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Full Length Research Paper

Railway security through the use of wireless sensor networks based on fuzzy logic

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Wireless sensor networks have been widely used in various areas, and their use in railway to reduce human and material losses has been a remarkable development. In this article, sensors placed in different places in railway are described and the way they recognize flaws in the railway is explained. The data read by the sensors are sent to the sink node to be processed. Fuzzy logic has been used to process these data.

Key words: Fuzzy logic, fuzzy control system, railway security system, learning, wireless sensor network (WSN).

INTRODUCTION

Accidents in railway lines include collision with snags, derailment and human losses due to movements of trains. Railway transportation is usually very safe for passengers, although railway accidents and train derailment still happen. To solve this problem, a railway security system is proposed in this article. Wired sensor networks are usually easy to employ, but implementation of these systems poses problems due to the length of railway lines. On the other hand use of wireless sensor networks promises a very interesting and practical option. With recent advances in wireless communication and in electronics, there has been a reduction in the price, power, and size of sensor nodes. There sensors include a microprocessor, a multi-byte RAM, a short-range, short-wave radio transmitter, and a small power source (like a battery). Sensors are employed so that the system can encounter the environment (Zhao and Guibas, 2004; Culler et al., 2004).

The main technique and the major aim of this system is to develop a new solution, based on a wireless network systems, for the problems faced in railway lines. The purpose in studying railway lines includes finding new methods to reduce the rate of accidents and improving the efficiency of railway-line maintenance.

WIRELESS SENSOR NETWORKS

Wireless sensor networks are wireless communication networks in which constructed when small sensor devices without any predetermined routers are jointly arrayed to sense happenings and events (Srovnal and Penhaker, 2007). A wireless sensor network consists of three units: sensor nodes, collection hardware and data processing (the sink node), and a remote-monitoring device (the control center). Sensor nodes are in charge of collecting data and sending it to the sink node (Pandian and Safeer, 2008).

Wireless sensor networks in railway

Figure 1 shows a wireless sensor network in a railway line. This network includes one or several control centers (sink nodes) which are connected to each other by wires. A large number of wireless sensor nodes are distributed throughout railway lines. Each of these distributed sensor nodes is able to collect the required data and to send it to the sink node (the control center) (Ganesan, 2002, Ding and Sivalingam, 2003; Sadeghi, 2008). In Figure 1,

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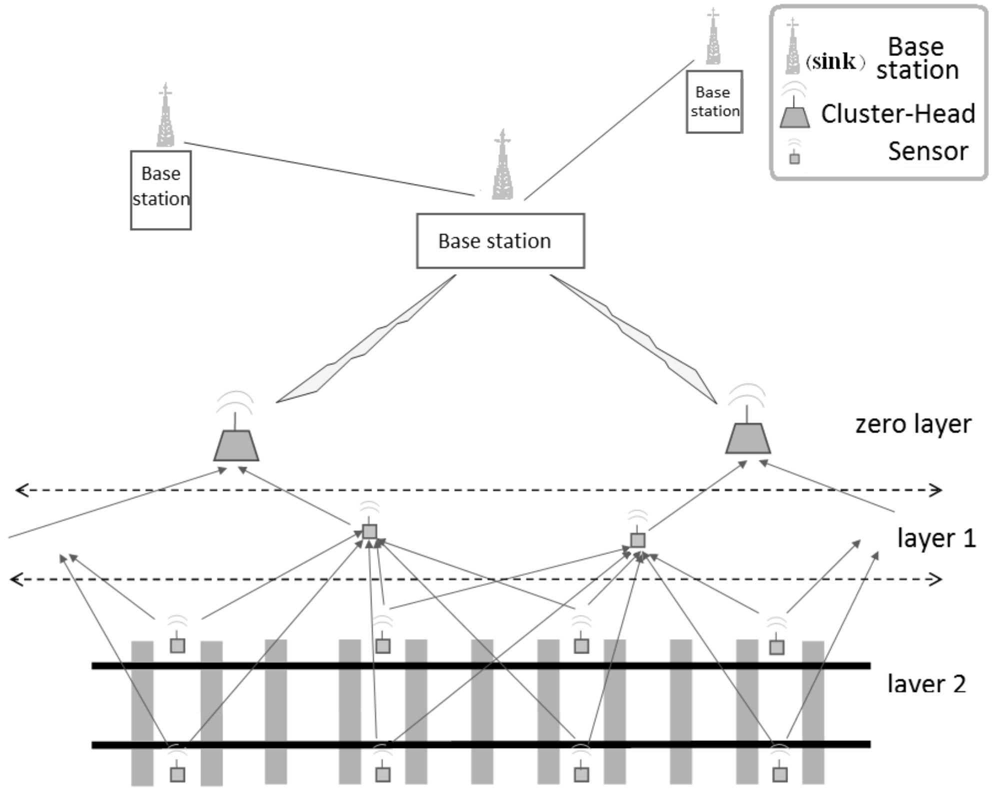

Figure 1. Source railway system with wireless sensor nodes and multi-layer routing.

multi-layer routing is also shown. It can be seen that each sensor sends the information gathered from the environment to two nearby cluster-heads. This routing tree is multi-layered. The sensor nodes in the lowest layer (layer 2) send their data packages to the next higher layer (layer 1) rather than sending them directly to a cluster-head or to the base station (the control center). Through distributing data in several steps, the power lost in transmitting data can be considerably reduced as compared to sending data directly in one step (www.railsonic.co.za/TechnicalInformation.pdf).

The cluster-head is a node that can convert several packages into one and send the combined package to be added to the collected information in the center; and thus there will be a reduction in the power spent in transmitting data in the network.

Sensors recognizing flaws in railway lines

Methods of recognizing chafe and breaks in railway lines

Breaks in railway lines are lines and are still one of the biggest causes of train derailment. The most common break is a crack in the crown of the rail that forms an approximate 70° angle with the horizon line. This flaw, due to its peculiar shape, is known as the kidney defect. Breaks in rail may vary from a narrow crack to the separation of a part of a rail. In some cases, the break happens inside the rail during its manufacturing process. To detect these defects, the ultrasonic method is employed: ultrasonic waves are injected into the rails by special transducers.

This high-energy signal is sent in two directions at predetermined intervals. The transmitted signal is propagated in the rail and is received by receivers. The nearby transmitters send ultrasonic waves with the same frequency but with different periods (Aboelela et al., 2006). In this way, the receivers will be able to recognize the direction (left or right) from which they receive the signal. If there is a break or chafe in the rail, the amplitude of the waves received by receivers will be reduced and an alarm signal will be sounded.

In Figure 2, the block diagram of the system of recognizing breaks is rails in the ultrasonic method are shown. To track cross (horizontal) defects that happen in the crown of the rail, the ultrasonic method is used: power is concentrated in the crown of the rail so that it becomes possible to track these defects as the ultrasonic waves are maximized (Hay and Hay, 2006). Cross defects are tracked as percentages in CSHA units. Ultrasonic sensors are alternately installed 1.75km apart from each other in the inside wall of the rail (on both

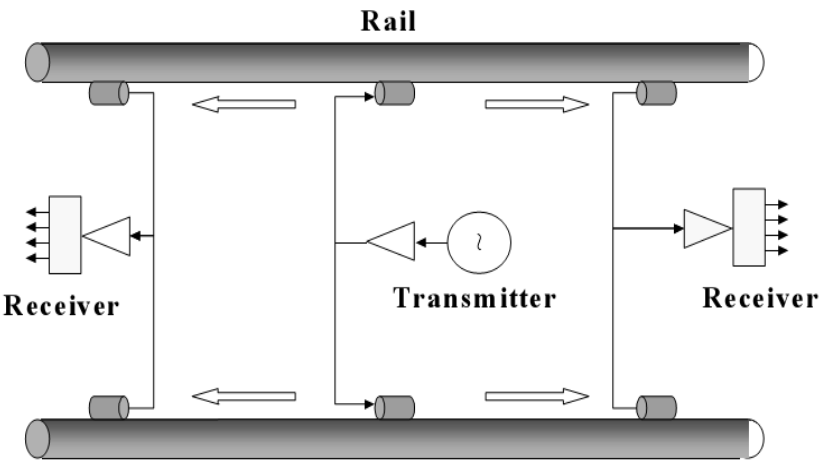

Figure 2. Block diagram of the ultrasonic broken rail detector system (UBRD).

rails); and they must be in complete contact with the crown of the rail, in this way by increasing the number of the rail which needs to be investigated. Figure 3 shows how ultrasonic sensors are positioned.

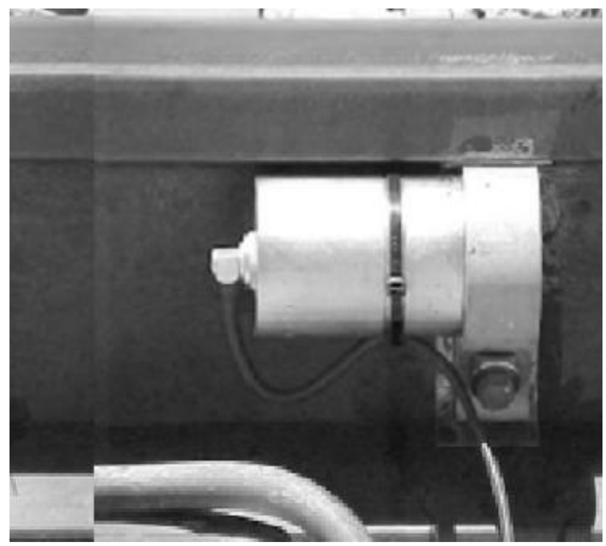

Figure 3. The positioning of ultrasonic sensors for transmitting and receiving waves.

The system for tracking objects and snags in rails

In this system, two methods are used:

1. In the image processing method, the systems for tracking objects on the rail are able to track stones, wood, metallic objects, animals, human beings, and vehicles (at railway crossings): the pictures continuously taken of the rail by one or two video cameras are analyzed by a system for processing pictures. There are many algorithms for tracking objects, but the basic performance of these algorithms is based on first tracking the rails and then on finding breaks on either of the two rails. The presence of a break signifies the presence of a foreign object on the rails.
2. In the leaky cable method, the system for recognizing objects and snags on rails is designed to be installed at places where there is a possibility of landslide covering rails with stones. The principle underlying the performance of the system is that whenever an object is located near a source radiating electromagnetic waves (like an antenna), it causes a change in the impedance of the source, and hence the intensity of the radiated waves will change. In this system, a leaky coaxial cable, which is laid on the rail bed on the ground, acts as a radiating source and the sensor system which injects waves into this cable continuously evaluates the volume of the return wave. Under normal conditions, the volume of the return wave is constant, which is considered the reference volume when the system is installed and starts operating. In case any foreign object gets near the cables, the radiation impedance will change and the sensor can reveal this change and sense this change as a sign of the presence of a foreign object on the rail. The block diagram of a system for recognizing objects on a rail in the leaky cable method is shown in Figure 4.

The message format

The message format (FLODA or Fuzzy logic based on data aggregation) in the wireless sensor network in railway lines is shown in Figure 5. In wireless sensor networks, the power used by each node depends on the cost of received and sent messages. According to the

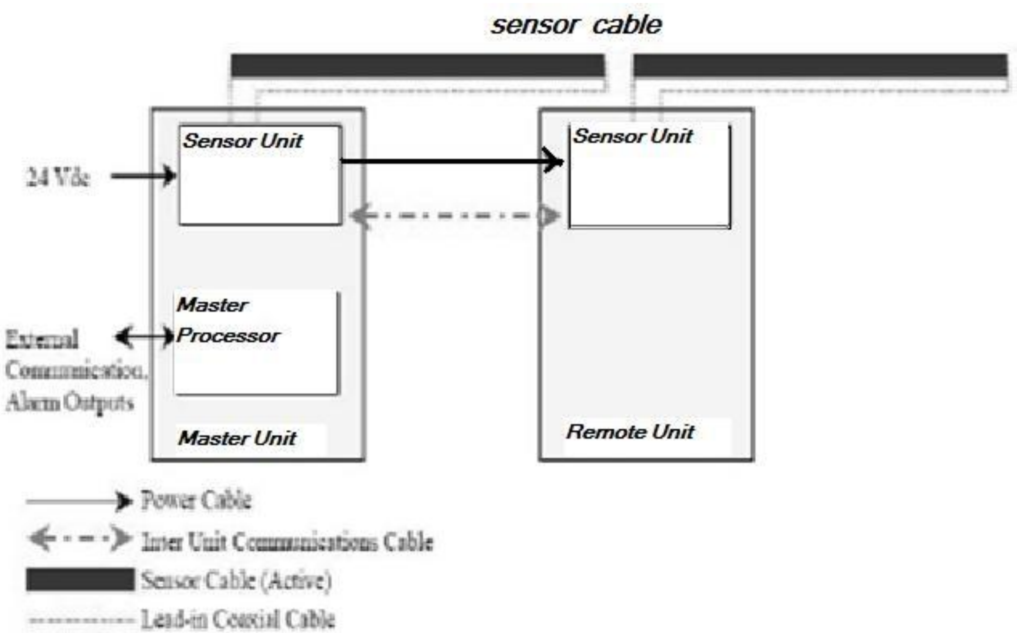

Figure 4. The block diagram of a system recognizing objects on rails in the leaky electromagnetic method.

ID	Area (start,end)	Type	F	μ_f	Time

Figure 5. The message format.
ID: Position of the identifier of transmitting nodes.
Area: Coordinates (start and end) of the area covered.
Type: The code of the phenomenon reported in the message. The size of this field must be bigger than $\log_2 P$ bits, where P is number of phenomena measured.
F: The fuzzy set which describes the quantity of the phenomenon reported. The size of this field must be bigger than $\log_2 S$ bits, where S is the number of fuzzy sets of the phenomena measured.
Time: Is used in synchronizing node time in WSN and will be used in the fuzzy deduction system in collective processing.

above description of the FLODA message, it becomes clear that Fuzzy logic has an important role in reducing the size of received and sent messages (Madden, 2002).

FUZZY CONCEPTS

The concept of Fuzzy logic was put forward by Dr. Lotfizadeh, an Iranian professor at the University of California, in Berkeley, as not only a control methodology but also as a way of processing data on the basis of authorizing membership in small groups rather than membership in cluster groups. This logic is the mathematical representation of the formation of human concepts and of reasoning concerning human concepts. Operations employed in using fuzzy logic are as follows (Passino and Yurkovich, 1998):

1. Determining the input and the output of the system.
2. Selecting the shape and boundaries of input membership functions (MF).
3. Converting input numerical variables into fuzzy variables.
4. Selecting the shape and boundaries of output membership functions (MF).
5. Determining suitable rules and applying them on the input.
6. Converting fuzzy answers to numerical values as the output.

Table 1. Fuzzy linguistic expressions for output/input variables of the system.

Item number	Parameters	Type	Linguistic expression
1	Temperature	Input	No freeze, low freeze, high freeze
2	Snag	Input	None, small, big
3	Chafe	Input	Low, med, high
4	Crack	Input	Low, med, high
6	Destruction	Output	Low, med, high, very high

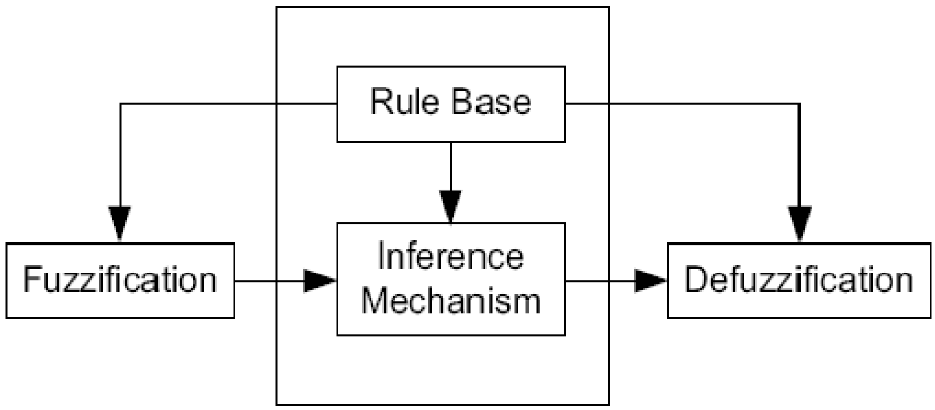

Figure 6. A model of Fuzzy control system designed for the control system.

Fuzzy logic is a simple rule on the basis of: IF x and y then z. In our proposed method, the sender and the receiver (the possible positions for these nodes) are used as the input and the reward function is used as the output. Monitoring of gas pipes has been carried out by using fuzzy logic; and the natural gas consumption pattern has been improved by measuring gas pressure and consumption so that gas pressure will not drop in a specific area and will be balanced in all gas pipes (Shamshirband, 2010).

Use of fuzzy logic in the proposed system

In this part, a series of linguistic variables, with the fuzzy sets related to them, are used to make decisions in investigating immediate and long-term problems in railway lines. These input linguistic variables are temperatures, snags, chafe, and cracks; and the decision made is determined as an output linguistic variable of the defect. The expressions of the linguistic variables are shown in Table 1. Limitations of sensors, according to standards, are as follows:

1. Acceptable temperature: (-70, +80°C)
2. Acceptable degree of snags: (0, 100%)
3. Acceptable degree of chafe: (0, 100%)
4. Acceptable degree of cracks: (0, 100%)
5. Acceptable degree of defect for the output parameter: (0, 100%)

In this system, sensors recognize temperature, snags, chafe, and cracks, this information is analyzed by the fuzzy deduction system (Figure 6), and the degree of defect is displayed as the output. In the fizzy deduction system, the Mamdani deduction mechanism has been used because it is easy and more suitable for designing fuzzy systems. Features and fuzzy linguistic synonyms for the Input/Output system variables are shown in Table 2.

Implementing the project in Matlab software

The input linguistic variable of temperature

The input linguistic variable of temperature is divided into the three subintervals of high freeze, low freeze, and no freeze, which are explained below.

1. High freeze: this set is on the basis of parabolic membership functions of the type zmf. In this set, the membership degree of one is assigned for temperatures below -30°C, the membership degree of 0 is given to temperatures higher than -20°C, and temperatures between -20 and -30°C receive membership degrees between zero and one. This range is shown in Figure 7.

Table 2. The features of the input/output variables of the system.

Item number	Parameters	Minimum	Maximum	Unit
1	Temperature	-70	80	°C
2	Snag	0	100	%
3	Chafe	0	100	%
4	Crack	0	100	%
5	Destruction	0	100	%

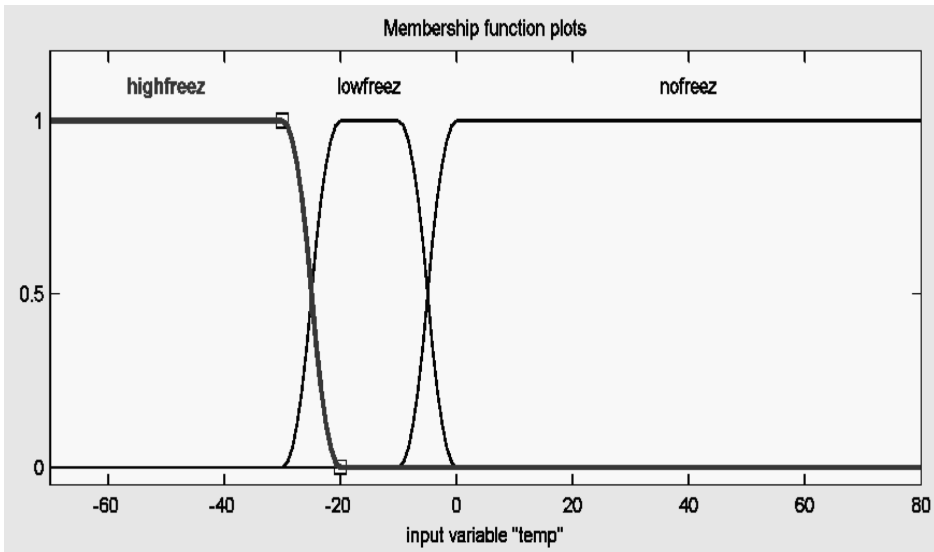

Figure 7. The Membership function of the input linguistic variable of temperature.

2. Low freeze: this set is on the basis of parabolic membership functions of the type pimf. In this set, temperatures below -30°C and above 0 receive the membership degree of one, and temperatures between -10 and -20°C are given the membership degree of one, and temperatures between -20 and -30°C and between -10 and 0°C are assigned membership degrees from 0 to 1. This range is shown in Figure 7.
3. No freeze: this set is on the basis of parabolic membership function of the type smf. In this set, the membership degree of zero is assigned to temperature below -10°C, the membership degree of one is given to temperatures above 10°C, and membership degrees between o and 1 are considered for temperatures between -10 and 0°C. This range is shown in Figure 7.

As an example, the membership functions of the temperature variable in fuzzy sets are given below:

$$\mu_{nf}(temp)\begin{cases} 0 & \alpha \le -10 \\ \dfrac{\alpha+10}{10} & -10 < \alpha < 0 \\ 1 & \alpha \ge 0 \end{cases}$$

$$\mu_{hf}(temp)\begin{cases} 0 & \alpha \le -30, \alpha \ge 0 \\ \dfrac{\alpha+30}{10} & -30 < \alpha \le -20 \\ \dfrac{-\alpha}{10} & -10 < \alpha \le 0 \\ 1 & -20 < \alpha < -10 \end{cases}$$

$$\mu_{hf}(temp)\begin{cases} 0 & \alpha \ge -20 \\ \dfrac{-\alpha-20}{10} & -30 < \alpha < -20 \\ 1 & \alpha \le -20 \end{cases}$$

The input linguistic variable of temperature

The input linguistic variable of snag is divided into three sub-intervals:

1. None: this set is based on parabolic membership functions of the type zmf. Values less than 15% are given the membership degree of 1, values bigger than 25% receive the membership degree of 0, and values between

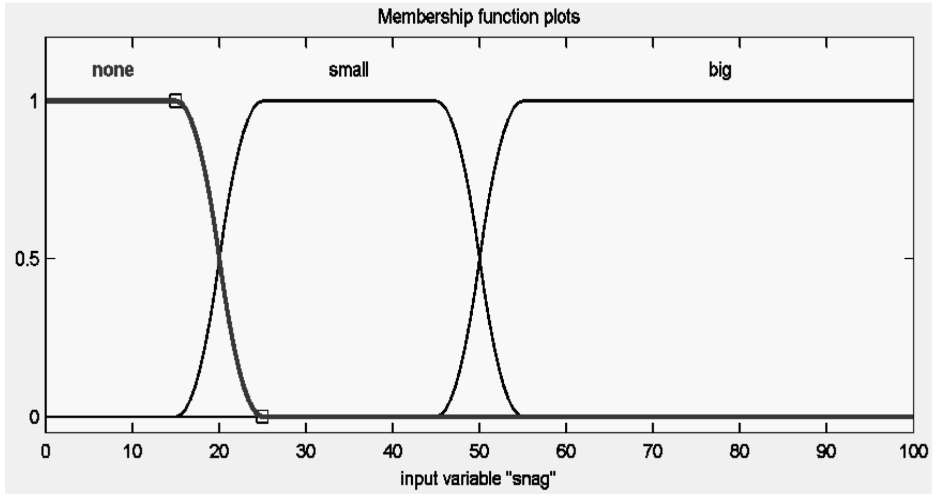

Figure 8. The input linguistic membership function of the variable snag.

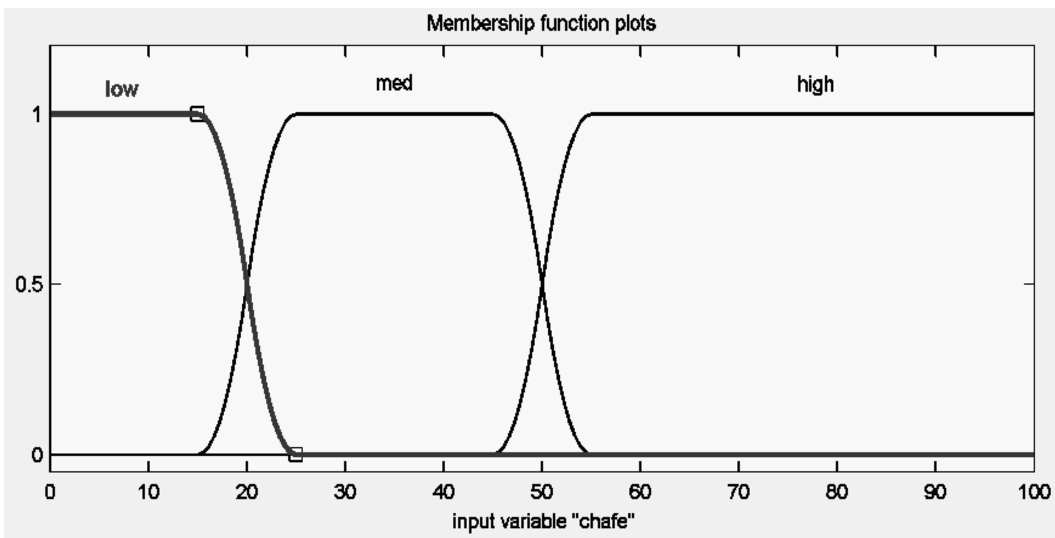

Figure 9. The input linguistic membership function of the variable chafe.

15 and 25% receive membership degrees from 0 to 1. This range is shown in Figure 8.

2. Small: this set is based on parabolic membership functions of the type pimf. Values less than 15% and more than 55% receive the membership degree of zero, values between 25 and 45% are given the membership degree of one, and values between 15 and 25% between 45 and 55% are assigned membership degrees from 0 to 1. This range is shown in Figure 8.

3. Big: this set is based on parabolic membership functions of the type smf. Values less than 45% are given the membership degree of zero, values greater than 55% receive the membership degree of 1, and values between 45 and 55% are assigned membership degrees from 0 to 1. This range is shown in Figure 8.

The Input linguistic variable of chafe

The input linguistic variable of chafe is divided into three sub-intervals: none, big, and small, which are described below.

1. Low: this set is based on parabolic membership functions of the type zmf. Values less than 15% receive the membership degree of 1, values more than 25% are given the membership degree of 0, and values between 15 and 25% are assigned membership degrees from 0 to 1. This range is shown in Figure 9.

2. Med: this set is based on parabolic membership functions of the type pimf. Values less than 15% and more than 55% receive the membership degree of 0, values between 25 and 45% are given the membership

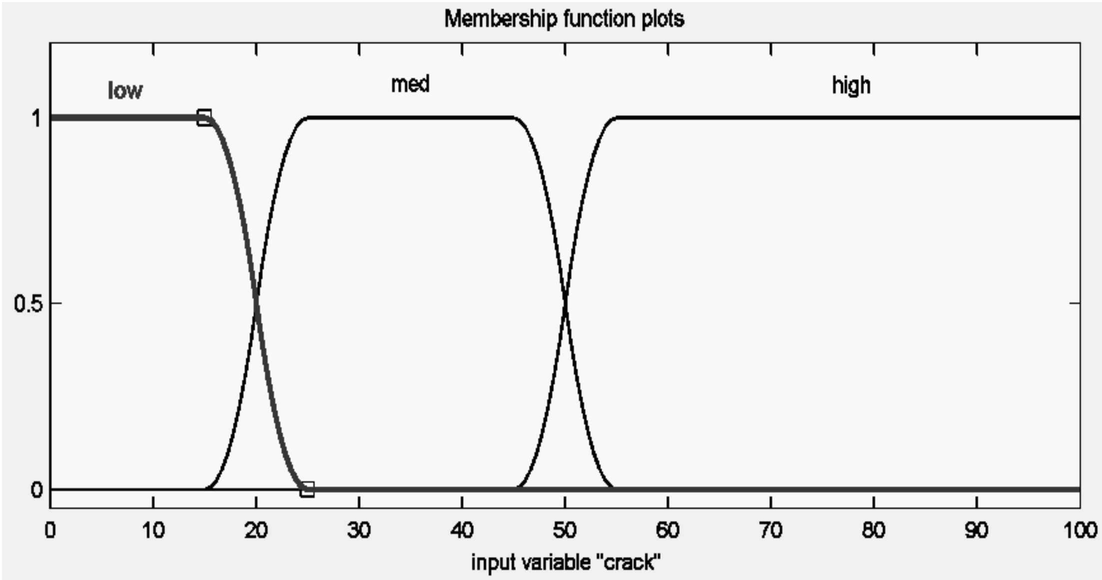

Figure 10. The input linguistic membership function of the variable crack.

degree of 1, and values between 15 and 25% and between 45 and 55% are assigned membership degrees from 0 to 1. This range is shown in Figure 9.

3. High: this set is based on parabolic membership functions of the type smf. Values less than 45% receive the membership degree of 0, values than 45% receive the membership degree of 0, values more than 55% are given the membership degree of 1, and values between 45% are assigned membership degrees from 0 to 1. This range is shown in Figure 9.

The input linguistic variable of crack

The input linguistic variable of crack is divided into three sub-intervals: low, high, and med, which are explained below.

1. Low: this set is based on parabolic membership functions of the type zmf. Values less than 15% are given the membership degree of one, values more than 25% receive the membership degree of 0, and values between 15 and 25% are assigned membership degrees from 0 to 1. This range is shown in Figure 10.

2. Med: this set is based on parabolic membership functions of the type pimf. Values less than 15% and more than 55% receive the membership degree of 0, values between 25 and 45% are given the membership degree of 1, and values between 15% and between 45 and 55% are assigned membership degrees from 0 to 1. This range is shown in Figure 10.

3. High: this set is based on parabolic membership functions of the type smf. Values less than 45% are given the membership degree of 0, values more than 55% receive the membership degree of 1, and values between 45 and 55% receive membership degrees from 0 to 1. This range is shown in Figure 10.

The input linguistic variable of destruction

The output linguistic variable of destruction is divided into four sub-intervals: very high, high, med, and low, which are described below.

1. Low: this set is based on parabolic membership functions of the type zmf. Values less than 10% are given the membership degree of 1, values more than 20% receive the membership degree of 1, values more than 20% receive the membership degrees from 0 to 1. This range is shown in Figure 11.

2. Med: this set is based on parabolic membership functions of the type pimf. Values less than 10% more than 40% receive the membership degree of 0, values between 20 and 30% are given the membership degree of 1, and values between 10 and 20% and between 30 and 40% are assigned membership degrees 0 to 1. This range is shown in Figure 11.

3. High: this set is based on parabolic membership functions of the type pimf. Values less than 30% and more than 60% receive the membership degree of 0, values between 40 and 50% are given the membership degree of 1, and values between 30 and 40% and between 50 and 60% are assigned membership degree from 0 to 1. This range is shown in Figure 11.

4. V_high: this set is based on parabolic membership functions of the type smf. Values less than 50% receive the membership degree of 0, values more than 60% are given the membership degree of 0, values more than 60% are given the membership degree of 1, and values

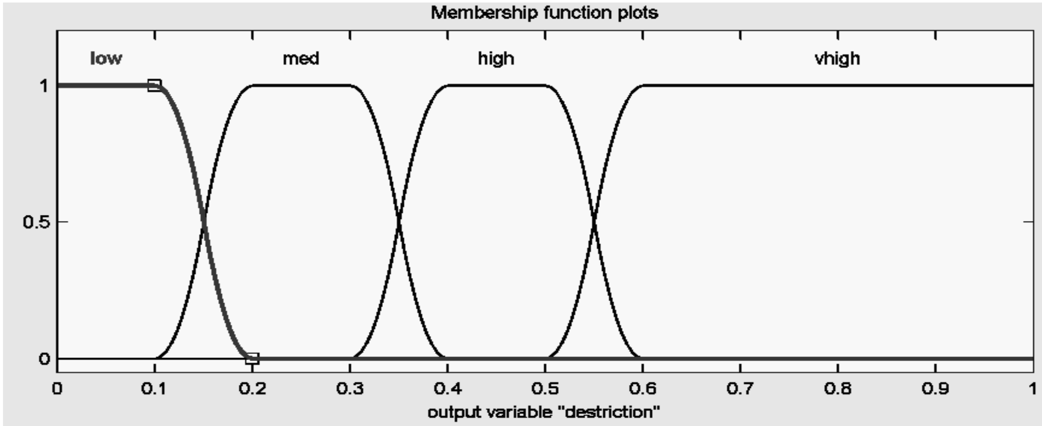

Figure 11. The output linguistic membership function of the variable destruction.

Table 3. The degree of the intensity of the variable.

Description	Degree of intensity
Little Description which does not affect transportation by train	Low
Description may limit transportation by train	Med
Description usually limits train speed	High
Description shuts down transportation by train	V-high

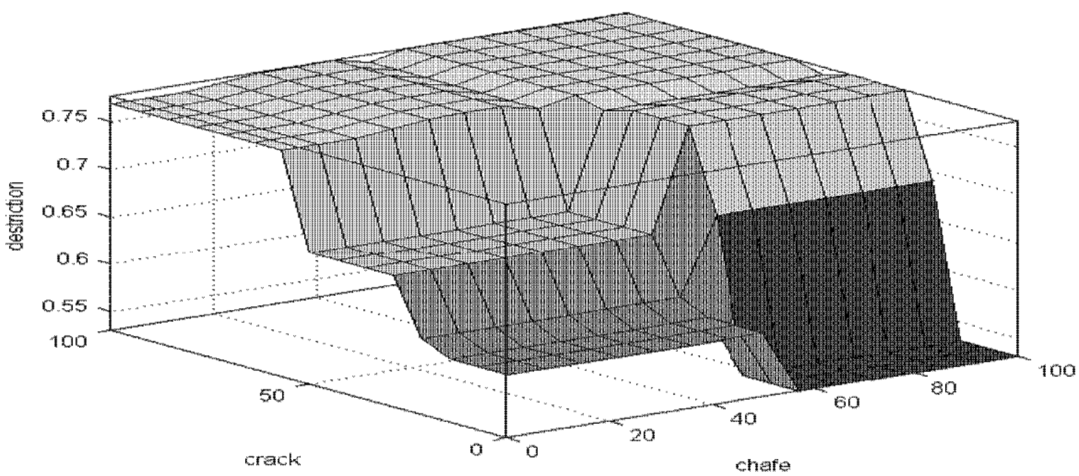

Figure 12. The output linguistic membership function of the variable destruction with the two input of crack and chafe.

between 50 and 60% are assigned membership degree 0 to 1. This range is shown in Figure 11. The Degree of the Intensity of the Variable is shown in Table 3.

The Output linguistic membership function of the variable destruction with the two input of Crack and chafe is shown in Figure 12 and The Output linguistic membership function of the variable destruction with the two input of snag and temperature is Figure 13.

Rules in fuzzy deductive system

After defining input and output linguistic variables and stating their Fuzzy sets, Fuzzy rules are used to establish a relationship between input and output Fuzzy variables. In this way, their relationship is found and on this basis the fuzzy rules are determined. Examples of these rules are shown in Table 4.

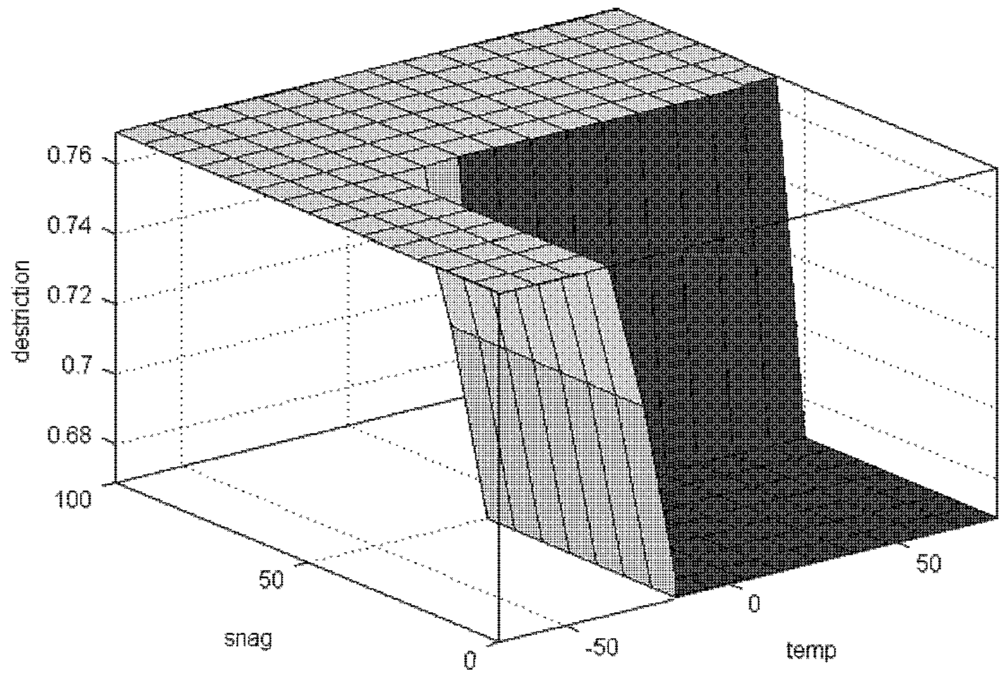

Figure 13. The output linguistic membership function of the variable destruction with the two input of snag and temperature.

Table 4. Some of the rules for recognizing destruction.

Rule number	Temperature	Snag	Chafe	Crack	Alarm
1	No freeze	None	Low	Low	Low
2	No freeze	None	Low	Med	Med
3	No freeze	None	Low	High	V- High
4	No freeze	None	Med	Low	V- High
…					
75	High freeze	Big	Low	High	V- High
76	High freeze	Big	Med	Low	V- High
77	High freeze	Big	Med	Med	V- High
78	High freeze	Big	Med	High	V- High
79	High freeze	Big	High	Low	V- High
80	High freeze	Big	High	Med	V- High
81	High freeze	Big	High	High	V- High

CONCLUSION

Train accidents all over the world, and human and material losses suffered in these accidents, have prompted scholars to tackle these accidents by using up-to-date technology and to ensure security in train transportation. In this article also, an attempt has been made to track problems such as snags on rails in suspicious areas, breaks in rail, etc. through the use of wireless sensor networks in which electromagnetic and ultrasonic sensors are used. Information thus gathered can be sent to control centers in time so that proper decisions are made and security is established by taking suitable actions.

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