

Fuzzy Algorithm for the Detection of Incidents in the Transport System

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ABSTRACT

In the paper it's proposed an algorithm for the management of traffic incidents, aimed at minimizing the impact of incidents on the road traffic in general. The proposed algorithm is based on the theory of fuzzy sets and provides identification of accidents, as well as the adoption of appropriate measures to address them as soon as possible. A criterion of algorithm's effectiveness is the time interval from beginning of accident until its complete elimination. In this paper the main stage of development of fuzzy algorithm are considered, linguistic variables and fuzzy rules are introduced, as well as it's reviewed an example of the work of the proposed algorithm.

KEYWORDS

Transport system, accident, fuzzy algorithm, monitoring, situational management, fuzzy situational network, knowledge base, fuzzy inference, fuzzy linguistic variables, fuzzy rules

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Introduction

Congestion on the roads is a major problem in many cities, and the constant increase of traffic flow on the roads worsens this problem. In urban areas, congestion can occur during the day (morning and/or evening), during the peak periods, but also in other hours (Toymentseva et al., 2016; Sultangazinov et al., 2016; Akhmadieva, 2015; Akhmadieva & Minnikhanov, 2015; Bulat & Volkov, 2016). Various researches have shown that about 60% of the causes of the congestion on the road are the result of occurred traffic accident (Hourdos, Garg & Michalopoulos, 2008).

One of the defining characteristics of modern road infrastructure is used in transport system technologies to monitor the current traffic situation. Nowadays roads are exposed by various risk of safety. The risk of safety is non-recurring and unpredictable events that lead to the appearance congestion (such as crash, construction works, broken vehicle, as well as other non-typical activity on the

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roads). Such congestion increases transportation time, excessive fuel consumption and air pollution.

The traffic incident management system is aimed at reducing such adverse effects (ITS Decision, 2016). The numerous systems deployed around the world, which help to reduce the duration of the incident (Ozby & Xiao, 2009). Design and development of effective process of traffic incident management is one of the main of problems and tasks in intelligent transport systems (ITS) (Parkany, 2005).

In any case, the process of incident management can be described as set of events in the following categories: detection, classification, response, recovery and elimination (Škorput & Mandžuka & Jelušić, 2010). As soon as possible after the occurrence of the incident, all these events must be implemented accurately, quickly and efficiently (Mitrovich & Gaetano, 2006).

For operative and effective incident management requires the integrated use of all incoming information about detected incidents from various sources and organization of all involved to resolve emergency services. This problem is difficult to solve because:

- Organized and technical fragmentation of existing emergency services;
- The absence of a common system to collect and summarize the information about any incidents on the roads, alert and cooperation of all concerned traffic services.

The absence of a unified system of detection and warning about the occurred incident leads to a lack of efficiency and coordination of joint actions of emergency services. It affects the scale of the negative consequences of traffic accidents.

In real life it is very difficult and hard to develop a set of standardized scenarios according to which events are taken to elimination of the existing incident. Therefore, it's necessary to develop algorithmic maintenance for accurate detection and analysis of traffic incidents which allows to automatically carrying out a primary diagnosis emerged incident and offer the best solutions to eliminate incident.

Materials and Methods

Fuzzy situational approach to the traffic incident management

Traffic incident management system has to deal with a lot of uncontrolled and uncontrollable factors that are difficult to predict and take into account in the planning of decisions, such as weather conditions, the condition of roads, the physical and moral driver of operators, etc. The occurrence of the incident generates uncertainty, which is the main characteristic in the incidents management in the terms of time of its occurrence, incident type, duration, types of involved vehicles, the incident accompanied by injuries or not, what type of malfunction are occurred in the car etc.

It should be noted that the construction of management's model by using a large amount of input data requires a lot of knowledge base, which leads to increase processing rules with increasing input pattern, which leads to reduced quality of fuzzy inference. Therefore, effective model of incident management must be carried not by parameters (factors), but the states (situations).

For traffic incident management system it's necessary to develop a decision support system based on the mathematical apparatus of assessing situations and selection based on them the required control action. Such a system may be implemented on the basis of fuzzy situational management (Simankov & Shopin, 2004).

Fuzzy situational approach (FSA) is a set of methods of the situational approach and fuzzy logic. The basic concept in the theory of situational management is the concept of "situation". Situation is characterized as a set of factors, describing the state of the control object at a time (Zadeh, 1976).

Fuzzy model of the system is based on the concept of input, structure of process and output stream. Such systems are divided into two important categories that differ in the method of presentation various types of information. One of the main directions in the fuzzy systems is a linguistic approach, based on the linguistic description of model.

Uncertainty is one of the most important characteristics in the decision-making process based on fuzzy logic. Human thinking is a qualitative that can be defined as linguistic terms, so fuzzy logic allows to process difficult to measure information.

Construction of fuzzy situational network

Situational fuzzy management (SFM) includes three basic steps: identification and assessment of the situation, the choice and decision-making, the formation of the control solutions (Nikolaev & Sapego, 2013). In order to implement SFM it's necessary to perform the following subtasks:

- Determination of typical fuzzy situations $\{\tilde{s}_1, \tilde{s}_2, \dots, \tilde{s}_n\}$,
- Determination of the closeness and the state of the control object,
- Formation of control decision R_j .

The situation is a set of factors that describe the state of the control object at a particular time (Nikolaev & Sapego, 2015). All state of the object described as a set of reference situations $\tilde{S} = \{\tilde{s}_1, \tilde{s}_2, \dots, \tilde{s}_n\}$, each of which represents set of linguistic values of features:

$$\tilde{S}_i = \{ \langle \mu_i(y_i)/y_i \rangle, y_i \in Y \} \quad (1)$$

where $\mu_i(y_i)$ is membership function of the linguistic variable (factors) y_i described the situation \tilde{s}_i . This function can take values $[0,1]$, where 0 is lack of membership, 1 is full membership.

$Y = \{y_1, y_2, \dots, y_m\}$ is variety of factors, their values describe the state of the control object.

It should be noted that a limited set of fuzzy situations can describe an almost infinite number of states of the control object. The main task of FSM, based on fuzzy logic, is to transfer from current state of system \tilde{s}_0 to target state \tilde{s}_i through a set of control decisions (Krieger, 2012):

$$\tilde{S}_0 \xrightarrow{R_j, S} \tilde{S}_i$$

Figure 1. The main task of FSM

Order to determine state of control object the current state of system \tilde{s}_0 must be compared with each fuzzy situation from some sets of typical fuzzy situations $\tilde{S} = \{\tilde{s}_1, \tilde{s}_2, \dots, \tilde{s}_n\}$. As a measures of the closeness can be used: the degree of fuzzy inclusion degree fuzzy equality, fuzzy degree of generality. Determination of the current state of the system leads to the need to choose the control decision R_j , based on the matrix of relations, describing effects of control decisions on factors) y_i .

For this it is necessary to specify the control decision according to the factors:

$$R_j = \{R_1^j, R_2^j, \dots, R_N^j\} \quad (2)$$

The control system based on fuzzy logic is implemented using fuzzy situational network. The system should be based on historical data on which to judge whether there was an incident on the road or not.

The implementation of the system based on fuzzy logic

Development and implementation of a system based on fuzzy logic is included in several stages, which is performed using the main provisions (Hu & Tang, 2003). The data provided to input of the fuzzy system are measured by sensors and are called precise input data. These data correspond to the real variables of the control's process. The data, generated at the system output, correspond to the output variable (controlled variables of process) and are called precise output data.

The system based on fuzzy logic consists of the following elements:

- Precise input data;
- Linguistic variables and terms,
- Fuzzy rules,
- Membership functions,
- Precise output data.

Figure 2 shows a typical structure of the system based on fuzzy logic (Alkandari, 2013):

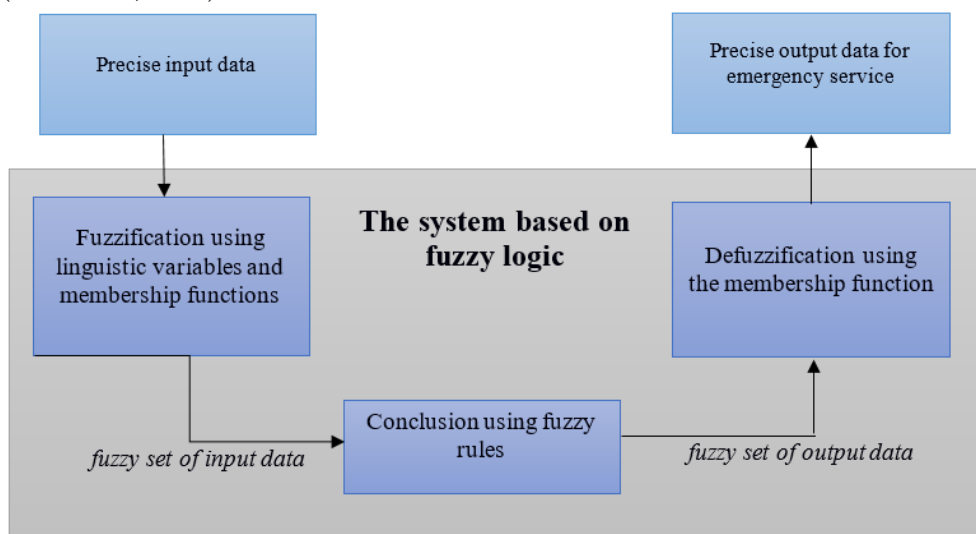


Figure 2. The structure of the system based on fuzzy logic

Fuzzification translates real values in the value of the logical-linguistic variables. Fuzzification is called the introduction of fuzziness. Defuzzification is a transition from the membership functions of the output linguistic variable in its clearer (numeric) value (Kong & Xue, 2006).

The analysis of multi-factor structure is an important problem in fuzzy control system (Cordon & Herrera, 1995). The system with a lot of input data and one output can be defined by conditional rule «IF - THEN». The first part of the rule (before the «THEN») is called preceding. The preceding part contains the linguistic variables that reflect the on the value of expert's knowledge, and is defined as a combination of separate conditions using logical operators «and» and «not». The second part (after «THEN») is called the result and corresponds to the control action. Fuzzy rules for multi-system can be defined as follows:

Rule 1: IF (X_1 is A_1^1) and (X_2 is A_2^1) ... (X_m is A_m^1) THEN (Y_1 is B_1^1) W_1

...

Rule i : IF (X_1 is A_1^i) and (X_2 is A_2^i) ... (X_m is A_m^i) THEN (Y_1 is B_1^i) W_i
(3)

...

Rule n : IF (X_1 is A_1^n) and (X_2 is A_2^n) ... (X_m is A_m^n) THEN (Y_1 is B_1^n) W_n

where X_1, X_2, \dots, X_m – input variables.

Y_1 – output variable defined current state of traffic flow.

$A_1^i, A_2^i, \dots, A_m^i$ – previously defined fuzzy attributes for each fuzzy variable.

B_1^i – output fuzzy term.

W_i – weighting factors, indicating the degree of confidence in the validity of obtained result ($i = 1..n$) This factor takes a value within the interval $[0;1]$. By default, the weight is assumed to be 1.

i – number of fuzzy rule $i = (1..n)$.

$n \in N$ – quantity of fuzzy rules.

$m \in N$ – quantity of input variables.

These terms are linguistic values represented as fuzzy subsets X_1, X_2, \dots, X_m and Y_1 . For the fuzzy rules with one input and one output (*IF (X is A_i) THEN (Y is B_i)*) fuzzy relation R_i is defined as the fuzzy intersection of fuzzy sets A_i and B_i :

$$\mathbf{R}_i = \mathbf{A}_i \cap \mathbf{B}_i \quad (4)$$

R_i is defined as the Cartesian product of the spaces $(X \times Y)$ and characterized by a membership function μ_R :

$$\mathbf{R}_i(\mathbf{x}, \mathbf{y}) = \mathbf{A}_i(\mathbf{x}) \wedge \mathbf{B}_i(\mathbf{y}), \mu_R \times \mathbf{Y} \rightarrow [0..1] \quad (5)$$

The membership function of fuzzy relations is:

$$\mu_R(\mathbf{x}, \mathbf{y}) = \vee_i \mathbf{R}_i(\mathbf{x}, \mathbf{y}) = \vee (\mathbf{A}_i(\mathbf{x}) \wedge \mathbf{B}_i(\mathbf{y})) \quad (6)$$

Thus, for a given fuzzy relation R_i from X to Y and to given fuzzy values of input A and fuzzy B is determined by max-min product:

$$\mathbf{B} = \cup (\mathbf{A} \circ \mathbf{R}) \quad (7)$$

$$\mu_B(\mathbf{y}) = \max \{ \min(\mu_A(\mathbf{x}), \mu_R(\mathbf{x}, \mathbf{y})) \} \quad (8)$$

Pattern can be derived for fuzzy systems with multiple inputs and one output:

$$\mathbf{R}_i^j = \mathbf{A}_{ij} \cap \mathbf{B}_i^k \quad (9)$$

где i - number of fuzzy rule, $i = (1..n), n \in N$

j - input variable, $j = (1..m), m \in N$

k - output variable, $k = 1$

Using the formula (6) for the subsystem with multiple inputs and one output for output B it's received the following pattern:

$$\mathbf{B}^1 = \cup (\mathbf{A}_1, \mathbf{A}_2, \dots, \mathbf{A}_m) \circ \mathbf{R}_i^j \quad (10)$$

where R is an m-dimensional fuzzy matrix, B^1 - one dimensional fuzzy inference. Thus, membership of function for multidimensional system in accordance with (5) may be defines as follows:

$$\mu_B(y) = \max \min \{ \mu_{A_1}(x_1) \times \mu_{A_2}(x_2) \times \dots \times \mu_{A_m}(x_m), \mu_R(x_1, x_2, \dots, x_m, y) \} \quad (11)$$

where $x_1 \in A_1, x_2 \in A_2, \dots, x_m \in A_m$

The membership function for R will be defined as follows for the studied system:

$$\mu_R = \max \{ \mu_{B_1}(x_1, x_2, \dots, x_m, y), \dots, \mu_{B_n}(x_1, x_2, \dots, x_m, y) \} \quad (12)$$

Fuzzy system based on multiple inputs and one output shows how each of the used components can affect the overall system performance.

Results

Developing algorithm of incident detection based on fuzzy logic

Application of fuzzy logic in the incident detection system allows making a decision under uncertainty. The phase of incident detection is a process of finding difficulties in traffic. The difficulty in traffic is the main sign that there was a road accident and requires a reaction for its elimination. This leads to the use of input data that must be relevant to the vehicles and the road. These data must be considered together, and should be compared with the corresponding values for further analysis. The main parameters of the traffic flow, which can characterize its current state, are a flow rate, a volume flow.

Necessary to analyze the input data received from the sensors. After processing the input data, using the previously entered fuzzy rules, will be taken action that will improve the situation in traffic or at least not allow it worse.

Components of the system based on fuzzy logic can be implemented by various methods. The totality of separate implementations of described above components of the fuzzy system determines the fuzzy inference algorithm. L. Zadeh (1976) developed the idea of the formalization of fuzzy control algorithm using the logical rules. For obtaining output of vaguely formulated data can use logical rules with vague predicates. Consider more detail the algorithm Mamdani fuzzy inference that will be used in this paper, as the most useful for the implementation of fuzzy control systems.

In this paper, an algorithm of fuzzy inference Mamdani will be considered as the most useful for the implementation fuzzy control systems. Mamdani algorithm describes several sequential steps (Mamdani, 2011). Each successive stage receives input values obtained in the previous step:

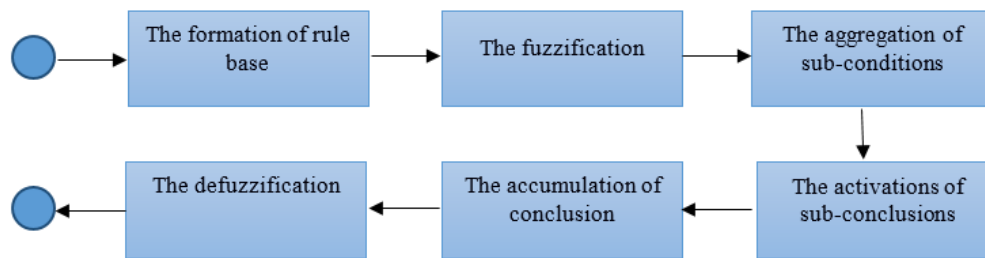


Figure 3. Phases of Mamdani algorithm

Consider in more detail each of the steps on the example of incident detection system, further linguistic parameters will be introduced.

Linguistic variables are input and output variables of the fuzzy system (Bingle, Zheng & Hongwei, 2008). Linguistic variables consist of words or sentences of a natural language, which allows to express certain conditions and to understand them without the need for measurement or calculation to make a definite conclusion, for example, "on the section of the road was filled with" instead of "on the section of the road was 100 cars."

The next linguistic variables in incident detection system will be used to determine the occurrence of incidents:

— Flow Rate = {small (SM_SP), medium (ME_SP), large (LA_SP)}

On sections of road where the accident occurred the rate of traffic flow will certainly be slower than in an area where nothing prevents movement. Therefore, this variable is necessary for the determining the occurrence of the incident.

— Changing of the speed = {small (SM_SP_CH), medium (ME_SP_CH), large (LA_SP_CH)}

Change of speed is the percentage ratio between the values that take from the two standing one after other sensors. The greater the difference in the values of road speed, the greater probability that the incident occurred between the sensors.

— Volume flow = {small (SM_V), medium (ME_V), large (LA_V)}

The volume flow is the number of vehicles crossing the road section in a predetermined unit of time. If the incident occurred on the road, the number of cars is less than in free motion. It should be noted pattern of volume on flow rate: if the vehicle speed is high and the volume is small, it is considered that the road is free. If the volume of vehicles remains unchanged, the flow rate drops, it means that traffic incident probability occurred.

— Changing of volume = {small (SM_V_CH), medium (ME_V_CH), large (LA_V_CH)}

Change of volume is the percentage ratio between the values that take from the two standing one after other sensors. The greater the difference between the number of vehicles, the greater probability that the incident occurred in the investigated area.

— Status of incident = {false, true}

This variable has two values: “false” – no incident, “true” – incident occurred.

Each specified linguistic variable measures certain traffic conditions; with these conditions form the rules governed the system. Stage of the determination of linguistic variables is an important step because they effect on the efficiency of the system. These variables must be translated into the fuzzy controller by using membership functions; therefore, they should be defined for the above variables.

In addition, it's necessary classification of accident. Classification is to determine the priority of the incident on the road traffic in general.

Determination of priority is necessary as well as definition of occurred incident, as after detection of the incident, corresponding of operation to eliminate incident must be run. It's therefore extremely important at the beginning for emergency services to pass degree of criticality of occurred incident as it affects on queue of reaction to the incident (Bartolini & Salle, 2004).

3 input variables are identified for the classification of the incident:

- Location of incident = {left (LE), medium (ME), right (RI), shoulder (SH)}
- Type of incident = {small (SM_A), medium (ME_A), large (LA_A)}

Type of incident will directly affect the classification of the incident, as if there was a large incident, such as leakage of dangerous substances - on such an incident response should be a priority, than if there was a car crash (small accidents).

- Vehicle category = {small (SM_T), medium TC (ME_T), large TC (LA_T)}
- Incident priority = {low (LO_EF), medium (ME_EF), high (HI_EF), critical (CR_EF)}

In the general classification of a road accident will taken into consideration all three of the variables. The output variable will be determined the response time on the event of a road accident. Influence will be determined using fuzzy rules.

Development of fuzzy rules

When an incident occurs, it is formed on the road a congestion. As soon as incident is considered to be cleaned, the road capacity is increased and congestion dissipates. Define fuzzy rules that are used to describe the relationship between inputs and outputs data, as the current state of road can determine using fuzzy rules. As a result, received 81 rules:

Table 1. Fuzzy rules for determining the current state of the road

#	Flow Rate	Changing of the speed	Volume flow	Changing of volume	Status of incident
1	Small (SM_SP)	Small (SM_SP_CH)	Small (SM_V)	Small (SM_V_CH)	true
2				Medium (ME_V_CH)	true
3				Large (LA_V_CH)	true
4			Medium (SM_SP)	Small (SM_V_CH)	true

5				Medium (ME_V_CH)	true
6				Large (LA_V_CH)	true
7			Large (ME_SP)	Small (SM_V_CH)	true
8				Medium (ME_V_CH)	true
9				Large (LA_V_CH)	true
10		Medium (ME_SP_CH)	Small (SM_V)	Small (SM_V_CH)	true
11				Medium (ME_V_CH)	true
12				Large (LA_V_CH)	true
13			Medium (SM_SP)	Small (SM_V_CH)	true
14				Medium (ME_V_CH)	true
15				Large (LA_V_CH)	true
16			Large (ME_SP)	Small (SM_V_CH)	true
17				Medium (ME_V_CH)	true
18				Large (LA_V_CH)	true
19		Large (LA_SP_CH)	Small (SM_V)	Small (SM_V_CH)	true
20				Medium (ME_V_CH)	true
21				Large (LA_V_CH)	true
22			Medium (SM_SP)	Small (SM_V_CH)	true
23				Medium (ME_V_CH)	true
24				Large (LA_V_CH)	true
25			Large (ME_SP)	Small (SM_V_CH)	true
26				Medium (ME_V_CH)	true
27				Large (LA_V_CH)	true
28	Medium (ME_SP)	Small (SM_SP_CH)	Small (SM_V)	Small (SM_V_CH)	true
29				Medium (ME_V_CH)	true
30				Large (LA_V_CH)	true
31			Medium (SM_SP)	Small (SM_V_CH)	false
32				Medium (ME_V_CH)	false

33			Large (LA_V_CH)	true	
34		Large (ME_SP)	Small (SM_V_CH)	false	
35			Medium (ME_V_CH)	true	
36			Large (LA_V_CH)	true	
37	Medium (ME_SP_CH)	Small (SM_V)	Small (SM_V_CH)	false	
38			Medium (ME_V_CH)	false	
39			Large (LA_V_CH)	true	
40		Medium (SM_SP)	Small (SM_V_CH)	false	
41			Medium (ME_V_CH)	false	
42			Large (LA_V_CH)	true	
43		Large (ME_SP)	Small (SM_V_CH)	false	
44			Medium (ME_V_CH)	false	
45			Large (LA_V_CH)	true	
46	Large (LA_SP_CH)	Small (SM_V)	Small (SM_V_CH)	false	
47			Medium (ME_V_CH)	true	
48			Large (LA_V_CH)	true	
49		Medium (SM_SP)	Small (SM_V_CH)	false	
50			Medium (ME_V_CH)	true	
51			Large (LA_V_CH)	true	
52		Large (ME_SP)	Small (SM_V_CH)	true	
53			Medium (ME_V_CH)	true	
54			Large (LA_V_CH)	true	
55	Large (LA_SP)	Small (SM_SP_CH)	Small (SM_V)	Small (SM_V_CH)	false
56			Medium (ME_V_CH)	true	
57			Large (LA_V_CH)	true	
58		Medium (SM_SP)	Small (SM_V_CH)	false	
59			Medium (ME_V_CH)	false	
60			Large (LA_V_CH)	true	

61		Large (ME_SP)	Small (SM_V_CH)	false
62			Medium (ME_V_CH)	true
63			Large (LA_V_CH)	true
64	Medium (ME_SP_CH)	Small (SM_V)	Small (SM_V_CH)	false
65			Medium (ME_V_CH)	false
66			Large (LA_V_CH)	true
67		Medium (SM_SP)	Small (SM_V_CH)	false
68			Medium (ME_V_CH)	true
69			Large (LA_V_CH)	true
70		Large (ME_SP)	Small (SM_V_CH)	false
71			Medium (ME_V_CH)	true
72			Large (LA_V_CH)	true
73	Large (LA_SP_CH)	Small (SM_V)	Small (SM_V_CH)	false
74			Medium (ME_V_CH)	false
75			Large (LA_V_CH)	true
76		Medium (SM_SP)	Small (SM_V_CH)	false
77			Medium (ME_V_CH)	false
78			Large (LA_V_CH)	true
79		Large (ME_SP)	Small (SM_V_CH)	false
80			Medium (ME_V_CH)	false
81			Large (LA_V_CH)	true

The algorithm of traffic incidents detection will produce one of the following results:

- $n = 1$ – normal traffic
- $n = 2$ – probability of occurrence of the incident
- $n = 3$ – incident is detected

The algorithm of the incidents detection system to as follows:

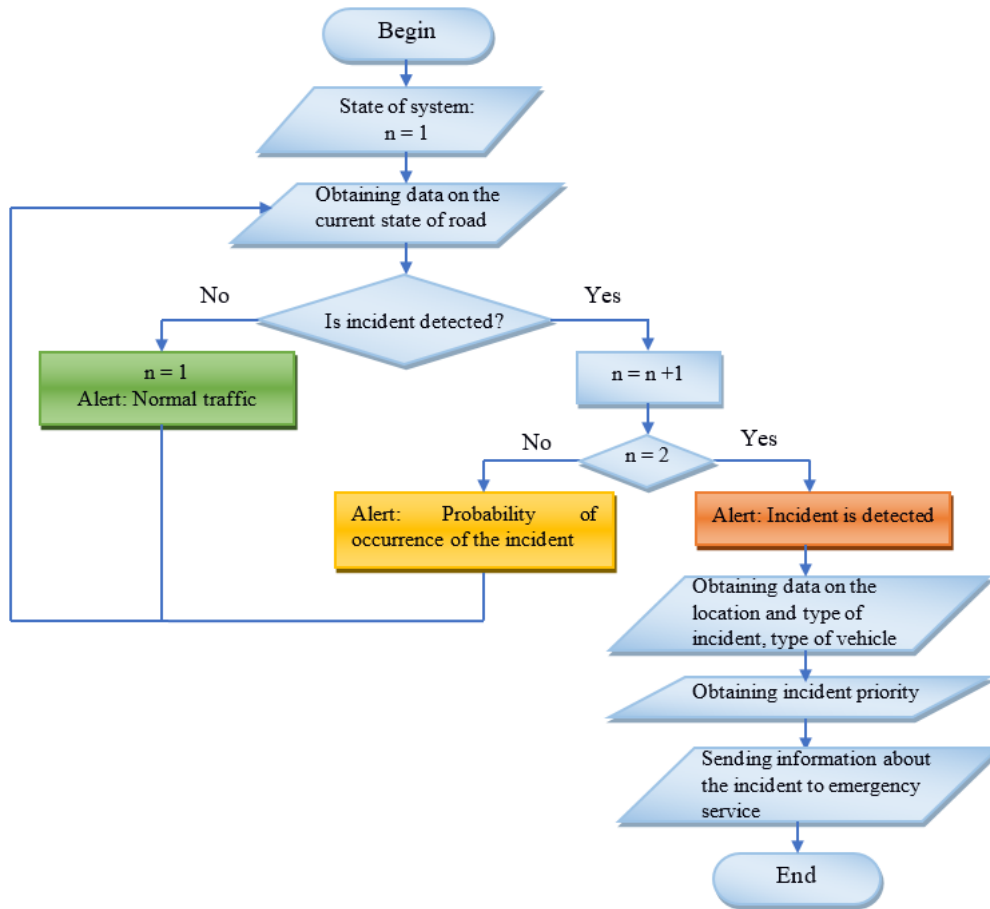


Figure 4. The algorithm of the incident detection system

During a certain period of time traffic conditions will be analyzed for occurrence of the incident. If the analysis shows that the movement is not normal, it is considered likely that the incident occurred (situation 2), or - a situation 1. If during 3 periods of measured time traffic is not normal it is considered that a road incident occurred, then the output will be situation 3. If the flow is returned to normal, it means that the incident has been eliminated, and the output will be situation 1 again. After the system has shown that the incident occurred, the step of incident classification is started.

Fuzzy rules for determining the incident priority is following:

Table 2. Fuzzy rules for determining the priority of the incident

#	Type of incident	Type of vehicle	Location of incident	Priority of incident
1	Small (SM_A)	Small (SM_T)	Left (LE)	Low (LO_EF)
2			Medium (ME)	Low (LO_EF)
3			Right (RI)	Low (LO_EF)
4			Shoulder (SH)	Low (LO_EF)
5		Medium (ME_T)	Left (LE)	Medium (ME_EF)
6			Medium (ME)	Medium (ME_EF)

7			Right (RI)	Medium (ME_EF)
8			Shoulder (SH)	Low (LO_EF)
9		Large (LA_T)	Left (LE)	Medium (ME_EF)
10			Medium (ME)	Medium (ME_EF)
11			Right (RI)	Medium (ME_EF)
12			Shoulder (SH)	Low (LO_EF)
13	Medium (ME_A)	Small (SM_T)	Left (LE)	Medium (ME_EF)
14			Medium (ME)	Medium (ME_EF)
15			Right (RI)	Medium (ME_EF)
16			Shoulder (SH)	Low (LO_EF)
17		Medium (ME_T)	Left (LE)	Medium (ME_EF)
18			Medium (ME)	Medium (ME_EF)
19			Right (RI)	Medium (ME_EF)
20			Shoulder (SH)	Low (LO_EF)
21		Large (LA_T)	Left (LE)	High (HI_EF)
22			Medium (ME)	High (HI_EF)
23			Right (RI)	High (HI_EF)
24			Shoulder (SH)	Medium (ME_EF)
25	Large (LA_A)	Small (SM_T)	Left (LE)	High (HI_EF)
26			Medium (ME)	High (HI_EF)
27			Right (RI)	High (HI_EF)
28			Shoulder (SH)	High (HI_EF)
29		Medium (ME_T)	Left (LE)	Critical (CR_EF)
30			Medium (ME)	Critical (CR_EF)
31			Right (RI)	Critical (CR_EF)
32			Shoulder (SH)	High (HI_EF)
33		Large (LA_T)	Left (LE)	Critical (CR_EF)
34			Medium (ME)	Critical (CR_EF)
35			Right (RI)	Critical (CR_EF)
36			Shoulder (SH)	Critical (CR_EF)

Determination of membership functions

A characteristic of a fuzzy set is membership function, which is responsible for the process of fuzzification necessary to compensate for the lack of inaccurate input data from sensors because the equipment cannot provide reliable indication for various reasons.

For term-sets certain linguistic variables that are uncertainty such as "is in the range", should be used trapezoidal membership function (Shtovba, 2007):

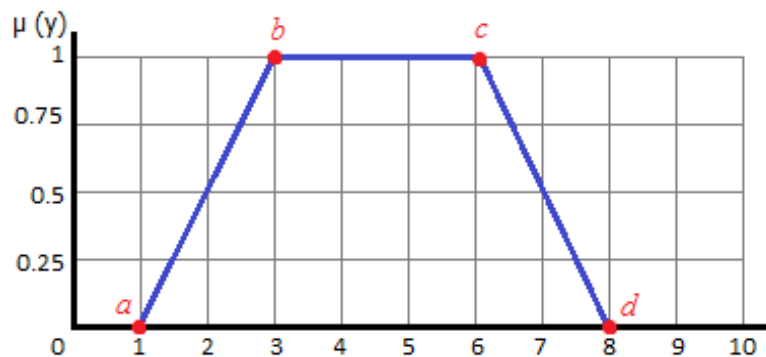


Figure 5. Example of a trapezoidal membership function

The trapezoidal membership function, in general, can be defined analytically by the following expression:

$$f(x, a, b, c, d) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{cases} \quad (13)$$

where a, b, c, d— some numerical parameters that take arbitrary real values and the ordered relationship: $a \leq b \leq c \leq d$. The parameters a and d describe the lower base of the trapezoid, and the parameters b and d - the upper. Furthermore, this membership function generates a normal convex fuzzy set with the characteristics: interval(a, d), boundaries(a, b)(c, d), core[b, c].

Define the membership functions for the linguistic variable (Manstetten & Maichle, 1996):

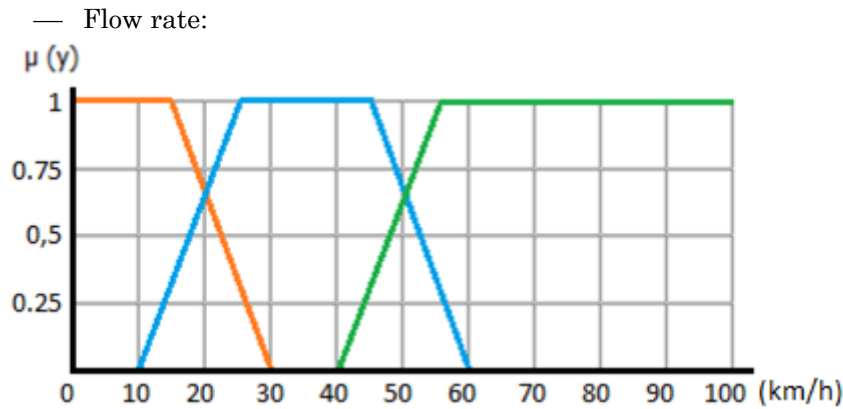


Figure 6. Membership function for the characteristic “flow rate”, where 1 - small (SM_SP), 2 - medium (ME_SP), 3 - large (LA_SP)

The value “small”: $\mu_{sm}(SP) = \begin{cases} 1, & SP \leq 15 \\ \frac{30-SP}{15}, & 15 \leq SP \leq 30 \end{cases} \quad (14)$

The value “medium”: $\mu_{me}(SP) = \begin{cases} \frac{SP-10}{15}, & 10 \leq SP \leq 25 \\ 1, & 25 \leq SP \leq 45 \\ \frac{60-SP}{15}, & 45 \leq SP \leq 60 \end{cases} \quad (15)$

The value “large”: $\mu_{la}(SP) = \begin{cases} \frac{SP-40}{15}, & 40 \leq SP \leq 55 \\ 1, & 55 \leq SP \end{cases} \quad (16)$

— Volume flow:

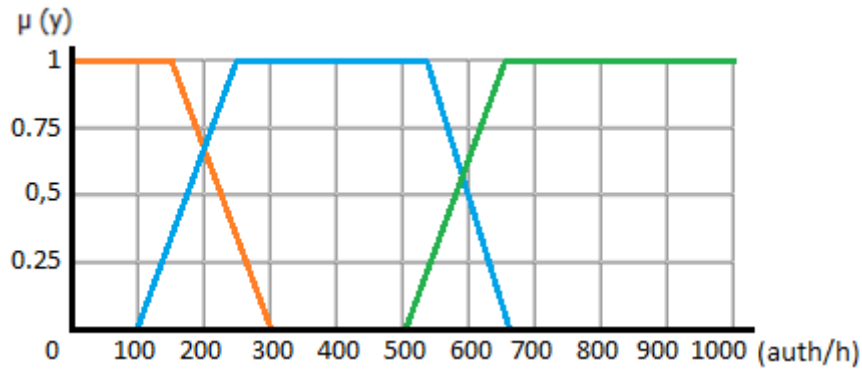


Figure 7. Membership function for the characteristic “volume flow”, where 1 - small (SM_V), 2 - medium (ME_V), 3 - large (LA_V)

$$\text{The value “small”}: \mu_{sm}(V) = \begin{cases} 1, & V \leq 150 \\ \frac{300-V}{150}, & 150 \leq V \leq 300 \end{cases} \quad (17)$$

$$\text{The value “medium”}: \mu_{me}(V) = \begin{cases} \frac{V-100}{150}, & 100 \leq V \leq 250 \\ 1, & 250 \leq V \leq 550 \\ \frac{650-V}{100}, & 550 \leq V \leq 650 \end{cases} \quad (18)$$

$$\text{The value “large”}: \mu_{la}(V) = \begin{cases} \frac{V-500}{150}, & 500 \leq V \leq 650 \\ 1, & 650 \leq V \end{cases} \quad (19)$$

— Changing of the speed and volume (for two of these settings will be used the same membership function):

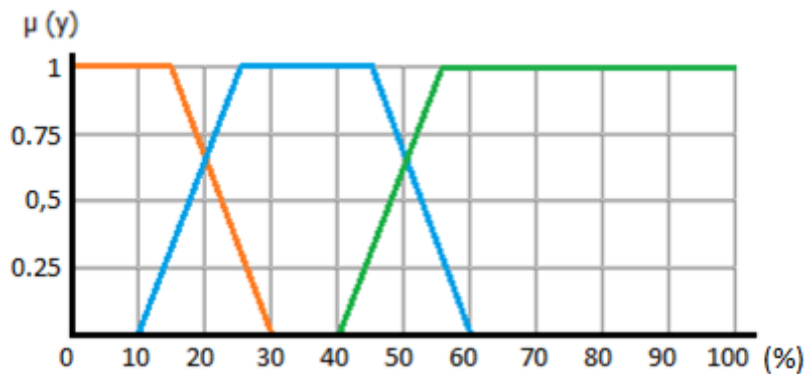


Figure 8. Membership function for the characteristic for changing of the speed and volume, where 1 - small (SM_CH), 2 - medium (ME_CH), 3 - large (LA_CH)

$$\text{The value “small”}: \mu_{sm}(CH) = \begin{cases} 1, & CH \leq 15 \\ \frac{30-CH}{15}, & 15 \leq CH \leq 30 \end{cases} \quad (20)$$

$$\text{The value "medium": } \mu_{\text{me}}(CH) = \begin{cases} \frac{CH-10}{15}, & 10 \leq CH \leq 25 \\ 1, & 25 \leq CH \leq 45 \\ \frac{60-CH}{15}, & 45 \leq CH \leq 60 \end{cases} \quad (21)$$

$$\text{The value "large": } \mu_{\text{la}}(\mathbf{CH}) = \begin{cases} \frac{CH-40}{15}, & 40 \leq \mathbf{CH} \leq 55 \\ 1, & 55 \leq \mathbf{CH} \end{cases} \quad (22)$$

After it's necessary to define the membership function for the following linguistic variables, which are responsible for the classification of the incident:

— Type of incident: into one classification integrates all possible types of incidents.

Table 3. Type of incident

Type of incident	Description
Small (SM_A)	1.1. Malfunction of vehicle: a tire puncture, mechanical / electrical failure, overheating 1.2. The presence of obstacles on the road (tree, etc)
Medium (ME_A)	2.1. Collision of vehicle without health damage, hit a stationary vehicles 2.2. Hit an obstacle (without health damage) 2.3. Other type of incident
Large (LA_A)	3.1. Ignition of vehicle 3.2. Causing harm to health 3.3. Spills of hazardous substances

— Type of vehicle

Currently, there are international and national classification systems for vehicles. For example, GOST R 52051 - 2003 "Motor vehicles and trailers. Classification and Definitions" acts in the Russian Federation since 2004.

In this research, it will be offered a simplified model of vehicle classification to facilitate selecting a category, but that is far as possible cover all possible vehicle types:

Table 4. Classification of vehicles

Classification of vehicles	Description
Small (SM_T)	Motorcycles, mopeds, ATVs, automobile of all classes
Medium (ME_T)	Passengers and Goods vehicles on the basis of passenger models (minibuses, minivans, pick-up trucks), tractors
Large (LA_T)	Passengers and Goods on the basis of freight models (all-terrain vehicles, special purpose vehicles), buses, trucks (cargo vans, dump trucks, trailers, and ballast tractors, container ships, tankers)

Discussion

Implementation of the developed algorithm

Consider the example of the algorithm the incident detection and its classification. Let monitoring system returned the following values:

— The rate from the first sensor – 30 km/h

- The rate from the following sensor – 47 km/h
- Volume of flow – 400 auth/h
- Volume of flow from the following sensor – auth/h

Calculate the percentage change in the parameters of speed and volume:

$$SP\ CH = \left| 100 - \frac{47 \cdot 100}{30} \right| = 57 \quad (23)$$

$$V\ CH = \left| 100 - \frac{565 \cdot 100}{400} \right| = 41,25 \quad (24)$$

Calculate for each parameter membership function according to the formulas 12 – 24:

Flow rate:	Volume of flow:
$\mu_{sm}(47) = 0$	$\mu_{sm}(565) = 0$
$\mu_{me}(47) = 0,86$	$\mu_{me}(565) = 0,85$
$\mu_{la}(47) = 0,47$	$\mu_{la}(565) = 0,43$

(25)

Changing of rate:	Changing of volume:
$\mu_{sm}(57) = 0$	$\mu_{sm}(41,25) = 0$
$\mu_{me}(57) = 0,2$	$\mu_{me}(41,25) = 1$
$\mu_{la}(57) = 1$	$\mu_{la}(41,25) = 0,08$

Next it's necessary to determine the degree of membership for each of the rules of the fuzzy inference system. According to the above calculated values of membership functions for each fuzzy rule it's received an activation of sub-conclusions using min-activation:

Table 5. Degree of membership for each fuzzy rule

#	Flow rate	Changing of rate	Volume of flow	Changing of volume	Degree of membership
1	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0;0;0;0\}=0$
2	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0;0;0;1\}=0$
3	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{la}(41,25)$	$\min\{0;0;0;0,08\}=0$
4	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0;0;0,85;0\}=0$
5	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0;0;0,85;1\}=0$
6	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{la}(41,25)$	$\min\{0;0;0,85;0,08\}=0$
7	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{la}(565)$	$\mu_{sm}(41,25)$	$\min\{0;0;0,43;0\}=0$
8	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{la}(565)$	$\mu_{me}(41,25)$	$\min\{0;0;0,43;1\}=0$
9	$\mu_{sm}(47)$	$\mu_{sm}(57)$	$\mu_{la}(565)$	$\mu_{la}(41,25)$	$\min\{0;0;0,43;0,08\}=0$
10	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0;0,2;0;0\}=0$
11	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0;0,2;0;1\}=0$
12	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{la}(41,25)$	$\min\{0;0,2;0;0,08\}=0$
13	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0;0,2;0,85;0\}=0$
14	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0;0,2;0,85;1\}=0$
15	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{la}(41,25)$	$\min\{0;0,2;0,85;0,08\}=0$
16	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{la}(565)$	$\mu_{sm}(41,25)$	$\min\{0;0,2;0,43;0\}=0$
17	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{la}(565)$	$\mu_{me}(41,25)$	$\min\{0;0,2;0,43;1\}=0$
18	$\mu_{sm}(47)$	$\mu_{me}(57)$	$\mu_{la}(565)$	$\mu_{la}(41,25)$	$\min\{0;0,2;0,43;0,08\}=0$
19	$\mu_{sm}(47)$	$\mu_{la}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0;1;0;0\}=0$



20	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0;1;0;1\}=0$
21	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{ja}(41,25)$	$\min\{0;1;0;0,08\}=0$
22	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0;1;0,85;0\}=0$
23	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0;1;0,85;1\}=0$
24	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{ja}(41,25)$	$\min\{0;1;0,85;0,08\}=0$
25	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{sm}(41,25)$	$\min\{0;1;0,43;0\}=0$
26	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{me}(41,25)$	$\min\{0;1;0,43;1\}=0$
27	$\mu_{sm}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{ja}(41,25)$	$\min\{0;1;0,43;0,08\}=0$
28	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;0;0;0\}=0$
29	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;0;0;1\}=0$
30	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;0;0;0,08\}=0$
31	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;0;0,85;0\}=0$
32	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;0;0,85;1\}=0$
33	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;0;0,85;0,08\}=0$
34	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{ja}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;0;0,43;0\}=0$
35	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{ja}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;0;0,43;1\}=0$
36	$\mu_{me}(47)$	$\mu_{sm}(57)$	$\mu_{ja}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;0;0,43;0,08\}=0$
37	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;0,2;0;0\}=0$
38	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;0,2;0;1\}=0$
39	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;0,2;0;0,08\}=0$
40	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;0,2;0,85;0\}=0$
41	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;0,2;0,85;1\}=0,2$
42	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;0,2;0,85;0,08\}=0,08$
43	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{ja}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;0,2;0,43;0\}=0$
44	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{ja}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;0,2;0,43;1\}=0,2$
45	$\mu_{me}(47)$	$\mu_{me}(57)$	$\mu_{ja}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;0,2;0,43;0,08\}=0,08$
46	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;1;0;0\}=0$
47	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;1;0;1\}=0$
48	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;1;0;0,08\}=0$
49	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;1;0,85;0\}=0$
50	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;1;0,85;1\}=0,85$
51	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;1;0,85;0,08\}=0,08$
52	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{sm}(41,25)$	$\min\{0,86;1;0,43;0\}=0$
53	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{me}(41,25)$	$\min\{0,86;1;0,43;1\}=0,43$
54	$\mu_{me}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{ja}(41,25)$	$\min\{0,86;1;0,43;0,08\}=0,08$
55	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;0;0;0\}=0$
56	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;0;0;1\}=0$
57	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{sm}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;0;0;0,08\}=0$
58	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;0;0,85;0\}=0$
59	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;0;0,85;1\}=0$
60	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{me}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;0;0,85;0,08\}=0$
61	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{ja}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;0;0,43;0\}=0$
62	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{ja}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;0;0,43;1\}=0$
63	$\mu_{ja}(47)$	$\mu_{sm}(57)$	$\mu_{ja}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;0;0,43;0,08\}=0$
64	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;0,2;0;0\}=0$
65	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;0,2;0;1\}=0$
66	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{sm}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;0,2;0;0,08\}=0$
67	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;0,2;0,85;0\}=0$
68	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;0,2;0,85;1\}=0,2$

69	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{me}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;0,2;0,85;0,08\}=0,08$
70	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{ja}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;0,2;0,43;0\}=0$
71	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{ja}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;0,2;0,43;1\}=0,2$
72	$\mu_{ja}(47)$	$\mu_{me}(57)$	$\mu_{ja}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;0,2;0,43;0,08\}=0,08$
73	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;1;0;0\}=0$
74	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;1;0;1\}=0$
75	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{sm}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;1;0;0,08\}=0$
76	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;1;0,85;0\}=0$
77	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;1;0,85;1\}=0,47$
78	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{me}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;1;0,85;0,08\}=0,08$
79	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{sm}(41,25)$	$\min\{0,47;1;0,43;0\}=0$
80	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{me}(41,25)$	$\min\{0,47;1;0,43;1\}=0,43$
81	$\mu_{ja}(47)$	$\mu_{ja}(57)$	$\mu_{ja}(565)$	$\mu_{ja}(41,25)$	$\min\{0,47;1;0,43;0,08\}=0,08$

The last step in the fuzzy inference is a stage of accumulation, which is getting fuzzy set (or association) for each of the output variables by max-associations:

$$\mu = \max\{\min\{\mu_{SP}(47), \mu_{SP\ CH}(57), \mu_V(565), \mu_{V\ CH}(41, 25)\}\} = 0,85 \quad (26)$$

Receive total value of 0.85 for the rule number 50. According to Table 5, the system will display the result of the status of the incident «true», meaning that there was an incident on the test section of the road. If incident is occurred on the road, it's necessary to define priority of incident.

Let the system received the following information about road incident: on the investigated section of the road two cars collided in the right lane. Therefore, the following inputs values enter into the system to determine the priority of the incident:

- Location of incident: right lane (RI).
- Type of incident: Medium (ME_T).

In accordance with the table 6 of fuzzy rule the priority of the incident will be defined as the Medium (ME_EF) (rule #19).

Conclusion

In this articles algorithm based on fuzzy logic was proposed for incident detection and defining its priority. It was considered the main stage of development of fuzzy algorithm: introducing linguistic variables and fuzzy rules, as well as example of operation of proposed algorithm was shown.

From sensors without human intervention on the proposed algorithm can obtain the quantitative characteristics of the traffic such as speed and volume of traffic. After receiving information about the type of incident, the location and type of vehicles proposed algorithm can determine the existence of the incident and the priority of the incident. The algorithm has shown its efficiency and can be used in the circuit of the automated systems of dispatching management, as well as intelligent transport systems.

Disclosure statement

No potential conflict of interest was reported by the authors.



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