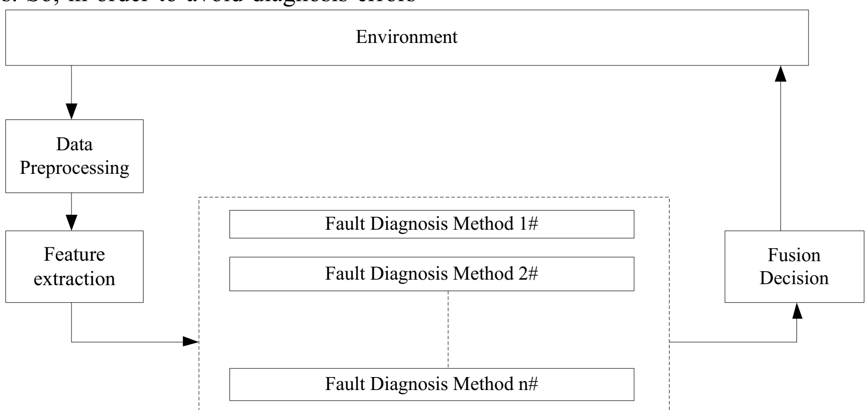

Fig.1 Structure schematic of the integrated system

2.1 Data preprocessing

The data preprocessing process transform the surface dynamometer card into the down-hole dynamometer card. In the practical operation, the surface dynamometer card can be directly collected, which is easily affected by the inertial load, rod vibration load, friction load and well depth, et al. If it is used to diagnose the down-hole conditions, some errors may appear. So, in order to eliminate effects of the deformation, viscous resistance, vibration and inertia of the sucker rod string and improve the diagnosis accuracy, the down-hole dynamometer card is used which can truly reflect working conditions of the subsurface pump. In this paper, the Fourier coefficient method is used to solve the one-dimensional wave equation proposed by Gibbs[1][2]. The following discussion is based on the analysis of the down-hole dynamometer card.

2.2 Feature extraction

The feature extraction process extracts the characteristics of the down-hole dynamometer card. Freeman chain code[3] is used to represent the boundary of the down-hole dynamometer card. According to our prior work[4], 12 eigenvector parameters which can describe typical characteristics of the dynamometer card are extracted, separately are “Degree of the zigzag”, “Degree of the bulge of the left-bottom corner”, “Degree of the bulge of the right-top corner”, “Degree of the Flatness”, “Degree of the lack of the left-top corner”, “Degree of the lack of the right-top corner”, “Degree of the lack of the right-bottom corner”, “Degree of the lack of the left-bottom corner”, “Degree of the sharp-load of the left-top corner”, “Degree of the sharp-unloading of the right-bottom corner”, “Degree of the rapid-unloading of the right-top corner” and “Degree of the Fatness”.

2.3 Fault diagnosis method

Four different methods are discussed, that are: PSO-SVM based method, matter extension theory based method, DCA based method and improved fuzzy ISODATA based method.

2.3.1 PSO-SVM based method

In this paper, SVM is used for classification of the down-hole dynamometer cards, and the related parameters of error penalty parameter C and the kernel function parameter g (Gauss kernel function is used) is optimally chosen by the PSO algorithm. The algorithm steps have discussed in our prior work[2], and a brief description of it is given in the following.

Step 1 Parameters Initialization.

Step 2 Calculate the update speed and the updated position of each particle according to the following equations:

$$\text{Max\_V[]} = w*\text{Max\_V[]} + c_1*\text{rand1}*(\text{pbest[]} - \text{present[]}) + c_2*\text{rand2}*(\text{gbest[]} - \text{present[]}) \quad (1)$$

$$\text{present[]} = \text{present[]} + \text{Max\_V[]} \quad (2)$$

where Max_V denotes the maximum velocity, w denotes inertia weight, c_1 and c_2 are learning factors, rand1() and rand2() are random values in (0,1), pbest[] denotes the individual extreme value of particle, gbest[] denotes the global optimum, present[] denotes the present value of particle.

Step 3 Use the evaluation function to evaluate all particles. When the current evaluation value of a particle is better than its historical evaluation value, it is regarded as the historical optimal evaluation value, and the current position vector of the particle is credited as the optimal one.

Step 4 Search for the global optimal solution. If it is better than the current historical optimal solution, update it; end the search if the termination condition is satisfied, otherwise go to step 2 for a new round of search.

2.3.2 Matter extension theory based method

The manual work mainly relies on the qualitative analysis, but the computer based method mainly depends on the quantitative analysis. However, the quantitative analysis is easy to meet difficulties if we want to know the correlation degree between the diagnostic samples and the typical fault types, as there are no enough training samples. To solve this problem, the matter extension theory[5] is used, and it has two advantages: a) the value of each feature can be extended to the interval form; b) the correlation function is used to calculate the correlation degree between the diagnostic sample and the typical fault types. In our prior work[6], the matter extension theory based method has been discussed, and here we give the fault diagnosis process as follows.

Let's define the typical fault set $F=\{F_1, F_2, \dots, F_n\}$, and F_i (i=1, 2, …, n) is represented by

$$\{c, v \mid (c_{ij}, v_{ij}), i = 1,2,\cdots,n, j = 1,2,\cdots,m\} \tag{3}$$

where c_{ij} is the jth feature element of F_i, v_{ij} is the value of it, and $v_{ij}^{'} = \langle a_{ij}^{'}, b_{ij}^{'} \rangle$ is the joint domain.

The correlation function between S and F_i is defined by

$$K_{ij}(v_j) = \begin{cases} \dfrac{\rho(v_j, v_{ij})}{\rho(v_j, X) - \rho(v_j, v_{ij})}, & v_j \notin v_{ij} \\ -\dfrac{\rho(v_j, v_{ij})}{\left|v_{ij}\right|}, & v_j \in v_{ij} \end{cases} \tag{4}$$

$$\rho(v_j, v_{ij}) = \left| v_j - \frac{v_{ija} + v_{ijb}}{2} \right| - \frac{v_{ijb} - v_{ija}}{2} \tag{5}$$

where i=1, 2, …, n; j=1, 2, …, m. $K_{ij}(v_j)$ denotes the correlation function between S and F_i under the jth feature; $\rho(v_j,v_{ij})$ denotes the distance between them; $\left|v_{ij}\right|$ denotes the length of the interval; X is the joint domain.

Then the correlation degree between S and F_i is defined as

$$I(F_i) = \sum_{j=1}^{m} \omega_{ij} K_{ij} \tag{6}$$

where $\omega_{ij} = (v_j / v_{ijb}) / \sum (v_j / v_{ijb})$ is the weight. v_j denotes the value of the jth feature; v_{ijb} denotes the maximum of the jth interval of F_i.

$I(F_i)<0$ denotes that S doesn't belong to this fault type; if $I(F_i)>0$, its value denotes the correlation degree between S and F_i; if all $I(F_i)$ are less than zero, it is considered that S doesn't belong to the current fault set F.

2.3.3 DCA based method

DCA[7] is used to project the observed data y into the designated fault mode $d_i \in R^{p\times 1}$ (having clear physical meaning). Then the corresponding designated component ω_i can be obtained to do fault detection. ω_i is denoted by

$$\omega_i = d_i^{\mathrm{T}} y \tag{7}$$

The following formula is obtained by sampling n times.

$$[\omega_{i1}, \omega_{i2}, \cdots, \omega_{in}] = [d_{i1}, d_{i2}, \cdots, d_{ip}] \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{p1} & y_{p2} & \cdots & y_{pn} \end{bmatrix} \tag{8}$$

where i=1, 2, ⋯, l.

Then, equation (8) can be expressed in matrix form as:

$$W = D^{\mathrm{T}} Y \tag{9}$$

where D is a matrix formed by orthogonal modes d_i, satisfying $D^{\mathrm{T}}D=I$.

Hence,

$$Y = DW \tag{10}$$

Therefore, Y can be explained by the following formula,

$$Y = \sum_{i=1}^{l} d_i \omega_i \tag{11}$$

where l is the number of designated modes.

This method has been discussed in our prior work[4], for the fault diagnosis based on DCA, all the designated modes are required to be orthogonal each other. However, in most applications, this condition cannot be satisfied. So, for an incompletely orthogonal mode, the designated mode set could be divided into some subsets in which the modes are completely orthogonal. Y can be denoted as:

$$Y = D_1 W_1 + D_2 W_2 + \cdots + D_i W_i + E \tag{12}$$

where D_i denotes the matrix of orthogonal subsets; and W_i denotes the corresponding designated mode subsets.

Y is firstly projected into the D_1 to do fault detection; then (Y–D_1W_1) is projected into the D_2 to do fault detection; likewise, it ends when all orthogonal subsets are detected.

2.3.4 Improved fuzzy ISODATA based method

In our prior work[8], an unsupervised learning method based on the improved fuzzy ISODATA algorithm is discussed to diagnose down-hole conditions of the beam pumping unit. In the following, the calculation steps are given briefly.

Step 1: Parameters initialization. Given a large enough initial temperature T_0, the initial optimal solution $S^{(0)} = (\widetilde{R}_{c\times n}^{(0)}, V_{c\times d}^{(0)})$, iterations at each temperature T is R. Let s=0.

Step 2: Process of "splitting" and "merging" are carried out, and the number of executions is no more than the permitted maximum iterations.

Step 3: Let s=0, 1, 2, …. New classification matrix $\widetilde{R}_{c\times n}^{(s)}$ is generated, and new clustering centers $V_{c\times d}^{(s)}$ are calculated.

Then the classification matrix is updated, and $\widetilde{R}_{c\times n}^{(s+1)}$ is obtained. The parameter of "the minimum distance between two classes (Md)" is randomly updated in (0,1]. Now the new solution is $S^{(s)}=(\widetilde{R}_{c\times n}^{(s+1)},V_{c\times d}^{(s)},Md^{(s+1)})$.

Step 4: Xie-Beni validity index (XB)[9] is used to evaluate the clustering results, that is:

$$XB(U,c)=\frac{1}{n}\frac{\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{q}\left\|x_k-v_i\right\|^2}{\min\limits_{\substack{1\le j\le c\\ i\ne j}}\left\|v_i-v_j\right\|^2} \tag{13}$$

where v_i denotes the clustering center of the ith class; u_{ik} denotes the membership of x_k belonged to the ith class. The smaller the XB is, the better the clustering results are.

Calculating $\Delta XB=XB(S^{(s+1)})-XB(S^{(s)})$, if $\Delta XB\le 0$, the new solution is accepted as the current solution; if $\Delta XB>0$, the new solution is accepted with a probability p.

$$p=exp(\frac{-[XB(S^{(s+1)})-XB(S^{(s)})]}{kT}) \tag{14}$$

When e=random [0,1]<p, the new solution $S^{(s)}$ is accepted as the current solution, otherwise, the previous solution is used.

Step 5: The current temperature is decreased, and Steps 2-4 are executed for L times.

Step 6: If the terminative condition is satisfied, the current solution is accepted as the optimal solution, and the algorithm is terminated; otherwise, the temperature is decreased according to the annealing way, which is continued to execute from the step 2, let s=s+1. The annealing way is defined by

$$T_t=\alpha\cdot T_0/\ln t \tag{15}$$

where t is the step; α is a constant between 0.5-0.99; T_0 is the initial temperature.

2.4 Fusion decision

The above four methods may obtain different conclusions, so it is necessary to find an effective method to obtain an integrated result. A multi-sources fusion decision method based on the D-S evidence theory is used in this paper, and a weight optimization based evidences fusion method to solve the conflict problem among different evidences in fusion process is proposed.

There are n evidence sources m_i (i=1, 2, … , n), the modification equation based on the weighted average method is defined as

$$m_{average}(\text{A})=\sum_{i=1}^{n}(\omega_i\cdot m_i(\text{A})) \tag{16}$$

where A denotes the focal element of the discernment frame; w_i denotes the weights of different evidences; and $m_i(A)$ denotes the Basic Probability Assignment (BPA) of the corresponding focal element.

Dempster combination rule uses orthogonal sum rule, denoted by $\oplus$. For different evidence sources m_1, m_2, …, m_n, the Dempster combination rule can be denoted as:

$$m(A)=(m_1\oplus m_2\oplus\cdots m_n)(A)=\begin{cases}0, & A=\varnothing,\\ \dfrac{\sum_{\cap A_i=A}\prod_{i=1}^{n}m_i(A_i)}{1-K}, & A\ne\varnothing.\end{cases} \tag{17}$$

where $K=\sum_{\cap A_i=\varnothing}\prod_{i=1}^{n}m_i(A_i)$ is called the conflict coefficient and 1-K denotes the normalization factor which is used to avoid the non-zero probability to be assigned to empty set.

2.4.1 Credibility of the evidence

In the combination process of different evidences, the evidence with high credibility should be given a greater weight; however, there is no unified method to calculate the credibility. Usually a distance between two BPA's is defined to measure the dissimilarity between two sources of evidence and it is considered that a bigger distance reflects a smaller credibility. The distance measure based similarity of two evidences m_1 and m_2 can be defined by

$$Sim(m_1,m_2)=1-Dist(m_1,m_2) \tag{18}$$

In this paper, a method to calculate the credibility among evidences is proposed.

Definition 1[10] Let's consider the discernment frame $\Theta=\{A_1,A_2,\cdots,A_i\}$, X is a subset in 2^{Θ}, let m(.) be a given BPA related with Θ, and the associated $BetP$ for any singleton $Y\in\Theta$ is given by

$$BetP(Y)=\sum_{X\subset 2^{\Theta},Y\subseteq X}\frac{1}{|X|}m(X) \tag{19}$$

where $|X|$ is the cardinality of subset X. The support degree between m_1 and m_2 is defined by

$$Sup_p(m_1,m_2)=\frac{\left(\sum_{\substack{A_i\in\Theta\\ |A_i|=1}}(min(BetP_{m_1}(A_i),BetP_{m_2}(A_i)))^p\right)^{\frac{1}{p}}}{\left(\sum_{\substack{A_i\in\Theta\\ |A_i|=1}}(max(BetP_{m_1}(A_i),BetP_{m_2}(A_i)))^p\right)^{\frac{1}{p}}} \tag{20}$$

Therefore, the credibility among evidences is defined by

$$Cred_p(m_i)=(\sum_{\substack{j=1\\ j\ne i}}^{n}Sup_p(m_i,m_j)/\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\ne i}}^{n}Sup_p(m_i,m_j)) \tag{21}$$

2.4.2 Optimization of the evidences fusion

The weight of every evidences are calculated by the credibility, which is defined by

$$w_i=\alpha\cdot(Cred_p(m_i)/\sum_{i=1}^{n}Cred_p(m_i)) \tag{22}$$

where $Cred_p(m_i)$ is obtained by equation (21).

There are two variables in w_i, that are p and α, and the reasonable selection of them will make the combination result more effectiveness. Here PSO algorithm is used to select the reasonable p and α, and the optimized target is the minimum K. The algorithm steps are as follows:

Step 1 Parameters initialization.

Step 2 New velocity and new position of each particle are updated according to equation (1) and equation (2), where w=0.5, c_1=2, c_2=2, rand1()=0.9, rand2()=0.4.

Step 3 The optimized target is the minimum K, and the optimized model is as follows:

$$\min_{p,\alpha}\{K = \oplus\{m_{n-2}, m_{average}\}(\varnothing)\} \tag{23}$$

where m_{n-2} denotes the combination result of the n-2 times; $m_{average}$ denotes the average value according to equation (16).

Step 4 Search for the global optimal solution, if its value is better than the current historical optimal solution, updating it; end the search if it satisfies the termination condition, otherwise go to Step 2 to a new round for searching.

3 CASE STUDY

A dynamometer card is used as the diagnostic sample, shown in Fig.2. The eigenvectors of the diagnostic sample is extracted according to the feature extraction method in the Section 2.2.

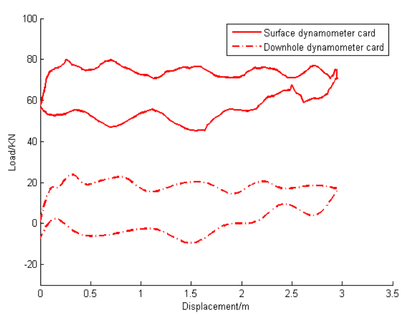

Fig.2 The diagnostic sample

(1) Invariant moment and PSO-SVM based method

The training set contains 228 samples, of which the input is 28 invariant moments of each sample and the output is fault type. Fault type 1-11 separately stand for "Normal", "gas interference", "insufficient liquid supply", "parted rod", "oil of high viscidity", "leaking travelling valve", "pump bumping (upstroke)", "pump bumping (downstroke)", "leaking standing valve", "sand operation", "piston goes outside of cylinder".

The diagnostic sample is considered as the testing set, and marked as the fault type 12. The diagnostic sample is classified into the fault type 9, shown in Fig.3. So, the fault type of the diagnostic sample is considered as the "leaking standing valve".

(2) Invariant moment and matter extension theory based method

For each fault type, number F_1-F_{11} denote "Normal", "Gas interference", "Insufficient liquid supply", "Parted rod", "Oil of high viscidity", "Leaking travelling valve", "Pump bumping (upstroke)", "Pump bumping (downstroke)", "Leaking standing valve", "Sand operation", "Piston goes outside of cylinder", respectively.

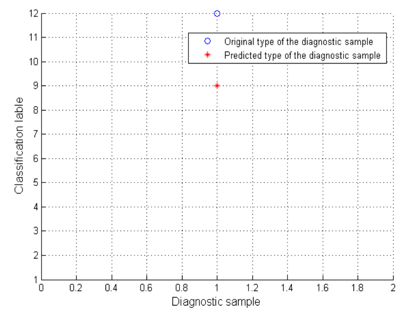

Fig.3 Classification of the diagnostic sample

The correlation degree between the diagnostic sample and each fault type are as follows: F_1/-0.0644, F_2/-0.3438, F_3/0.0567, F_4/-0.3216, F_5/-0.0209, F_6/-0.1335, F_7/-0.0944, F_8/-0.1409, F_9/-0.1480, F_{10}/-0.0815, F_{11}/-0.0983.

According to the above conclusions, the diagnostic sample is considered to be the fault type 3 or 9 as the $I(F_3)$ and $I(F_9)$ are all greater than zero, of which correlation degrees are 0.0567 and 0.1480. Then the following equation is used to calculate the occurrence rate of the two fault types.

$$diag_{Fi} = I(F_i) / (\sum_{I(F_i)>0} I(F_i)) \tag{24}$$

where i=1, 2, …, 11. So, the occurrence rate of the "Leaking standing valve" is considered to be 72.3%, and it of the "Insufficient liquid supply" is 27.7%.

(3) Freeman chain code and DCA based method

The observed data (the diagnostic sample) is projected into each designed mode, and the results are shown in Fig.4, where d_1-d_{14} represent 14 typical faults of the sucker-rod pumping wells, "Gas interference", "Insufficient liquid supply", "Parted rod", "Oil of high viscidity", "Leaking travelling valve", "Leaking standing valve ", "Leaking travelling and standing valves", "Pump bumping (upstroke)", "Pump bumping (downstroke)", "Sand production", "Pump blocked", "Wax deposition", "Piston goes outside of cylinder" and "Large anti-impact stroke".

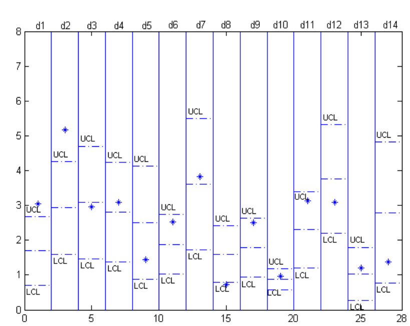

Fig.4 DCA of the diagnostic sample

It can be seen from Fig.4, the designed component of the diagnostic sample is beyond the upper and lower control lines in d_1, d_2 and d_8. So, the conclusion is obtained, that is {"Gas interference", "Insufficient liquid supply", "Pump bumping (upstroke)"}=100%.

(4) Freeman chain code and improved fuzzy ISODATA based method

The curve eigenvectors of 228 training samples are extracted based on the Freeman chain code. Then all of them are considered as one data set to complete the automatic clustering, and the clustering results are shown in Fig.5.

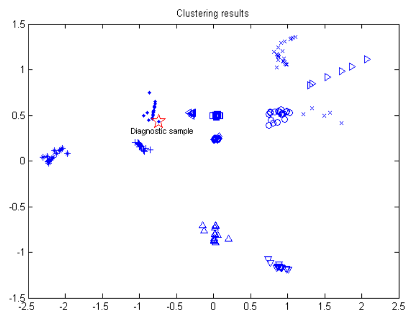

Fig.5 Clustering result of 229 samples

According to the analysis of the data set (229 samples), the diagnostic sample is classified into the type of "Insufficient liquid supply" automatically.

Let's consider the discernment frame Θ= {A, B, C, D}, in which, A denotes "Insufficient liquid supply", B denotes "Gas interference", C denotes "Leaking standing valve" and D denotes "Pump bumping (upstroke)". Then the body of evidence is constructed as follows,

m_1: m_1 (C)=1;
m_2: m_2 (A)=0.277, m_2(C)=0.723;
m_3: m_3 (A, B, D)=1;
m_4: m_4 (A)=1.

where m_1, m_2, m_3 and m_4 respectively denote the four different methods.

The fusion conclusions obtained by the proposed combination method are as follows,

m(A)=0.5327, m(B)=0.0127, m(C)=0.3287, m(A, B, D)=0.1259.

According to our integrated diagnosis conclusions, the occurrence rate of the "Insufficient liquid supply" is 53.27%, the "Gas interference" is 1.27%, the "Leaking standing valve" is 32.87%, {"Insufficient liquid supply", "Gas interference" and "Pump bumping (upstroke)"} is 12.59%.

We use the human's experience to analyze the diagnostic sample in Fig.2, the graphic characteristics of the dynamometer card are: "lack of the bottom right, faster loading and slower unloading, and slight raised upper right", which stand for the feature of "Insufficient liquid supply", "Gas interference", "Leaking standing valve" and "Pump bumping (upstroke)", but we cannot give the occurrence degree of each fault type. According to the fusion result of our integrated method, an overall analysis conclusion can be given which are more in line with the actual production requirements.

4 CONCLUSIONS

In this paper, an integrated diagnosis method is proposed to diagnose down-hole working conditions of the beam pumping unit. First, the Freeman chain code based method is used to extract characteristics of the down-hole dynamometer card; then, four different classification methods are used to do fault detection; Finally, an fusion decision method based on the weight optimization is proposed to fusion the different conclusions obtained by the four methods, which can increase the focus ability and decrease the conflict coefficient at the same time.

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