

Applying GA and Fuzzy Logic to Breakdown Diagnosis for Spinning Process

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Abstract

In this study, an effective search methodology based on fuzzy logic is applied to narrow down search range for the possible breakdown causes. Moreover a genetic algorithm (GA) is employed to directly find the intervals of solution to the inverse fuzzy inference problem during diagnosis procedure. Through the assistance of the developed intelligent diagnosis system, an inspector can be easier and more effective to find various possible occurred breakdown causes by judging from the observed symptoms during manufacturing process. An application of the developed intelligent diagnosis system to tracing the breakdown causes occurred during spinning process is reported in this study. The results show that the accuracy and efficiency of the diagnosis system are as promising as expected.

Keywords

Fuzzy Logic, Inverse Fuzzy Inference, Genetic Algorithm, Breakdown Diagnosis

1. Introduction

It is crucial for a manufacturing process to be of an intelligent diagnosis system to help effectively find out the occurred problems and eliminate them in no time when breakdowns occur. However, nowadays the inspecting & tracing process for the breakdowns causes during producing product in manufacturing industry still heavily depends on the expertise of an experienced technician. In general a junior inspector is lacking in the knowledge or the experience needed for tracing out break down causes from the occurred problems. Results of inspection and diagnosis are exclusively influenced with mental and physical conditions of an inspector. It is not only time-consuming but also economically infeasible for an enterprise to retrain a new operator to expert at the specific technical knowledge

of engineering, once the trained operator leaves the job. For the sake to help solve the above-mentioned problems, an intelligent diagnosis system is developed by using fuzzy logic and genetic algorithm (GA) in this study.

A good diagnosis system should have the capability to help find the possible causes incurring the defects of product. Fuzzy sets theory is a handy tool for expert information formalization while simulating cause-effect connections in technical and medical diagnostic problems [1] [2]. The model of a diagnostic object, as a rule is built on the basis of compositional Zadeh rule of inference which connects input and output variables of an object (causes and effects) using fuzzy relation matrix [3]. The problem of diagnosis can be formulated in the form of the direct and inverse fuzzy logical inference.

The direct logical inference suggests finding diagnoses (output variables or effects) according to observable internal parameters of the object state (input variables or causes). At present, the majority of fuzzy logic applications to the diagnosis problems adopt the direct logical inference [4] [5] [6] [7]. Several diagnosis systems have been developed to trace breakdowns occurred during manufacturing. Xu *et al.* [4] treated vibration signals of machinery in unsteady operating conditions by using instantaneous power spectrum (IPS) and genetic programming (GP), generating excellent symptom parameters GP-SP for failure diagnosis, and failure of machinery in unsteady operating conditions is diagnosed. Chen *et al.* [5] traced multi-fault state for plant machinery using wavelet analysis, genetic programming (GP), and possibility theory. The wavelet analysis is used to extract feature spectra of multi-fault state from measured vibration signal for the diagnosis. Hsu *et al.* [6] developed a diagnosis system, which is based on fuzzy reasoning to monitor the performance of a discrete manufacturing process and to justify the possible causes.

In the case of inverse logical inference some renewal of causes takes place (of the object state parameters) according to observable effects (symptoms). The inverse logical inference is used much less due to the lack of effective algorithms solving fuzzy logical equation system. It is required to develop a more effective approach to finding solution to inverse fuzzy logic problem during diagnosing breakdown causes. Although the effective algorithm for solving the inverse fuzzy logic problem has been researched [8] [9] [10] and reported in many studies [1] [2] [4] [5] [11] [12] [13], the proposed methods need proceeding with complicate compare procedures. In order to solve the above-mentioned problems, in this study, the search for the solution to fuzzy logical equation is of an optimization problem solved by genetic algorithm (GA) [14]. We present a GA-based approach to directly find the intervals of solution to the inverse fuzzy inference problem. Moreover an effective search algorithm based on fuzzy reasoning is applied to narrow down search range for the possible breakdown causes. Through the assistance of the developed diagnosis system, an operator can more easily and effectively find various possible breakdown causes by judging from the observed symptoms during manufacturing process. Thus, the manufacturing efficiency can be improved dramatically because the occurred breakdowns can be

eliminated in no time based on the problem-incurred causes being effectively traced out.

2. Fuzzy Logical Equation

Let the relationship between symptoms and causes in a diagnosis process be represented as r_{ij} . Thus, the relationship between cause i and symptom j in a diagnosis system can thus be illustrated as that between i and j in an diagnosis situation when a relationship exists between breakdown cause i and symptom j , the r_{ij} is shown as 1; otherwise it is 0. Assume that matrix \mathbf{R} is composed of elements r_{ij} of size $m \times n$, matrix \mathbf{A} is a row matrix consisting of m elements, and matrix \mathbf{B} is a row matrix consisting of n elements, respectively. The relationship between causes and symptoms in a diagnosis system can thus be shown as the following.

$$\mathbf{A} \circ \mathbf{R} = \mathbf{B} \quad (1)$$

where

$$\mathbf{R} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix}$$

$$\mathbf{A} = (a_1 a_2 \cdots a_m)$$

$$\mathbf{B} = (b_1 b_2 \cdots b_n).$$

Calculated result from Equation (1) by max-min composition (Zadeh and Kacprzyk, 1992) yields

$$V_i(a_i \wedge r_{ij}) = b_j \quad (2)$$

where V : max, \wedge : min, $i = 1, 2, \dots, m$, and $j = 1, 2, \dots, n$.

The diagnostic procedure seems quite simple using given matrix \mathbf{A} and matrix \mathbf{R} to find the solution of matrix \mathbf{B} because there exists only one specific solution. Yet using matrix \mathbf{B} and \mathbf{R} to find matrix \mathbf{A} , which can fit the requirement of Equation (1), will be rather more sophisticated because more than one solution exists. Such kind of vague relations existing between breakdown causes and symptoms are called fuzzy relations. A fuzzy set, defined originally by Zadeh [15], is an extension of a crisp set. Crisp sets allow only full membership or no membership at all, whereas fuzzy sets [11] [12] [13] [16] [17] allow partial membership. The diagnostic procedure, usually proceeding with given matrices \mathbf{R} and \mathbf{B} to find the solution of matrix \mathbf{A} that fits the requirements of Equation (1), is an inverse problem of fuzzy relation equation. If the solution of matrix \mathbf{A} can be found, then the breakdown cause is obtained.

3. Solutions to the Inverse Problems

Assuming that matrices \mathbf{A} , \mathbf{B} , and \mathbf{R} in Equation (1) are all fuzzy set [18] [19], to find the solution of matrix \mathbf{A} in Equation (1) from given matrices \mathbf{B} and \mathbf{R} is an inverse problem of a fuzzy relational equation. For instance, when $m = n = 1$, the

solution, represented as a^* , of the inverse problem of $b = a \wedge r$ can be shown as

$$\begin{cases} a^* = b & \text{if } b < r \\ a^* = [b, 1] & \text{if } b = r \\ a^* = \phi & \text{if } b > r \end{cases} \quad (3)$$

Relationships between b , r , and a can be illustrated as in **Figure 1**, from which we can conclude that when $b < r$ and $b = r$, it is true for $a = b$ and $a = [b, 1] = [r, 1]$ respectively. But when $b > r$ because there is no a , the solution is ϕ . In accordance with the magnitudes of b and r , there exist three kinds of solutions (*i.e.*, point, set, and ϕ). From **Figure 1**, we can conclude that a solution exists for $b = a \wedge r$ unless the magnitude of r is less than that of b .

Finding of fuzzy set A amounts to the solution of the fuzzy logical Equations system:

$$\begin{aligned} b_1 &= (a_1 \wedge r_{11}) \vee (a_2 \wedge r_{21}) \cdots \vee (a_m \wedge r_{m1}) \\ b_2 &= (a_1 \wedge r_{12}) \vee (a_2 \wedge r_{22}) \cdots \vee (a_m \wedge r_{m2}) \\ &\dots \quad \dots \quad \dots \quad \dots \\ b_n &= (a_1 \wedge r_{1n}) \vee (a_2 \wedge r_{2n}) \cdots \vee (a_m \wedge r_{mn}) \end{aligned} \quad (4)$$

which is derived from Equation (2). The solution to the problem of fuzzy logical equations (*i.e.*, Equation 2) is formulated in this way. Vector $a = (a_1, a_2, \dots, a_n)$, which satisfies limitations of $a_i \in [0, 1]$, $i = 1, 2, \dots, m$, should be found and provides the least distance between expert and analytical measures of effects significances, that is between the left and the right parts of Equation (2).

Minimizing

$$\sum_{j=1}^n \left(b_j - \bigvee_i (a_i \wedge r_{ij}) \right)^2. \quad (5)$$

In general, Equation (2) can have no solitary solution but a set of them. Therefore, according to Equation (5), a form of intervals can be acquired as the solution to the fuzzy logical equations system and illustrated as follows.

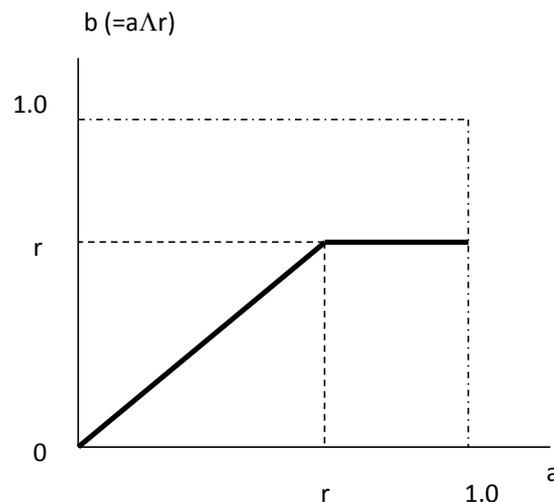


Figure 1. Graph of $b = a \wedge r$.

$$a_i = [a_i^l, a_i^u] \subset [0, 1], \quad i = 1, 2, \dots, m, \tag{6}$$

where a_i^l (a_i^u) is the low (upper) boundary of cause a_i significance measure.

Formation of intervals a_i (i.e., $[a_i^l, a_i^u]$) is done by way of multiple optimization problem solution to Equation (5) and it begins with the search for the null solution of it.

The null solution to optimization problem in Equation (5) is illustrated as $a^{(0)} = (a_1^{(0)}, a_2^{(0)}, \dots, a_n^{(0)})$, where $a_i^{(0)} \in [a_i^l, a_i^u]$, $i = 1, 2, \dots, m$. The upper boundary (a_i^u) is found in range $[a_i^{(0)}, 1]$ and the low (a_i^l) in range $[0, a_i^{(0)}]$. Let $a^{(k)} = (a_1^{(k)}, a_2^{(k)}, \dots, a_n^{(k)})$ be some k th solution of optimization problem in Equation (5). While searching for upper boundaries (a_i^u) it is suggested that $a_i^{(k)} \geq a_i^{(k-1)}$, and while searching for low boundaries (a_i^l) it is suggested that $a_i^{(k)} \leq a_i^{(k-1)}$. It is shown in the **Figure 2** where the arrows correspond to direction of the search.

The upper and low boundary can be found as the following steps.

- 1) Randomly find an optimal solution (i.e., $a^{(0)}$) based on Equation (5).
- 2) Search dynamics of upper solutions boundaries (i.e., $a_i^{(k)} \geq a_i^{(k-1)}$).
 {If $a^{(k)} \neq a^{(k-1)}$, then $a_i^u(a_i) = a_i^{(k)}$, $i = 1, 2, \dots, m$, $k = 1, 2, \dots, p$.
 Else if $a^{(k)} = a^{(k-1)}$, then the search is stopped.}
- 3) Search dynamics of low solutions boundaries (i.e., $a_i^{(k)} \leq a_i^{(k-1)}$).
 {If $a^{(k)} \neq a^{(k-1)}$, then $a_i^l(a_i) = a_i^{(k)}$, $i = 1, 2, \dots, m$, $k = 1, 2, \dots, p$.
 Else if $a^{(k)} = a^{(k-1)}$, then the search is stopped.}

4. Developing Search Mechanism

To solve a problem, the GA randomly generates a set of solutions for the first generation. Each solution is called a chromosome that is usually in the form of a binary string. According to a fitness function, a fitness value is assigned to each solution. The fitness values of these initial solutions may be poor; however, they will rise as better solutions survive in the next generation. A new generation is

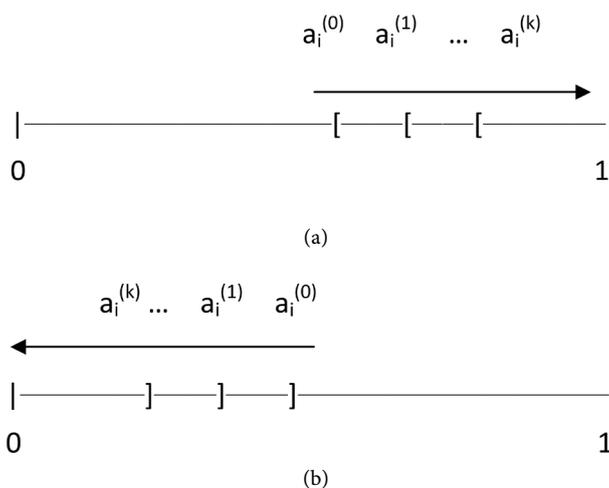


Figure 2. Search for upper (a) and low (b) boundary of the interval.

produced through the following three basic operations [14] [20].

- 1) Randomly generate an initial solution set (population) of N strings and evaluate each solution by fitness function.
- 2) If the termination condition does not meet, do
 - Repeat {Select parents for crossover.
 - Generate offspring.
 - Mutate some of the numbers
 - Merge mutants and offspring into population.
 - Cull some members of the population.}
- 3) Stop and return the best fitted solution.

4.1. Encoding and Decoding A Chromosome

In order to apply GAs to our problem, we firstly need to encode the elements of matrix A as a binary string. The domain of variable a_i is $[d_i^l, d_i^u]$ and the required precision is dependent on the size of encoded-bit. The precision requirement implies that the range of domain of each variable should be divided into at least $(d_i^u - d_i^l)/(2^n - 1)$ size ranges. The required bits (denoted with n) for a variable is calculated as follows and the mapping from a binary string to a real number for variable a_i is straightly forward and completed as follows.

$$a_i = d_i^l + s_i (d_i^u - d_i^l) / (2^n - 1) \tag{7}$$

where s_i is an integer between $0 - 2^n$ and is called a searching index.

After finding an appropriate s_i to put into Equation (7) to have an a_p which can make fitness function to come out with a fitness value approaching to “1”, the desired parameters can thus be obtained. Combine all of the parameters as a string to be an index vector, *i.e.* $A = (a_1, a_2, \dots, a_m)$, and unite all of the encoder of each searching index as a bit string to construct a chromosome shown as below.

$$P = p_{11} \dots p_{1j} p_{21} \dots p_{2j} \dots p_{i1} \dots p_{ij} \quad p_{ij} \in \{0,1\}; \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n; \tag{8}$$

Suppose that each a_i was encoded by n bits and there was m parameters then the length of Equation (8) should be an N -bit ($N = m \times n$) string. During each generation, all the searching index s_i of the generated chromosome can be obtained by Equation (9).

$$s_i = p_{i1} \times 2^{n-1} + p_{i2} \times 2^{n-2} + \dots + p_{in} \times 2^{n-n} \quad i = 1, 2, \dots, m; \tag{9}$$

Finally the real number for variable a_i can thus be obtained from Equation (7) and Equation (9). The flow chart for the encoding and decoding of the parameter is illustrated in **Figure 3**.

4.2. Chromosome

A main difference between genetic algorithms and more traditional optimization search algorithms is that genetic algorithms work with a coding of the parameter set and not the parameters themselves [14]. Thus, before any type of genetic search can be performed, a coding scheme must be determined to represent the

parameters in the problem in hand. In finding the solution (i.e., matrix \mathbf{A}) of a fuzzy logical inference problem, a coding scheme for the elements of matrix \mathbf{A} must be determined and considered in advance. Suppose that matrix \mathbf{A} is a row one of n elements. A multi-parameter coding, consisting of n sub-strings, is required to code each of the n variables (i.e., elements) into a single string. In this study, a binary coding is utilized and the bit-sizes of the encoding for the elements of Matrix \mathbf{A} are as follows. The bit-size of each element of matrix \mathbf{A} is set to 7 bits. Thus a chromosome string consisting of $N(=n \times 7)$ bits can be formed and its layout is shown in Figure 4.

4.3. Fitness Function

The target is to minimize the distance between the observed values (i.e., b_j) and the calculated ones (i.e., $V_i(a_i \wedge r_{ij})$) shown as Equation (5). The fitness of GA used in search mechanism can thus be set as Equation (10). This approach will allow the GA to find the minimum difference between them when the fitness function value is maximum (i.e., approaches to 1).

$$\text{Fitness} = 1 - \sum_{j=1}^n \left(b_j - \bigvee_i (a_i \wedge r_{ij}) \right)^2 \tag{10}$$

where V : max, \wedge : min, $i = 1, 2, \dots, m$, and $j = 1, 2, \dots, n$.

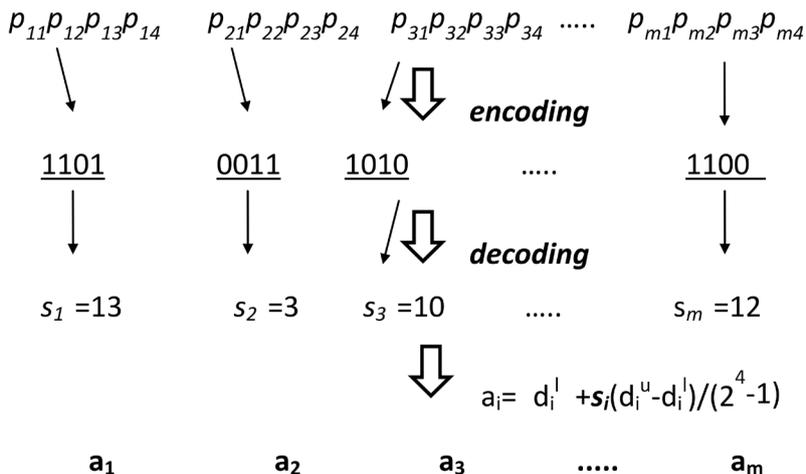


Figure 3. Flow chart for the encoding and decoding of a variable with 4-bit precision.

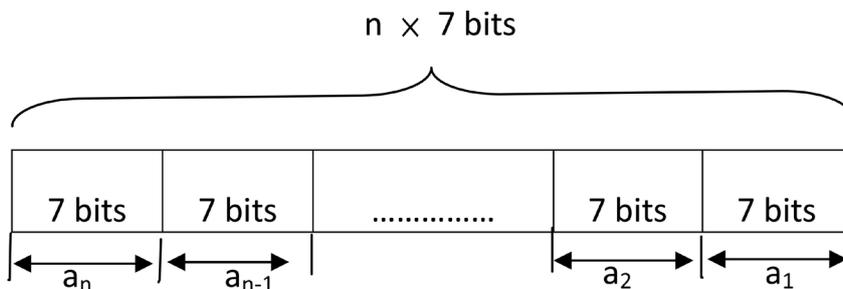


Figure 4. Layout of chromosome.

4.4. Make the Diagnostic Procedure More Effective

In order to develop a more effective diagnosis system, which is capable of tracing the possible breakdown causes from the categories of defects and providing an immediate response, it is necessary to sketch an effective searching algorithm for the diagnosis procedure. The methodology used in research [21] is employed in the study. Firstly, we define the following symbols:

$$A_i = \{a_1, a_2, \dots, a_m\} = \text{cause set}$$

$$B_j = \{b_1, b_2, \dots, b_n\} = \text{symptom set}$$

$$R_{ij} = (r_{ij})_{m \times n} = \text{fuzzy relation matrix of size } m \times n \text{ between } a \text{ and } b$$

where

$a_1 - a_m$: m kinds of breakdown causes,

$b_1 - b_n$: n kinds of symptoms, and

r_{ij} : the fuzzy truth value between the i th kind of cause and the j th kind of symptom.

The fuzzy truth values of r_{ij} s are acquired empirically from experts of engineering using the following linguistic values [20] [22] (e.g., completely true, very true, true, rather true, rather rather true, and unknown) of the linguistic variable “truth.” Their meaning is defined as follows.

- 1) completely true: Once a_i occurs then b_j appears.
- 2) very true: When a_i occurs, b_j will appear very definitely.
- 3) true: When a_i occurs, b_j will appear very probably.
- 4) rather true: When a_i occurs, b_j will appear probably.
- 5) rather rather true: When a_i occurs, b_j will appear seldom.
- 6) unknown: When a_i occurs, b_j will never appear.

Generally speaking, in a diagnosis problem, the symptoms can be divided into two kinds of categories, the positive symptom set (J_1), consisting of those symptoms that have been observed by the operator, and the negative one (J_2), consisting of those symptoms that have not yet been observed by the operator. When only certain symptoms have been observed by the operator, the diagnosis process can proceed. It is impossible for all the symptoms of the system to appear at one time, so that $J_1 \neq \phi$ and $J_2 \neq \phi$.

Actually during tracing a certain kind of breakdown cause through the observed symptoms, the reliability of diagnostic results should be very high as long as all possible symptoms for this kind of breakdown are all observed [19]. However, if there are many other symptoms (not the observed ones) that should have appeared but have not yet done so, then the reliability of diagnostic results of this kind of breakdown cause will be very low.

We can thus conclude that the diagnostic range can be narrowed effectively by neglecting those breakdown causes seldom noticed a_i . For instance, breakdown causes that are in accordance with the circumstance of

$$\bigvee_{j \in J_2} R_{ij} < \text{rather rather true}$$

should firstly be investigated. That is, the searching range of the diagnosis can be

narrowed from $i \in I (= \{i | i = 1, 2, \dots, m\})$ down to

$$i \in I_1 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{rather} \quad \text{rather} \quad \text{true} \right\} \right).$$

A relationship should occur between the breakdown causes searched a_i and the observed symptoms b_j . In other words, the condition of

$$\bigvee_{j \in J_1} R_{ij} > \text{unknown}$$

should be true. Therefore the searching range of diagnosis I_1 can be reconstructed as

$$I_1 = \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{rather} \quad \text{rather} \quad \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\}.$$

In a practical diagnostic procedure in the real world, the members in I_1 are much fewer than those in cause set I (consisting of m members). Thus, an efficient searching method can be obtained.

Nevertheless, in a practical diagnostic procedure, while searching for the members of the set searching range I_1 , the circumstance of $I_1 = \phi$ can happen. Then a wider searching range should be reset to search once again. Yet the wider the searching range is set, the less reliable the breakdown cause found through this diagnostic procedure is. In order to achieve both effectively narrowing the diagnostic searching range and specific reliability of the diagnostic result, the extension of the searching range in a diagnosis procedure should have a proper limitation. Therefore, there are three kinds of searching range selected in this study. These sets and their reliability are represented as

$$I_1 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{rather} \quad \text{rather} \quad \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\} \right),$$

which has the greatest reliability and from which the diagnostic result that is found can be regarded as the actual “cause”;

$$I_2 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{rather} \quad \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\} \right),$$

which is less reliable than I_1 and from which the diagnostic result that is found can be regarded as “very probable”; and

$$I_3 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\} \right),$$

which is the least reliable, and from which the diagnostic result that is found can be regarded as “probable”.

The flow chart of the system’s diagnostic procedures is illustrated in **Figure 5**. Finally after searching for the members of the searching ranges I_1 , I_2 , and I_3 using the effective diagnostic procedure mentioned above, there probably exists the circumstance of $I_1 = I_2 = I_3 = \phi$. Then the system will select five a_s of greater L_i value as the suspected breakdown causes for further diagnosis:

$$L_i = \sum_{j \in J_1} R_{ij} \tag{11}$$

where

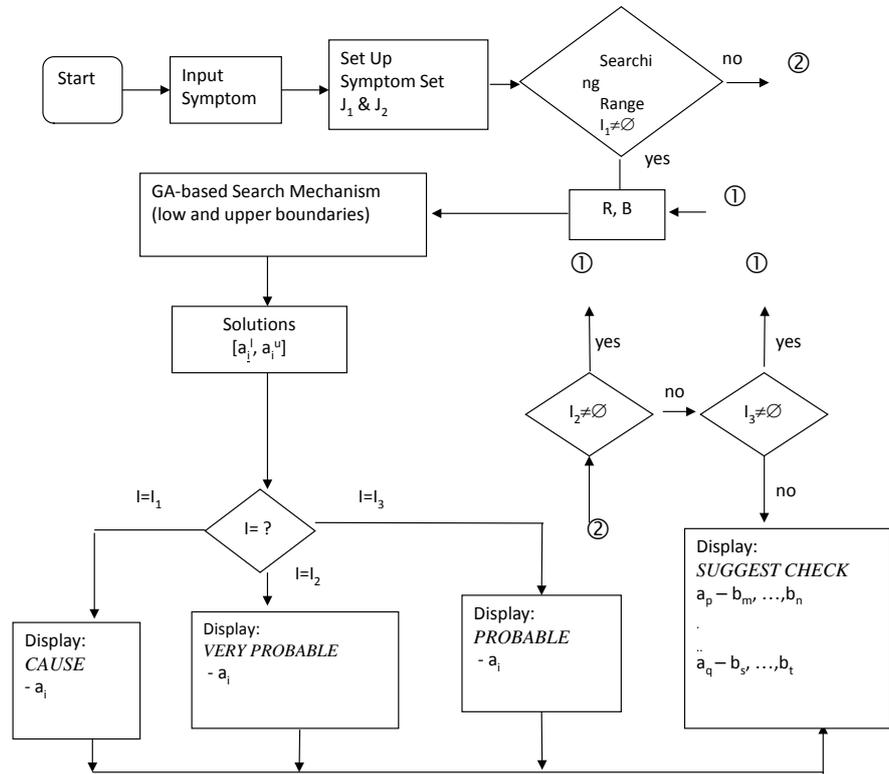


Figure 5. Flow chart of diagnostic procedure for diagnosis system.

R_{ij} : the fuzzy truth value between the i th kind of breakdown cause and the j th kind of symptom.

J_1 : the positive symptom set.

5. Results and Assessment of the System

5.1. System Implementation

An application of the intelligent diagnosis system to tracing the breakdown causes occurred during spinning was reported in this study. There were 6 kinds of defects that are most likely found during spinning and 20 possible occurrence causes of these defects all chosen from and referred to the reports [22] on the occurrence causes and the effects of the defects in spinning.

1) Symptom Set and Cause Set

The cause set A and the symptom set B consist of the above-mentioned 20 causes and 6 kinds of defects respectively and the elements of each of the two are illustrated as below.

SYMPTOMS

b_1 smash

b_2 stick-out on the edge of cone

b_3 ribbon-shaped defects around cone's surface

b_4 ring-shaped defects

b_5 spindle-shaped defects

b_6 too much happening in yarn's cut-off

CAUSES

- a_1 mal-set for Bobbin holder
- a_2 mal-functioned pulley tension caused by neps or cotton trash
- a_3 bobbin slipping from slot
- a_4 gap occurred between bobbin and sketch
- a_5 improper setting of skeleton
- a_6 improper yarn's adjunction
- a_7 big gap on top of cone
- a_8 lack of yarn tension
- a_9 defects in cylinder-slot
- a_{10} too big gap between bottom of bobbin and cylinder
- a_{11} forward shifting during bobbin's circulation
- a_{12} un-smooth spindle-spinning
- a_{13} too big gap on top of cone
- a_{14} over-heavy tension pulley
- a_{15} mal-positioned tension device
- a_{16} mal-functioned back-forth motion
- a_{17} too much yarn tension
- a_{18} mal-positioned empty bobbin
- a_{19} mal-positioned de-knotter
- a_{20} mal-positioned plug base of bobbin

2) Fuzzy Relation Matrix

All the truth values of members of fuzzy relation matrix R are illustrated as **Table 1**. The fuzzy truth value of each r_{ij} in **Table 1** was acquired empirically from experts of textile engineering and technical references [22] [23] on causes and effects of the yarn defects in spinning. By using the linguistic values (e.g., completely true, very true, true, rather true, rather rather true, and unknown) of the "truth" linguistic variable, the fuzzy truth value of each r_{ij} in the fuzzy relation matrix R of the diagnosis system thus can be characterized. Furthermore, for making it feasible for the computer to execute the logic operation processing, the fuzzy truth value of each linguistic value (e.g., completely true, very true, true, rather true, rather rather true, and unknown) is characterized by specific weight value (e.g., 1.0, 0.8, 0.6, 0.4, 0.2, and 0.0) respectively and is listed in **Table 1**, in which A-E represent 1.0, 0.8, 0.6, 0.4, and 0.2, respectively and the blank represents 0.0.

5.2. Diagnosis Example

After the operator examines the defects (breakdown causes) occurred on the yarns, "ring-shaped defects" (*i.e.*, b_4) formed during winding process is found so that symptom " b_4 " is input into the system to proceed with the diagnosis. According to the diagnosis procedure shown in **Figure 4**, the positive and negative symptom sets are $J_1 = \{b_4\}$, $J_2 = \{b_1, b_2, b_3, b_5, b_6\}$ respectively. Firstly, the searching range is narrowed from $I (= \{i | i = 1, 2, \dots, 20\})$ down to

Table 1. Fuzzy relationship between causes and symptoms.

$a_i \backslash b_j$	b_1	b_2	b_3	b_4	b_5	b_6
a_1	A		A	A	B	
a_2	B					
a_3	B					
a_4	C					
a_5	C					
a_6	D					
a_7			A			
a_8		B			A	A
a_9		C				D
a_{10}	A	D				D
a_{11}	A		A	A	B	
a_{12}			A			
a_{13}			B			
a_{14}			C			
a_{15}		E		B		D
a_{16}			E	B		C
a_{17}					A	A
a_{18}	A		A		B	
a_{19}						A
a_{20}						C

$$I_1 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{rather} \quad \text{rather} \quad \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\} \right) \text{ and}$$

$$\left(i.e., I_1 = \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < 0.2, \bigvee_{j \in J_1} R_{ij} > 0 \right\} \right)$$

$$I_2 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{rather} \quad \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\} \right)$$

$$\left(i.e., I_2 = \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < 0.4, \bigvee_{j \in J_1} R_{ij} > 0 \right\} \right).$$

There is no breakdown cause a_p which lives up to the I_1 and I_2 conditions (Lin et al., 1995). Thus the situation (*i.e.*, $I_1 = I_2 = \emptyset$) is found. Next, the searching range is more broadened up to

$$I_3 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\} \right) \left(i.e., I_3 = \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < 0.6, \bigvee_{j \in J_1} R_{ij} > 0 \right\} \right)$$

to investigate the possible breakdown causes. There is a suspected one (*i.e.*, a_{15}), which regarded as “probable”, found under the searching range $I_3 (\neq \emptyset)$ after checking fuzzy relation matrix shown in **Table 1** based on the above-set $J_1 (= \{b_4\})$ and $J_2 (= \{b_1, b_2, b_3, b_5, b_6\})$. Following the suggestion of the “probable” breakdown cause a_{15} (*i.e.*, mal-positioned tension device) from the system, the operator can immediately check it up. It is found nothing wrong with a_{15} after the operator’s inspection. Excluding the “probable” breakdown cause a_{15} , the system provides the operator with five suspected breakdown causes shown as follows.

SUGGEST again CHECK	
$a_1 - b_1, b_3, b_4 , b_5$	$(L_1 = 3.8, J_1 = \{y_4\})$
$a_{11} - b_1, b_3, b_4 , b_5$	$(L_{11} = 3.8, J_1 = \{y_4\})$
$a_{16} - b_3, b_4 , b_6$	$(L_{16} = 1.6, J_1 = \{y_4\})$
$a_{15} - b_2, b_4 , b_6$	$(L_{15} = 1.4, J_1 = \{y_4\})$

where the symptoms with lines to both sides denote the already-recognized ones. The operator re-inspects the product defects in relation to the suspected causes and their related symptoms suggested by the system, and he/she find that there is another two more “stick-out on the edge of cone” (*i.e.*, b_2) and “too much happening in yarn’s cut-off” (*i.e.*, b_6). Therefore he can re-input b_2 , b_4 and b_6 into the system to proceed with the further diagnosis. According to the observed symptoms, the positive and negative symptom are obtained as $J_1 = \{b_2, b_4, b_6\}$ and $J_2 = \{b_1, b_3, b_5\}$ respectively. Firstly, the searching range is set to

$$I_1 \left(= \left\{ i \mid \bigvee_{j \in J_2} R_{ij} < \text{rather} \quad \text{rather} \quad \text{true}, \bigvee_{j \in J_1} R_{ij} > \text{unknown} \right\} \right)$$

to investigate the possible break down causes. The found diagnostic result can be regarded as the actual “cause”. There are five suspected breakdowns (*i.e.*, $a_9, a_{10}, a_{15}, a_{19}, a_{20}$) found based on the searching range $I_1 (\neq \emptyset)$ after checking fuzzy relation matrix shown in **Table 1** based on the above-set $J_1 (= \{b_2, b_4, b_6\})$ and $J_2 (= \{b_1, b_3, b_5\})$. The number of possible breakdown causes are effectively reduced from 20 (*i.e.*, a_1, a_2, \dots, a_{20}) down to 5 (*i.e.*, $a_9, a_{10}, a_{15}, a_{19}, a_{20}$). The obtained vectors, *i.e.*, \underline{A} and \underline{R} , are as follows.

$$\underline{A} = (a_9, a_{10}, a_{15}, a_{19}, a_{20}), \quad \underline{R} = \begin{pmatrix} 0.6 & 0 & 0.4 \\ 0.4 & 0 & 0.4 \\ 0.2 & 0.8 & 0.4 \\ 0 & 0 & 1 \\ 0 & 0 & 0.6 \end{pmatrix}$$

Let the obtained relation matrix \underline{R} has the following form.

	b_2	b_4	b_6	
$\underline{R} =$	a_9	0.6	0	0.4
	a_{10}	0.4	0	0.4
	a_{15}	0.2	0.8	0.4
	a_{19}	0	0	1.0
	a_{20}	0	0	0.6

As the result of product examination the inspector find out there are three defects (*i.e.*, symptoms) occurred, *i.e.*, $b_2 = 1, b_4 = 1, b_6 = 1$. As mentioned above, there is no solution for $b = a \wedge r$ if the magnitude of r is less than b . Therefore the values of $b_2, b_4,$ and b_6 are adjusted to the maximum values of the respective columns in \underline{R} matrix and shown as follows.

$$b_2 = \max r_{i2} = 0.6, \quad b_4 = \max r_{i4} = 0.8, \quad b_6 = \max r_{i6} = 1.0,$$

where $i = 9, 10, 15, 19$, and 20 .

Once the vectors, *i.e.*, \mathbf{R} and \mathbf{B} , are obtained, we can proceed with the 3-step method mentioned in Section 3 to search for the upper and low boundaries.

Firstly, following the three steps mentioned in Section 4, we encode the unknown occurring possibility of breakdown causes (*i.e.*, $a_9, a_{10}, a_{15}, a_{19}$, and a_{20}) by using a binary coding method. The bit-size of each of them is set to 7 bits in this study. Thus a chromosome illustrated in **Figure 4** can be formed as a 35 ($= 5 \times 7$)-bit string. The search ranges of variable $a_9, a_{10}, a_{15}, a_{19}$, and a_{20} are set to be the same as $[0, 1]$ (*i.e.*, $[d_i^l, d_i^u]$, $i = 9, 10, 15, 19$, and 20). Through proceeding with the search mechanism of GA based on Equations (7) and (9), we can find a solution, whose fitness approaches to 1, as the optimal one. Fitness function simulation runs with the crossover, mutation, and reproduction operations under conditions of crossover probability, mutation probability, random seed, and initial population being set to 0.3, 0.033, 0.8 and 30 respectively. **Figure 6** shows the simulation graph for the best fitness and average fitness of the 50 generations. It shows that after 46th generation the solution is not improved. Therefore, we choose vector (0.60, 0.00, 0.99, 0.98, 0.25), which is generated from the 50th generation and has fitness = 0.9998 as the optimal solution. Therefore a null solution $a_i^{(0)}$ is found and shown as follows.

$$a_9^{(0)} = 0.60, a_{10}^{(0)} = 0.00, a_{15}^{(0)} = 0.99, a_{19}^{(0)} = 0.98, a_{20}^{(0)} = 0.25$$

Secondly, by means of the null solution, we can search for the upper and low boundaries. **Table 2** and **Table 3** illustrate the searched results for the upper and low ones respectively. When search the upper boundaries, the search ranges of variable $a_9, a_{10}, a_{15}, a_{19}$, and a_{20} are set different to each other as $[0.60, 1], [0, 1], [0.99, 1], [0.98, 1]$ and $[0.25, 1]$ (*i.e.*,

$$[d_9^{l(0)}, d_9^{u(0)}], [d_{10}^{l(0)}, d_{10}^{u(0)}], [d_{15}^{l(0)}, d_{15}^{u(0)}], [d_{19}^{l(0)}, d_{19}^{u(0)}] \text{ and } [d_{20}^{l(0)}, d_{20}^{u(0)}]).$$

Through proceeding with the search mechanism of GA, we can find a solution, whose fitness approaches to 1, as the optimal one. An optimal solution after generations of GA search can be obtained as follows.

$$a_9^{(1)} = 0.66, a_{10}^{(1)} = 0.80, a_{15}^{(1)} = 0.99, a_{19}^{(1)} = 0.99, a_{20}^{(1)} = 0.43$$

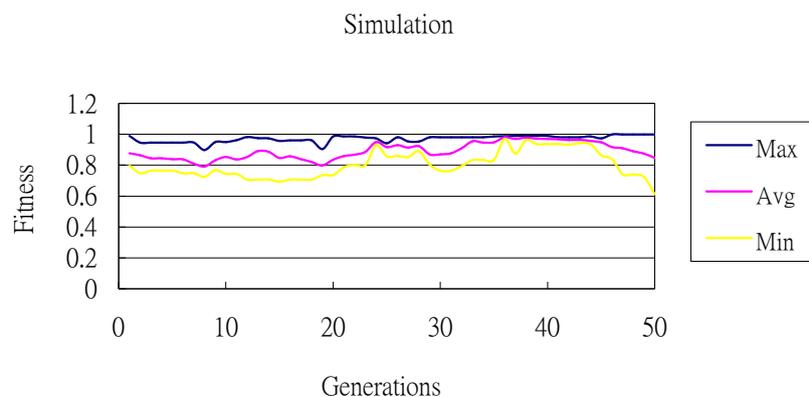


Figure 6. Simulation results.

By narrowing down the search range step by step, the upper boundaries of $a_9^u, a_{10}^u, a_{15}^u, a_{19}^u$ and a_{20}^u can be acquired. **Table 2** shows the searched results after five iterations. Finally, the obtained values of $a_9, a_{10}, a_{15}, a_{19}$, and a_{20} remains the same (i.e., $a_i^{(6)} = a_i^{(5)}$), the search is stopped.

When search the low boundaries, the search ranges of variable $a_9, a_{10}, a_{15}, a_{19}$ and a_{20} are set different to each other as $[0, 0.60], [0, 0], [0, 0.99], [0, 0.98]$, and $[0, 0.25]$ (i.e., $[d_i^{l(0)}, d_i^{u(0)}], i = 9, 10, 15, 19, 20$). Through proceeding with the search mechanism of GA, we can find a solution, whose fitness approaches to 1, as the optimal one. An optimal solution after generations of GA search can be obtained as follows.

$$a_9^{(1)} = 0.46, a_{10}^{(1)} = 0.00, a_{15}^{(1)} = 0.78, a_{19}^{(1)} = 0.70, a_{20}^{(1)} = 0.11$$

By narrowing down the search range step by step, the low boundaries of $a_9^l, a_{10}^l, a_{15}^l, a_{19}^l$, and a_{20}^l can be acquired. **Table 3** shows the searched results after five iterations. Finally, the obtained values of $a_9, a_{10}, a_{15}, a_{19}$, and a_{20} remains the same (i.e., $a_i^{(6)} = a_i^{(5)}$), the search is stopped.

Table 2 and **Table 3** shows that the solution to fuzzy logical equation can be expressed in the form of intervals

$$a_9 = [0,1], a_{10} \in [0,1], a_{15} \in [0.36,1], a_{19} \in [0.44,1], a_{20} \in [0,1].$$

The obtained solution allows making a diagnosis conclusion. The cause of the observed defects should be considered as a_{19} (i.e., mal-positioned de-knotter), because of which has a higher solution boundary than the other four. Excluding

Table 2. Genetic search for upper boundaries of the intervals.

N	a_9	a_{10}	a_{15}	a_{19}	a_{20}
0	0.60	0.00	0.99	0.98	0.25
1	0.66	0.80	0.99	0.99	0.43
2	0.87	0.93	1.00	1.00	0.66
3	0.90	0.97	1.00	1.00	0.93
4	0.92	0.99	1.00	1.00	0.95
5	1.00	1.00	1.00	1.00	1.00
6	1.00	1.00	1.00	1.00	1.00



increasing

Table 3. Genetic search for low boundaries of the intervals.

N	a_9	a_{10}	a_{15}	a_{19}	a_{20}
0	0.60	0.00	0.99	0.98	0.25
1'	0.46	0.00	0.78	0.70	0.11
2'	0.35	0.00	0.61	0.58	0.01
3'	0.12	0.00	0.48	0.56	0.00
4'	0.03	0.00	0.44	0.52	0.00
5'	0.00	0.00	0.36	0.44	0.00
6'	0.00	0.00	0.36	0.44	0.00



decreasing

the obtained solution, system supports five a_i s of greater L_i value as the suspected breakdown causes for further diagnosis. They are illustrated as follows.

SUGGEST again CHECK	
$a_1 - b_1, b_3, b_4 , b_5$	$(L_1 = 3.8, J_1 = \{y_2, y_4, y_6\})$
$a_{11} - b_1, b_3, b_4 , b_5$	$(L_{11} = 3.8, J_1 = \{y_2, y_4, y_6\})$
$a_8 - b_2 , b_3, b_6 $	$(L_8 = 2.8, J_1 = \{y_2, y_4, y_6\})$
$a_{17} - b_3, b_6 $	$(L_{17} = 2.0, J_1 = \{y_2, y_4, y_6\})$
$a_{10} - b_1, b_2 , b_6 $	$(L_{10} = 1.8, J_1 = \{y_2, y_4, y_6\})$

where the symptoms with lines to both sides denote the already-recognized ones.

Through the assistance of the diagnosis system, the operator can obtain three derived suspected breakdown causes $a_9, a_{10}, a_{15}, a_{19}$ and a_{20} , which have a reliability of “cause” because the searching range is J_1 , to help him/her in troubleshooting and eliminating the breakdown. In this experimental case, after the technician for maintenance in the mill proceeding with the troubleshooting, the exact breakdown cause is confirmed to be a_{19} (*i.e.*, mal-positioned de-knotter). From the diagnostic case illustrated as above, the accuracy of the implementation of this system is approvable. Even when the diagnostic result is not the exact breakdown cause, nevertheless, the system will still provide the operator with some suspected ones for further check. This system can thus achieve the demand of providing with a solution in any circumstance during diagnosing in the real world.

6. Conclusion

The determination on the breakdown causes becomes more effective and efficient by adopting a GA-based diagnosis procedure proposed in the study. It was constructed that using the fuzzy set theory, which does not simply perform the routine calculations like those developed by the conventional programming algorithm, can be more flexible and effective to find the solution to fuzzy logical equation by genetic algorithm. The developed diagnosis model is of the nature of human capability in recognition and evaluation of uncertain linguistic description. Through the assistance of the developed diagnosis model, even a new inspector, who lacks in the expertise and experience in the spinning engineering field, can still easily find out the breakdown causes occurred during manufacturing process and then eliminate them. Furthermore, it is expected that the developed diagnosis model can be applied to other industries for the troubleshooting of machines or facilities as long as the relation matrix for the application in specific field is provided.

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