A FUZZY-GUIDED GENETIC ALGORITHM FOR QUALITY ENHANCEMENT IN THE SUPPLY CHAIN

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Abstract: To respond to the globalization and fierce competition, manufacturers gradually realize the challenge of demanding customers who strongly seek for products of high-quality and low-cost, which implicitly calls for the quality improvement of the products in a cost-effective way. Traditional methods focused on specified process optimization for quality enhancement instead of emphasizing the organizational collaboration to ensure qualitative performance. This paper introduces artificial intelligence (AI) approach to attain quality enhancement by automating the selection of process parameters within the supply chain. The originality of this research is providing an optimal configuration of process parameters along the supply chain and delivering qualified outputs to raise customer satisfaction.

1 INTRODUCTION

World has witnessed the increasing use of Artificial Intelligence (AI) for operations management(OM) with the purpose of finding optimal solutions to various problems including quality assurance along the supply chain (Kobbacy et al., 2007). Manufacturers therefore face the challenge of demanding customers who strongly seek for products of high-quality and low-cost, which implicitly calls for the quality improvement of the products in a cost-effective way. One problem is that different combinations of parameter setting within diverse processes involved in a supply chain network may affect the quality of the finished products to a great extent, whereas the engineers always keep different views upon these settings by their personal experiences. Hence it is crucial to find out the optimal parameter settings for the manufacturing processes regarding the experts' knowledge in order to obtain better productivity and quality. The paper thus presents a fuzzy guided-genetic algorithm (GA) to identify possible solutions for quality enhancement in supply chain network.

2 LITERATURE REVIEW

All the organizational activities can be described by processes and are characterized by a large number of interdependent sub-processes with assorted factors that influencing the quality level (Bernardy and Scherff, 1998). Quality assurance can be attained by supervision, review of historical data records and the assignment of domain experts (Heinloth, 2001). Optimal supply chain performance requires the overview of individual process parameters on various functional levels, from the shop floor to the whole organization. Therefore AI techniques are raised to complement the conventional techniques in optimizing the processes involved with better-finished quality (Yang et al., 2007). The advantage of knowledge-based systems to assist engineers solving decision-making problems on manufacturing activities is gradually realized and developed by researchers (Bayraktar, 1998; Tana et al., 2006).

GA and Fuzzy theory have been proven to excel in solving combinatorial optimization problems (Wang et al, 1998; Yu et al., 2006; Chiang et al., 2007; Lau et al., 2009). Hwang and He (2006) suggest that GA makes no limitation on the search space of optimization problems. Besides, GA searches for the optimum solutions through a population of solutions instead of a single solution, which makes it more possible to obtain the optimum solutions or near optimum solutions.

Our research is intended to propose a framework of intelligent system for process knowledge

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integration, generating a set of fuzzy-represented rules for enhancing the finished quality along the entire workflow.

3 THE KNOWLEDGE-BASED FUZZY-GA FRAMEWORK

3.1 Chromosome Encoding

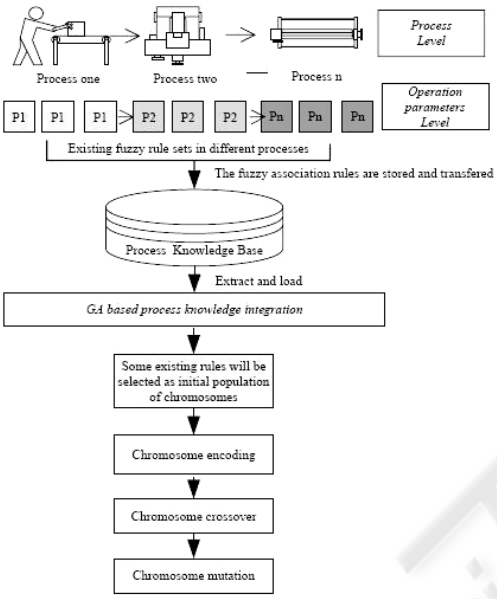

Figure 1: The proposed framework.

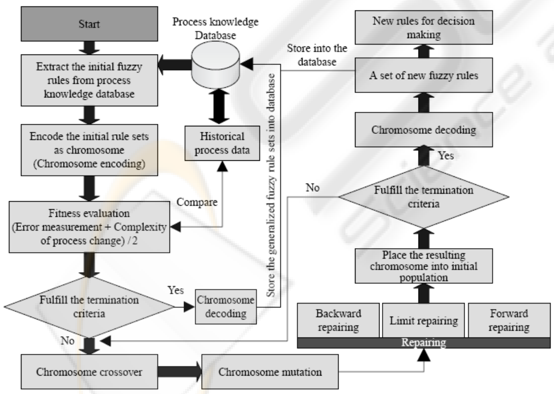

Figure 2: Information flow of the proposed algorithm (Reference: Ho et al, 2008).

Fig. 1 depicts the overview of the entire proposed knowledge-based framework, while Fig. 2 shows the corresponding information flow.

The initial rules extracted from process knowledge base are used to form the initial population of the GA. The first issue is chromosome encoding.

Table 1: Relevant Notations.

	Nomenclature
P_p	Total number of process parameters
D_r	Total number of defects
P	Index set of process parameters, $P = \{1,2,\ldots, P_p\}$
D	Index set of defects, $D = \{1,2,\ldots, D_r\}$
A	Index set of membership functions of process parameters, $A = \{1,2,\ldots, 6P_p\}$
B	Index set of membership functions of defects, $B = \{1,2,\ldots, 6D_r\}$
y_j	Parametrical value of the generated rules represented in chromosomes
y_j'	Parametrical value of the test objects
w_j	The weight of the j^{th} parameter
n	The total number of test objects selected for comparison
$c_{p_{iv}}$	Center abscissa of the membership function $\tilde{F}_{p_{iv}}$ for process parameter
$c_{d_{ix}}$	Center abscissa of the membership function $\tilde{F}_{d_{ix}}$ for defect
$w_{p_{iv}}$	Half the spread of the membership function $\tilde{F}_{p_{iv}}$ for process parameter
$w_{d_{ix}}$	Half the spread of the membership function $\tilde{F}_{d_{ix}}$ for defect
l_{P_p}	Lower bound of process parameter
u_{P_p}	Upper bound of process parameter
l_{D_r}	Lower bound of defect rate
u_{D_r}	Upper bound of defect rate

Definition 1. $C_h = \{1,2,\ldots,M\}$ represents the index set of chromosomes where M is the total number of chromosomes in the population.

Definition 2. $G_{m\times t}$ represents a gene matrix generated for the population where

$$G_{m\times w}=\left[\begin{array}{cccc|cccc|cccc|cccc} p_{11} & p_{12} & \cdots & p_{1a} & d_{11} & d_{12} & \cdots & d_{1b} & k_{11} & k_{12} & \cdots & k_{1c} & q_{11} & q_{12} & \cdots & q_{1d} \\ p_{21} & p_{22} & \cdots & p_{2a} & d_{21} & d_{22} & \cdots & d_{2b} & k_{21} & k_{22} & \cdots & k_{2c} & q_{21} & q_{22} & \cdots & q_{2d} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{ma} & d_{m1} & d_{m2} & \cdots & d_{mb} & k_{m1} & k_{m2} & \cdots & k_{mc} & q_{m1} & q_{m2} & \cdots & q_{md} \end{array}\right]$$

$$=\left((p_{iu})_{m\times a}(d_{ix})_{m\times b}(k_{iy})_{m\times c}(q_{iv})_{m\times z}\right)$$

$$p_{iv} = random\left[l_{P_p}, u_{P_p}\right], d_{ix} = random\left[l_{D_r}, u_{D_r}\right],$$

$$k_{i,\tau} = c_{piv}, k_{i,\lambda} = w_{p_{iv}}, q_{i,\tau} = c_{dix}, q_{i,\lambda} = w_{dix}$$

$$\forall i \in C_h, \forall v \in P, \forall x \in D, \forall y \in A, \forall z \in B, \tau = 1,3,5,\ldots\ldots;$$

$$\lambda = 2,4,6,\ldots\ldots; m = M, a = P_p, b = D_r, c = 6P_p, d = 6D_r$$

Note that the decoding method of an element in the first sub-matrix $(p_{iv})_{m\times b}$ or second sub-matrix $(d_{ix})_{m\times s}$ of $G_{m\times w}$ to a linguistic variable is given by (i) 0: ignore, (ii) 1: low, (iii) 2: medium, and (iv) 3: high. For any row of the third sub-matrix $(k_{iy})_{m\times e}$ of $G_{m\times w}$, a group of six consecutive values $k_{i(6\rho-5)}, k_{i(6\rho-4)}, k_{i(6\rho-3)}, k_{i(6\rho-2)}, k_{i(6\rho-1)}, k_{i(6\rho)}$ in the matrix forms a single set $\tilde{F}_{p_{iv}} = \{c_{p_{iv}} - w_{p_{iv}}, w_{p_{iv}}, c_{p_{iv}}, w_{p_{iv}}, c_{p_{iv}} + w_{p_{iv}}, w_{p_{iv}}\}$ for process parameter p_v where $\rho = 1,2,3,......$. Also, for any row of the fourth sub-matrix $(q_{iz})_{m\times n}$ of $G_{m\times w}$, a group of <u>*six*</u> consecutive values $q_{i(6\rho-5)}, q_{i(6\rho-4)}, q_{i(6\rho-3)}, q_{i(6\rho-2)}, q_{i(6\rho-1)}, q_{i(6\rho)}$ in the matrix forms a single set $\tilde{F}_{d_{ix}} = \{c_{d_{ix}} - w_{d_{ix}}, w_{d_{ix}}, c_{d_{ix}}, w_{d_{ix}}, c_{d_{ix}} + w_{d_{ix}}, w_{d_{ix}}\}$ for defect rate d_x where $\rho = 1,2,3,......$. For both two cases, there are totally *6* genes in the sets of membership functions shown in Fig. 3.

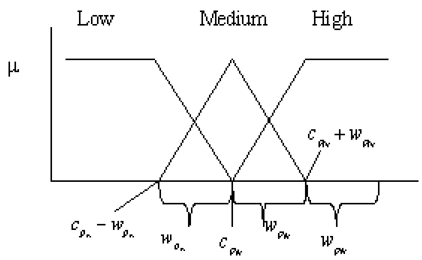

Figure 3: Membership functions of process parameters.

$\tilde{F}_{p_{iv}}$ consists of aggregated membership functions which relate to a fuzzy rule set is assumed to be isosceles-triangle functions.

$c_{p_{iv}}$ is the center abscissa of $\tilde{F}_{p_{iv}}$.

$w_{p_{iv}}$ represents half the spread of $\tilde{F}_{p_{iv}}$.

In "$c_{p_{iv}}$", "p_{iv}" indicates that the *v-th* feature test is included, while *i* specifies the order of all the condition levels of each feature test. For instance, $c_{p_{i1}}$ stands for the center abscissa of the 1st process test, within the whole membership function matrix.

Definition 3. $B_{m\times 1}$ denotes a random number matrix generated for selection and crossover where $B_{m\times 1} = (b_i)_{m\times 1}$

$b_i = random[0,1], \forall i \in C_h, m = M$.

Definition 4. $C_{h\_c} = \{1,2,.....,S\}$ denotes the index set of the chosen chromosomes in the crossover where *S* is the total number of chosen chromosomes

Definition 5. $G'_{m\times w}$ indicates the gene matrix in which the *Q* chromosomes chosen in crossover are stored where

$$G'_{m\times w} = \left((p'_{iu})_{m\times a}(d'_{ix})_{m\times b}(k'_{iy})_{m\times c}(q'_{iv})_{m\times z}\right)$$

3.2 Fitness Evaluation

To have a good set of process parameters, the genetic algorithm selects the best chromosome for mating according to the fitness function suggested below.

$$\text{Fitness Funtion} = \text{accuracy with error rate}$$

$$Accuracy = \frac{\text{objects correctly matched within error range}}{\text{total number of objects}}$$

where

$$\text{Error rate } (\varepsilon) = \sum_{j=1}^{m} w_j \frac{(y_j - y_j')^2}{2n}$$

Each chromosome is evaluated by calculating its mean-square error for the error measurement. As each chromosome is represented as the fuzzy rule, the quality of the chromosome is then validated by comparing its defuzzified output with the actual output of the test samples. The centre of gravity (COG) is used as the defuzzification method to obtain the crisp values of the finished quality level.

3.3 Chromosome Crossover

Crossover is a genetic operation aiming at producing new and better offspring from the selected parents, while the selection is determined by a crossover rate. The current crossover methods include single-point crossover, two-point crossover, multi-point crossover, uniform crossover, random crossover, etc. In our paper Uniform crossover is selected.

3.4 Chromosome Mutation

Mutation is intended to prevent all solutions in the population from falling into the local minima. It does this by preventing the population of chromosomes from becoming too similar to each other, which might slow down or even stop evolution. Mutation operation randomly changes the offspring resulting from crossover, given that the value of the mutation rate must range within 0 and 1. In our paper a bit-flip mutation is used.

3.5 Chromosome Repairing

If the membership function is not in ascending order, the new offspring should be modified by exchanging the gene order in accordance with the definition of

$$\tilde{F}_{p_{iv}} = \{c_{p_{iv}} - w_{p_{iv}}, w_{p_{iv}}, c_{p_{iv}}, w_{p_{iv}}, c_{p_{iv}} + w_{p_{iv}}, w_{p_{iv}}\}$$

4 CASE EXAMPLE AND DISCUSSION OF RESULTS

ABC Co. Ltd. is one of the leading manufacturers of sliders for computer disk drives. ABC offers a wide range of magnetic head-gimbal assembly, head-stack assembly and small spindle motors to different magnetic recording media industries. The workflow starts from receiving the order; and the wafer is the raw material to be processed to the slider under different processes. When the integrated workflow is finished, the specifications of the finished products in term of quality features are also recorded in order to investigate the correlation between process parameters and finished quality. The modifications of the process parameters along the logistics workflow will be suggested to minimize the defects in every stage within the workflow based on the generalized fuzzy rules in proposed system. In order to illustrate the effectiveness of the proposed fuzzy–Genetic algorithm for knowledge processing, the algorithm has been applied for setting the parameters for the reactive ion etching process. The process parameter domain (listed in Table 2) contains 65 cases from a manufacturer of magnetic hard disks. The proposed approach was implemented in MatLab 2007, and the code is executed by a regular PC. GA will be deployed to find out the optimal process parameter settings. In the experiments, the operation frequency for uniform crossover and mutation was set at 0.8 and 0.01 respectively. The stopping criterion is set as 100 generations.

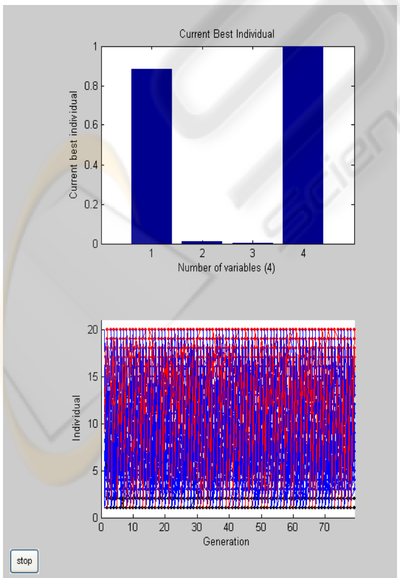

Figure 4: Numbers of generations with respect to best individual and genealogy.

The top left graph of Fig. 4 plots the expected number of children versus the raw scores at each generation and the genealogy of individuals. The best individual is obtained by plotting the vector entries of the individual with the best fitness function value in each generation. It is found that RF Power (variable 1) and O_2 (variable 4) are the best individuals. Bottom left graph of Fig. 4 plots the genealogy of individuals.

Table 2: Fuzzy terms of the case parameters.

RIEC Customer requirement	Etch Depth (D)	12550nm
	Shallow Specification (W)	1450nm
RIE process parameter	Pressure (PR)	5-15mTorr Ignore (0) Low(1) Medium (2) High (3)
	RF Power (RFP)	50- 150 Watts Ignore (0) Low(1) Medium (2) High (3)
	CHF_3	1- 60 sccm Ignore (0) Low(1) Medium (2) High (3)
	O_2	1-60 sccm Ignore (0) Low(1) Medium (2) High (3)
	Wall Angle(WA)	19 – 26 Ignore (0) Low(1) Medium (2) High (3)
	Cycle Time(CT)	1 - 1.5 hour Ignore (0) Low(1) Medium (2) High (3)
	Airgroove Roughness (AR)	35 - 60 nm Ignore (0) Low(1) Medium (2) High (3)
Defect	vacuum defect E11	5% - 10% (0)Low(1) Medium (2) High
	vacuum defect E3	5% - 10% (0)Low(1) Medium (2) High

The process parameter generated by Fuzzy-GA is above 95% matched with the experiment done by Winnall and Winderbaum (2000) and it shows that the result is promising.

5 CONCLUSIONS

In this paper, the design and implementation of a process knowledge integration system, incorporating the fuzzy theory and GA to attain quality improvement in industrial processes, is introduced. Implementing the proposed decision support model in the slider manufacturer through the demonstration in the case study has been successful. The significance of this paper is related to the introduction of a knowledge discovery approach to support the optimization process based on expert advice derived from past experience, capitalizing on the essential features and capabilities of the essential features of a knowledge representation technique and optimization technology. The principles and techniques can be extended to different industries with modifications to the fitness function and structure of chromosome. By incorporating the error measurement and complexity of process change into the fitness evaluation, the generalized fuzzy rule sets can be less complexity and higher accuracy. An extension of different measures can also be incorporated in order to improve the quality of generalized rules. Future work will entail other fuzzy learning methods to dynamically adjust the membership functions of various process parameters for enhancing the accuracy of the system.

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