

Розроблено структуру та архітектурну ієрархію локомотивних СППР. Алгоритм дій машиніста локомотива представлено нечітким імовірнісним графом. Вагові коефіцієнти переходів між вершинами завдані нечіткими числами, значення яких записані в матриці графа. Вибір варіанта рішення локомотивної СППР реалізовано за адитивним критерієм. Опис динамічної бази знань проведено з використанням продукційної моделі представлення знань

Ключові слова: керування локомотивом, прийняття рішень, інтелектуальна система, база знань, нечіткий класифікатор

Разработана структура и архитектурная иерархия локомотивных СППР. Алгоритм действий машиниста локомотива представлен нечетким вероятностным графом. Весовые коэффициенты переходов между вершинами заданы нечеткими числами, значения которых записаны в матрице графа. Выбор варианта решения локомотивной СППР реализован по аддитивному критерию. Описание динамической базы знаний проведено с использованием продукционной модели представления знаний

Ключевые слова: управление локомотивом, принятие решений, интеллектуальная система, база знаний, нечеткий классификатор

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IMPROVING THE PROCESS OF DRIVING A LOCOMOTIVE THROUGH THE USE OF DECISION SUPPORT SYSTEMS

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1. Introduction

The functioning of the ergatic system “train – locomotive driver” is conditioned by a number of factors, the main of which are the quality and timeliness of decision-making. Gradually the systems of driving a locomotive are developing in the direction of decreasing the role of locomotive crews in the process of driving the train, which allows reducing harmful influence of the human factor on the safety and effectiveness of the operation of rolling stock. The final stage of this development will be a transition to a fully automated control of trains.

At present, “the human factor” in operating a locomotive still plays a significant role and reduces transportation safety. This is illustrated by the accident that happened in Spain in 2013, where the accident involving a high-speed train occurred as a result of exceeding the speed by the driver, 80 people died and more than 140 were injured. Over the period from 2011 to 2015, 130 people throughout the world were killed as a result of the railway accidents caused by locomotive brigades [1]. Thus, the problem of improving the quality of driving decisions that a driver takes is relevant and requires further development of theoretical principles of its solution.

2. Literature review and problem statement

Nowadays a number of systems of automatic driving both long-distance trains [2] and local trains have been imple-

mented [3]. For the automation of local trains and subway trains, the company Bombardier designed a new generation of train control systems CITYFLO 650 [4], which currently operates in thirteen cities around the world. In the subways of Santiago, Paris, Hong Kong and Beijing, Alstom company is implementing its design for automated train control [5]. The project Urbalis is supposed to increase the train frequency, at the same time ensuring high safety and increased comfort for passengers. An analysis of these foreign designs allows us to conclude that the use of automated train driving systems is a promising area of research that allows us either to reduce significantly or eliminate completely the negative impact of the human factor on traffic safety. However, a common drawback of these systems is the existence of limited number of parameters that are monitored, the increase in which leads to making the algorithms of automated systems operation even more complicated, which is the cause of a considerable rise in their price. On the other hand, the readjustment, when it is necessary to take into account specific conditions of a particular section, is very difficult in such systems. The projects lack the capacity to accumulate experience and to control the traffic independently in terms of improving the indices of previous travels, that is, the self-learning function is missing. This caused the locomotive driving systems to develop in the direction of intellectualization [6]. New methods and structures of intelligent driving systems for the rail transport are being developed [7] and the methods of forecasting technical condition of the rolling

stock are being improved [8]. But the cited sources do not consider the process of making decisions by a locomotive crew, although this process is one of the most important. Its successful implementation allows a considerable increase in traffic safety and reduction of transportation costs. In [9], the intelligent system of driving a subway train was developed, but in order to use it on railways, it is necessary to solve a number of additional problems, namely, to develop mechanisms of interaction between the system and a dispatcher and other trains in the section, to train the system to make driving decisions at the wide range of changes of profile and the track plan, etc.

The current state of theoretical studies, aimed at improving the driving processes on railways, makes it possible to select two directions of solving this problem. The first direction is automation (from the automation of certain operations to the introduction of automated control of technological processes). In particular, Petri nets [10], the methods of finite automata [11–13] and the assertion mechanisms are used for this purpose. The second direction is associated with the use of the methods of artificial intelligence and paying more attention not to simulating a control object, but rather to formalizing the driving activity of a person-operator [14–16]. The advantages of the second approach are the possibility of making driving decisions by the system itself under conditions of uncertainty and incompleteness of information, and the possibility of self-learning and accumulating experience.

An analysis of the scientific literature leads to the conclusion that the modern development of the theory of systems of driving a locomotive, the software and the element base does not allow achieving a fully autonomous motion of trains. A transition stage to the unmanned locomotive driving is the implementation of intelligent locomotive decision support systems. At present, theoretical framework for the implementation of this task is not sufficiently developed. Such issues as the definition of the structure of a locomotive intelligent system, development of mathematical apparatus for describing fuzzy situations when driving a locomotive, and modeling the process of the system's self-learning have not been studied enough. Left unaddressed is the question of development of dynamic knowledge bases for locomotive decision support systems.

3. The aim and tasks of the study

The aim of this work is to improve the process of driving a locomotive using intelligent decision support system for locomotive crews.

Achievement of this goal requires solution of the following tasks. It is necessary to develop a structure and architectural hierarchy of DSS for locomotive crews, which should include the possibility of controlling the occurrence of emergency and development of dangerous situations, as well as the capacity of self-learning and saving the experience of driving. Due to a wide range of factors affecting a train and a locomotive crew, and the existence of a considerable number of qualitative characteristics of the process, it is necessary to represent them in a formal view. The most appropriate is to use the methods of fuzzy mathematics and logic. Result of the locomotive DSS is the driving solution that is recommended under current situation. Therefore, there is the task of developing an approach to making driving decisions under conditions of uncertain train situation.

4. Methods and tools for designing locomotive decision support systems

4.1. Structure and architectural hierarchy of DSS for locomotive crews

A distributed DSS for locomotive crews is a complex system with comprehensive interaction of the locomotive onboard systems located at a great distance; the quality of its organization determines efficiency of the system as a whole.

If P is the set of possible principles of constructing the system and its components; F is the set of interconnected functions performed by the system; A is the set of interconnected onboard locomotive systems, then, according to [15], the problem of synthesis of rational structure of a distributed DSS comes down to defining a set of principles of construction ($p \in P$), a set of functions performed by the system ($f \in F(p)$), a set of elements capable to implement the chosen principles and to perform functions ($\bar{A} \in A$). It is also necessary to find the optimum display of elements of the set f on the elements of set \bar{A} . When selecting the option of the structure of a complex system, there are two possible types of display $f \rightarrow \bar{A}$: the first one is when each task is performed only by one of several possible nodes of the system, and the second one is when the task is performed by several nodes of the system. The requirements to locomotive systems demand the second option of implementation.

When designing the optimal structure of distributed DSS, we will imply the process of gradual solution of the problems of synthesis of the main elements and parts of the system. The following problems are solved iteratively.

As a result of analysis of the existing types of intelligent systems, the hierarchies and algorithms of their work, and taking into account the working conditions of locomotive crews and railway transport as a whole, we developed the parameters of locomotive DSS (given in Table 1).

Table 1

Characteristics of DSS for locomotive crews

The feature, by which DSS is categorized	Parameter name	Parameter description
Type of structuring of the problems solved	Poorly structured	Output parameters include both quantitative and qualitative elements
Character of distribution	Spatially and functionally distributed	Consists of separate linked local locomotive DSS, which can solve a general problem together only
Character of assessing results of decision	Decisions which are objectively assessed	Assessment of result is based on clearly assigned criteria that determine goal achievement: fuel consumption, distance run between overhauls, traffic safety, etc.
Character of situation in which DSS makes decision	Situation if emergency	Decision making about driving a train is characterized by lack of time and rapidly changing situation.
Type of computer analysis of situation	Dynamic	There is a set of scenarios of train driving, of which the most effective in the given moment is chosen

As a result of implementation of stages of the synthesis of locomotive SSD, the structure shown in Fig. 1 was obtained.

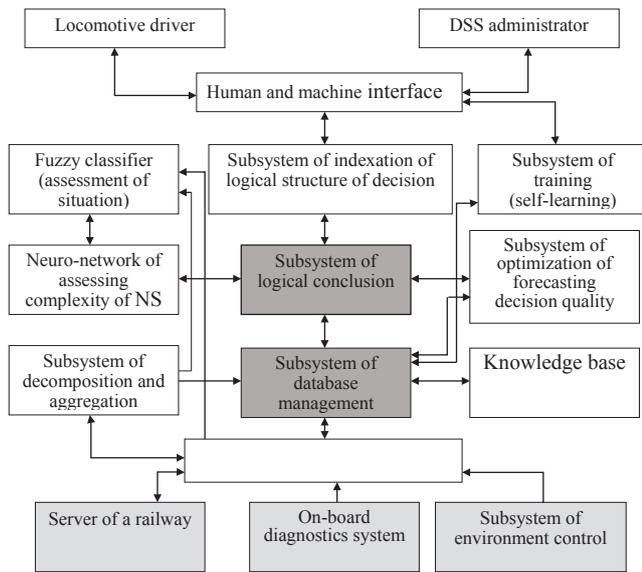


Fig. 1. Structure of on-board locomotive DSS

The features of the presented structure include the existence of subsystems of forecasting and optimization of the quality of decisions, assessment of the complexity of current emergency situation, and the connection to the server. It gives the possibility to implement the function of prediction of traffic events at early stages and to make driving decisions, which ensure adequate level of safety.

4. 2. Formalization of fuzzy situations in the process of train driving

The states of a control object can be assessed by the values of features – distinctive traits of the object. For example, assume that the control object is the locomotive that moves with the train. The main requirements for the system of driving are providing the safety of motion by identifying dangerous emergency situations and taking action to resolve them, as well as providing the most efficient mode of train driving (minimizing operating costs).

In this case, the main states of the control object can be assessed according to the values of the features “State of signals”, “Motion speed”, “Free section of railway track ahead”, “Distance to the traffic light (signal)”, “Distance to obstacle”, “Readings of control instruments”, “Current of traction motors”, etc. It is clear that the number of features (capacity of the set of features) is determined by the objectives of driving the object and the peculiarities of the driving system.

There is a sufficiently developed mathematical apparatus for determining the state of control object (pattern recognition methods [17, 18], fuzzy clustering [19], etc.). It is proposed to construct intelligent DSS for a locomotive driver using the method developed in [20]. The set of values of the features that describe the state of control object at a certain moment will be called the situation. Let us use the simplest approach for the construction of decision making unit: a “decisive table” is formed, that is, the conformity between all possible situations and a certain set of driving decisions. The size of the table is determined by the number of situations which, in turn, depends on the degree of concretization of values of the features.

If p is the number of features, m_i is the number of values of the feature $y_i \in Y (i \in J = \{1, 2, \dots, p\})$, then the number of possible situations does not exceed $m_1 \times m_2 \times \dots \times m_p$.

The situations for compiling the decisive table are supposed to be obtained as a result of questioning an expert (in this case, an experienced train driver). Naturally, when describing the situations, an expert will focus on characteristic “typical” situations that arise while driving locomotives. The number of typical situations is much smaller than the total number of situations, but to describe them, it is more convenient for an expert to use verbal meanings of features, representing the meanings of the correspondent linguistic variables, for example (“Motion speed”, T_1, D_1), (“Distance to the obstacle”, T_2, D_2), where T_1 is the term-set of the linguistic variable “Motion speed”, $T_1 = \{“high”, “medium”, “low”\}$, respectively, $T_2 = \{“long”, “not long”, “medium”, “small”\}$.

Therefore, all possible states of control object can be described by the set of typical situations, each of which is a set of linguistic meanings of features.

A set of fuzzy values of features that characterize the states of control object will be called the fuzzy situation. A formal definition of the “fuzzy” situation is as follows: Assume $Y = \{y_1, y_2, \dots, y_p\}$ is the set of features, the values of which describe the states of control object. Every feature $y_i (i \in J = \{1, 2, \dots, p\})$ is described by the appropriate linguistic variable $\langle y_i, T_i, D_i \rangle$, where $T_i = \{T_1^i, T_2^i, \dots, T_{m_i}^i\}$ is the term-set of linguistic variable y_i , (a set of linguistic meanings of feature, m_i is the number of values of a features); D is the basic set of feature y_i . To describe the terms $T_j^i (j \in L = \{1, 2, \dots, m_i\})$, that correspond to the values of feature y_i , fuzzy variables $\langle T_j^i, D_i, C_j^i \rangle$ are used, that is, the value T_j^i is described by the fuzzy set C_j^i in the basic set D_i :

$$C_j^i = \{ \langle \mu_{C_j^i}(d) / d \rangle, d \in D_i \}. \tag{1}$$

The fuzzy situation s is a fuzzy set of the second level [21]

$$s = \{ \langle \mu_s(y_i) / y_i \rangle, y_i \in Y \}, \tag{2}$$

where

$$\mu_s(y_i) = \{ \langle \mu_{\mu_s(y_i)}(T_j^i) / T_j^i \rangle, j \in L, i \in J \}. \tag{3}$$

An example of fuzzy situation that characterizes a certain state that occurred in the process of driving a locomotive:

$$\{ \langle \langle \langle 0,1 / “high” \rangle, \langle 0,8 / “medium” \rangle, \langle 0,4 / “low” \rangle \rangle / “Motion speed” \rangle, \langle \langle 0,6 / “long” \rangle, \langle 0,8 / “not long” \rangle, \langle 1,0 / “medium” \rangle, \langle 0,6 / “small” \rangle \rangle / “Distance to obstacle” \rangle \}.$$

In the decisive table, the driving decision “Use service braking” may correspond to this fuzzy situation.

Therefore, a limited set of fuzzy situations can describe virtually an infinite number of states of control object.

4. 3. The models that simulate decision making processes

The ultimate goal of driving activity of the train driver is obtaining a positive result – to drive the train to the destination with the minimization of risk of occurrence of transport emergency [22]. The goal is achieved in stages by solving the partial tasks. Let us consider the algorithm of activity of a train driver as a person-operator.

The most important element of driving activity of driver is decision making. To perform a simulation of this process, it is necessary to consider all factors and actions preceding decision making and to determine logical connections between them. To solve this task, it is the most natural to solve this problem using the methods of graph theory [23, 24].

The algorithm of actions of a locomotive driver while driving a train will be presented in the form of fuzzy probabilistic graph, shown in Fig. 2 [16]. For any *j*-th vertex of the probabilistic graph, the condition of stochasticity is satisfied. The task of analyzing the process of driving a train comes down to the graph aggregation, shown in Fig. 2, using the rules of equivalent transformations for sequential and parallel arcs, and for the arcs-loops [24].

The vertices of the given graph are the operations performed by a driver, and logical conditions are weighed by fuzzy probabilistic-temporal characteristics of transition from one operation to another. This graph consists of the following operations [16]:

1 – control of the condition and engagement of railway track ahead; 2 – control of signals ahead; 3 – control of the condition of a locomotive; 4 – control of condition of the train; 5 – analysis of conformity of driving mode with current conditions of driving the train (plan and profile of the track, high-speed mode, distances to signals or dangerous places, weather conditions, etc.); 6 – making a driving decision; 7 – assessment of the condition of railway track ahead; 8 – assessment of meaning of the signal; 9 – assessment of technical condition of locomotive; 10 – assessment of the condition of the train; 11 – assessment of effectiveness of train driving decision that was made; 12 – identification of dangerous situation; 13 – transition to the mode of eliminating an emergency situation.

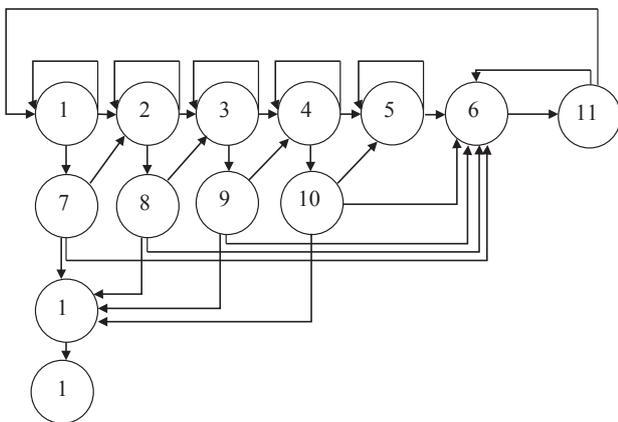


Fig. 2. Fuzzy probabilistic graph of algorithm of activity of a locomotive driver when driving a train

Weight coefficients of transitions between the vertices are assigned by fuzzy numbers, the values of which are recorded in the graph matrix (Tables 2, 3). The values of these coefficients were obtained by the method of expert assessments.

The conclusions after analyzing the equivalent graph obtained by the use of algorithm of aggregation are as follows [16]:

– the minimal time from the analysis of the situation and assessment of effectiveness of the previous driving decision to making the next driving decision (including decisions not to perform any actions) is in the range of [5,66; 13,75] s;

– after the assessment of effectiveness of the driving decision that was made, in about 1–2 % of all cases a driver has to identify a dangerous situation. The time required for this is in the range of [4,9; 9,38] s.

Table 2

Weight coefficients of transitions between vertices of graph in α -level description (probability)

i/j	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0,1	0,3	–	–	–	–	0,6	–	–	–	–	–	–
2	–	0,1	0,3	–	–	–	–	0,6	–	–	–	–	–
3	–	–	0,1	0,3	–	–	–	–	0,6	–	–	–	–
4	–	–	–	0,1	0,3	–	–	–	–	0,6	–	–	–
5	–	–	–	–	0,1	0,9	–	–	–	–	–	–	–
6	–	–	–	–	–	–	–	–	–	–	1	–	–
7	–	0,6	–	–	–	0,3	–	–	–	–	–	0,0	–
8	–	–	0,6	–	–	0,3	–	–	–	–	–	0,0	–
9	–	–	–	0,6	–	0,3	–	–	–	–	–	0,0	–
10	–	–	–	–	–	0,9	–	–	–	–	–	0,0	–
11	0,9	–	–	–	–	0,1	–	–	–	–	–	–	–
12	–	–	–	–	–	–	–	–	–	–	–	–	1
13	–	–	–	–	–	–	–	–	–	–	–	–	–

Table 3

Weight coefficients of transitions between vertices of graph in α -level description (time of transition)

i/j	1	2	3	4	5	6	7	8	9	10	11	12	13
1	2	0,5	–	–	–	–	1	–	–	–	–	–	–
2	–	0,5	0,5	–	–	–	–	0,5	–	–	–	–	–
3	–	–	2,5	0,5	–	–	–	–	1,5	–	–	–	–
4	–	–	–	4	5	–	–	–	–	1,5	–	–	–
5	–	–	–	–	4	4	–	–	–	–	–	–	–
6	–	–	–	–	–	–	–	–	–	–	8	–	–
7	–	0,5	–	–	–	4	–	–	–	–	–	3	–
8	–	–	0,5	–	–	4	–	–	–	–	–	3	–
9	–	–	–	0,5	–	4	–	–	–	–	–	3	–
10	–	–	–	–	–	4	–	–	–	–	–	3	–
11	2	–	–	–	–	4	–	–	–	–	–	–	–
12	–	–	–	–	–	–	–	–	–	–	–	–	1
13	–	–	–	–	–	–	–	–	–	–	–	–	–

These parameters indicate that the speed of making decisions by a driver might and must be enhanced. The decrease in the time necessary for the identification of emergency situations directly affects traffic safety, and the more the current speed is, the more important it is to have the possibility to identify an emergency in the shortest possible time and to start clearing it.

4. 4. Methods of decision making of locomotive DSS under conditions of uncertainty of the input data

The model of the problem of decision making in [25] is represented in the form: $\langle t, X, R, A, F, G, D \rangle$, where *t* is the task setting (for example, to choose one best alternative or to organize the entire set of alternatives); *X* is the set of feasible alternatives; *R* is the set of criteria of assessing the degree of achieving the set objectives; *A* is the set of scales of measurement by the criteria (scales of items, ordinal, interval), *F* is the display of a set of feasible alternatives in a set of criteria assessments; *G* is the system of advantages

of decisive element; D is the decisive rule that displays the system of preferences.

All methods of solving multi-criteria problems can be reduced to three groups [15]:

- the method of main index;
- the method of resulting indicator;
- the lexicographic methods (methods of successive concessions).

We will implement the selection of the decision variant of SSD by the adaptive criterion. Based on the experience of driving locomotives, a driver makes the following elementary decisions (to drive a diesel locomotive) in the process of motion: to set the driving wheel to the higher (lower, zero) position; setting the brake controller of driver into the “Service braking” position (“Emergency braking”, “Cutting off the brake supply line”, “Braking”, “Train position”); feeding sand under the wheel pairs of a locomotive; signaling; not performing any actions.

Thus, the set of variants of decisions for locomotive DSS is known in full. It is necessary to arrange m solutions a_1, a_2, \dots, a_m , which are assessed by n criteria C_1, C_2, \dots, C_n . The corresponding assessment is $R_{ij}, i=[1;m], j=[1;n]$. Relative importance of each criterion is assigned by the coefficient W_j , in this case,

$$\sum_{j=1}^n W_j = 1.$$

Then the weight assessment of the i -th variant is defined as

$$R_i = \sum_{j=1}^n W_j R_{ij}. \tag{4}$$

Assume that the assessments of options by the criteria and coefficients of relative importance are assigned by functions of belonging, respectively, $\mu_{R_{ij}}(r_{ij})$ and $\mu_{W_j}(w_j)$.

In this case, the values W_j and R_{ij} are fuzzy numbers. Extended binary arithmetic operations with fuzzy numbers are determined through appropriate operations with clear numbers using the principle of generalization.

Based on the main task of railway transport, namely, safe and timely transportation of cargo and passengers with the minimum use of energy resources for traction of trains, we propose a simplified set of criteria of assessing the quality of driving. C_1 =«current state of traffic safety», C_2 =«current fuel consumption (electric power)», C_3 =«complying with the traffic schedule».

Locomotive DSS will present a set of devices that will ensure execution of the following functions:

- gathering operational information about condition of the environment;
- including traffic schedule;
- saving databases on locomotive crews;
- storing and using knowledge base of the system;
- delivering the results of system’s performance to the driver.

To solve the set tasks, the indices given in Fig. 3 are used as the source data for the DSS.

Analyzing the working conditions of locomotive crews, it is possible to distinguish the following functions of a person, which directly influence the efficiency of using TRS and safety and need support with the help of the intelligent system [26]:

- 1) recognition of emergency situation;
- 2) setting the driving wheel of a driver;
- 3) determining the moment and depth of brake conduit deaeration;
- 4) determining the technique of clearing the faults of locomotive.

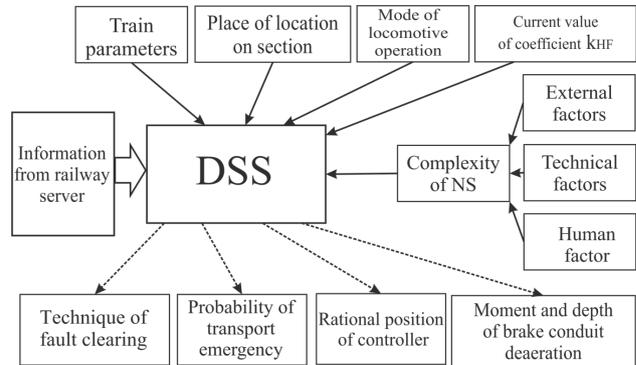


Fig. 3. List of data at the input and output of DSS under design

4. 5. Determining a current state of train as a control object

In the system being developed, the unit responsible for assessing the states of control object is the necessary part. The functioning of the unit of assessment of state (UAS) is based on the simulation of actions of the person who makes decisions (PMD); for this purpose, the information, received from PMD, is used. That is why the specified block is included in the model of driving, which simulates the behavior of PMD in the process of driving an object. Suppose the information delivered to the input of the UAS can be of three types: fuzzy, clear and fuzzy multiple. The type of information is defined by the type of sensors of driving system. Let us conditionally distinguish three major types of sensors:

- “fuzzy sensors” (person-operator, who delivers verbal information about the state of control object to the output of UAS);
- “clear sensors” (certain sensors that deliver specific numeric information to the output of UAS);
- “analog sensors” (sensors that deliver to the output of UAS continuous functions of belonging of fuzzy sets, which are converted to the vectors of degrees of belonging by the analog to digital converter).

4. 6. The basics of the system of self-learning of intelligent locomotive DSS

Self-learning will imply a complex of methods and algorithms for setting and functioning of intelligent systems of driving traction rolling stock. The proposed structure of the system is shown in Fig. 4.

The system, while analyzing the data about the state of parameters that affect train motion, generates driving signals that are the most feasible under current situation (that is, recommendations for driving TRS). These signals through the interface part are delivered to the knowledge base for further verification for adequacy and efficiency.

Fuzzy classifier (FC) is the main element of the system of self-learning. The effectiveness of training the system and eventually the safety of train motion depend on its work.

FC is a fuzzy knowledge base, to the input of which the signals about current state of the traction rolling stock and

the environment are delivered. For training (creation and refining the rules of fuzzy knowledge base), an external knowledge base is used, which reflects the range of driving signals depending on the current train situation. It is formed as a result of real travels and shows how train drivers executed control of the rolling stock.

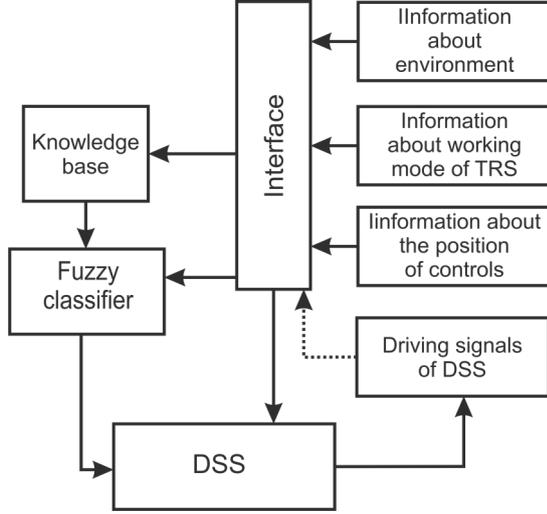


Fig. 4. Structure of self-learning system

Let us express the vector of informative features of classification object through $X=(x_1, x_2, \dots, x_n)$, and the classes of decisions through t_1, t_2, \dots, t_C . In our case, the fuzzy classifier is a display of $X \rightarrow y \in \{t_1, t_2, \dots, t_C\}$, which is implemented by means of a fuzzy knowledge base. Fuzzy knowledge base of this display will be written down as [27]:

If $(x_1 = \delta_{1j} \text{ and } x_2 = \delta_{2j} \text{ and } \dots \text{ and } x_n = \delta_{nj} \text{ with the weight } w_j)$,

then

$$y = d_j, \quad j = \overline{1, m}, \quad (5)$$

where m is the number of rules; $d_j \in \{t_1, t_2, \dots, t_C\}$ is the value of the consequent of the j -th rule; $w_j \in [0, 1]$ is the weight coefficient which sets reliability of the j -th rule, $j = \overline{1, m}$; δ_{ij} is the fuzzy term that evaluates the feature x_i in the j -th rule $i = \overline{1, n}, j = \overline{1, m}$.

4. 7. Development of mathematical model of dynamic knowledge base

In a general case, the productive model can be represented in the following form [25]:

$$N = \langle A, U, C, I, R \rangle, \quad (6)$$

where N is the name of the product; A is the range of product use; U is the condition of using the product; C is the core of the product; I are the post-conditions of productions which are implemented with positive production sales; R is the comment, informal explanation (substantiation) of production, the time of entry to the knowledge base, etc.

To design a knowledge base for driving a locomotive, we need to define parameters U, C, I . Parameter A will be the same for all the productions belonging to the designed data-

base; parameter R does not participate directly in the work of the system and is auxiliary.

The core of the production can be presented in the following form:

$$C = (z_{j1} \& z_{j2} \& \dots \& z_{ji} \Rightarrow d_{j1} \& d_{j2} \& \dots \& d_{ji}), \quad (7)$$

where $z_{j1} \dots z_{ji}$ are the values of conditions; $d_{j1} \dots d_{ji}$ are the values of actions.

For each sequence number of conditions, the set of values is defined in the process of designing the database, that is, $z_{ji} \in Z_i$.

The mode of using knowledge is as follows. An intelligent system receives the data about the current train situation in the form $(z_{j1} \& z_{j2} \& \dots \& z_{ji})$. Then the obtained data are compared to the productions obtained previously. There are productions in which conditions coincide with the current conditions. DSS, according to the defined rules, chooses which production should be used in the current moment.

In general, the work of knowledge base is described by the following algorithm. When the base is working in the mode "Accumulation", productions new entry and specification takes place. If the production identical to the current conditions of driving a train is found in the knowledge base, its weight among other productions is enhanced by increasing the parameter I . If the current conditions of driving a train and driving actions of the locomotive crew (position of the control instruments of locomotive) do not coincide with any of the existing productions, a new production with current values $(z_{j1} \& z_{j2} \& \dots \& z_{ji})$ and $(d_{j1} \& d_{j2} \& \dots \& d_{ji})$ is entered into the base.

When the base is working in mode "Use", DSS constantly monitors current train situation and compares it with existing productions. In the case of coincidence, the DSS provides recommendations for driving based on the experience of the knowledge base. If the current situation does not correspond to any of the existing productions, the DSS is not capable to recommend any driving actions, and the set of recommended driving actions is nullified.

Formally, the way the knowledge base works is described by the following expressions [28]:

$$U = \langle \text{Accumulation} \rangle \begin{cases} \text{if } C_{pot} \in O_{baza}; C_{baza\ i} \equiv C_{pot}, I_i = I_i + 1, \\ \text{if } C_{pot} \notin O_{baza}; C_{baza\ k+1} \equiv C_{pot}, I_{k+1} = 1, \end{cases} \quad (8)$$

$$U = \langle \text{Use} \rangle \begin{cases} \text{if } C_{pot} \in O_{baza}; C_{baza\ i} \equiv C_{pot}, D_{pot} \equiv D_{baza\ i}, \\ \text{if } C_{pot} \notin O_{baza}; D_{pot} \equiv \emptyset, \end{cases}$$

where C_{pot} is the current value of conditions of driving a train and the position of control instruments of locomotive; O_{baza} is the set of all the productions entered into the knowledge base; $C_{baza\ i}$ is the separate production of the knowledge base; k is the number of productions in the knowledge base; $i \in [1; k]$ is the sequential number of productions in the knowledge base; I_i is the parameter that characterizes the number of observations of the i -th product in the course of compiling the knowledge base; D_{pot} are the current driving actions of a locomotive crew, recommended by DSS (the position of control instruments of a locomotive); $D_{baza\ i}$ is the list of driving actions included in the i -th production: $D_{baza\ i} = (d_{j1} \& d_{j2} \& \dots \& d_{ji})_i$.

5. Discussion of results of research into intelligent locomotive DSS

The model of driving a train by using the theory of fuzzy probabilistic graphs was developed, which allowed estimating the speed of decision making by a driver. With the probability of more than 0,5, the minimum time that passes from the analysis of the situation and the assessment of effectiveness of the previous driving decision (including decision not to perform any action), is in the range of [5,66; 13,75] s. The time required for the identification of emergency situation is in the range of [4,9; 9,38] s.

For the possibility to use intelligent DSS, the description of the current state of control object (train) is expressed as a fuzzy situation. The necessary condition of correctness of the developed influences of driving system is a reliable assessment of conditions under which the object of control is. Its states are estimated by the values of features – distinctive traits of an object, such as “Motion speed”, “Free railway track section ahead”, “Distance to the traffic light (signal)”, “Distance to the obstacle”, “Readings of control instruments”, etc.

The system, while analyzing data about the state of parameters that affect the train motion, generates driving signals, which are the most practical under current situation (that is, recommendations for driving TRS). The structure of the vector of informative features (the list of features and their presentation in a clear or fuzzy form) for the locomotive system was defined. Training the fuzzy classifier includes finding the vector which minimizes the distance between the results of logical conclusion and experimental data from the sample.

Mathematical model of dynamic knowledge base was developed. The knowledge base can work in two modes: “Accumulation” (productions entry and specification takes place) and “Use” (intelligent system constantly monitors the current train situation and compares it to the existing productions). In the process of mathematical description of performance of the knowledge base, we used current values of conditions of train driving and the position of the control instruments, the set of all productions that are entered into the knowledge base and the current driving actions of a locomotive crew.

The results presented in the work are only the initial stage in the development of locomotive intelligent systems. The need to separate the locomotive DSS from the systems of general purpose is caused by the existence of specific features of rail transport functioning, namely, a large price of operator’s errors, which can result not only in significant

material losses, but also in death of people. In the systems that are being developed it is necessary to take into account such specific features as:

- compliance with traffic schedule under conditions of existence of a whole polygon of control objects (trains);
- large kinetic energy of a moving train;
- big impact of a track profile (route coordinates) on the effectiveness of driving;
- physiological requirements for locomotive crews, etc.

Therefore, these studies require further improvement and development for practical use of their results.

Presented results have a number of restrictions of their application. Thus, in the list of data at the input and output of the designed DSS, the human factor, that influences the complexity and development of emergency situations is used. At present, this parameter is not formalized enough due to the complexity and a great number of qualitative factors that influence it. In addition, the simulation of the driving activities was carried out under the driver’s standard mode of operation. In case of an emergency situation, the actions of a driver are aimed at its clearing and localization in the shortest possible time. Therefore, to simulate the actions of a locomotive crew under extreme situations, it is necessary to conduct additional research.

7. Conclusions

1. The structure of the locomotive DSS, which is characterized by the existence of subsystem of assessment of complexity of the current train situation, was developed. This made it possible to take into account the traffic safety index when making driving decisions. The self-learning of intellectual system is implemented using the fuzzy classifier. The authors developed a model of knowledge base that is capable of making new entries in the process of its usage and to keep the records of statistics of decisions, which were implemented when driving a train.

2. Fuzzy situations were presented in the form of sets of the second level, which allowed describing an infinite number of states of control object with a limited set of terms. Based on a fuzzy graph, the model of making decisions by a driver was developed, which made it possible to assess the quality of driving.

3. It is proposed to make train driving decisions on the basis of the utility criterion that takes into account safety, energy costs for traction of trains, and compliance with traffic schedule.

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