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Creation of a model of automated traction control of shunting locomotives by using artificial intelligence methods

In the paper, a mathematical model of the automated traction transmission control system of the shunting locomotive was developed, using methods of fuzzy logic and the method of expert evaluations. The Mamdani algorithm was used for the proposed model. The algorithm includes the knowledge base of an intelligent system, which uses a production model to formalize and represent knowledge in memory, combining elements of logical and network management approaches. The resulting automated traction transmission control model of the shunting locomotive offers its optimal driving mode for a specific train and section. The model uses the generated fuzzy knowledge base. The result of the model calculation is a control signal for the movement of the shunting locomotive on 4 motors, using partially the 3rd and fully the 4th and 5th positions of the driver's controller. This mode of movement allows to reduce fuel consumption for shunting of the locomotive with partial loads on the traction electric transmission.

***Keywords**: railway transport, rolling stock, diesel locomotive, traction electric transmission, Mamdani method.*

Introduction. The development of railway transport requires constant improvement of locomotive management methods, in particular, shunting locomotives, which play an important role in the organization of railway transport. Efficient use of locomotives is a major task for railways. For the years 2021-2023, the main operating indicators of railway transport have significantly deteriorated: freight traffic, passenger traffic, average daily locomotive productivity. The operating fleet of shunting locomotives has exaggerated its average age by almost 40 years. Operating diesel locomotives during shunting work mostly use partial load modes. To improve operating conditions, it is necessary to carry out modernization and introduce new modern methods of automated control and diagnostics of locomotives.

Analysis of recent research and problem statement. In the materials of the international conference [1], the methods and prospects of using artificial intelligence in railway transport were considered. The paper [2] presents the theoretical rationale for the development of a knowledge base for intelligent locomotive DSS. The approach and structure of the self-learning system of intelligent DSS is proposed, the advantage of which is the presence of a fuzzy classifier that works according to the set criteria and determines a fuzzy image of the current train situation. The works [3 ,4] propose an approach to intelligent operation of trains based on a combination of expert knowledge and data mining algorithms, also investigated the operation of the urban rail transport system (URTS) with the support of machine learning (ML), including obstacle perception, infrastructure perception, passenger flow forecasting, forecasting train delays, failure forecasting, remaining service life forecasting, train operation and control optimization, train dispatch optimization and train ground communication optimization. The article [5] discusses the general control algorithms of the automatic train control system, namely: control using artificial neural network algorithms and fuzzy control using a fuzzy controller, which is an important part of the whole system, which consists of fuzzification, defuzzification, knowledge base and fuzzy conclusion In the study [6], the technology of fuzzy forecasting is used to ensure effective operating conditions of rolling stock. Analysis of foreign articles [7, 8] reveals the essence of energy modeling of railway transport. Locomotive traction force simulations are a fundamental part of such models. In the article [9], the structure of an intelligent decision support system for locomotives is developed. Formal indicators of the quality of the train management process were obtained. The work theoretically substantiates the definition of weighting factors for each partial criterion of management quality. The study [10] presents a systematic review of the literature on the current state of artificial intelligence in railway transport, covering maintenance, automatic control of rolling stock, traffic safety. In [11], an efficient analysis method based on fuzzy data and fuzzy thinking is proposed for large volumes of data of China's high-speed train control system. In work [12], a mathematical model was developed for determining the traction and energy indicators of the ChME3 shunting locomotive when working on four and two parallel-connected traction electric motors. As a result of the use of various options for connecting the TM, it is possible to save fuel for maneuvering work at partial loads, depending on the operating conditions.

Analyzing the above literature, it can be noted that the process of controlling locomotives using artificial intelligence methods is in a stage of constant development. The advantages of the works include the prepared theoretical base for the creation of intelligent management systems. In each work, the factors that affect the movement of the locomotive and the control signals necessary for individual elements of the control system are investigated. Among the shortcomings should be attributed: the lack of consideration of the work of each of the elements of traction electric transmission of locomotives separately, for the possibility of creating an adequate fuzzy knowledge base of the automated control system; inflexibility of systems that are designed for a specific type of locomotive and use a limited knowledge base.

Having considered the disadvantages and advantages of the above works, it is possible to say that the most promising methods for creating a model of automated control of traction transmission of a shunting locomotive at partial loads are methods of fuzzy logic. One of the most convenient programming tools in the field of fuzzy logic is the Fuzzy Logic (MATLab) environment. To create the model, the Mamdani method [13] is used, whose activity diagram consists of the formation of the base and rules, fuzzification, aggregation of preconditions, activation of subassembly, accumulation of conclusions, and defuzzification.

The purpose and tasks of the study. The main purpose of the research is the development of a mathematical model of automated traction control of shunting locomotives by using artificial intelligence methods. To solve this problem, it is proposed to use methods of fuzzy logic, in particular, the Mamdani algorithm. With the help of the algorithm, a fuzzy knowledge base and a scheme of automated control of traction transmission of a shunting locomotive are formed. The quality of the system directly depends on the structure, content and management algorithms of the knowledge base. The main functions of knowledge bases include: collecting and analyzing information, creating and storing rules, as well as the possibility of self-learning and adaptation [14, 15, 16].

Research Objectives.

1. Develop the structure and operational algorithm for a fuzzy knowledge base of the intelligent traction transmission control system of the shunting locomotive.

2. Perform fuzzification of the model's input data using fuzzy logic methods.

3. Design a structural diagram of an automated traction transmission control system of the shunting locomotive with self-learning capabilities.

Materials and methods of research. To date, intelligent control systems have received significant development in technology [17, 18, 19]. Intelligent control systems are systems that are able to «Understand» and learn, taking into account the object of control, the external environment and operating conditions. The main difference between such systems is the presence of a mechanism for complex knowledge processing. A key architectural feature that distinguishes intelligent control systems from traditional control systems is the ability to acquire, store, and process knowledge to perform control functions. Intelligent systems based on methods of fuzzy logic, artificial neural networks and genetic algorithms are increasingly used in various industries, including railway transport. These technologies make it possible to create more adaptive, reliable and efficient systems that are able to better respond to changing conditions and uncertainties than traditional control methods [20, 21].

The creation of intelligent control systems is based on two main principles of Fig. 1.

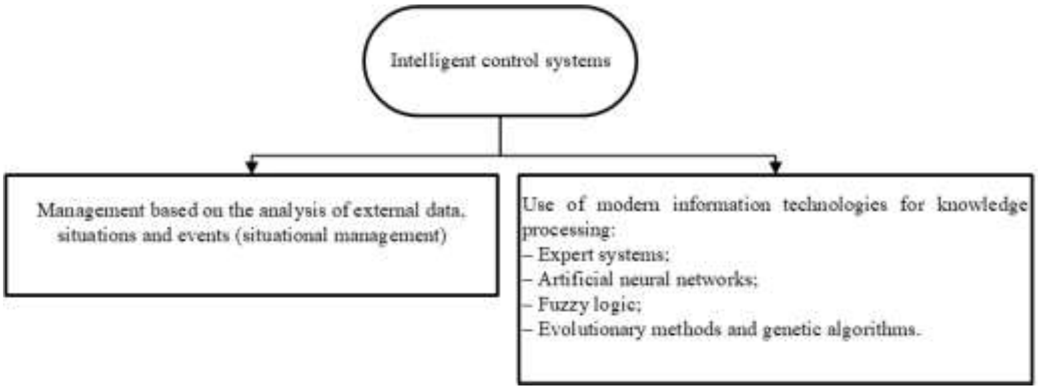


Fig. 1. **Basic principles of creating an intelligent control system**

The concept of intelligence involves:

– the ability to work with formalized human knowledge (as in the case of expert systems and fuzzy logic);

– the use of human learning and thinking methods (as in artificial neural networks and genetic algorithms).

The quality of work of artificial intelligence systems directly depends on the structure, content and algorithms of knowledge base management. The main functions of knowledge bases include: collecting and analyzing information, creating and storing rules, as well as the possibility of self-learning and adaptation. In addition, the integration of new data, its validity, and the effective use of information for decision-making are important aspects.

For intelligent automated control of traction electric transmission of a shunting locomotive, the following system with the possibility of self-learning is proposed, shown in Fig. 2.

Self-learning is a complex of methods and algorithms for setting up and functioning of automated control systems for traction transmission of shunting locomotives [2, 9].

The Mamdani algorithm is used to create the system. The algorithm works according to the "black box" principle [13]. In the intermediate stages, the apparatus of fuzzy logic and the theory of fuzzy sets are used. Due to the use of fuzzy systems, it is possible to manipulate the usual numerical data, but to use the flexible possibilities that fuzzy inference systems provide. It is implemented due to the rules (Rule), which consist of conditions (Condition) and conclusions (Conclusion), which in turn are fuzzy statements (Statement). A fuzzy statement includes a linguistic variable (Variable) and a term that is represented by a fuzzy set (Fuzzy Set). A membership function is defined on the fuzzy set, the value of which can be obtained using the getValue() method. This is a method defined in the Fuzzy Setlface interface. When performing the algorithm, it will be necessary to use the "activated" fuzzy set (Activated Fuzzy Set), which in a certain way redefines the membership function of the fuzzy set (FuzzySet). The algorithm also uses the union of fuzzy sets (Union of Fuzzy Sets). A union is also a fuzzy set and therefore has a membership function (defined by Fuzzy Setlface). The Mamdani Algorithm (Mamdani

Algorithm) includes all stages and uses a rule base (List<Rule>) as input data. Also, the algorithm provides for the use of "activated" fuzzy sets (ActivatedFuzzySet) and their unions (UnionOfFuzzySets).

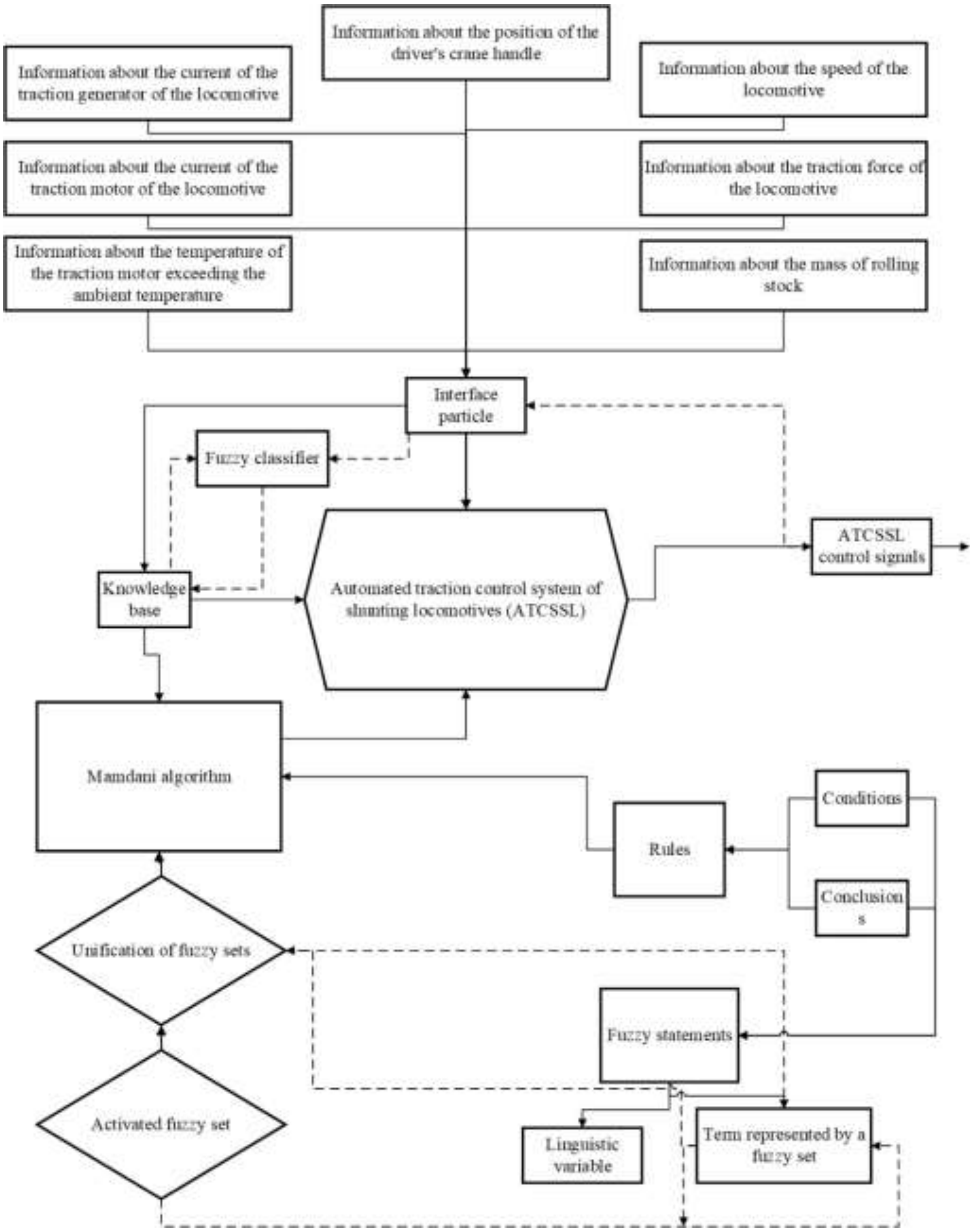


Fig. 2. **Automated traction control system of a shunting locomotive (ATCSSL)**

Before moving on to the operation of the algorithm itself, it is necessary to familiarize yourself with the following definitions:

A fuzzy variable has the following form:

$$<\alpha, X, A>, \quad (1)$$

where α – the name of the fuzzy variable;
X – the definition area of the fuzzy variable;

A – the fuzzy set on the universe X.

The linguistic variable has the following form:

$$<\beta, \text{T, X, G, M}>, \tag{2}$$

where β – the name of the linguistic variable;
T – the set of its values (terms);
X – the universe of fuzzy variables;
G – the syntactic procedure for creating new terms;
M – the semantic procedure that forms fuzzy sets for each term of a given linguistic variable.

Let’s call a fuzzy expression an expression of the form:

$$<\beta \text{ IS } \alpha>, \tag{3}$$

where β – the linguistic variable;
α – one of the terms of the variable.

Formation of the rule base of the Mamdani algorithm.

A rule base is a set of rules, where each sub-conclusion corresponds to a certain weight factor.

The rule base can look like this (for example, rules of different constructions are used):

$$\begin{aligned}
&RULE_1: \ IF \ «Condition_1» \ THEN \ «Conclusion_1» \ (F1) \ AND \ «Conclusion_2» \ (F2)\\
&RULE_2: \ IF \ «Condition_2» \ AND \ «Condition_3» \ THEN \ «Conclusion_3» \ (F3);\\
&\ldots\\
&RULE_n: \ IF \ «Condition_k» \ THEN \ «Conclusion_(q-1)» \ (F_{q-1}) \ AND \ «Conclusion_q» \ (F_q),
\end{aligned} \tag{4}$$

where F_i - the weighting coefficients, which mean the degree of confidence in the truth of the received sub-conclusion (i=1,2,…, q), where q – the total number of sub-conclusions in the rule base. By default, the weighting factor is assumed to be equal to 1.

Linguistic variables present in the conditions are called inputs, and in the conclusions, they are called outputs.

Fuzzification of input variables by the Mamdani algorithm.

This stage is often called blurring. The generated rule base and array of input data A = {a_1, a_2, ..., a_m}, are input, where m – the number of input variables. This array contains the values of all input variables. The purpose of this stage is to obtain truth values for all preconditions from the rule base. It happens as follows: for each of the preconditions there is a value $b_i = \mu(a_i)$, where μ(ai) – the membership function for the fuzzy set. In this way, a set of bi values (i = 1, 2, ..., k) is obtained, where k is the total number of preconditions in the rule base. The array of input data is formed in such a way that the i-th element of the array corresponds to the i-th input variable (the variable number is stored in the integer field "id").

Aggregation of sub-conditions by the Mamdani algorithm.

As already mentioned above, the condition of the rule can be complex, that is, include sub-conditions connected with each other using the logical operation "AND". The purpose of this stage is to determine the degree of truth of the conditions for each rule of the fuzzy inference system. For each condition, it is possible to find the minimum truth value of all its sub-conditions. Formally, it looks like this:

$$c_j = \min\{b_i\}, \tag{5}$$

where j=1, 2, …, n (n – the number of fuzzy production rules);
i – the number from the set of numbers of sub-conditions in which the j-th input variable participates.

Activation of sub-conclusions.
At this stage, there is a transition from conditions to sub-conclusions. For each sub-conclusion there is a degree of truth $d_i = c_i \cdot F_i^{'}$ where i = 1, 2, ..., q. Then, a set with a new membership function is assigned to each i-th sub-conclusion. Its value is determined as a minimum from di and the value of the membership function of the term from the sub-conclusion. This method is called min-activation, which is formally written as follows:

$$\mu_i^{'}(x) = \min\{d_i, \mu_i(x)\}, \tag{6}$$

where $\mu_i^{'}(x)$ – the "activated" membership function;
$\mu_i(x)$ – the term membership function;
d_i – the degree of truth of the i-th sub-conclusion.

Accumulation of conclusions.

The goal of this stage is to obtain fuzzy sets (or their union) for each of the output variables. This is done as follows: the i-th output variable is assigned a union of sets $E_i \cup D_j$ where j - the number of sub-inferences in which the i-th output variable (i = 1, 2, …, s) participates, where s is the number of input variables. The union of two fuzzy sets is represented as a third fuzzy set with the following membership function:

$$\mu_i^{`}(x) = \max\{\mu_1(x), \mu_2(x)\}, \tag{7}$$

where $\mu_1(x), \mu_2(x)$ – the membership functions of the combined sets.

Defuzzification of output variables.

The purpose of defuzzification is to obtain a quantitative value (crisp value) for each of the original linguistic variables [13]. The i-th output variable and the set E_i (i = 1,2, ..., s) belonging to it are considered, where s is the number of input variables. Then, using the defuzzification method, the final quantitative value of the output variable is found. In this implementation of the algorithm, the method of the center of gravity (center of gravity) is used, according to which the value of the i-th output variable is calculated according to the formula:

$$y_i = \frac{\int_{min}^{max} x \cdot \mu_i(x)dx}{\int_{min}^{max} \mu_i(x)dx}, \tag{8}$$

where $\mu_i(x)$ – the membership function of the corresponding fuzzy set E_i;
min and *max* – the boundaries of the universe of fuzzy variables;
y_i – the defuzzification result.

The management process is as follows. Information about the locomotive enters the interface part. From the interface part, the information is divided into two streams. The first is a knowledge base designed to accumulate information about the traction transmission management of a diesel locomotive. The second is a fuzzy classifier (FC). FC is a fuzzy knowledge base, the input of which is provided with information about the current state of traction rolling stock. An external knowledge base is used for training (creating and clarifying the rules of a fuzzy knowledge base), which displays the spectrum of control signals depending on the current train situation. It was created based on the results of real trips in the "Darnytsia" locomotive depot and shows how drivers controlled rolling stock. At the output of the classifier, there are the control signals generated in accordance with the rules of the fuzzy knowledge base.

The task of the Mamdani algorithm is to generate a control signal for the automated traction control system of the shunting locomotive (ATCSSL). The system, analyzing data on the state of the parameters affecting the train movement, generates control signals that are most appropriate in the current situation (that is, recommendations for controlling the traction transmission of the locomotive).

The control signal of the ATCSSL system is supplied to the motor shutdown units, which operate on the basis of thyristors.

According to the train situation, current will flow through the motor shutdown units to the traction electric motor shutdown contacts, and then to the coils of the train contactors. Based on this, the traction generator receives excitation after turning on the train contactors and supplies current to the power circuit. The current flowing through the windings of the traction electric motor creates a torque on the motor armature shafts, which is transmitted to the wheel pairs of the diesel locomotive through the traction reducers.

According to Fig. 1, FC contacts the knowledge base, which contains and updates information about the actual actions of drivers during train movement [2]. Based on these data, a training sample of M input-output pairs is formed:

$$(X_r, Y_r),\ r = \overline{1, M}, \tag{9}$$

where X_r – the vector of information features of the object of classification;

$Y_r \in (t_1, t_2, \ldots, t_C)$ where $(t_1, t_2, \ldots, t_C)$ – the decision classes;

$r = \overline{1, M}$ – the r-th line of sample M.

Let's introduce the following notations:

P – the vector of the parameters of the membership functions of fuzzy terms of the knowledge base (9);

W – the vector of weight coefficients of knowledge base rules;

$F(K, X_r) \in (t_1, t_2, \ldots, t_C)$ – the result of classification based on a fuzzy base with parameters $K = (P, W)$ at the input value X_r from the r-th line of the sample (9).

Learning a fuzzy classifier consists in finding the vector K that minimizes the distance between the results of the logical conclusion and the experimental data. Let's consider the method of calculating this distance, which is called the learning criterion [2, 9]. The distance between the desired and actual behavior of the model can be determined by the accuracy of the classification on the training sample. Then training the fuzzy classifier

$$\frac{100\%}{M} \Sigma_{r=\overline{1,M}} \Delta_r(K) \rightarrow \min, \tag{10}$$

where $\Delta_r(K) = \begin{cases} 1, \text{ if } y_r \neq F(K, X_r) \\ 0, \text{ if } y_r = F(K, X_r) \end{cases}$ – object classification error Xr.

The advantages of this criterion are its simplicity and clear meaningful interpretation. The percentage of errors is often used as a criterion for training various pattern recognition systems [9] The objective function (10) takes discrete values, which makes it difficult to use fast gradient optimization methods, especially for small training samples.

To determine the management actions that must be implemented in a specific train situation, it is necessary to form a database [12]. An example of such a format can be the database shown in Table 1.

Table 1. **An example of a database**

Frame #	Values characterizing the mode of train movement						Regulation of control bodies			
	Mass of the composition, t	Traction force, kN	Speed, km/h	Traction generator current, A	TM current, A	The temperature of excess above the TM surrounding environment, °C	Operator's controller handle position	Crane handle item No. 395 position	Crane handle item No. 254 position	The number of connected TMs
1	763	187.8	1.8	1619	809	3	4	2	2	4
2	763	171.5	2.6	1513	757	5	4	2	2	4
3	763	157.7	3.3	1422	711	7	4	2	2	4
4	763	145.9	3.9	1342	671	9	4	2	2	4
5	763	135.7	4.5	1272	636	11	4	2	2	4
6	763	126.8	5.1	1210	605	13	4	2	2	4
7	763	118.9	5.6	1154	577	14	4	2	2	4
8	763	112.0	6.0	1104	552	16	4	2	2	4
9	763	105.8	6.5	1059	529	17	4	2	2	4
10	763	100.3	6.9	1018	509	18	4	2	2	4
11	763	95.4	7.3	980	490	20	4	2	2	4
12	763	90.9	7.7	946	473	21	4	2	2	4
13	763	86.8	8.1	915	457	22	4	2	2	4
14	763	83.1	8.4	886	443	23	4	2	2	4
15	763	79.7	8.7	859	429	24	4	2	2	4
16	763	76.6	9.1	834	417	25	4	2	2	4
17	763	73.8	9.4	811	405	26	4	2	2	4
18	763	71,2	9,6	789	394	27	4	2	2	4
19	763	68.7	9.9	769	384	28	4	2	2	4
20	763	66.5	10.2	750	375	29	4	2	2	4
21	763	64.4	10.4	732	366	29	4	2	2	4
22	763	62.5	10.7	715	357	30	4	2	2	4
23	763	60.7	10.9	699	350	31	4	2	2	4
24	763	59.0	11.2	684	342	32	4	2	2	4
25	763	57.4	11.4	670	335	32	4	2	2	4

Let's design an automated control system for traction electric transmission of a shunting locomotive with the following inputs:

1 – composition mass;
2 – traction force;
3 – speed;
4 – traction generator current;
5 – traction motor current;
6 – temperature rise of the traction electric motor above the surrounding environment;

For inputs, it is necessary to perform phasing. In the section «Required position of control bodies», the signals «Operator's controller handle position», «Crane handle item No. 395 position», «Crane handle item No. 254 position» and «Number of connected TMs» should be implemented as distinct sets. On the basis of Table 1, a fuzzy knowledge base of the form of Table 2 is formed.

Table 2. **Knowledge base example**

Rule #	The value of the signal level at the input						Required position of the controls			
	1	2	3	4	5	6	Operator's controller handle position	Crane handle item No. 395 position	Crane handle item No. 254 position	The number of connected TMs
1	middle	low	very_low	low	high	middle	position is 4ps	position is 2	position is 2	nted is 4ted
2	middle	middle	very_low	middle	high	middle	position is 4ps	position is 2	position is 2	nted is 4ted
…	…	…	…	…	…	…	…	…	…	…
n	middle	very_high	very_high	very_high	high	middle	position is 4ps	position is 2	position is 2	nted is 4ted

The number of rules n in the knowledge base is determined by the number of all possible combinations of input signal levels. For each variant, its own combination of signals is formed at the input, which go to the control bodies.

The self-learning process consists in the fact that during the movement of the train, a periodic survey of the values of the input signals and the signals of the number of connected TMs is performed. The current value of the signals from the control bodies for this rule is compared with the values in the knowledge base. Next, the section of the knowledge base «Number of TMs connected TMs» is adjusted taking into account the new experience gained during movement.

For the formalization and presentation of knowledge in the memory of information systems, there are a number of models that can be structured as follows:

– Logical models – use formal logical systems, where knowledge is presented in the form of facts and rules, with the help of which conclusions are made. They are based on logical operators and form the basis for building logical conclusions.
– Network models – represent knowledge in the form of graphs or networks, where nodes correspond to objects, and edges between them reflect relations. An example can be a semantic network that illustrates the relations between concepts.
– Frame models – knowledge is organized in the form of frames, which are data structures for representing stereotyped situations. The frame contains slots corresponding to the attributes of the object and values describing the state of the object. Frames are useful for modeling knowledge in the context of situations or scenarios.
– Production models – use a set of "if" rules (productions) that determine which actions should be performed under certain conditions. These rules allow to draw conclusions and make decisions based on the available information.

Each of the models of knowledge representation in artificial intelligence has its limitations and shortcomings.

A production model combining elements of logical and network approaches is used for the task of controlling the traction transmission of a shunting locomotive. From logical models, the concept of inference rules, which are called products, is borrowed, and from network models – the representation of knowledge in the form of a semantic network.

A semantic network (Fig. 3) is a form of graphical representation of knowledge, where nodes represent objects or concepts, and edges between nodes reflect relations between these objects or concepts. This structure allows to visually represent and model knowledge, establish edges and draw logical conclusions.

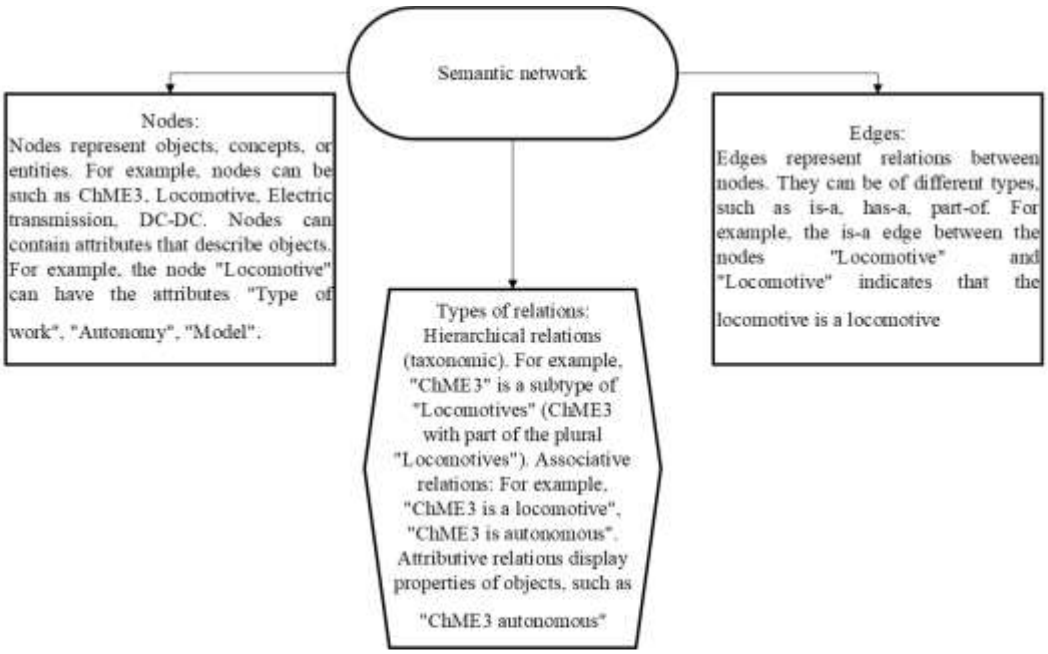


Fig. 3. **Basic elements of the semantic network**

In general, the production model can be presented in the following form:

$$N =< A,U,C,I,R >, \tag{11}$$

where N – the name of the product;
A – the scope of product application;
U – the condition of product use;
C – the product core;
I – the post-conditions of products, which are actualized in case of positive sales of products;
R – the comment, informal explanation (justification) of products, time of entry into the knowledge base, etc.

To design the knowledge base of traction transmission control of a shunting locomotive, it is necessary to determine the parameters U, C, I. Parameter A will be the same for all products belonging to the base being designed, and parameter R does not directly participate in the operation of the system and is auxiliary.

The product core can be presented in the following form:

$$C = (z_{j1} \& z_{j2} \& \ldots \& z_{ji} \Rightarrow d_{j1} \& d_{j2} \& \ldots \& d_{ji}), \tag{12}$$

where $z_{j1, j2,} \ldots, z_{ji}$ – the value of the conditions;
$d_{j1, j2,} \ldots, d_{ji}$ – the value of actions.

For each serial number of the conditions, a set of values is defined during the design of the base, i.e. $z_{ji} \in Z_i$.

For example, there is a set of conditions Z_k – «Tractive force». In the process of designing the base, it is determined that the values given in Table 3 should be entered into this set. In fact, the values of the elements of the set given in Table 3 are fuzzy linguistic variables. Therefore, their acquisition is completely determined by the methods of fuzzy logic.

The use of linguistic values makes it possible to design the base using the usual language of communication, which greatly simplifies both the design process itself and the analysis of the system's performance.

Table 3. **Value of the «Traction force» set**

Designation of the element of the set	The value of the element of the set
z_{1k}	"very low"
z_{2k}	"low"
z_{3k}	"middle"
z_{4k}	"high"

However, there are also such sets where the use of fuzzy variables is impossible. To describe the set "Operator's controller handle position" in the knowledge base, the following values are used: «1st position», «2nd position2, «3rd position», «4th position», «5th position», «6th position», «7th position», «8th position»; the set «Crane handle item No. 254 and No.395 position» consists of one position «2-train», if necessary, the set can be expanded to include all braking positions of the cranes; the set «Number of connected TMs» has three positions: «Work for 2 TMs», «Work for 4 TMs», «Work for 6 TMs». The given values are formal and the signals from the corresponding sensors are used in the base without transformations.

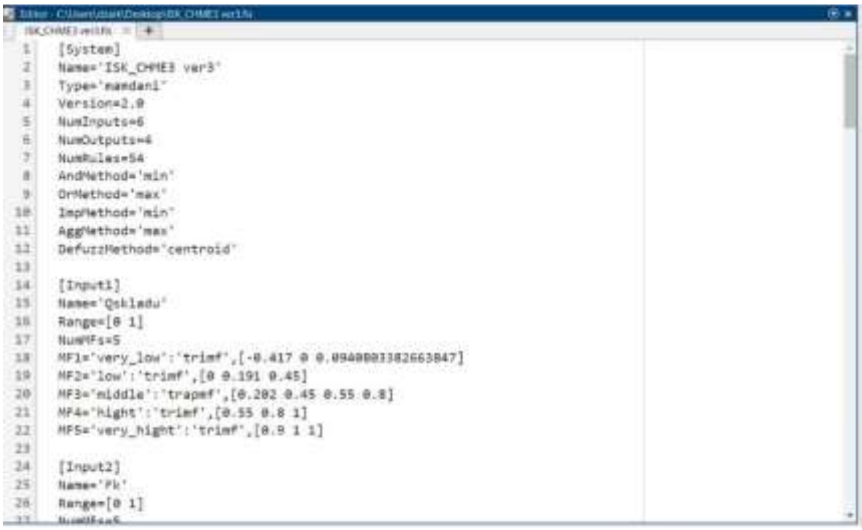
Similarly, to the description of the conditions, for each sequence number of the action, a set of values is defined during the design of the base $d_{ji} \in D_i$ i.e., where D_i – the type of the decision function.

Both distinct and phased variables are used to describe actions $d_{j1,j2}, \ldots, d_{j,i}$.

One of the most convenient programming tools in the field of fuzzy logic is the Fuzzy Logic environment of the MATLab application program package [22, 23, 24]. Rules in the form of logical products "If a condition, then an action" were used to create a knowledge base [25]. For its study, the

"Number of connected TEDs" on the partial loads of the traction electric transmission was chosen as the control action.

When designing a fuzzy knowledge base of the automated traction control system of a shunting locomotive, the structure shown in Fig. 4, 5. The input signals of which correspond to the data in Table 1.



```
[System]
Name='ISK_CHME3 ver3'
Type='mamdani'
Version=2.0
NumInputs=6
NumOutputs=4
NumRules=54
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Qskladu'
Range=[0 1]
NumMFs=5
MF1='very_low':'trimf',[-0.417 0 0.0940003382663847]
MF2='low':'trimf',[0 0.191 0.45]
MF3='middle':'trapmf',[0.202 0.45 0.55 0.8]
MF4='hight':'trimf',[0.55 0.8 1]
MF5='very_hight':'trimf',[0.9 1 1]

[Input2]
Name='Fk'
Range=[0 1]
```

Fig. 4. **M-file of the structure of input and output data of the knowledge base**

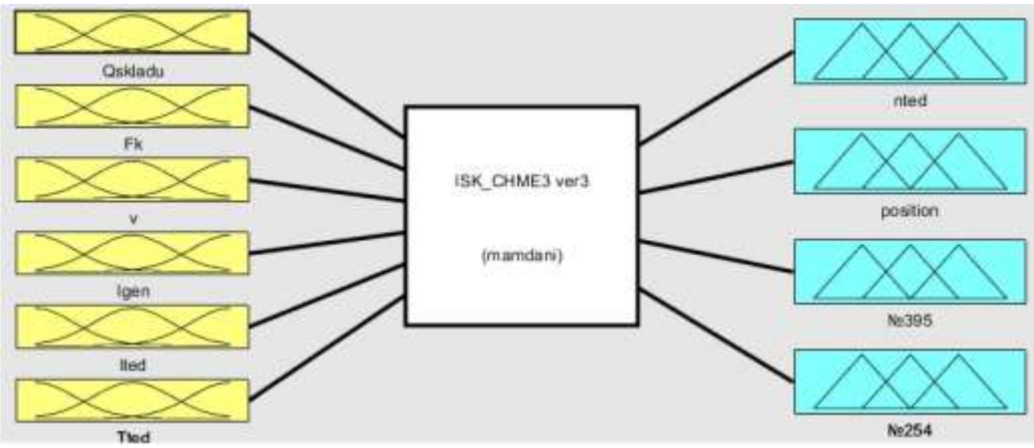


Fig. 5. **The structure of input and output data of the knowledge base**

All input signals are normalized in the interval [0;1]. To represent them in the form of fuzzy values, a set of characteristic functions is assigned for each input signal [2, 26]. Figures 6 and 7 show the fuzzification of part of the input values, namely: «Component masses», «Traction forces». They are represented by the following fuzzy values: «very_low», «low», «middle», «high», «very_high».

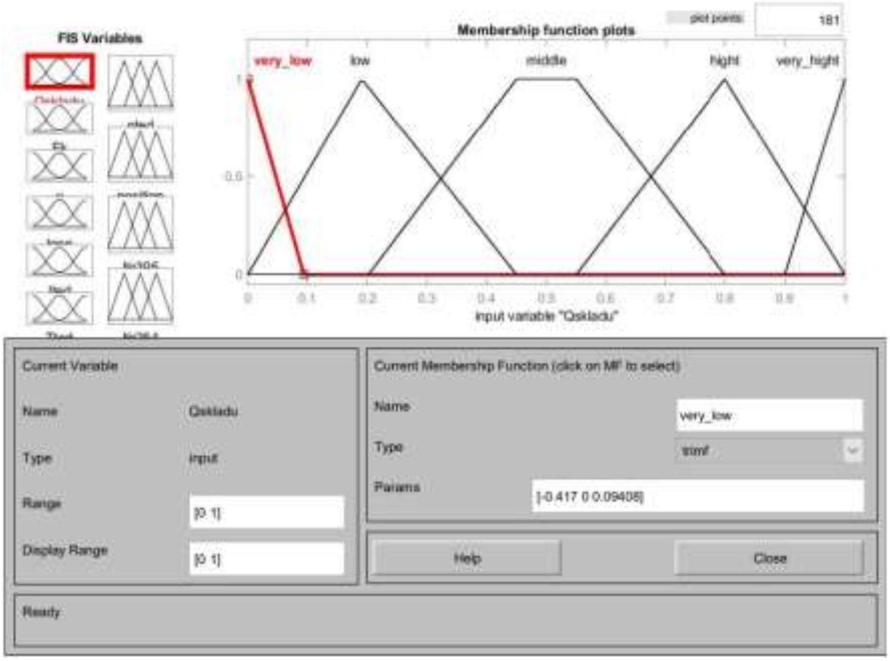


Fig. 6. **Fuzzification of the «Composition mass» value**

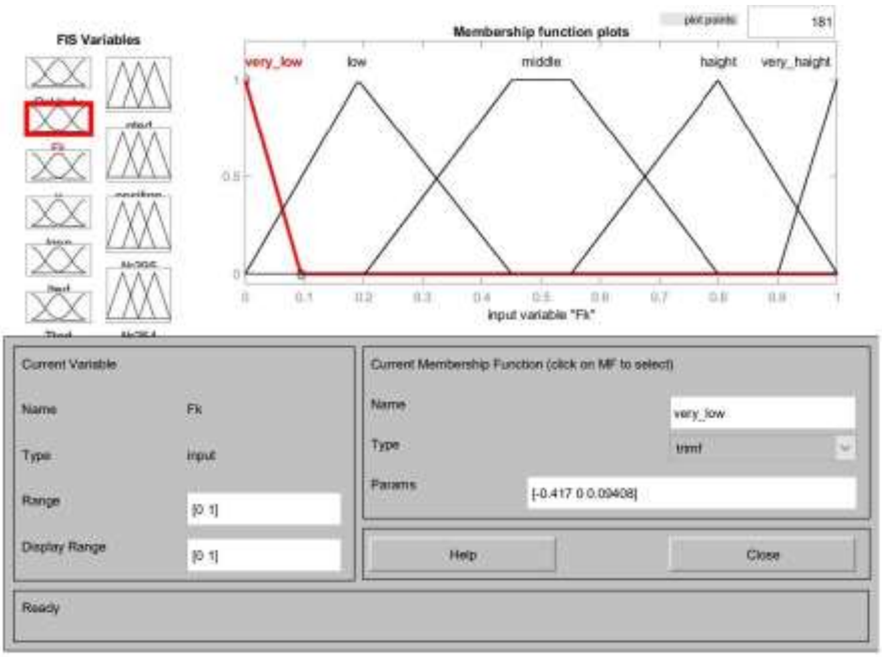


Fig. 7. **Fuzzification of the «Traction force» value**

Figures 8 and 9 show the phasing of the output distinct values "Operator's controller handle position" and "Number of connected TMs".

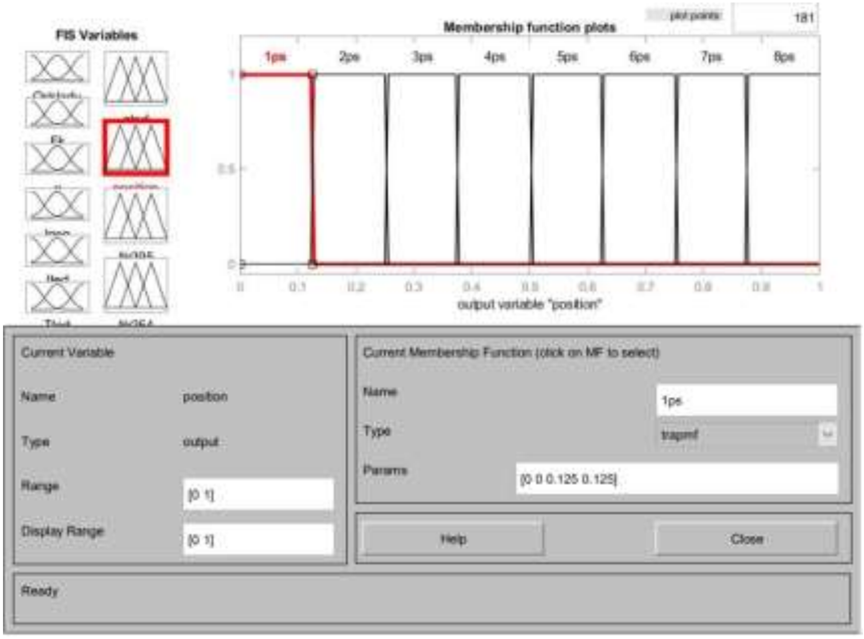


Fig. 8. **Fuzzification of the «Operator's controller handle position» value**

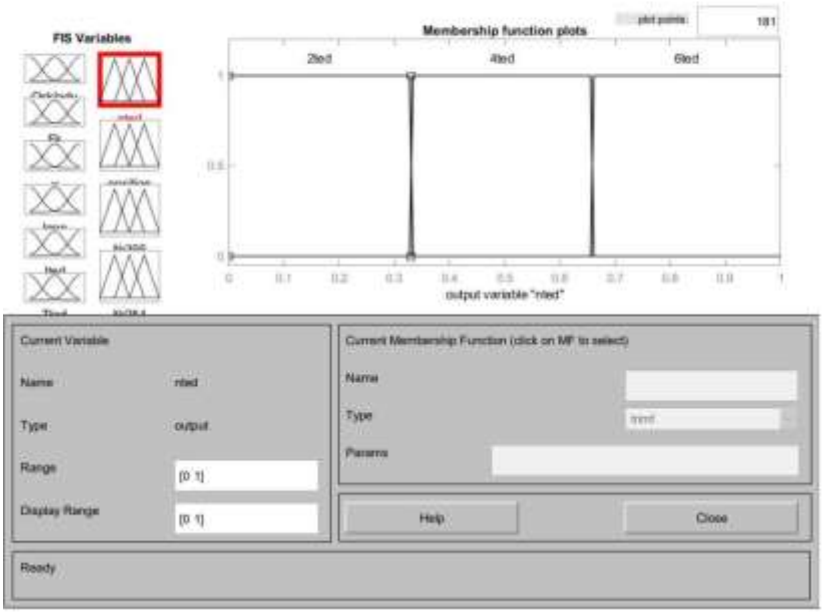


Fig.9. **Fuzzification of the «Number of connected TMs» value**

Using the method of expert evaluations and the logic of managing traction rolling stock in the Fuzzy Logic Designer package, a knowledge base was created, part of which is presented in Fig. 10.

Several lines from the knowledge base shown in Figure 10 have the following form:

If (Qskladu is middle) and (Fk is low) and (v is very_low) and (Igen is low) and (Ited is haight) and (Tted is middle) **then** (nted is 2ted)(position is 3ps)(№395 is 2)(№254 is 2) (1);

If (Qskladu is middle) and (Fk is middle) and (v is very_low) and (Igen is middle) and (Ited is high) and (Tted is middle) **then** (nted is 4ted)(position is 3ps)(№395 is 2)(№254 is 2) (1).

The results of the calculation of the model of the automated control of the traction transmission of the ChME3 shunting locomotive make it possible to investigate the dependence of the output variable on the input using the Fuzzy Logic Surface function (Fig.11-Fig 13).

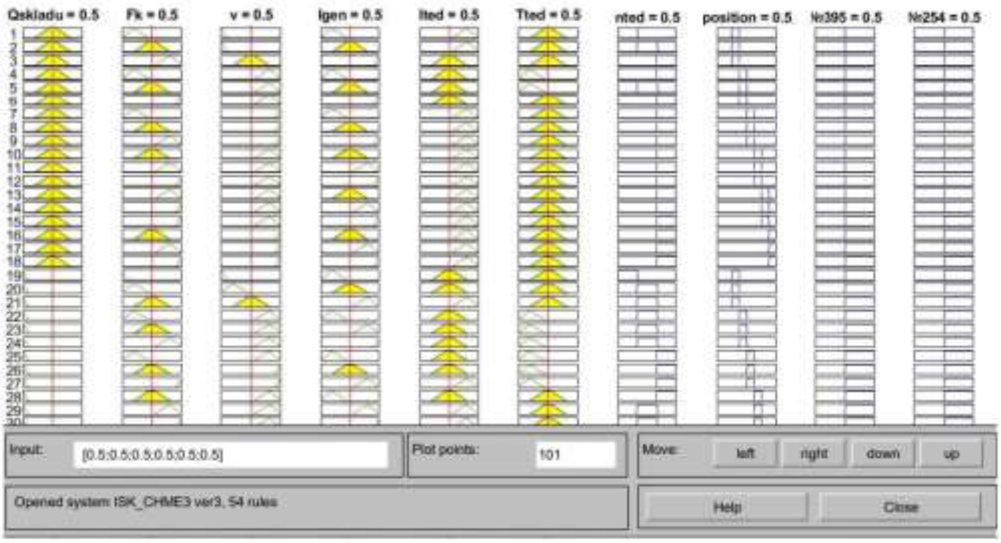


Fig.10. **General view of the rules in the knowledge base**

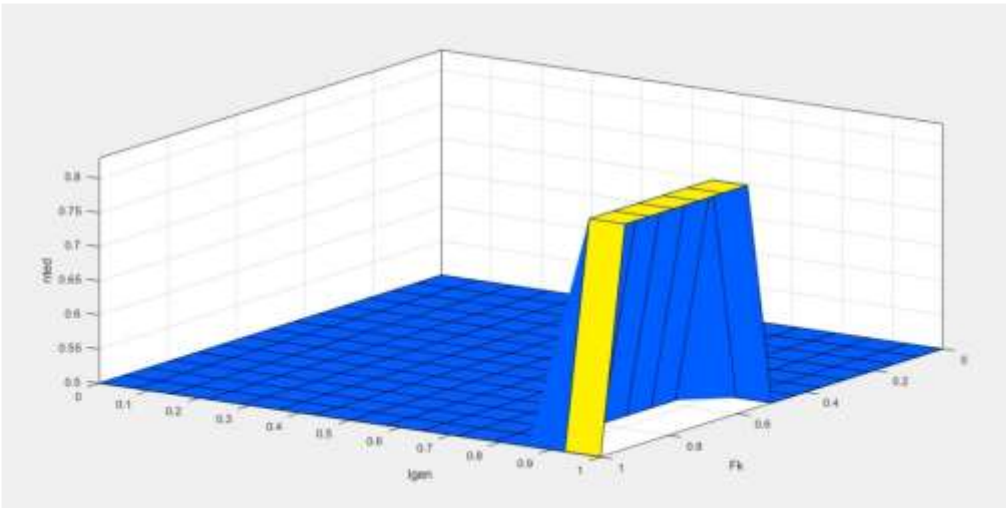


Fig.11. **Three-dimensional surface of the dependence of the «Number of connected TMs» output variable on the «Traction force» and «Traction generator current» inputs**

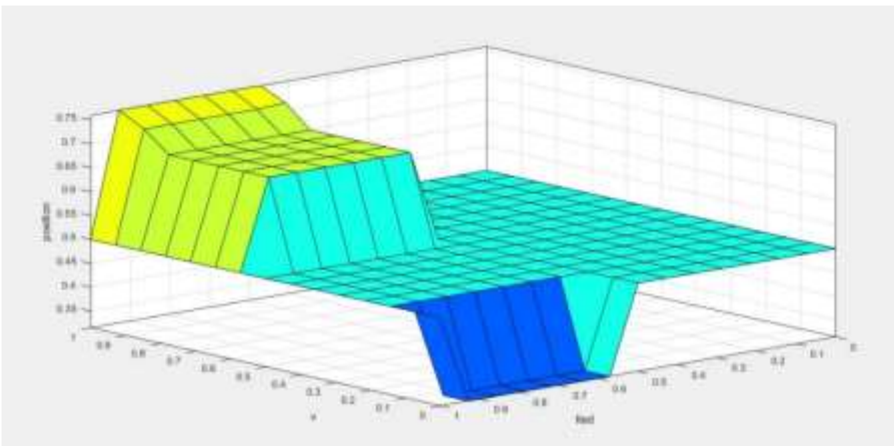


Fig.12. **Three-dimensional surface of the dependence of the «Operator's controller handle position» output variable on the «Speed» and «TM current» inputs**

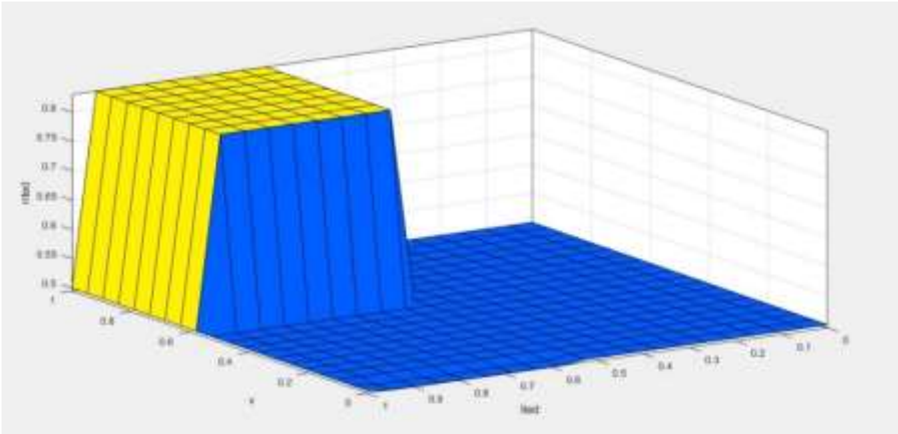


Fig.13. **Three-dimensional surface of the dependence of the «Number of connected TMs» output variable on the «Speed» and «TM current» inputs**

Assessment of shortcomings and prospects for the development of the given research. In the process of developing the automated system, a list of factors influencing the decision-making of the traction electric transmission of the shunting locomotive was determined (table 1). It should be noted that this list of factors may change and expand according to the locomotive series and operating conditions. A production model combining elements of logical and network approaches is used for the task of controlling the traction transmission of a shunting locomotive. The main disadvantages of which include the complexity of managing a large number of rules, when the number of rules increases, it becomes difficult to manage their order of execution and interaction. This can lead to conflicts and errors in conclusions. Performance issues, running a large number of rules can take a long time, especially if the rules are complex or have many conditions. Support and updates, changes in knowledge or rules require constant updating of the production base, which can be a time-consuming process. For the proposed system, 54 fuzzy logical rules are used, for further research it is proposed to expand the base by adding rules for the performance of shunting work by a locomotive with 15 4-axle cars. The results of the calculation of the automated model of the traction transmission control of the shunting locomotive are control signals. With the help of which, it is possible to implement the optimal mode of movement for a specific train and operation area. For further research, it is proposed to investigate various series of shunting diesel locomotives, their technical condition of traction electric transmissions. To analyze a larger number of areas of operation, for the possibility of creating a universal fuzzy knowledge base of the system.

In this form, the model of the automated traction transmission control system of the locomotive shows its adequacy. Trapezoidal and triangular characteristic functions are mainly used for fuzzification of input and output values. In further research to increase the quality and accuracy of the system, it is necessary to investigate the choice and justification of each membership function for the input signals. For the system, the range of concepts in the plural of the function is used, such as: [very low, low, middle, high, very high]. To improve the performance of the system in future studies, the list of these concepts should be expanded to: [very low, low, below middle, middle, above middle, high, very high], expanding these concepts increases the complexity of the structure, but will add flexibility to the system.

Conclusions. The paper presents a mathematical model of the automated traction control system of the shunting locomotive. Using the methods of fuzzy logic, the fuzzy knowledge base of the system has been formed and theoretically substantiated. The scheme of the automated control system of the traction transmission of the shunting locomotive with the possibility of self-learning has been developed.

The obtained results of the system work allow to realize quite a variety of control modes of the traction transmission of the shunting locomotive, which differ from those adopted during traction calculations and specified in the mode maps. Rational train driving modes vary significantly depending on operating conditions, which makes it impossible to determine a single optimal mode for all possible traffic scenarios on a specific section. This is explained by the fact that even on the same site, operating conditions can change quite often. In addition, the technical characteristics of traction gears and individual locomotives may deviate from the passport values within certain limits depending on their actual technical condition, which also affects the choice of the optimal driving mode. The results of the operation of the automated traction transmission control model of the shunting locomotive are control signals that allow to implement your optimal mode of movement for a specific train and section. Using the created knowledge base, the system implements the movement of the shunting locomotive on 4 TMs using partially the 3rd, and fully the 4th and 5th positions of the driver's controller. This mode of movement allows to reduce fuel consumption for shunting of the locomotive with partial loads on the traction gear.

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Створення моделі автоматизованого управління тяговою передачею маневрових локомотивів шляхом використання методів штучного інтелекту

В роботі розроблено математичну модель автоматизованої системи управління тяговою передачею маневрового локомотива, використовуючи методи нечіткої логіки та метод експертних оцінок. Для запропонованої моделі використовується алгоритм Мамдані. Алгоритм включає базу знань інтелектуальної системи, яка для формалізації та представлення знань в пам'яті використовує продукційну модель, поєднуючи елементи логічних та мережевих підходів керування. Отримана автоматизована модель управління тяговою передачею маневрового локомотива пропонує свій оптимальний режим руху для конкретного поїзда та ділянки. Модель використовує створену нечітку базу даних. Результатом розрахунку моделі є керуючий сигнал для руху маневрового локомотива на 4-х двигунах, використовуючи частково 3-тю та повністю

4-ту та 5-ту позицію контролера машиніста. Такий режим руху дозволяє зменшити витрати палива на маневрову роботу локомотива при часткових навантаження на тягову електричну передачу.

***Ключові слова**: залізничний транспорт, рухомий склад, тепловоз, тягова електропередача, метод Мамдані.*