Intelligent Process Quality Control System for Mass Customization

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***Abstract*—For complicated and variable environment for mass customization, how to deal with the problems of monitoring dynamic and variable quality fluction,diagnosing the abnormal variation and adjusting the process at the right moment, is a difficult problem that mass customization faces in process quality control. An intelligent process quality control system model for mass customization, which integrates quality prevention, analysis, diagnosis and running intelligent quality control system. This model dealt mainly with constructing and running intelligent quality control system, integrated several enabling technologies such as process quality analysis based on similarity process, process quality diagnosis based on Elman and expert system of process quality adjustment. It is basis of realizing network, intelligent and automatic process quality control.**

***Index Terms*—process quality control, mass customization, process quality analysis, process quality diagnosis, process quality adjustment**

I. INTRODUCTION

With the development of society and economic, the single customer has deepened into the firm's focus than ever. Enterprises are facing an uninterrupted trend toward individualization in all areas of life. Individualized customization is becoming an effective way of meeting with customer individual requirements. [1, 2]

Mass customization is defined that in the networked manufacturing platform, having the goal of customer satisfaction, modern management concept and advanced manufacturing technology are applied, through product structure and its related process reconfiguration, the product that meets the customer individualized requirements is produced, standardization and diversification of production are realized, thus enterprise make profits. [3, 4]

Mass customization breaks a new way that enterprise provides diversified and customized product quickly and constantly, but how to maintain stable product quality and meet the customer individualized requirements constantly, which is the most critical and difficult problem. However, process quality is the element of product quality, the quality of each process influences final product quality directly or indirectly. Thus, the core of quality control of manufacturing process is process quality control [5]. Nevertheless, conventional process quality control is static quality management and control based on production inspection and statistical quality report forms, can't realize dynamic, real-time production quality control and forecast, the effect and benefit of it are limited largely.

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Recently, lots of scholars and researchers have studied the process quality control in multi-type& small batch production process, and obtained some achievements. GUH R S proposed an on-line inspection model based on hybrid learning control chart; YU Z H put forward to a method of quality control oriented small batch based onBayesian decision; MIAO R designed a method of monitoring process mean and process variance based on the probability integral transform theory. In sum, these methods solved parts of problems in process quality control to some extent, but could only judge whether maching process is normal, couldn't indcate which kind of abnormal took place and the reasons. That is to say, they can't diagonse and adjust the process quality really.

So, an intelligent process quality control system in the production process of mass customization, which integrates quality prevention, analysis, diagnosis and adjustment, and corresponding functional modules and framework are all put forward on the basis of information technologies such as network, data base etc in the background of heavy machine industry. It can realize dynamic, real-time analysis, diagnosis and adjustment of process quality control in production process of mass customization so that assure stable state of process quality for a long time, which improves flexibility of productivity and product quality to meet customer requirements.

II. ARCHITECTURE OF INTELLIGENT PROCESS QUALITY CONTROL SYSTEM

According to the characters of production proces and the theory of quality control, total structure of intelligent process quality control system for mass customization is designed(it is shown in Fig.1), which includes three modules: process quality analysis, process quality diagnosis, process quality adjustment.

Process Quality Analysis. Process quality status in manufacturing locale is monitored in real time by the module, according to the character values of inspection quality, quality controls and control chart were determined, raw grinding quality data are translated into the same distribution quality data so that form control chart and calculate grinding capability in real time.

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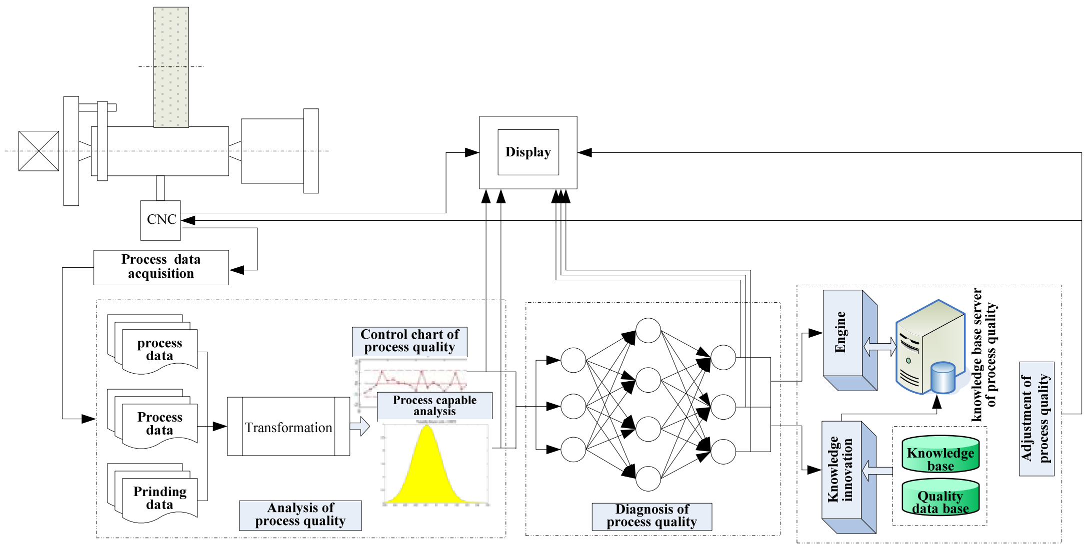

Fig. (1) Total structure of dynamic quality control system in the grinding process

Process Quality Diagnosis. The control chart and process capability determined by process quality analysis module are diagnosed by the module. Elman network is applied to diagnosis multi-factor quality problems so that look for the key factor that influenced quality character, then optimum factor combination is found. It provides technical support to process quality adjustment.

Process Quality Adjustment. According to experiences, process quality control information gathered and influencing factors of grinding quality found by process quality diagnosis module, improved scheme of process quality is determined by export system of process quality adjustment, then process quality is adjusted in time to assure stable status of process quality in a long time.

III. KEY ENABLING TECHNOLOGIES OF INTELLIGENT PROCESS QUALITY CONTROL SYSTEM

Process Quality Analysis Based on Similarity Process. Similarity attributes or characters of similarity factors mapped similarity quality status of inter-process. Different processes of similarity process are set quality control points of quality analysis, whose quality data are transformed into the same distribution quality data so that meet sample requirement of control chart, quality analysis based on similarity process is realized. The algorithm is the following:

Theorem: In normal distribution, if random variable $X \sim N(\mu,\sigma^2)$, $Y = ax+b$, then $Y \sim N(\mu_i,\sigma_i^2)$. In the formula, both a and b are constant. [6]

Assume: under normal condition, m kinds of quality data, that is actual measurement after processed: $X_{ij} \sim N(\mu_i,\sigma_i^2)$, $(i=1,2,\cdots,m, j=1,2,\cdots,n_i)$. The quality data are standardized:

$$Z_{ij} = \frac{X_{ij}-M_i}{T_i} = \frac{X_{ij}-\frac{1}{2}(USL_i+LSL_i)}{USL_i-LSL_i} \tag{1}$$

In Eq. (1), X_{ij} is No. *j* quality characteristic value of No. *i* part, which came from the same analogical procedure, Z_{ij} is the value that is achieved through X_{ij} transformation, M_i is No. *i* part's target value (the centre of tolerance range), T_i was tolerance range of No. i part. USL_i is upper limit of T_i, LSL_i is lower limit of T_i.

Test of variance consistency. It is to test whether the variances of the data which are converted from different processes in similar process are equal. If there are no obvious differences between the converted data of the first product and of the second product, then $\sigma_1^2=\sigma_2^2$. $\overline{Z_i}$ is the sample average, S_i^2 is the sample standard deviation, then:

$$\frac{(n_1-1)S_1^2}{\sigma_1^2} \sim \chi^2(n_1-1), \quad \frac{(n_2-1)S_2^2}{\sigma_2^2} \sim \chi^2(n_2-1) \tag{2}$$

When $S_1^2=(n_1-1)\sum_{j=1}^{n_1}(Z_{1j}-\overline{Z_1})^2$, $S_2^2=(n_2-1)\sum_{j=1}^{n_2}(Z_{2j}-\overline{Z_2})^2$ then:

$$\frac{S_1^2}{S_2^2} \sim F(n_1-1,n_2-1) \tag{3}$$

When significant level α is given, the original hypothesis will be refused whether $F > F_{\alpha/2}$ or $F > F_{1-\alpha/2}$.

Test of mean value consistency. It is to test whether the mean values of the first product and the second product after the data are converted from the different processes in the similar process are not obviously different, namely, $\mu_1=\mu_2=\cdots=\mu_m=\mu$.

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Actually it is to test whether the means of several normal populations which have the same variance are equal, and it can be done by single factor analysis of variance method as shown in Table 1.

Table 1. Single factor Analysis of variance

Difference	Inter-process	Same process
Variance sum	$S_D^2 = n\sum_{i=1}^{k}(\overline{Z}_i - \overline{Z})^2$	$S^2 = \sum_{i=1}^{k}\sum_{j=1}^{n}(\overline{Z_{ij}} - \overline{Z}_i)^2$
Free dimension	$k-1$	$k(n-1)$
Mean square deviation	$MS_D^2 = \frac{S_D^2}{k-1}$	$MS^2 = \frac{S^2}{[k(n-1)]}$
F	MS_D^2 / MS^2	

The mean value of the similar process can be estimated after test:

$$\overline{Z} = \frac{1}{\sum_{i=1}^{n} k_i}\sum_{i=1}^{n}\sum_{j=1}^{k_i} Z_{ij} = \frac{1}{\sum_{i=1}^{n} k_i}\sum_{i=1}^{n}\sum_{j=1}^{k_i}\frac{X_{ij} - \frac{1}{2}(USL_i + LSL_i)}{USL_i - LSL_i} \tag{4}$$

Where n is the number of the parts, k is the number of the parts which is in the same group. Therefore, the estimated value of the standard variance of the similar process is:

$$S_Z = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{k_i}(Z_{ij} - \overline{Z})^2}{(\sum_{i=1}^{n} k_i) - 1}} \tag{5}$$

Where n is the number of the parts, k is the number of the parts which is in the same group.

The process quality control charts represent the information of process quality, and recognizing the status of the process quality accurately is the core of the diagnosis and control of the process quality. The quality personnel can find the reasons for out-of-control process from persons, machines, materials, methods, circumstance and measurement by efficient recognition of abnormal mode of control charts to provide basis for modifying process quality.

Process Quality Diagnosis Based on Elman. The process quality control charts represent the information of process quality, and recognizing the status of the process quality accurately is the core of the diagnosis and control of the process quality. The quality personnel can find the reasons for out-of-control process from persons, machines, materials, methods, circumstance and measurement by efficient recognition of abnormal mode of control charts to provide basis for modifying process quality.

Abnormal modes of the process quality control charts. The most common abnormal modes of the process quality control charts are ascending trend mode, declining trend mode, upward step mode, downward step mode, period mode[7], it is shown as Fig. 2.

The data of the control chart can be described as follows for the control chart modes:

$$y(t) = u + x(t) + d(t),\ t = 1, 2, \dots, T \tag{6}$$

$y(t)$ is the parameter of process quality; u is the mean value of the quality parameters under the condition of controlled process; $x(t) \sim N(0,\sigma)$, $x(t)$ was the derivation of random Gaussian distribution of the quality parameter, σ was the standard variance of the distribution; $d(t)$ was the abnormal interference.

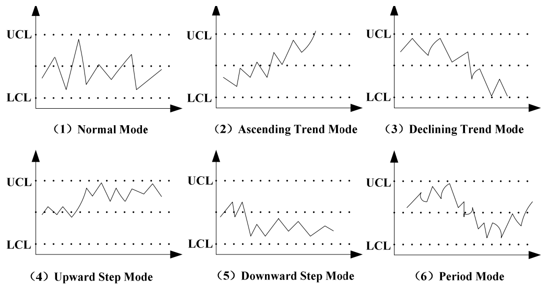

Fig.(2) Six patterns of control char

In normal mode: $d(t) = 0$;

In period mode: $d(t) = a\sin(2\pi t / T)$, where T is the variation period, a is the range;

In trend mode: $d(t) = \pm dt$, where +, - represent ascending or declining trends respectively, and the parameter d is the gradient;

In step mode: $d(t) = \pm vs$, where +, - represent ascending or declining steps respectively, and v is the step position which value is zero before step and 1 after step, s is step amplitude.

Abnormal pattern recognition of the control chart based on the Elman network. The Elman network is a typical RNN which stores the internal state based on the basic structure of BP as the function which is able to map the characteristics of the same generation to enable the system to adapt time-varying characteristics[8]. In terms of the network convergence, the Elman network which is under multi-dimensional inputs is global convergent. There are commonly four layers in the ANN of Elman feedback (It is shown as Fig.3.): input layer, intermediate layer (hidden layer), inheritance layer and output layer.

The nonlinear state space expressions of the Elman network are:

$$y(k) = g(w^3 x(k)) \tag{7}$$

$$x(k) = f(w^1 x_c(k) + w^2(u(k-1))) \tag{8}$$

$$x_c(k) = x(k-1) \tag{9}$$

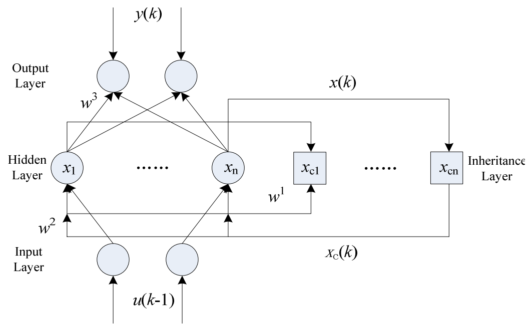

Fig.(3) Model of Elman network

y, x, u and x_c respectively indicate output node vector of M dimensions, intermediate layer node unit vector of n dimensions, N-dimension input vector and n-dimension feedback status vector; w^3, w^2, w^1 respectively indicate the connection weights of intermediate layer to output layer, input layer to intermediate layer and inheritance layer to intermediate layer; $g(\cdot)$ is the transfer function of output neurons which is the linear combination of the output of intermediate layer; $f(\cdot)$ is the transfer function of intermediate layer to neurons, and it often uses function S.

Error square sum function is used for the network performance function:

$$E(w)=\sum_{i=1}^{n}[y_k(w)-Y_k(w)]^2 \tag{10}$$

In Eq. (9), $y_k(w)$ is the target output vector.

The standard deviation D and maximum error E of the difference between predictive value and actual value measure the network predicting performance:

$$D=\sqrt{\frac{1}{M}\sum_{i=1}^{M}(y_i-Y_i)^2} \tag{11}$$

In Eq. (11), y_i is the actual value; Y_i is the network predictive value.

The input of the sample is the characteristics values of product quality, and the number of the characteristics values is the number of neurons in input layer. For the network output is the mode type, the number of the output layer neurons is six and the output target value is listed in Table 2.

Table 2. Goal value of output

pattern	1	2	3	4	5	6
Normal	1	0	0	0	0	0
Ascending trend	0	1	0	0	0	0
downward trend	0	0	1	0	0	0
Ascending step	0	0	0	1	0	0
downward step	0	0	0	0	1	0
period	0	0	0	0	0	1

Because the transfer function between the network intermediate layer and output layer is the logarithm Sigmoid function, the range of the network output values is (-1, 1). Then the mode of a neuron is ensured to input when the output of some neuron is greater than of equal to 0.5 and the output of other neurons are less than 0.5.

Expert system of process quality adjustment. The process quality adjustment expert system which is based on the knowledge-based design method transforms the expert knowledge and the prior knowledge of technologists in the field of process quality control to the expert system in the computer to control the process quality efficiently and intelligentize the process quality adjustment work. Therefore, process quality adjustment expert knowledge base and reasoning mechanism are established (It is shown as Fig.4.). In the knowledge base, the production rule representation was applied as the knowledge representation, and its expression form is: IF (premise or condition) THEN (result or action) WITH CF = (reliability). The factors which influence the process quality are mainly the aspects such as personnel, equipment, material, method, environment and measurement, and the process adjustment rules could be formulated respectively according to these six aspects when establishing the knowledge base. (Table 3.)

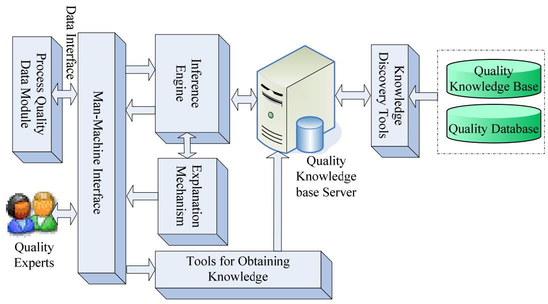

Fig. (4) Architecture of process quality adjustment expert system

THEN (result or action) WITH CF = (reliability).

The rules can be expressed as:

R1 : If ascending trend or declining trend

Then replace grinding wheel With CF = 0.8

R2 : If period mode

Then adjust operator and inspect environment facility With CF = 1.

Table 3. Diagnosis results corresponding to process adjusting measurements

Results	Measurement
Normal	——
Points approaching control limits	To set grinding process
	To adjust operators
	To inspect raw material
	To inspect part defects
Ascending/downward trend	To change or repair grinding wheel
	To adjust operator turns
	To inspect workshop temperature
Ascending/downward step	To inspecting new frock, fixture and machine parts applied or not
	To inspecting standard changes
	To inspecting operator status
Period	To adjust workshop environment,such as controlling temperature change, changing maintenance period and inspecting voltage pulsation etc.

IV. A Case Study

Here it will take the excircle turning processes of eight different parts on double inlet and outlet tube mill from some heavy tool enterprise as example to explain the simulation process of the network. The quality characteristic of each process of these eight different parts is the size of the excircle diameter ϕ, and the precision requirement are $40^{+0.020}_{+0.003}$, $100^{+0.024}_{+0.002}$, $160^{+0.029}_{+0.002}$, $200^{+0.031}_{+0.003}$, $80^{+0.023}_{+0.003}$, $120^{+0.028}_{+0.003}$, $225^{+0.033}_{+0.004}$, $125^{+0.021}_{+0.002}$ respectively. The concrete transformation results are listed in Table 4.

TABLE 4.
$\overline{X}$ TRANSFORMATION

No.	X_{ij}	Z_{ij}	R_i
1	40.011	-0.029	——
2	40.010	-0.088	0.059
3	40.016	0.265	0.353
4	40.012	0.029	0.236
5	40.014	0.147	0.118
6	40.008	-0.205	0.205
7	100.013	0.000	0.205
8	100.016	0.136	0.136
9	100.011	0.091	0.045
10	100.009	-0.182	0.273
11	160.017	0.056	0.238
12	160.014	-0.056	0.112
13	160.012	-0.129	0.073
14	200.014	-0.107	0.022
15	200.021	0.143	0.250
16	80.008	-0.250	0.393
17	80.014	0.050	0.300
18	80.017	0.200	0.150
19	80.013	0.000	0.200
20	80.010	-0.200	0.200
21	120.011	-0.180	0.002
22	120.019	0.140	0.320
23	120.012	-0.140	0.280
24	225.015	-0.121	0.019
25	225.021	0.086	0.207
26	125.011	-0.026	0.112
27	125.007	-0.155	0.129
28	125.016	0.155	0.310

The input vector for recognizing network Elman is constructed by the 28 points on the control chart which is constituted by the converted standard data Z_{ij} by the time distribution. It is *P*=[-0.029, -0.088, 0.265, 0.029, 0.147, -0.205, 0.000, 0.136, 0.091, -0.182, 0.056, -0.056, -0.129, -0.107, 0.143, -0.250, 0.050, 0.200, 0.000, -0.200, -0.180, 0.140, -0.140, -0.121, 0.086, -0.026, -0.155, 0.155]. The parameters of the control chart are: UCL=0.462,CL=-0.255,LCL=-0.513; the control chart is shown as Fig. 6.

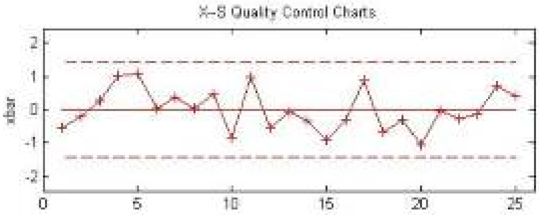

Fig.6 Control chart of similarity process

Step 1: Input sample data. The sample data include initialized quality eigenvalues of the control chart and the expected output codes according to them. In this case matrix *P* and *T* are inputted into the network;

Step 2: Network training. It is to train the Elman network by simulating the network training data through the Monte Carlo method which is namely Eq. 6 according to the previous structure and learning algorithm in the network design. It is verified by the simulation that the recognition accuracy can meet the requirement (It was shown as Table 5.)

Step 3: Output the result of the network calculation according to the process of network calculation. The output value in this case after network calculation is *T*'=[0.4610, 0.3925, -0.1356, 1.0199, -0.0615, -0.4283], and the error between the output value and the expected output of upward step mode *T*=[0,0,0,1,0,0] can meet the requirement. The Elman network training figure is Fig. 7.

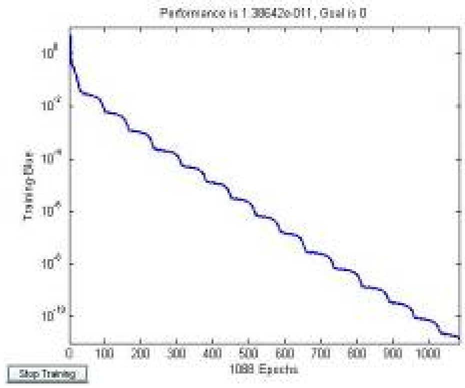

Fig.7 Training simulation of Elman

TABLE IV
CONTRAST OF ELMAN OUTPUT VERIFICATION

No.	Output goal	Output of Elman	Pattern
1	（100000）	（1.0000,-0.0005,0.0165,-0.0867,-0.0000,0.0213）	Normal
2	（010000）	（0.0108,0.9419,-0.0003,-0.0093,-0.0203,0.0021）	Ascending trend
3	（001000）	（0.0012,-0.0005,0.9458,0.0001,0.0032,-0.0106）	Downward trend
4	（000100）	（0.0587,-0. 0004,-0.0013,0.9091,-0.0408,0.0001）	Ascending step
5	（000010）	（0.0001,0.0185,0.0191,-0.0408,0. 9641,0.0251）	Downward step
6	（000001）	（-0.0169,0.0004,0.0812,-0.0327,0.0301,1.0201）	period

V. CONCLUSIONS

Aiming at the new requirements of quality control for mass customization, an intelligent process quality control mode which integrated quality prevention, analysis, diagnosis and adjustment is put forward, its function modules and architecture are analyzed, and the key enabling technology for realizing intelligent process quality control is given. The intelligent process quality control method for individualized customization which is a kind of process quality control modes to provides a new way for the enterprises to realize mass customization.

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