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An expert system to support the optimization of ion plating process: an OLAP-based fuzzy-cum-GA approach

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Abstract

To cope with the issue of 'brain drain' in today's competitive industrial environment, it is important to capture the relevant experience and knowledge in order to sustain the continual growth of company business. Studies indicate that a system, which is able to support optimization to enhance knowledge acquisition, is still needed. To address this issue, this paper proposes an expert system to support the optimization process based on expert advice derived from past experience. The expert system named fuzzy-based with Genetic Algorithm and On Line Analytical Processing embraces three emerging technologies including (i) fuzzy logic for mimicking the human thinking and decision-making mechanism, (ii) Genetic Algorithm for optimizing the analyzed knowledge, and (iii) On Line Analytical Processing for supporting data mining process through the capturing of relevant knowledge in terms of fuzzy rules for future decision-making as well as providing a mechanism to apply the obtained knowledge to support industrial processes. To validate the feasibility of the approach, a case study on the optimization of ion plating process has been conducted with promising results.

Keywords: Expert system; Fuzzy logic; Genetic algorithm; On-line analytic processing; Database management system

1. Introduction

The issue of 'brain drain' in today's competitive industrial environment becomes significant. The loss of knowledge due to the departure of skillful employee is an issue that needs to be addressed. Apparently, it is important to capture relevant experience and knowledge in order to sustain the continual growth of company business. In this respect, the study in the domain of knowledge learning is of paramount importance in terms of capturing and reusing of tacit and explicit knowledge.

For a company to remain world competitive, it must, among other things, have an effective data processing capability. Studies indicate that the interest of processing information to enhance business and industrial operations started 10 years ago. However, organized information needs to be fully developed to the level of knowledge, which can then be captured and shared to support the growth of enterprises. Managing knowledge becomes significant because knowledge is one of the most strategic weapons that can lead to sustained increase in company profits (O'Dell & Grayson, 1998; Nonaka, Toyoma, & Konno, 2000; Teece, 2000).

Within the decade, there are several factors including vast amount of data generated, mass storage devices, high computing power, automatic learning techniques as well as the competitions and chaos among companies, contributing to the need for the development of expert systems which are meant to capture relevant domain knowledge. This paper attempts to propose an on Line analytical processing-based system (named fuzzy-based with Genetic Algorithm and On Line Analytical Processing (fuzzy-GOLAP)), embracing emerging technologies such as OLAP, fuzzy logic and Genetic Algorithm (GA), applying in the ion plating process with the objective to capture relevant knowledge and achieve optimization of process parameters. The proposed system embraces three emerging technology including (i) fuzzy logic for mimicking the human thinking and decision-making mechanism, (ii) GA for optimizing the analyzed knowledge, and (iii) OLAP for supporting data mining process through the capturing of relevant knowledge in terms of fuzzy rules for future decision-making as well as providing a mechanism to apply the obtained knowledge to support industrial process. To validate the feasibility of the approach in industrial

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environment, a case study has been adopted to demonstrate the ability of the proposed system.

2. Related study

In the past turning data into knowledge relies on manual analysis and interpretation. In fact, such manual data analysis is becoming impractical in many domains as data volumes grow exponentially (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). For example, Wal-mart alone generates around 20 million transactions a day and NASA's earth-observing system to be launched in 2000 produced 50 GB of image data per hour (Cios, Pedrycz, & Swiniarshi, 1998). A decade before, many researchers have predicted the phenomenon happened in the industrial environment and proposed different models in order to capture the industrial domain knowledge. Veloso and Borrajo (1994) explained that modern industrial processes require advanced computer tools that should adapt to the user requirements and to the tasks being solved. As a result, a learning system is proposed, HAMLET, which is integrated in a planning architecture, PRODIGY, and acquires control knowledge to guide PRODIGY to efficiently produce cost-effective plans.

Furthermore, Geng, Jamshidi, Cacrroll, and Kisner (1991) pointed out that many researchers are interested in the study of Iterative Learning Control Systems (ILCS) which is one of the simplest cases of learning control systems found for dealing with repetitive tasks of industrial robots and other engineering systems. Learning control scheme can be applied to the system characterized by an imprecise knowledge of their dynamical behavior as well as possible changes in operating environment. In a way similar to a human being learning a desired motion pattern through repeated trials, ILCS is able to make changes according to the output error of the system for each successive repetitive operation and progressively improves the performance until the operation is learnt.

To support the function of capturing knowledge from data and readable by the engineers easily, fuzzy logic is suggested to represent the captured knowledge in the system. Lu, Chen, and Hamilton (2000) stated that fuzzy logic provides a more intuitive method for expressing engineering concepts. It allows engineers to use a linguistic description of problems during knowledge encoding. For example, engineers often use fuzzy terms such as high, low, good, better, cool, hot, etc. to describe the nature of problem. Sugeno and Yasukawa (1993) and Emami, Turksen, and Goldenberg (1998) proposed to use systematic approaches to build linguistic fuzzy model which is effective in embedding the human knowledge. Setnes, Babuska, Kaymak, and van Nauta-Lemke (1998) discussed data and knowledge, both of them can be easily combined when building fuzzy models based on natural language. A simplified rule base makes it easier to assign qualitatively meaningful linguistic terms to the fuzzy sets, and it reduces the number of terms needed. It becomes easier for experts to validate the model and users can understand better and more quickly the operation of the system. In industrial environment, Sforna (2000) has applied this method on a power company customer database to support large customers billing activity. Wang, Dillon, and Chang (2001) have developed a data mining approach for fuzzy classification rule generation with four phases. Last and Kandel (2001) have presented a systematic approach to analyze the data of relevant process in the semiconductor industry based on the Information-Fuzzy Network (IFN).

In recent years, researchers use intelligent methods to discover knowledge from data through the process of data analysis algorithms such as artificial neural network, GA, etc. Funabashi and Maeda (1995) and Ishibuchi, Fujioka, and Tanaka (1993) proposed to use supervised learning to optimize hybrid system, thereby combining the techniques of artificial neural network and fuzzy logic. Dicherson and Kosko (1996), Kosko (1992), and Lin and Lee (1991) proposed to combine unsupervised and supervised learning to find out the optimization of parameters. Berenji and Khedkar (1992), Bogdan and Kovacjc (1996) Jang (1992), Kovacic, Bogdan, and Crnosija (1995), and King, Burnham, and James (1995) have tried to improve the performance of fuzzy controller with implementation of neural nets and reference model. Karr and Gentry (1993) exploited simple GA to alter the membership functions used in a conventional fuzzy logic controller (FLC). Park, Kandel, and Langholz (1994) adopted a genetics-based learning mechanism to raise the efficiency of the proposed fuzzy reasoning model. Mester (1995) incorporated GA into the optimization of a fuzzy rules set.

Recent study on the relevant topics indicates that whilst a number of approaches have been designed and implemented to capture knowledge from vast amount of data using various techniques and methodologies, an expert system, which is able to achieve knowledge from high amount of data in terms of fuzzy rules for future decision-making process and provide a mechanism to apply the obtained knowledge in similar types of industrial processes, is still an area that requires more in depth study and investigation. In particular, this proposed system is able to support process optimization, which depends largely on the availability of useful and relevant knowledge. This issue is addressed in this paper with the introduction of fuzzy-GOLAP which is able to capture knowledge and perform data analysis from different sources of data repositories with disparate data models.

3. Architecture of fuzzy-GOLAP

Fuzzy-GOLAP is developed for capturing domain knowledge by transforming vast amount of industrial data and applying the knowledge into relevant industrial processes. The proposed system is shown in Fig. 1.

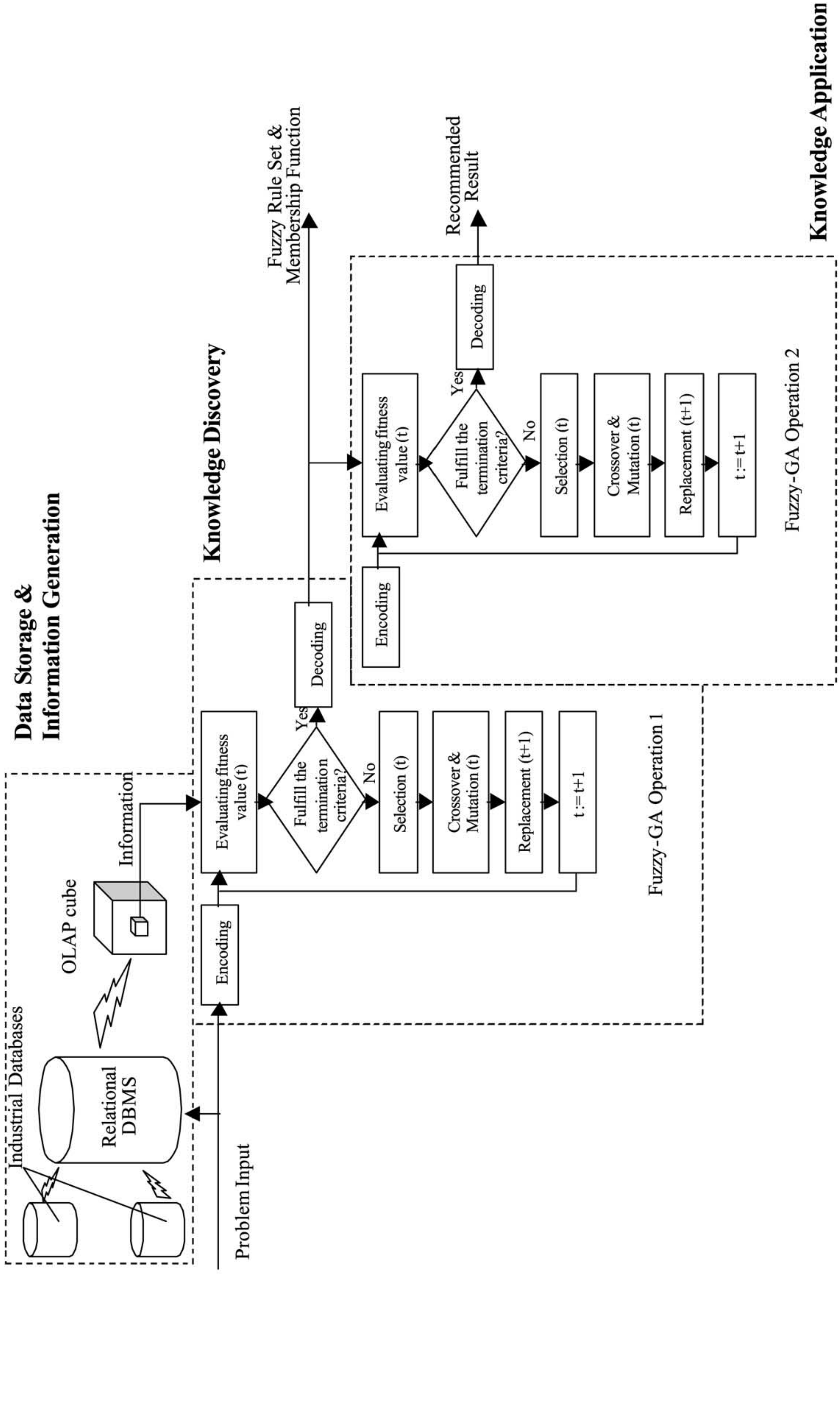

Fig. 1. Architecture of fuzzy-GOLAP.

Generally, it can be divided into three components including data storage and information generation, knowledge discovery and knowledge application.

In data storage and information generation, relational Data Base Management System (DBMS) and OLAP are used to collect, select and manage the industrial data. Data generated from industrial processes is arranged and stored in industrial process databases, which may be stored in different locations. DBMS is used to collect the relevant data through Internet at anytime and in anywhere. After the collection, data will be arranged and transformed into information by simple mathematics calculation or statistic function in the data cube of OLAP (Berson & Smith, 1997). Such information can be the summation of all items or percentage of the result. The managed data will be collected and sent to the knowledge discovery component to generate knowledge.

In the knowledge discovery component, the first GA operation is applied for discovering domain knowledge represented by fuzzy rule set with their associated membership functions based on vast amount of data and problem input. Fixed number of chromosomes to form a population will be randomly generated. Each chromosome is encoded with a fuzzy rule set and associated membership function but the number of fuzzy rule is different so that the chromosomes vary in length. The problem input helps to find out the suitable information derived from the previous component and used to evaluate the goodness of chromosomes through the fitness function. Good parent chromosomes will be sorted out by the fitness value for mating with genetic operators such as crossover and mutation. The optimum fuzzy rule set and associated membership function will be found out after reaching terminal criteria and decoding.

In the knowledge application component, the second GA operation is applied for using the knowledge derived in the previous component in the industrial process in order to improve and control the process quality. Fixed number of chromosome to form a population will be randomly generated. Each chromosome is encoded with a set of process parameter. Number of process parameter is limited so that the length of all chromosomes is fixed. The derived fuzzy rule set evaluates the goodness of chromosomes in population through fuzzification, fuzzy inferencing and defuzzification. Genetic operators operate on the good parent chromosomes, which are selected based on their fitness values. The optimum process parameters will be found after reaching terminal criteria and decoding.

4. Case study—ion plating

4.1. Problem description

Ion plating is a hybrid vacuum coating process that combines the benefits of vacuum evaporation and sputtering. It is generally applied to high energy plasma deposition methods in which the surface to be coated is subjected to a small flux of high energy ions and a much larger number of energetic neutrals before and during the deposition of the coating (Ahmed, 1987). The applications of the ion plating technique are becoming more popular and have been reported in various industrial areas, ranging from production of films for decorative uses to corrosion protection.

This case study focuses on one type of ion plating process—Ion Plating Gold (IPG) which dissolves titanium (Ti) in high voltage and high vacuum condition, and then solidifies in ionized condition prior to plating it with gold (Au). Gold is identified as 'weak peel off' with high intensity, however, Ti under the gold plating, which is made close to gold color in ionized process by injecting gas, is strong enough to remain the gold color. And the set up of ion plating has been shown in Fig. 2.

Due to the complexity of ion plating process, improper parameter setting could lead to various types of defects that have significant influence on the quality of plated parts. Generally, there are many parameters in industrial process which will generate several thousands of combination such as the parameter set with their range of IPG as listed in Table 1. However, so far, the setting is decided by the experience and intuitive sense of skillful operators based on trial-and-error methods. Actually, this method is time consuming and the process cost is relatively high. Therefore, fuzzy-GOLAP can help the operator to find out the optimum parameter set in a shorter time period, thereby capturing the knowledge for reuse and reference of similar processes.

The process flow chart of ion plating with fuzzy-GOLAP is shown in Fig. 3. The whole process starts from the customer order. The customer needs to specify three basic requirements including required thickness, color and basement material. In the case described in this paper, customer requires 0.5 μm thickness, 1N color and copper for basement material. These customer requirements will be put into fuzzy-GOLAP to find out the optimum parameters value. Defect statistics will be calculated after the optimum parameter set is applied in the actual ion plating process and all data will be stored in the relational DBMS.

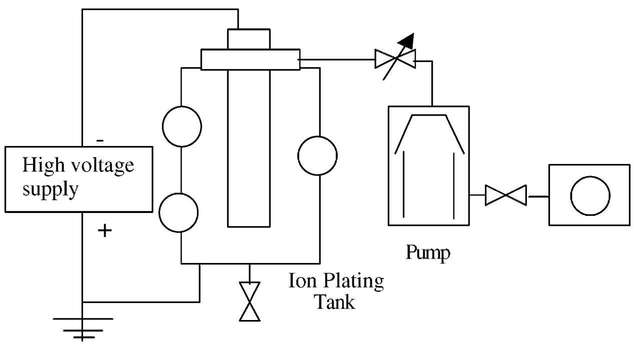

Fig. 2. Schematic diagram of ion plating set up.

Table 1
Ion plating parameter and the range

Symbol	IPG process parameter	Range
TH	Thickness	0.5–1.0 μm
C	Color	{White (1), Black (2), 1N (3), 2N (4)}
BM	Basement material	{Stainless Steel (1), Copper (2), Alloy (3)}
t_{Ti}	Time for Ti	1–5 min
t_{TiN}	Time for TiN	20–35 min
t_{Au}	Time for Au	5–15 min
t_v	Time to initial vacuum	12–26 min
t_{clean}	Time for cleaning	8–12 min
t_{ARC}	Time for ARC opened	25–35 min
t_s	Time for sputtering process	5–15 min
t_{cool}	Time for cooling	14–26 min
RS	Rotation speed	0.5–1.5 rpm
I_v	Initial vacuum	1.8–2.2 $(\times 10^{-})$ Pa
I_T	Initial temperature	145–155 °C
T_{cool}	Temperature for cooling	75–95 °C
Q_{clean}	Ar quantity for cleaning	186–200 sccm(%)
Q_{Ti}	Ar quantity for Ti	120–130 sccm(%)
Q_{Au}	Ar quantity for Au	110–130 sccm(%)
Q_{cool}	Ar quantity for cooling	143–157 sccm(%)
Q_{TiN}	N_2 quantity for TiN	220–240
B	Bias	0–0.4 kV
SV	Sputtering voltage	0.1–0.8 kV

4.2. Data storage and information generation

In the relational DBMS, the related or similar past experience can be found by using the customer requirements as the keywords for making queries. In order to analyze the past experience, the process-related data is selected. Fig. 4 shows the database structure which includes 10 tables, covering Customer requirement, Customer, Order, Order details, Task, Task setting, Task defect, Tank, Supplier and employee. These tables have recorded all data about the ion plating.

Data selection is done by adopting OLAP in which data cube is formed to store and manage the data that is selected by the integration of database systems through Internet. The cube is able to store the aggregated data for providing multidimensional view of the data. The OLAP cube (Fig. 5) can be used to explore the data by performing slice-and-dice on the data, drilling down and rolling up the database. In spite of processing data analysis, it can be operated in online mode, meaning that the analysis can be performed in real-time manner. As the industrial data is stored in specific databases (not in the corporate database) therefore the corporate data will remain unaffected whilst the data in data cube is updated regularly.

In Fig. 6, the information achieved from OLAP cube can be divided into three components such as customer requirements, process parameters and defect statistic. At the top of the form, order number and process category are displayed. The following three items are the customer requirements, and the next are the 19 process parameters, which are responses to the process settings. The bottom category is the 10 defect statistics items, which are commonly found on the plated products. Actually, the database only stores the number of defects for different categories and OLAP cube performs the calculation for the required information such as the defect percentage which is more meaningful than the simple data in this case.

Past records about the process cover all these three categories. The selection of process parameters depends on the customer requirements and the number of defect depends on the parameters chosen. Besides, the time and departments may generate different data. Therefore, database and OLAP are necessary to manage and achieve the information for the knowledge discovery.

4.3. Knowledge discovery

Knowledge represented in terms of fuzzy rule set and the associated membership functions is obtained by passing

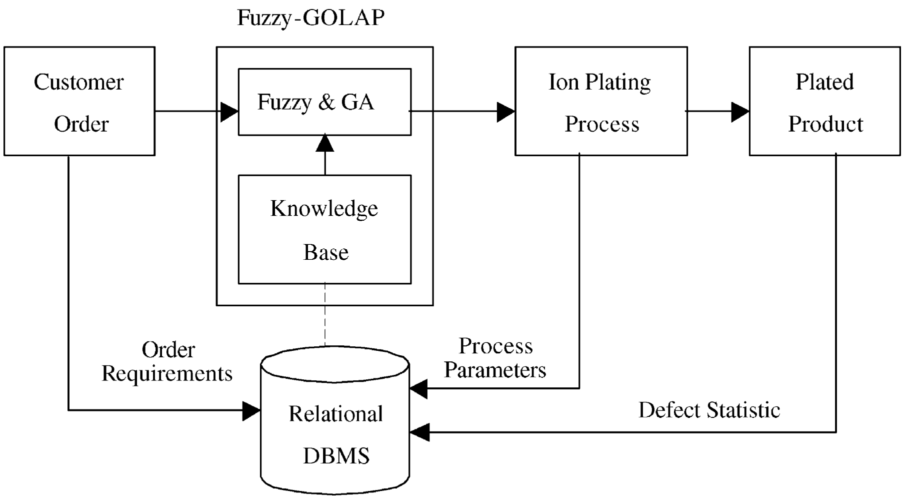

Fig. 3. Flow chart of case study.

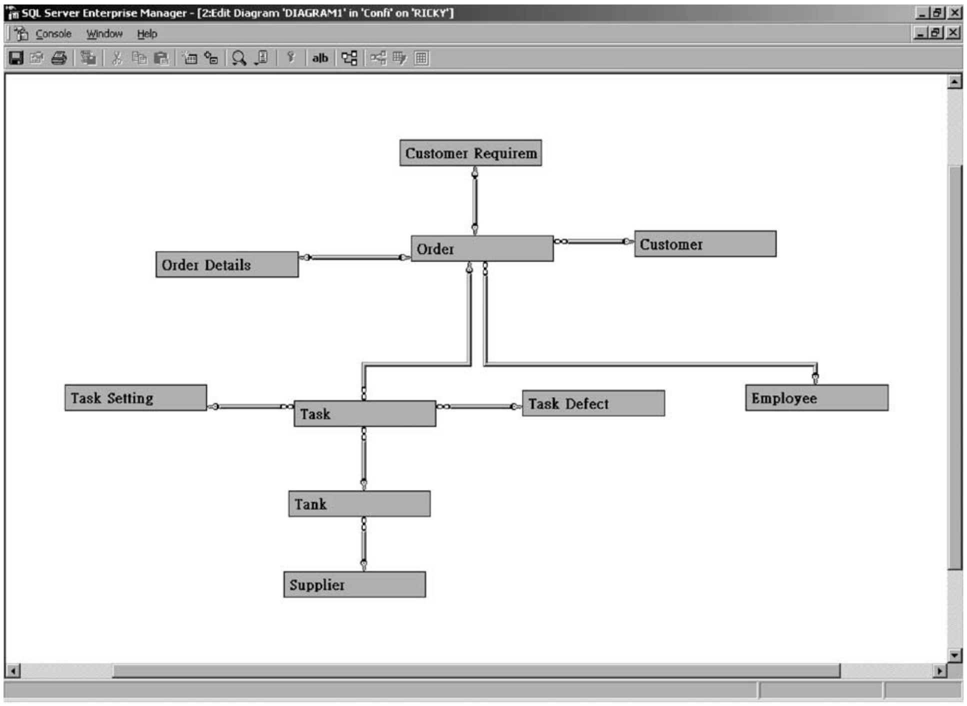

Fig. 4. Database structure of ion plating case (only case related is shown).

the customer requirements into the fuzzy-GA operation. In the operation, encoding is the first step to encode a chromosome, which includes a fuzzy rule, set and associated membership functions. The chromosomes lengths are not the same since the number of rule in a chromosome and the number of objects, in a fuzzy rule is different. Each fuzzy rule includes two part, one is the condition part which consists of customer requirements and process parameter whilst the other is the resultant part which consists of defect statistics item. Real number is used in

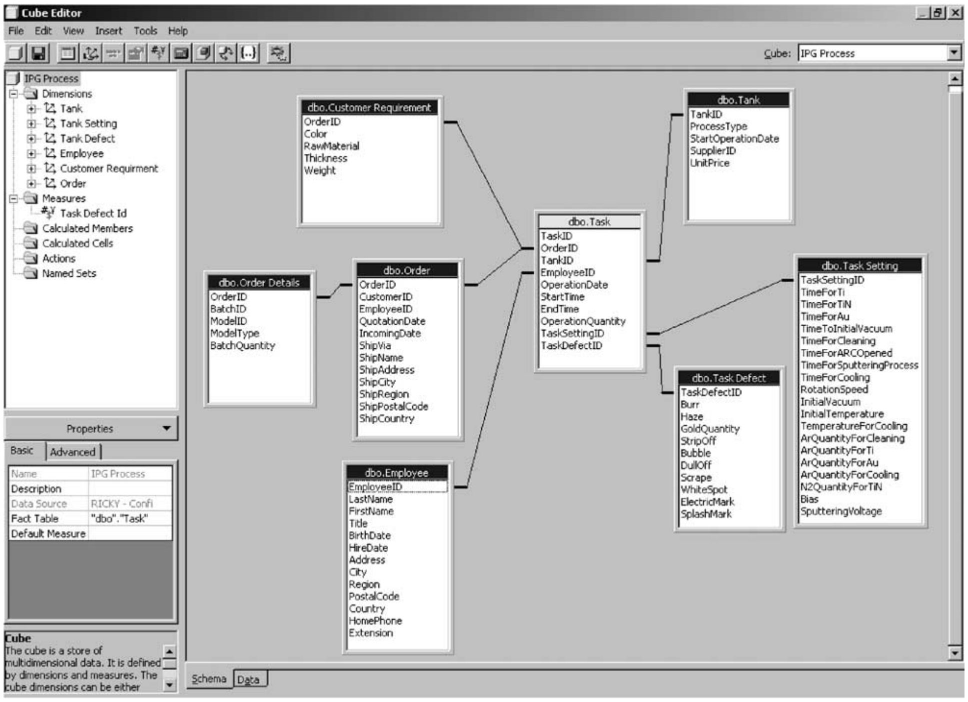

Fig. 5. OLAP cube of ion plating case (only case related is shown).

ORDER 138 RECORD		
IPG Parameters	**Values**	
Required Thickness	0.5μm	Customer Requirements
Color	1N	
Basement material	Copper	
Time for Ti	2mins	Process Parameters
Time for TiN	24mins	
Time for Au	10mins	
Time to initial vacuum	20mins	
Time for cleaning	10mins	
Time for ARC opened	30mins	
Time for Sp opened	10mins	
Time for cooling	20mins	
Rotation speed	1Rev/min	
Initial vacuum	2.0×10^{-2}Pa	
Initial Temp.	153°C	
Temp for cooling	82°C	
Ar quantity for cleaning	198sccm(%)	
Ar quantity for Ti	123sccm(%)	
Ar quantity for Au	120sccm(%)	
Ar quantity for cooling	147sccm(%)	
N_2 quantity for TiN	235	
Bias	0.2kV	
Sputtering voltage	0.4kV	
Burr	**1.5%**	Defect Statistics
Haze	**2.3%**	
Gold Quantity	**2%**	
Strip Off	**1.8%**	
Bubble	**2.1%**	
Dull Off	**2.2%**	
Scrape	**0.8%**	
White Spot	**1.6%**	
Electric Mark	**2%**	
Splash Mark	**2.6%**	

Fig. 6. Order record achieved from OLAP cube.

encoding chromosome and the fuzzy term representation of the variable is shown in Table 2. The generic pattern of the chromosome is fixed as shown below. Also, Fig. 7 shows the encoding of membership function:

Generic Pattern:
$FR_1,FR_2\ldots FR_n,MF_{tTi},MF_{tTiN}\ldots MF_B\ldots MF_{SM}$
Fuzzy Rule:
$FR_q = \{TH,C,BM,t_{Ti},t_{TiN},t_{Au},t_v,t_{clean},t_{ARC},t_s,T_{cool},RS,I_v,I_T,T_{cool},Q_{clean},Q_{Ti},Q_{Au},Q_{cool},Q_{TiN},B,SV,BU,H,GQ,SO,Bu,DO,S,WS,EM,SM\}$
Membership Function:
$MF_B = \{m_{low},b_{low},m_{medium},b_{medium},m_{high},b_{high}\}$

where m, middle; b, breath

Two example chromosomes are given in Fig. 8 to exhibit the encoding process according to the pattern and the representation of the variable. Furthermore, it is noted that the first three codes of each fuzzy rule are the same since they represent the same customer requirements. The other codes are randomly generated within their range which is shown in Table 2, e.g. the code for the variable of ‘Time for Ti’ allows 0, 1, 2 or 3 only. Initial population, which consists of several chromosomes, is defined after the encoding process and then the fitness value of each chromosome is evaluated to investigate the goodness of the chromosome for mating.

To evaluate chromosomes, the information obtained through the OLAP process, such as the information shown in Fig. 6, is needed. The information collected

Table 2
Fuzzy term of each variable

Symbol	IPG process parameter	Range
TH	Thickness	0.5–1.0 μm
C	Color	{White (1), Black (2), 1N (3), 2N (4)}
BM	Basement Material	{Stainless steel (1), Copper (2), Alloy (3)}
t_{Ti}	Time for Ti	{Ignore (0), Short (1), Medium (2), Long (3)}
t_{TiN}	Time for TiN	{Ignore (0), Short (1), Medium (2), Long (3)}
t_{Au}	Time for Au	{Ignore (0), Short (1), Medium (2), Long (3)}
t_v	Time to initial vacuum	{Ignore (0), Short (1), Medium (2), Long (3)}
t_{clean}	Time for cleaning	{Ignore (0), Short (1), Medium (2), Long (3)}
t_{ARC}	Time for ARC opened	{Ignore (0), Short (1), Medium (2), Long (3)}
t_s	Time for Sputtering process	{Ignore (0), Short (1), Medium (2), Long (3)}
t_{cool}	Time for cooling	{Ignore (0), Short (1), Medium (2), Long (3)}
RS	Rotation speed	{Ignore (0), Low (1), Medium (2), High (3)}
I_v	Initial vacuum	{Ignore (0), Low (1), Medium (2), High (3)}
I_T	Initial Temperature	{Ignore (0), Low (1), Medium (2), High (3)}
T_{cool}	Temperature for cooling	{Ignore (0), Low (1), Medium (2), High (3)}
Q_{clean}	Ar quantity for cleaning	{Ignore (0), Low (1), Medium (2), High (3)}
Q_{Ti}	Ar quantity for Ti	{Ignore (0), Low (1), Medium (2), High (3)}
Q_{Au}	Ar quantity for Au	{Ignore (0), Low (1), Medium (2), High (3)}
Q_{cool}	Ar quantity for cooling	{Ignore (0), Low (1), Medium (2), High (3)}
Q_{TiN}	N_2 quantity for TiN	{Ignore (0), Low (1), Medium (2), High (3)}
B	Bias	{Ignore (0), Low (1), Medium (2), High (3)}
SV	Sputtering voltage	{Ignore (0), Low (1), Medium (2), High (3)}
BU	Burr	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
H	Haze	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
GQ	Gold quantity	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
SO	Strip off	{Ignore (0), Not Accepted (1), Accepted (2), Highly Accepted (3)}
Bu	Bubble	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
DO	Dull off	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
S	Scrape	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
WS	White spot	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
EM	Electric mark	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}
SM	Splash mark	{Ignore (0), Not accepted (1), Accepted (2), Highly accepted (3)}

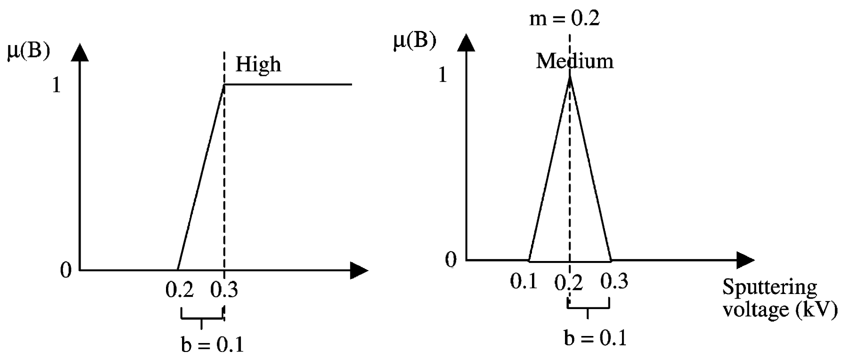

Fig. 7. Encoding of membership function.

from OLAP is divided into two sets, one is the training set and the other one is the test set with the ratio around 70–30%. Training set is used to evalutate the fitness of fuzzy rule set during the operation. Test set is used to test the derived fuzzy rule set for measuring the accuracy. The relative information is passed into relative fuzzy term in chromosomes to calculate the fitness value using the fitness function. In this case, the fitness function is designed by two variables, accuracy and complexity and it is necessary to maximize to the fitness function by increasing the accuracy and decreasing the complexity of the chromosome (Wang, Hong, & Tseng, 1998). The fitness function, accuracy and complexity are calculated by the following equations:

$$\text{Maximize } F(x) = \text{Accuracy}(x)/\text{Complexity}(x)$$

$$\text{Accuracy}(x) = \left(\frac{\text{total number of rules fired in } i\text{th chromosome}}{\text{total number of rules in } i\text{th chromosome}} * \frac{\text{total sum of normalized matching object in } i\text{th chromosome}}{\text{total number of rules fired in ith chromosome}}\right)$$

$$= \frac{\text{total sum of normalized matching object in } i\text{th chromosome}}{\text{total number of rules in } i\text{th chromosome}}$$

where total sum of normalized matching object in ith chromosome

$$= \sum_{i=1}^{\text{total number of rule have fired}} \left([\frac{\text{total number of objects correctly matched in 'Then' part}}{\text{total number of objects in 'Then' part}}]_i \right)$$

$$\text{Complexity(x)} = \left(\frac{\text{number of rules in } i\text{th chromosome}}{\text{max. number of rules in same population}} * \frac{\text{average number of object in } i\text{th chromosome}}{\text{average number of object in max. object chromosome in same population}}\right)$$

$$\text{where average number of object in } i\text{th chromosome} = \frac{\text{total sum of object in } i\text{th chromosome}}{\text{number of rules in } i\text{th chromosome}}$$

where average number of object in max. object chromosome in same population

$$= \frac{\text{total sum of object in max. object chromosome}}{\text{number of rules in max. object chromosome}}$$

Take the chromosome$_1$ to demonstrate the evaluation based on fitness function:

Chromosome$_1$:

0.50,3,2,0,1,0,2,0,1,1,3,2,0,0,1,0,3,2,1,1,0,0,2,1,1,0,0,0,3, 2,2,0,…,0.1,0.1,0.2,0.1,0.3,0.1…

Assuming the total number of rule in chromosome$_1$ is 10, the total number of rules fired after passing the training set is 6 and the maximum number of rules in a chromosome in the same population is 16 then, the total sum of normalized matching object is

$$\sum_{i=1}^{6} \left\{ \frac{2}{6}, \frac{1}{5}, \frac{3}{5}, \frac{4}{4}, \frac{5}{7}, \frac{3}{7} \right\}$$

Next, the average number of object in chromosome$_1$ is 14.8 (148/10) and the average number of object in max. object chromosome in same population is 14.733 (221/15).

Therefore, the accruacy (x) is 0.3273 (3.273/10) and the complexity (x) is 0.6275 ((10/16) $*$ (14.8/14.733)) and the fitness value of chromosome$_1$ is 0.522 (0.3273/0.6275).

Example of chromosome$_1$:

$$\underbrace{0.50,3,2,0,1,0,2,0,1,1,3,2,0,0,1,0,3,2,1,1,0,0,2,1,1,0,0,0,3,2,2,0}_{FR_{1\ \text{Chromosome 1}}},\ldots,\underbrace{0.1,0.1,0.2,0.1,0.3,0.1}_{MF_{B\ \text{Chromosome 1}}}\ldots$$

Example of chromosome$_2$:

$$\underbrace{0.50,3,2,1,0,0,0,2,2,3,1,2,2,3,3,1,2,1,0,0,1,0,2,2,0,0,3,3,1,2,0,3}_{FR_{1\ \text{Chromosome 2}}},\ldots\underbrace{0.2,0.1,0.3,0.2,0.4,0.2}_{MF_{B\ \text{Chromosome 2}}}\ldots$$

Fig. 8. Example of chromosomes.

The chromosomes are ranked in descending order based on their fitness value after evaluation. The top 10 chromosomes are sorted out and stored in the control population, which identifies the 10 highest fitness value chromosomes. For the successive generations, each new generated chromosome compares with the chromosomes in control population based on fitness value. If the new one is higher in value, it will replace the old one and subsequently stored in control population. Then the chromosomes in control population will be re-ranked. While the generation indicates that the trend of fitness value is declining, all chromosomes in control population will replace the 10 lowest fitness value chromosomes in processing population.

After the fitness value of each chromosome has been evaluated, the mechanism will check whether or not the control population fulfils the terminal criteria. There are two criteria in this case, (i) the process has run over 5000 generations, (ii) the difference between the highest fitness value and the lowest one in control population is not more than 0.001.

If the termination criteria have not been fulfilled, selection, crossover and mutation will be applied on the process population to generate a new population. The first step is a selection process for investigating the parent chromosomes that perform crossover. The process population is ranked according to the fitness value and then every chromosome will be assigned a fitness value based on the position in the individual ranking. The worst will have fitness 1, second worst 2 etc. and the best will have fitness N which is the number of chromosomes in population.

Following the selection process, the next genetic operation is crossover which is the process to generate the new chromosome. In this case, two-substring crossover method is applied with 0.8 operation frequency.

Crossover of chromosomes with crossover rate at 80%:

Chromosome$_1$:

0.50,3,2,0,1,0,2,0,1,1,3,**2,0,0,1,0,3,2,1,1,0,0,**2,1,1,0,0,0,3,2,2,0,…,0.1,**0.1,0.2,0.1,**0.3,0.1...

Chromosome$_2$:

0.50,3,2,1,0,0,0,2,2,3,1,**2,2,3,3,1,2,1,0,0,1,0,**2,2,0,0,3,3,1,2,0,3,…,0.2,**0.1,0.3,0.2,**0.4,0.2...

Chromosome$_1$':

0.50,3,2,0,1,0,2,0,1,1,3,**2,2,3,3,1,2,1,0,0,1,0,**2,1,1,0,0,0,3,2,2,0,…,0.1,**0.1,0.3,0.2,**0.3,0.1...

Chromosome$_2$':

0.50,3,2,1,0,0,0,2,2,3,1,**2,0,0,1,0,3,2,1,1,0,0,**2,2,0,0,3,3,1,2,0,3,…,0.2,**0.1,0.2,0.1,**0.4,0.2...

Fig. 9. Crossover of chromosome$_1$ and chromosome$_2$.

Mutation of chromosome with mutation rate at 5%:

Chromosome$_1$:

0.50,3,2,0,1,**0**,2,0,1,1,3,**2**,0,0,1,0,3,2,1,**1**,0,0,2,1,1,0,0,0,3,**2**,2,0,…,0.1,**0.1**,0.2,0.1,0.3,**0.1**...

Chromosome$_1$':

0.50,3,2,0,1,**1**,2,0,1,1,3,**1**,0,0,1,0,3,2,1,**2**,0,0,2,1,1,0,0,0,3,**3**,2,0,…,0.1,**0.0**,0.2,0.1,0.3,**0.2**...

Fig. 10. Mutation of chromosome$_1$ and chromosome$_2$.

Optimum chromosome:

$$\underbrace{0.50,3,2,0,0,1,0,0,0,1,0,0,0,1,2,0,0,0,0,0,2,1,0,0,1,2,3,0,0,0,2,1}_{FR_{1\ \text{Optimum Chromosome}}},\ldots,\underbrace{0.0,0.1,0.1,0.1,0.3,0.2..}_{MF_{B\ \text{Optimum Chromosome}}}$$

Fig. 11. Optimum chromosome in case study.

The demonstration of crossover using chromosome$_1$ and chromosome$_2$ is shown in Fig. 9. After crossover, mutation is applied to increase the variability of the population by introducing a small amount of random search. Fig. 10 shows the mutation with 0.05 operation frequency. The new generated chromosomes replace the old process population to form the new one and the fitness value is evaluated again.

Once the termination criterion has been fulfilled, decoding will be implemented on the highest fitness value chromosome in the control population. The optimum chromosome in this case is shown in Figs. 11–13 shows the first three fuzzy rules in optimum fuzzy rule set and associated membership functions after decoding, respectively. The decoded knowledge can be used in knowledge application part and used by engineers directly.

4.4. Knowledge application

To apply the knowledge discovered above, another fuzzy-GA operation is used. In this operation, chromosomes are encoded randomly with the genetic pattern shown below. The fixed number of variables and their range with the same length of all chromosomes are shown in Table 1. All the process parameters have been encoded in a chromosome. The example of the chromosome$_1$ and chromsome$_2$ are listed below:

Genetic pattern:
TH,C,BM,t_{Ti},t_{TiN},t_{Au},t_v,t_{clean},t_{ARC},t_s,t_{cool},RS,I_v,I_T,T_{cool},-Q_{clean},Q_{Ti},Q_{Au},Q_{cool},Q_{TiN},B,SV
Chromosome$_1$:
0.50,3,2,3,20,10,15,08,30,11,15,1.0,2.0,147,80,200,130,12-0,150,220,0.10,0.3
Chromosome$_2$:
0.50,3,2,5,26,08,17,12,27,08,18,1.2,1.9,147,87,193,126,11-6,148,235,0.15,0.2

The evaluation of every chromosome to find out the fitness value used by the optimum fuzzy rule set and associated membership functions is shown in Figs. 12 and 13, shows the operations of fuzzification, fuzzy inferencing and defuzzification. The chromosome$_2$ is used to demonstrate the fuzzy operations and Figs. 14 and 15 shows the fuzzification and fuzzy inferencing operation, respectively. Centre of Gravity (COG) is used for defuzzification in this case and the equation is shown

Decoding of the optimum chromosome:

FR$_1$: If **thickness** is 0.50 and
color is 1N and
basement material is copper and
time for Au is short and
time for sputtering process is short and
initial temperature is low and
temperature for cooling is medium and
bias is medium and
sputtering voltage is low
Then **gold quantity** is not accepted and
strip off is accepted
bubble is highly accepted and
electric mark is accepted and
splash mark is not accepted

FR$_3$: If **thickness** is 0.5 and
color is 1N and
basemenet material is copper and
time for TiN is medium and
time for Au is medium and
time for ARC opened is short and
time for sputtering process is medium and
bias is medium
Then **burr** is accepted and
haze is not accepted and
bubble is accepted and
dull off is not accepted and
scrape is not accepted and

Decoding of the optimum chromosome:

FR$_1$: If **thickness** is 0.50 and
color is 1N and
basement material is copper and
time for Au is short and
time for sputtering process is short and
initial temperature is low and
temperature for cooling is medium and
bias is medium and
sputtering voltage is low
Then **gold quantity** is not accepted and
strip off is accepted
bubble is highly accepted and
electric mark is accepted and
splash mark is not accepted

Fig. 12. The first three rules in optimum fuzzy rule set after decoding.

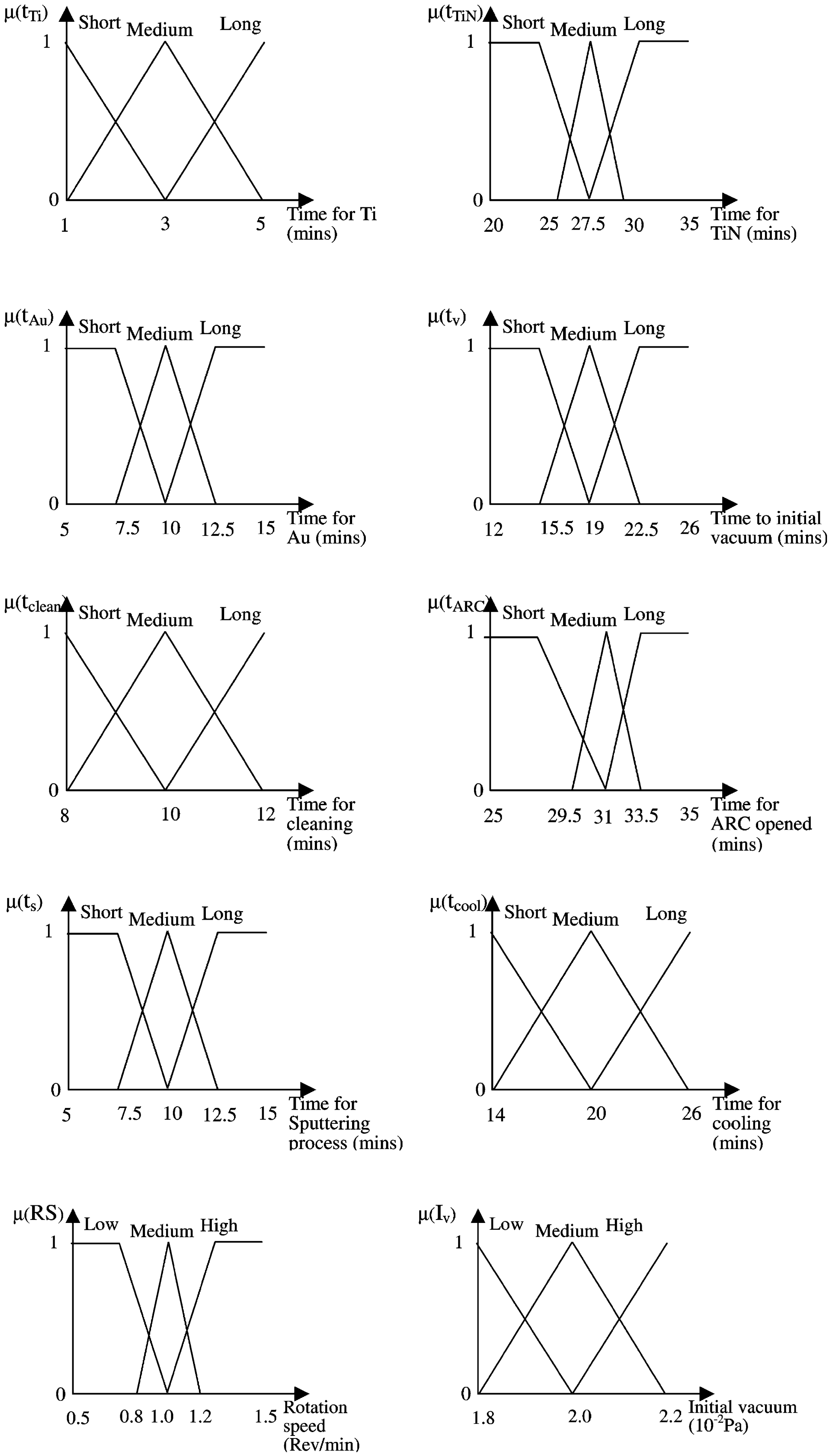

Fig. 13. Optimum associated membership functions.

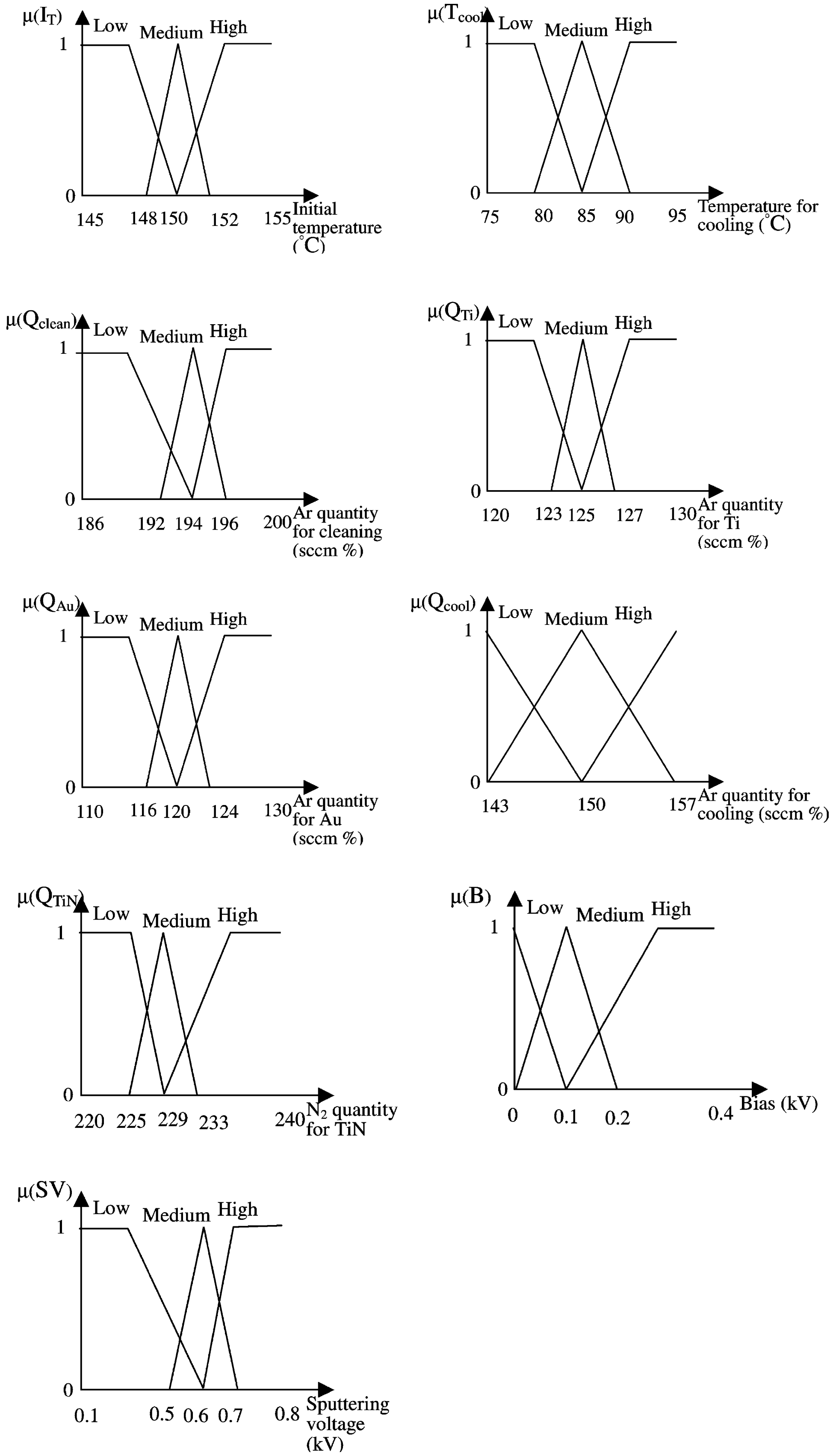

Fig. 13 (*continued*)

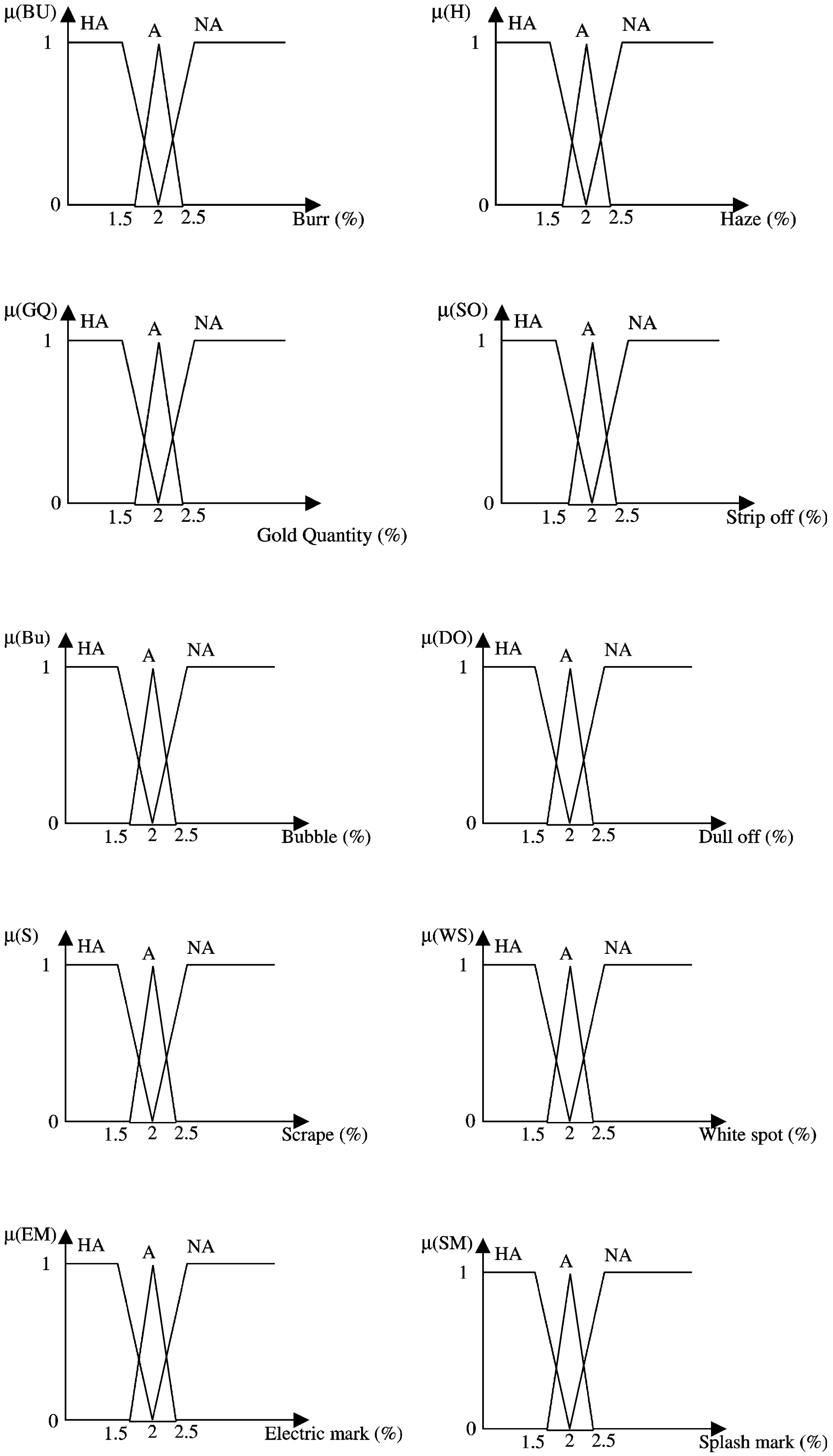

Fig. 13 (*continued*)

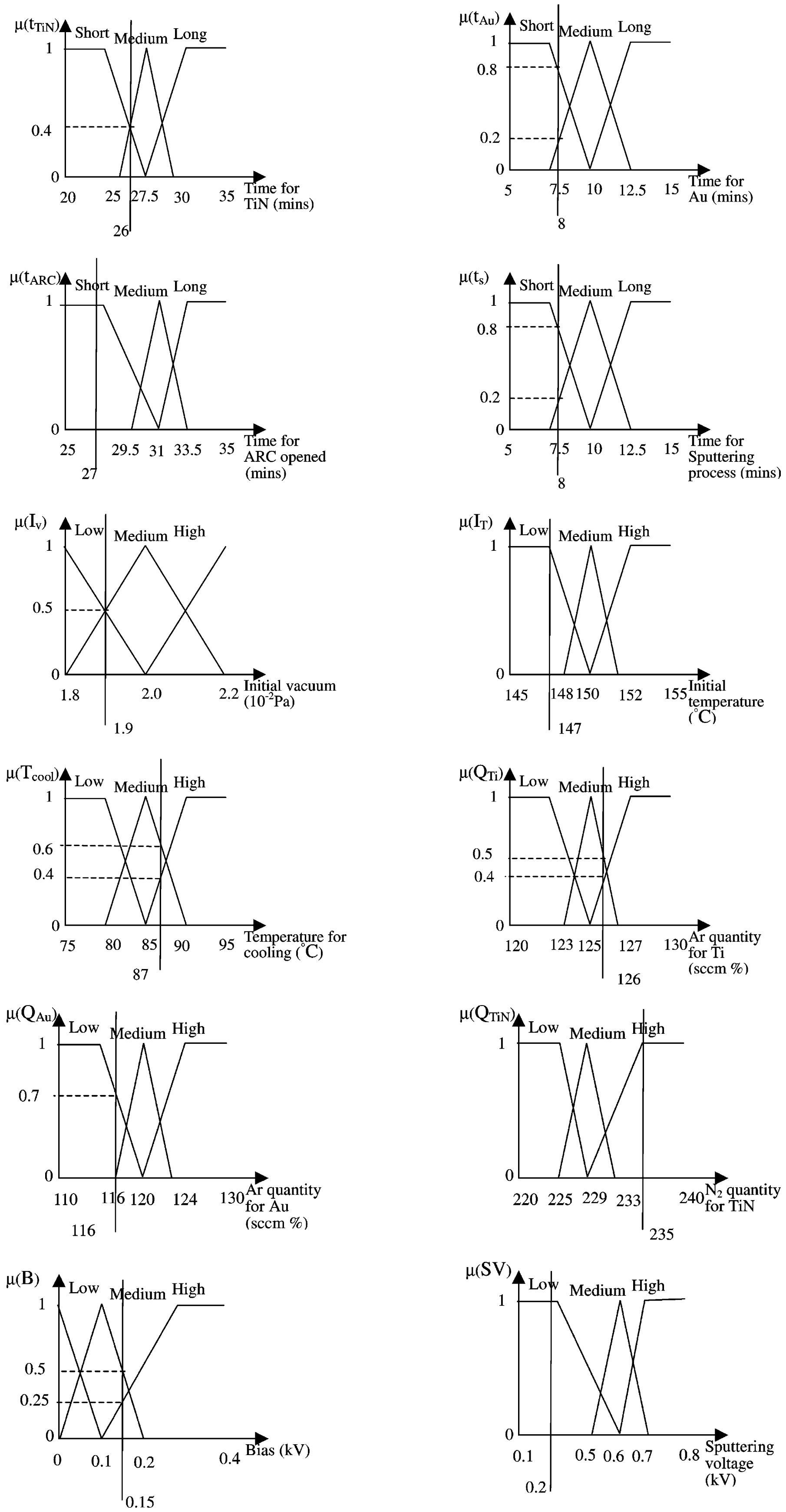

Fig. 14. The fuzzification of the chromosome$_2$.

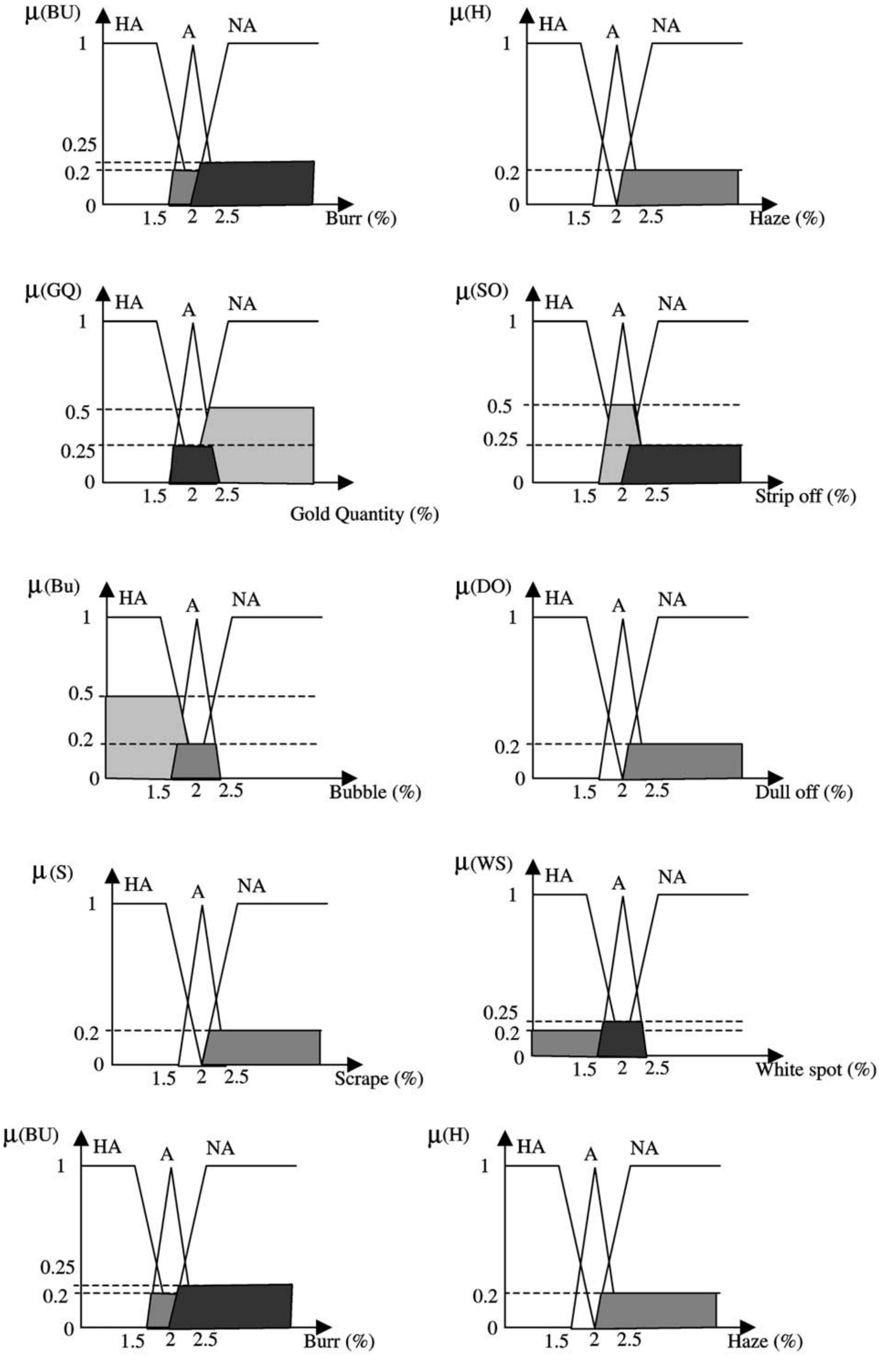

Fig. 15. The fuzzy inferencing of chromosome$_2$.

below with result listed in Table 3

$$Y = \frac{\sum_{j=1}^{N} w_j \overline{C_j A_j}}{\sum_{j=1}^{N} w_j \overline{A}_j}$$

The defects in this case include burr, haze, gold quantity, strip off, bubble, dull off, scrape, white spot, electric mark and splash mark. The defect percentages are 2.73, 3, 2.8, 2.56, 1.17, 3, 3, 1.2, 2 and 2.85, respectively. These results will go through the transformation diagram which is shown in Fig. 16, transferring the defect percentage into the defect level. After the transformation, the defect levels are 1.27, 1, 1.2, 1.44, 2.83, 1, 1, 2.8, 2 and 1.15, respectively. The fitness equation is the summation of all defect levels and the goal is

Table 3
Defuzzification of chromosome$_2$

Fuzzy term	Area (A)	Center of gravity (C)	Weight (w)	ACw	Aw
Defuzzification of Burr					
Accepted	0.18	2	1	0.36	0.18
Not accepted	0.469	3	1	1.41	0.469
				$Y = 2.73$	
Defuzzification of haze					
Not accepted	0.38	3	1	1.14	0.38
				$Y = 3$	
Defuzzification of gold quantity					
Accepted	0.219	2	1	0.438	0.219
Not accepted	0.875	3	1	2.625	0.875
				$Y = 2.8$	
Defuzzification of strip off					
Accepted	0.375	2	1	0.75	0.375
Not accepted	0.469	3	1	1.41	0.469
				$Y = 2.56$	
Defuzzification of bubble					
Highly accepted	0.875	1	1	0.875	0.875
Accepted	0.18	2	1	0.36	0.18
				$Y = 1.17$	
Defuzzification of dull off					
Not accepted	0.38	3	1	1.14	0.38
				$Y = 3$	
Defuzzification of scrape					
Not accepted	0.38	3	1	1.14	0.38
				$Y = 3$	
Defuzzification of white spot					
Highly accepted	0.38	1	1	0.38	0.38
Accepted	0.094	2	1	0.188	0.094
				$Y = 1.2$	
Defuzzification of electric mark					
Accepted$_{0.5}$	0.375	2	1	0.75	0.375
Accepted$_{0.2}$	0.18	2	1	0.36	0.18
				$Y = 2$	
Defuzzification of splash mark					
Accepted	0.219	2	1	0.438	0.219
Not accepted$_{0.5}$	0.875	3	1	0.625	0.875
Not accepted$_{0.2}$	0.38	3	1	1.14	0.38
				$Y = 2.85$	

to maximize the fitness value. Summarizing the defect levels, the fitness value of chromosome$_2$ is 15.69.

The control population is the same as the previous fuzzy-GA operation. It ensures the trend of fitness value, which is

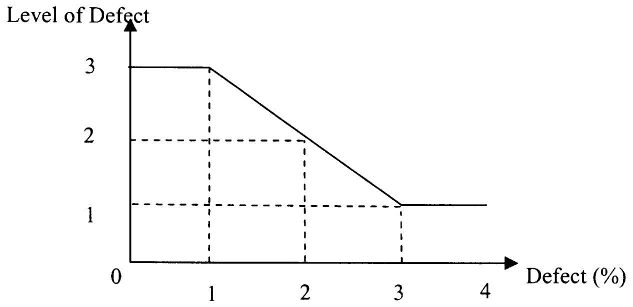

Fig. 16. Transformation diagram for level of defect against defect (%).

Crossover of chromosomes with crossover rate at 80%:

Chromosome $_1$:
0.50,3,2,3,20,10,15,**08,30,11,15,1.0,2.0,147,80,200,**130,120,150,220,0.10,0.3
Chromosome $_2$:
0.50,3,2,5,26,08,17,**12,27,08,18,1.2,1.9,147,87,193,**126,116,148,235,0.15,0.2

Chromosome $_1$':
0.50,3,2,3,20,10,15,**12,27,08,18,1.2,1.9,147,87,193,**130,120,150,220,0.10,0.3
Chromosome $_2$':
0.50,3,2,5,30,08,19,**08,30,11,15,1.0,2.0,147,80,200,**121,119,148,233,0.05,0.2

Fig. 17. Crossover of chromosome$_1$ and chromosome$_2$.

increasing. Furthermore, it is used to check whether or not the process has reached the terminal criteria. There are two criteria in this case, (i) the process has run over 5000 generations, (ii) the difference between the highest fitness value and the lowest one in control population is not more than 0.01.

Selection, crossover and mutation are the subsequent processes if the terminal criteria are not reached. Similarly with the selection in the previous fuzzy-GA operation, the process population is ranked according to the fitness value and then every chromosome will be assigned fitness based on the position in the individual ranking. The crossover in this moment takes 0.8 operation frequency for two-substring crossover process 0.05 operation frequency is used in the mutation process. Figs. 17 and 18 demonstrate how crossover and mutation are applied in chromosome$_1$ and chromosome$_2$, respectively.

Decoding is applied in the highest fitness value chromosome in control population if any one of the terminal criteria is reached. In this case, the optimum chromosome is shown below:

Optimum chromosome:
0.50,3,2,3,25,10,20,10,30,10,20,1.0,2.0,150,80,196,126,120,147,230,0.10,0.6

After decoding the optimum chromosome, the process parameter values are shown in Table 4. This result indicates the optimum process parameters for the customer requirements and this set of parameter can be repeatedly used if the customer requirements are the same. After using the optimum parameter in the ion

Mutation of chromosome with mutation rate at 5%:

Chromosome $_1$:
0.50,3,2,3,20,10,15,**08**,30,11,15,1.0,2.0,147,80,**200**,130,120,150,220,0.10,**0.3**

Chromosome $_1$':
0.50,3,2,3,20,10,15,**09**,30,05,15,1.0,2.0,150,80,**199**,130,120,150,220,0.10,**0.5**

Fig. 18. Mutation of chromosome$_1$ and chromosome$_2$.

Table 4
Decoding of the optimum chromosome

IPG parameters	Values	IPG parameters	Values
Required thickness	0.5 μm	Rotation speed	1 rpm
Color	1N	Initial vacuum	2.0×10^{-2} Pa
Raw material	Copper	Initial temperature	150 °C
Time for Ti	3 min	Temp for cooling	80 °C
Time for TiN	25 mins	Ar quantity for cleaning	196 sccm (%)
Time for Au	10 min	Ar quantity for Ti	126 sccm (%)
Time to initial vacuum	20 min	Ar quantity for Au	120 sccm(%)
Time for cleaning	10 min	Ar quantity for cooling	147 sccm (%)
Time for ARC opened	30 min	N_2 quantity for TiN	230
Time for sputtering process	10 min	Bias	0.1 kV
Time for cooling	20 min	Sputtering voltage	0.6 kV

plating tank, the defect statistic data is recorded and stored in the database for the following knowledge discovery component.

At the present stage, test results indicate that the proposed fuzzy-GOLAP approach is feasible, and such feasibility has been illustrated via the ion plating process in plating company. The result indicates that significant improvement can be achieved after adopting the optimum process parameters in compliance with the adoption of the proposed approach. However, it should be noted that the result obtained so far is yet to be considered as perfect and further refinements of the proposed methodology are needed.

5. Conclusion

This paper describes an OLAP-based fuzzy-cum-GA system, focusing on applying the approach in ion plating process. The proposed system proves to be effective based on the results obtained through a case study in a reference site. The significant contribution of this paper is related to the introduction of an expert system to support the optimization process based on expert advice derived from past experience, capitalizing on the essential features and capabilities of several emerging technologies fuzzy logic, GA and OLAP. It is expected that this proposed expert system will contribute to the capturing and the subsequent management of relevant experience as well as useful knowledge so as to sustain the continual growth of company business.

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