ARCHIVES OF TRANSPORT
Volume 71, Issue 3, 2024

ISSN (print): *0866-9546*
e-ISSN (online): *2300-8830*
DOI: *10.61089/aot2024.gaevsp41*

THEORETICAL BASICS OF THE SELF-LEARNING SYSTEM OF INTELLIGENT LOCOMOTIVE DECISION SUPPORT SYSTEMS

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***Abstract**:*

Analysis of works in the field of artificial intelligence allows to make an assumption that today there is a sufficiently developed theoretical basis for the development of intelligent control systems for locomotive control. This will minimize the risks associated with the human factor on the railways. The paper presents the theoretical rationale for the development of a knowledge base for intelligent locomotive control systems. 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. Learning a fuzzy classifier consists in finding a vector K that minimizes the distance between the results of logical inference and experimental data from the sample. The knowledge base is implemented using linguistic variables formalized by 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. Also, the knowledge base has the possibility of constant self-improvement. This happens in two ways. The first is by adding new rules to the knowledge base in case the current situation does not match the existing ones in the base, in which case an additional rule is created and checked for adequacy. The second way is a mechanism for ranking rules in the knowledge base. If the control action of the locomotive driver coincided with the recommendation of DSS in the current situation, then the rating of this recommendation (rule) increases, and in the future the rule selection algorithm will choose one or another control action for the current situation that has the highest rating (that is, it has already been verified several times person). The experiment has shown that the use of intelligent DSS has positive results. On average, the DSS made the correct train control decisions faster than the locomotive driver.

Keywords: *railway, traffic safety, intelligent control*

To cite this article:

Gorobchenko, O., Holub, H., Zaika, D., (2024). Theoretical basics of the self-learning system of intelligent locomotive decision support systems. Archives of Transport, 71(3), 169-186. DOI: https://doi.org/10.61089/aot2024.gaevsp41

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1. Introduction

At the current stage of development of rolling stock control systems, it is possible to use new approaches and algorithms of the theory of artificial intelligence, which allow the most effective use of all the latest achievements in the areas of hardware and mathematical support. Automatic control of rolling stock can increase the safety and reliability of locomotive operation, reduce the amount of energy consumption, and reduce the intensity of the driver's workload (Shvets, 2023; Albrecht et al., 2016(p.1); Albrecht et al., 2016(p.2); Gorobchenko, 2021). The structure and main elements of an automated train control system based on elements of the theory of artificial intelligence are proposed in (Gorobchenko & Nevedrov, 2020). The work (Janota et al., 2022) is dedicated to the analysis of human errors in the railway transport sector and the comparison of three technologically different railway traffic control systems, which have varying degrees of automation—from manual, semi-automatic to almost fully automated (computer-based). Study (Holub et al., 2023) examines decision-making problems and analyzes methods for modeling power supply processes for traction rolling stock. Special attention is given to the synthesis methods of intelligent mathematical models, developed based on the theory of differential transformations. These methods allow for determining the complete informativeness of the recorded primary data and contribute to improving energy efficiency through the use of models with increased intellectual complexity and dimensionality. Additionally, one of the human reliability assessment (HRA) methods is applied to the three levels of automation. An automatic method of controlling a computer data processing system (Wang et al., 2022) based on artificial intelligence is also known. The system has the structure and functions of the train autopilot system, which optimizes the train movement in the curve, introduces the basic principles of fuzzy generalized predictive control. Works (Yin et al., 2016; Zhu et al., 2023) propose an approach of intelligent operation of trains based on a combination of expert knowledge and data mining algorithms. One of the proposed ones is a regression algorithm called CART (Classification And Regression Tree), other algorithms are based on the deep deterministic gradient (STOD) and on the basis of the normalized preference function (STON). The proposed algorithms can implement continuous locomotive control and optimize several critical objectives without using an offline speed profile. An approach for the intelligent operation of trains is also proposed, based on the combination of expert knowledge and data mining algorithms. The study examines the operation of an Urban Rail Transit System (URTS) with machine learning (ML) support, including obstacle perception, infrastructure perception, passenger flow prediction, train delay prediction, fault prediction, remaining service life prediction, optimization of train operation and control, optimization of train dispatching, and optimization of ground communications for trains. A discussion on future challenges and development directions of ML-based URTS is also presented. In the article (Zhou et al., 2022), the general control algorithms of the automatic train control system are considered, 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 inference. This open-loop controller is responsible for eliminating the disturbance-induced deviation during train operation using a proportional controller, an integral controller, and a differential controller. An important task for the implementation of intelligent train control systems is the data presentation. One of the approaches to such a representation in the form of fuzzy parameters is given in.

In (Shen & Yan, 2017), a two-layer control structure of the automatic train control system is considered: the upper level control consists in optimizing the target speed curve, and the lower level control consists in tracking the optimal target speed curve by urban rail transport. For upper-level control, a multi-objective model of train operation is first created with energy consumption indicators, movement time accuracy as optimization indexes, and the entropy weight method is applied to solve the weight factor of each index. A genetic algorithm is also used to optimize the model and obtain the optimal target speed curve. The study (Butko et al., 2015) uses the technology of fuzzy forecasting to ensure effective operating conditions of rolling stock, which opens up great potential for controlling complex systems. In work (Liu et al., 2019), the current train situation is presented as a fuzzy situation. The received input fuzzy situation is compared with all typical situations in the memory of the intelligent system. This approach makes it possible to implement the fastest and simplest algorithm for determining the state of a train during movement for an intelligent control system. In the article (Cao et al., 2018), a system for controlling the boxing of locomotive wheels is proposed based on fuzzy logical inference, which prevents wheel boxing and simultaneously monitors the profile of the section and the speed on it. By means of FOC (field-oriented control) in which the hysteresis unit generates a switching signal for the inverter to produce the appropriate voltage and control the angular velocity of the traction electric motor. In the work (Zhang et al., 2021), the control principle of the auxiliary power supply system of the Maglev train in Qingyuan is studied, and a simulation model is constructed in MATLAB/SIMULINK. A fuzzy PID controller is proposed to improve the control method, using a genetic algorithm to optimize the membership functions and fuzzy rules. A model of the fuzzy PID controller is created to compare the output performance of the device under different control methods. Since the conventional PID controller parameters cannot be adaptively adjusted, a fuzzy PID controller method based on fuzzy control theory is proposed. Considering the complexity of determining the membership function parameters and the discrepancy between the fuzzy control rules and the charging device, a genetic algorithm program is developed to optimize the membership functions and control rules. In the study (Dias et al., 2024), an innovative use of a multilayer perceptron combined with a membership function for binary classification of HOT BOX and HOT Wheel issues is proposed, improving fault prediction and preventing accidents. The multilayer perceptron with a membership function is noted for its ability to learn from nonlinear and complex patterns in this dataset. Its ability to update patterns with new data helps avoid frequent overfitting, providing a more efficient and adaptive solution. The work (Liu et al., 2023) examines a train tracking algorithm based on the Siamese network, which is accurate, efficient, and has significant development potential. Its output is a detection map showing the probability that any position in the search area is the center of the target bounding box, with the maximum value of the detection map being the center of the target bounding box predicted by the algorithm. Fuzzy logic inference is also introduced into the tracking process to analyze the reliability of the detection map. In the study (Tang et al., 2022), a systematic literature review on the current state of artificial intelligence in railway transport is presented, covering maintenance, automatic rolling stock control, and traffic safety. The use of intelligent systems provides additional support in improving maintenance operations, leading to increased safety, can support optimization models to solve maintenance planning problems, and can utilize a wide range of data from sensors, visual images, and materials. In (Moaveni et al., 2022), an effective method of analysis based on fuzzy data and fuzzy thinking is proposed for large volumes of data of China's high-speed train control system. In the article (Yang et al., 2017), the K-means clustering method is used to identify repeated occurrences of delays on the highly loaded railway lines of Copenhagen. Clusters define behavioral data that is generated automatically and continuously by the railway signaling system. The results of the method show when it is necessary to correct actions, indicating cases where trains were repeatedly delayed. This method can identify and distinguish different conditions that affect the movement of a train on the same section.

In the article (Zhang, 2017) it is proposed to use a recurrent neural network with LSTM (long-short-term memory) to detect and identify malfunctions in railway transport, testing of this system showed that the network correctly classifies and detects malfunctions with an accuracy of 99.7%.

The analysis of works in the field of artificial intelligence allows to make an assumption that today there is a sufficiently developed theoretical basis for the development of intelligent decision support systems (DSS) for locomotive control. This will minimize the risks associated with the human factor on the railways. In 2020-2023, a number of accidents and disasters with human casualties occurred on the world's railways (Office of Rail and Road, 2021; Commission for Railway Regulation, 2021; European Union Agency for Railways, 2022; Finnish Transport and Communications Agency, 2022; European Union Agency for Railways, 2023), despite the fact that the traction rolling stock involved in these accidents was equipped with modern powerful automation systems. Automated control systems have approached the limit of their development and can no longer guarantee the occurrence of traffic in-

cidents, the main source of which is a person (Volodarets et al., 2019; Akishev et al., 2023). The way out of this situation can be the integration of artificial intelligence systems into the automatic control of rolling stock, which allow taking into account a wider range of factors during movement and predicting the occurrence and development of abnormal situations in order to prevent them at the initial stage.
Thus, based on the results of the analysis formulated above, the main hypothesis of the presented study is formulated as follows: the intelligent locomotive decision support system (DSS) should use a knowledge base created based on the actions of the locomotive driver in all train situations. The criterion for the quality of training the knowledge base is the number of matches between the control decisions made by the system and those made by the locomotive driver under identical train operation conditions. In the future, when transitioning from DSS to an autonomous intelligent control system, the quality criteria should be indicators related to traffic safety, energy consumption, schedule accuracy, and so on. At the same time, appropriate adjustments will be made in the self-learning system of the intelligent locomotive control system.
The quality of work of artificial intelligence systems is directly related to the quality of the structure, content, and control algorithms of the knowledge base. The main functions of knowledge bases include collecting information, creating and storing rules, and self-learning. The purpose of this work is to develop a theoretical basis for the creation of knowledge bases of intelligent locomotive control systems. For this it is necessary to:
- develop a structure of self-study;
- describe the process and develop classification criteria for the current train situation;
- determine the list of information signals for control and description of the current train situation;
- develop the principles of self-learning of the intellectual system;
- conduct an experimental study and evaluate the effectiveness of the proposed intellectual DSS.

2. Materials and methods

In this work, self-learning will be understood as a complex of methods and algorithms for setting up and functioning of intelligent rolling stock (RS) control systems. The structure of the system shown in Figure 1 (Gorobchenko, 2021; Gorobchenko et al., 2019) is proposed for use.

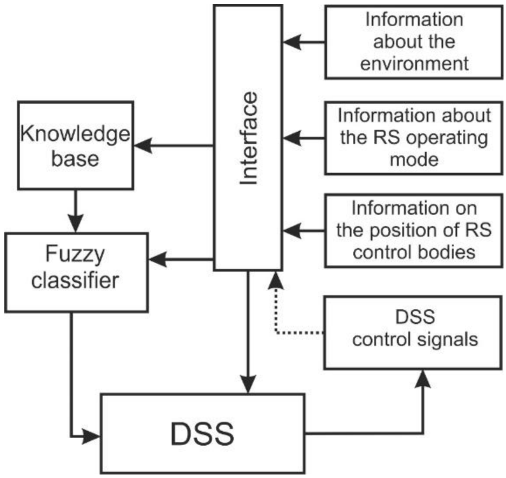

Fig. 1. Structure of the self-learning system

The self-learning process is as follows. Information about the state and changes of the environment, about the current mode of operation of the locomotive, about the position of the control bodies using the interface part is divided into several streams. The knowledge base is designed to accumulate information about traffic control. The task of the fuzzy classifier is to generate a control signal for intelligent DSS. 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 (i.e., recommendations for RS control) These signals through the interface part are submitted to the knowledge base for further verification of their adequacy and effectiveness.
Fuzzy classifier and approaches to its construction. The fuzzy classifier (FC) is the main element of the self-learning system shown in Figure 1. The efficiency of system learning and the rest of the safety of the train depend on its operation (Gorobchenko, 2021; Gorobchenko et al., 2019).
FC is a fuzzy knowledge base (Fig. 2.), which receives signals about the current state of the traction rolling stock and the environment. An external knowledge base is used for training (creating and clarifying the rules of a fuzzy knowledge base), which displays a spectrum of control signals depending on the current train situation. It is created as

a result of real journeys and shows how drivers controlled rolling stock. At the output of the classifier, there are control signals generated in accordance with the rules of the fuzzy knowledge base.

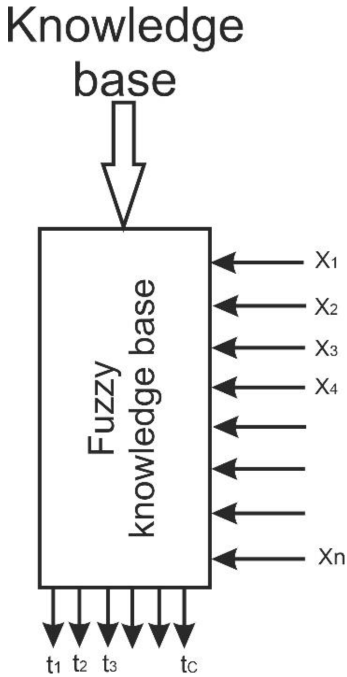

Fig. 2. The structure of the fuzzy classifier

The initial set of features is defined in an informal manner, based on the specialist's experience and personal preferences. Formal methods are applied to the training sample *A* to verify this initial system for sufficiency and necessity. Among all possible feature systems, a system is considered sufficient if, for given *S* and *D*, it ensures that the costs *N* do not exceed a certain threshold N_0. The costs *N* here refer to the measurement costs of the features (N_x) and the costs of losses caused by recognition errors (N_r):

$$N = N_x + N_r, \tag{1}$$

A sufficient system of minimal complexity (cost) is necessary. Thus, in practice, a combinatorial problem of this type is solved on the training sample A.

$$\beta = \frac{'_{\beta \in B} \, \square}{C, D, A, N_0}, \tag{2}$$

where $C =< c_1, c_2, \dots, c_k >$ – list of considered train situations;
D – type of decision function;
B – set of all possible feature systems;
X – informative set of descriptive features;
N – expenses;
N_0 – threshold value of expenses.

The costs of measurements depend on the number and types of features to be measured, as well as the number of digits required to represent the measurement results. For obvious reasons, significant attention is focused on reducing the number of measured features, i.e., finding an informative subsystem of n features (X_n) among g features in the original system (X_g).

The decisive criterion for feature informativeness in pattern recognition tasks is proposed to be the loss magnitude R. Even if the distributions of the population are known, computing losses is associated with significant machine time costs. Therefore, attempts are made to find criteria that are simpler to compute yet strongly correlate with the loss estimation R. If the distribution of realizations of each pattern conforms to a normal distribution with diagonal covariance matrices (resulting in iso-density surfaces being spheres of equal radius), then the measure of difficulty of recognition D, inversely proportional to expected losses, can be represented by the average Euclidean distance between the means of all pairs of patterns (Gorobchenko, 2021):

$$D = (1/C_k^2) \sum_{i,j=1}^{k} \rho(ij), \tag{3}$$

where $\rho(ij)$ – The Euclidean distance between the means of the *i*-th and *j*-th patterns

Let's denote by $X = (x_1, x_2, \dots, x_n)$– the vector of informative features of the classification object, and by $t_1, t_2, \dots, t_c$ – the decision classes. In our case, a fuzzy classifier is a mapping $X \rightarrow y \in \{t_1, t_2, \dots, t_c\}$implemented using a fuzzy knowledge base. The fuzzy knowledge base of this mapping is written as follows:

$$If\left(x_1 = \Theta_{1j} \text{ and } x_2 = \Theta_{2j} \text{ and } x_n = \Theta_{nj} \text{ with weight } \mathrm{w}_j\right), \tag{4}$$
then $y = d_j, j = \overline{1, m},$

where m – the number of rules;
$d_j \in \{t_1, t_2, \dots, t_c\}$ – the value of the consequent of the j-th rule;
$w_j \in [0.1]$–the weighting factor that determines the reliability of the j-th rule, $j = \overline{1, m}$;
Θ_{ij} – a fuzzy term that evaluates feature xi in the j-th rule $i = \overline{1, n}$ $j = \overline{1, m}$..
The degree of fulfillment of the j-th rule for the input vector$X * = (x_1 *, x_2 *, \dots, x_n *)$ is calculated as follows:

$$\mu_j(X *) = w_j \left(\mu_j(x_1 *)^{\mu_j(x_2 *)^{\cdots^{\mu_j(x_n *)}}}\right), \quad j = \overline{1, m}, \tag{5}$$

where$\mu_j(x_i *)$– the degree of membership of the value x_i* to the fuzzy term Θ_{1_j};
^ – the t-norm, which is implemented by the minimum operation.
The degree of membership of the input vector X* to the classes $t_1, t_2, \dots, t_c$ is calculated by the following expression:

$$\mu_{ts}(X *) = \underset{\forall j : dj = ts}{agg} (\mu_j(X *)), s = \overline{1, C}, \tag{6}$$

where agg – the aggregation of the results of fuzzy inference for each rule of the knowledge base, which is implemented by the operation of the maximum over the degrees of membership.
The result of the logical conclusion will be represented by the following fuzzy set:

$$\widetilde{y *} = \frac{\mu_{t1}(X *)}{t_1}, \frac{\mu_{t2}(X *)}{t_2}, \dots, \frac{\mu_{tC}(X *)}{t_C}, \tag{7}$$

As a result of the classification, let's designate the solution with the maximum degree of membership in the fuzzy set of equation (8):

$$y * = \arg\max\left(\mu_{t1}(X *), \mu_{t2}(X *), \dots, \mu_{tC}(X *)\right), \tag{8}$$

According to Figure 1, the fuzzy classifier contacts the knowledge base, which contains and updates information about the real actions of drivers during train movement. 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, $Y_r \in (t_1, t_2, \dots, t_C)$.
Let's introduce the following notations:
P – vector of the parameters of the membership functions of fuzzy terms of the knowledge base (6);
W – vector of weight coefficients of knowledge base rules (4);
$F(K, X_r) \in (t_1, t_2, \dots, t_C)$ – 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 logical inference and experimental data from the sample (9). Let's consider 3 ways of calculating this distance, which are called learning criteria.
Criterion 1. The distance between the desired and actual behavior of the model can be determined due to the accuracy of the classification on the training sample. Then training the fuzzy classifier:

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

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 X_r.
The advantages of criterion 1 lie in its simplicity and clear meaningful interpretation. The error rate is often used as a criterion for training various pattern recognition systems. The objective function (10) takes discrete values, which makes it difficult to use fast gradient optimization methods, especially for small training samples.
Criterion 2. The quality of learning can be related to the distance between the result of logical inference in the form of a fuzzy set (7) and the value of the output variable in the training sample. For this, the value of the initial variable in the training sample (9) is transformed into the following fuzzy set:

$$\begin{cases} \tilde{y} = (\frac{1}{t_1}, \frac{0}{t_2}, \dots, \frac{0}{t_C}) \text{ if } y = t_1 \\ \tilde{y} = (\frac{0}{t_1}, \frac{1}{t_2}, \dots, \frac{0}{t_C}) \text{ if } y = t_2 \\ \dots \dots \dots \dots \dots \dots \dots \dots \\ \tilde{y} = (\frac{0}{t_1}, \frac{0}{t_2}, \dots, \frac{1}{t_C}) \text{ if } y = t_C \end{cases} \tag{11}$$

Accordingly, the learning of a fuzzy classifier consists in finding such a vector K that:

$$\sqrt{\frac{1}{M}\Sigma_{r=\overline{1,M}}D_r(K)} \to min, \quad (12)$$

where $D_r(K) = \Sigma_{r=\overline{1,C}}((\mu_{tj}(y_r) - \mu_{tj}(K, X_r))^2$ – distance between the actual and desired output fuzzy sets when classifying the r-th object from the training sample (12);
$\mu_{tj}(y_r)$ – degree of membership of the r-th object from the training sample to the class t_j according to (4);
$\mu_{tj}(K, X_r)$ – degree of membership of the output of the fuzzy model with parameters K of the class t_j with the input vector X_r.
The objective function in problem (12) does not contain a plateau, so the optimization can be implemented by gradient methods. However, in some cases, the fuzzy knowledge base optimal according to (12) does not ensure the minimal infallibility of the classification (10). This is explained by the fact that objects close to the class boundaries make almost the same contribution (D) to the learning criterion (12) both during correct and incorrect classification.
Criterion 3. This learning criterion inherits the advantages of the previously discussed approaches. The idea is to increase the contribution to the learning criterion for falsely classified objects. As a result, the optimization problem takes the following form:

$$\sqrt{\frac{1}{M}\Sigma_{r=\overline{1,M}}(\Delta_r(K) \cdot penalty + 1) \cdot D_r(K)} \to min, \quad (13)$$

where $penalty > 0$ – penalty coefficient.
Problems (12) and (13) become equivalent at $penalty \to 0$. At$penalty \to \infty$ reliefs of the objective functions, problems (10) and (13) will be similar. When learning according to criterion 3, the choice of the direction of movement to the optimum is determined by erroneously classified objects. This behavior mimics the adaptive optimization method, in which falsely recognized objects are presented more frequently for retraining.
Membership functions and rule weights can be configured simultaneously and separately. When setting only the weighting factors (W), the volume of calculations can be significantly reduced, since the degrees of membership included in (2) $\mu_j(x_1 *), \mu_j(x_2 *), \ldots, \mu_j(x_n *)$ do not depend on them. To do this, at the beginning of the optimization, let's calculate the degree of fulfillment of the rules with single weighting coefficients $(w_j, j = \overline{1,m})$ for each object of the training sample:

$$g_j(X_r) = \mu_j(x_{r1})^\wedge\mu_j(x_{r2})^\wedge \ldots ^\wedge\mu_j(x_m), j = \overline{1,m}, r = \overline{1,M}, \quad (14)$$

Next, for the new weighting coefficients, the degree of object membership to classes will be calculated according to the following formula:

$$\mu_{ts}(X_r) = \underset{\forall j: dj=ts}{agg}(w_j \cdot g_j(X_r)), s = \overline{1,C}, \quad (15)$$

Let's consider the task of determining the control action that needs to be implemented in a specific train situation. The database consists of values characterizing the mode of train movement, the environment and the position of the controls at this moment in time. An example of such a format can be the database shown in Table 1.
Let's design a fuzzy classifier with the following inputs:
1 – speed;
2 – main generator current;
3 – brake line pressure;
4 – skidding signal;
5 – work of 2 sections;
6 – mass of the train;
7 – number of axes;
8 – bowing of the current track element;
9 – distance to the beginning of the next track element;
10 – bowing of the next track element;
11 – traffic light signal;
12 – distance to the signal;
13 – ambient air temperature.
Let's determine that inputs 4, 5, and 11 should remain clear. For other inputs, fuzzification is required. There are several widely known methods for this. On the basis of table 1, a fuzzy knowledge base of the form of table 2 is formed. In the section "Required position of control bodies", the signals "KM handle position" and " Position of the crane handle item No. 254" should be implemented as fuzzy.

Table 1. An example of a database

	Values characterizing the mode of train movement							**Environment**							**Regulation of control bodies**			
Frame No.	**Speed, km/h**	**Current of the main generator, A**	**GM pressure, atm**	**Skid signal**	**Work of 2 sections**	**Mass of the composition, t**	**Number of axes**	**Slope of the current profile element,‰**	**Distance to the beginning of the next element, m**	**Slope of the next profile element,‰**	**Traffic light signal**	**Distance to the signal, m**	**Air temperature, °C**	**KM handle position**	**The position of the crane handle item No. 395**	**The position of the crane handle item No. 254**	**Sand supply**
1	40	3180	5,5	0	2	3300	172	1	1150	4	green	850	4	10	2	2	0
2	40	3180	5,5	0	2	3300	172	1	1010	4	green	710	4	10	2	2	0
3	41	3200	5,5	0	2	3300	172	1	900	4	green	600	4	12	2	2	0
4	41	3300	5,5	0	2	3300	172	1	800	4	green	500	4	13	2	2	0
5	43	3300	5,5	0	2	3300	172	1	710	4	green	410	4	13	2	2	0
6	44	3320	5,5	0	2	3300	172	1	590	4	green	290	4	13	2	2	0
7	46	3500	5,5	0	2	3300	172	1	500	4	green	200	4	13	2	2	0
8	48	3480	5,5	0	2	3300	172	1	400	4	yellow	100	4	13	2	2	0
9	48	3500	5,5	0	2	3300	172	1	305	4	yellow	1150	4	13	2	2	0
10	49	3490	5,5	0	2	3300	172	1	200	4	yellow	1010	4	13	2	2	0
11	48	3490	5,5	0	2	3300	172	1	90	4	yellow	900	4	13	2	2	0
12	49	3470	5,5	0	2	3300	172	4	700	5	yellow	800	4	13	2	2	0
13	50	3450	5,5	0	2	3300	172	4	610	5	yellow	710	4	13	2	2	0
14	49	3450	5,5	0	2	3300	172	4	500	5	yellow	590	4	13	2	2	0
15	49	3430	5,5	0	2	3300	172	4	420	5	green	500	4	13	2	2	0
16	49	3450	5,5	0	2	3300	172	4	300	5	green	400	4	13	2	2	0
17	50	3450	5,5	0	2	3300	172	4	200	5	green	305	4	13	2	2	0
18	48	3500	5,5	0	2	3300	172	4	95	5	green	200	4	13	2	2	0
19	48	3490	5,5	0	2	3300	172	5	1300	-1	green	90	4	13	2	2	0
20	47	3550	5,5	0	2	3300	172	5	1205	-1	green	1305	4	13	2	2	0
21	47	3540	5,5	0	2	3300	172	5	1110	-1	green	1210	4	13	2	2	0
22	46	3600	5,5	0	2	3300	172	5	1000	-1	green	1100	4	13	2	2	0

Fuzzy terms are given by the Gaussian membership function:

$$\mu(x) = exp(-\frac{(x-b)^2}{2 \cdot c^2}) \quad (16)$$

where b – the coordinate of the maximum;
c>0 – the concentration coefficient.
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 (Kelarestaghi et al., 2018; Podrigalo et al., 2018).
The self-learning process consists in periodically polling the input signal values and control position signals while the train is moving. The current value of the signals from the control bodies for this rule is compared with the values in the knowledge base (Zhang & Lu, 2020). Next, the section of the knowledge base "Required position of the controls" is adjusted taking into account the new experience gained during the movement (Mikhalevich et al., 2019; Bugayko et al., 2023).

Table 2. Database example

The value of the signal level at the input														**Required position of the controls**		
Rule No.	1	2	3	4	5	6	7	8	9	10	11	12	13	**The position of the driver's controller**	**Brake lever position**	**Sand supply**
1	small	big	normal	0	2	big	average	small ascent	big	average ascent	green	above average	medium	high	low	0
2	small	big	normal	0	2	big	average	small ascent	big	average ascent	green	above average	big	high	2	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
n	high	very small	normal	0	2	very big	very big	very big ascent	very small	Average rise	yellow	average	low	average	2	0

Development of a mathematical model of a dynamic knowledge base. The knowledge base plays the main role in implementing the process of intelligent control of rolling stock (Bugayko et al., 2023). Representation of knowledge is the formalization and structuring of knowledge, with the help of which the main characteristics are displayed (Vermesan et al., 2023; Nedashkovskaya, 2018): internal interpretability, structuredness, connectivity, semantic metrics, activity.
For the formalization and representation of knowledge in the memory of information systems, there are a number of models that can be structured as follows:
logical models; network models; frame models; mathematical models, production models.
Logical models based on first-order predicate calculus involve describing a domain or problem as a set of axioms. The structuring of knowledge above was achieved using this model. Its advantages include the clarity and transparency of logical structures. However, when implemented on a computer, this approach proves to be challenging both from the perspective of software developers and users alike.
Frame models are an abstract representation of certain perception stereotypes. They distinguish between frame templates, or prototypes, stored in a knowledge base, and frame instances, which are created to reflect real factual situations based on incoming data.
A semantic network is a directed graph where nodes represent concepts and edges represent relationships between them.
Production models can be considered the most widespread. A production model is a rule-based model that allows to represent knowledge in the form of "If (condition), then (action)" statements. A production model was used to model the knowledge base of the locomotive DSS.
In general, the production model can be presented in the following form:

$$N =< A, U, C, I, R >, \tag{17}$$

where N – product name;
A – scope of product application;
U – condition of product use;
C – product core;
I – post-conditions of products, which are actualized in case of positive sales of products;
R – comment, informal explanation (justification) of products, time of entry into the knowledge base, etc.
To design a knowledge base for locomotive control, 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 core of the product can be presented in the following form:

$$C = (z_{j1} \& z_{j2} \& \dots \& z_{ji} \Rightarrow d_{j1} \& d_{j2} \& \dots \& d_{ji}), \tag{18}$$

where, $z_{j1} \dots z_{ji}$– value of the conditions;
$d_{j1} \dots d_{ji}$– 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 – "Current slope of the track profile". In the process of designing the database, 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. The value of the "Current profile slope" set

Designation of the set element	**Value of the set element**
z_{1k}	«small ascent»
z_{2k}	«average ascent»
z_{3k}	«big ascent»
z_{4k}	«small descent»
z_{5k}	«average descent»
z_{6k}	«big descent»

However, there are also such sets where the use of fuzzy variables is impossible. For example, to describe the set "Traffic light signal" in the database, the following values are used: "red", "yellow", "green"; the set "Number of working sections" (for locomotives) consists of two elements: "1" and "2". The given values are clear and the signals from the corresponding sensors are used in the base without transformations.

Similarly to the description of the conditions, for each serial number of the action, a set of values is defined during the design of the base, i.e. $d_{ji} \in D_i$. Both distinct and phased variables are used to describe actions $d_{j1} \ldots d_{ji}$.

Parameter I of formula (14) is post-production sales. In our case, in order to determine the adequacy of the actions offered when a certain list of conditions is met, the "Number of observations" parameter was entered into the knowledge base, which is parameter I. This allows to assess, at the initial stage of filling the knowledge base, how often in response to the conditions$(z_{j1}\&z_{j2}\& \ldots \&z_{ji})$ those or other actions $(d_{j1}\&d_{j2}\& \ldots \&d_{ji})$. Then, when assessing the situation, the DSS will use this information and make decisions that were most often encountered in the past, or invite additional data about the current situation to make a final decision.

Element U in formula (17) is a condition for using products. In our case, the knowledge base has the ability to work in two modes – the accumulation of knowledge and the use of knowledge by intelligent DSS. The accumulation of knowledge is carried out by monitoring the current train situation $(z_{j1}\&z_{j2}\& \ldots \&z_{ji})$ and controlling actions of locomotive crews $(d_{j1}\&d_{j2}\& \ldots \&d_{ji})$ and entering this data into the database in the form of (18).

The mode of using knowledge is as follows. The intelligent system receives data about the current train situation in the form $(z_{j1}\&z_{j2}\& \ldots \&z_{ji})$. Next, the obtained data are compared with the products obtained earlier. There are products in which the conditions coincide with the current ones. According to the defined rules, DSS chooses which products should be used at the current moment in time.

In general, the work of the knowledge base is described by the following algorithm. When the database is in the "Accumulation" mode, products are replenished and updated. If a product identical to the current conditions of train operation is found in the knowledge base, then its weight among other products is increased by increasing parameter I. If the current conditions of train operation and the control actions of the locomotive crew (positions of the locomotive control bodies) do not coincide with any existing products, then new products are added to the database with current values $(z_{j1}\&z_{j2}\& \ldots \&z_{ji})$ and $(d_{j1}\&d_{j2}\& \ldots \&d_{ji})$.

When the base is operating in the "Usage" mode, the DSS constantly monitors the current train situation and compares it with existing products. In the event of a match, the DSS provides control recommendations based on the experience of the knowledge base. If the current situation does not correspond to any existing products, then the DSS is unable to recommend any control actions and the set of recommended control actions is reset to zero.

Formally, the knowledge base operation process is described by the following expressions:

$$U = \text{"Accumulation"} \begin{cases} \text{at } C_{cur} \in 0_{\text{base}};\, C_{\text{base i}} \equiv C_{\text{act}}, I_i = I_i + 1 \\ \text{at } C_{cur} \notin 0_{\text{base}};\, C_{\text{base k+1}} \equiv C_{\text{act}}, I_{k+1} = 1, k = k + 1 \end{cases}$$
$$U = \text{"Usage"} \begin{cases} \text{at } C_{cur} \in 0_{\text{base}};\, C_{\text{base i}} \equiv C_{\text{act}}, D_{\text{act}} \equiv D_{\text{base i}} \\ \text{at } C_{cur} \notin 0_{\text{base}};\, D_{cur} \equiv \emptyset \end{cases}, \qquad (19)$$

where C_{cur} – current value of the train driving conditions and the position of the locomotive controls;
O_{base} – set of all products entered into the knowledge base;
C_{base} – separate products of the knowledge base;
k – number of products in the knowledge base;
$i \in [1; k]$ – serial number of products in the knowledge base;
I_i – parameter that characterizes the number of observations of the i-th product during the filling of the knowledge base;
D_{cur} – current control actions of the locomotive crew, recommended by DSS (regulations of locomotive control bodies);
$D_{\text{base i}}$ – a list of control actions included in the i-th products: $D_{\text{бази i}} = (d_{j1}\&d_{j2}\& \ldots \&d_{jy})_i$.

3. Results and discussion

The MATLAB software package, namely Fuzzy Logic Designer, was used to test the above theoretical propositions. Rules in the form of logical products "If a condition, then an action" were used to cre-

ate a knowledge base. For our experiment, the position of the main locomotive control bodies and the signal to feed sand under the wheels were chosen as actions. but it should be noted that the list of control actions when designing real intelligent control systems should be expanded in accordance with the list of job duties of the driver during train movement.
When designing a fuzzy knowledge base, the structure shown in Figure 3 was obtained. The list of input signals here corresponds to the data in Table 1.
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 to each input signal. For an example, Figure 4 shows the fuzzification of the "Train speed" value. It is represented by the following vague values: "very low", "low", "average", "high", "very high".
According to the logic of the control of traction rolling stock and on the basis of a survey of experienced drivers, a knowledge base was created in the Fuzzy Logic Designer package, a part of which is presented in Figure 5.
One line from the knowledge base shown in Figure 5 has the following form:

IF (Speed=low & Generator_current=high & Brake_line_pressure=high & Skidding_signal=no_skidding & Work_of_2_sections=2_section & Mass_of_the_train=high & Number_of_axes=low & Bowing_of_the_current_track_element=lift & Distance_to_the_beginning_of_the_next_track_element=high & Bowing_of_the_next_track_element=lift & Traffic_light_signal=green & Distance_to_the_signal=high & Ambient_air_temperature=average)
THEN Position_controller=high, Brake_lever_position=no_brake, Sand_supply=no_sand_supply
Experimental studies were conducted at the training complex for locomotive drivers, which was installed at the State University of Infrastructure and Technologies. During the experimental trips, the simulator program and the program of the decision support system based on the developed knowledge base were launched in parallel. Control actions of the locomotive driver and system recommendations were monitored. Four working experienced train drivers took part in the experiment, the section on which the experiment was conducted from the "Kyiv-Passenger" station to the "Fastiv" station.

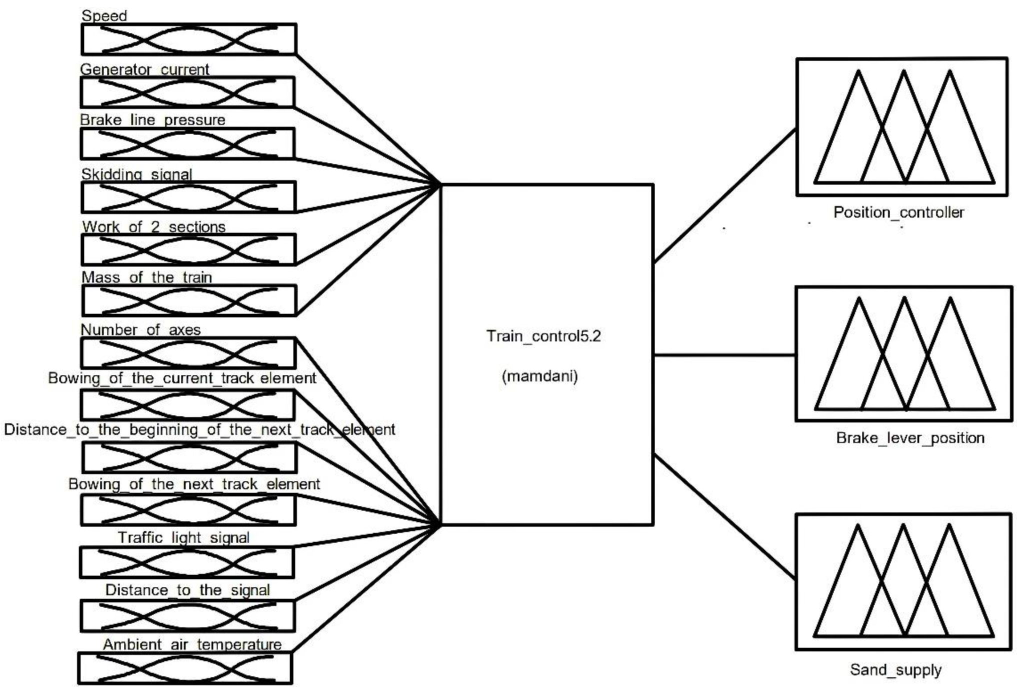

Fig. 3. The structure of input and output data of the knowledge base

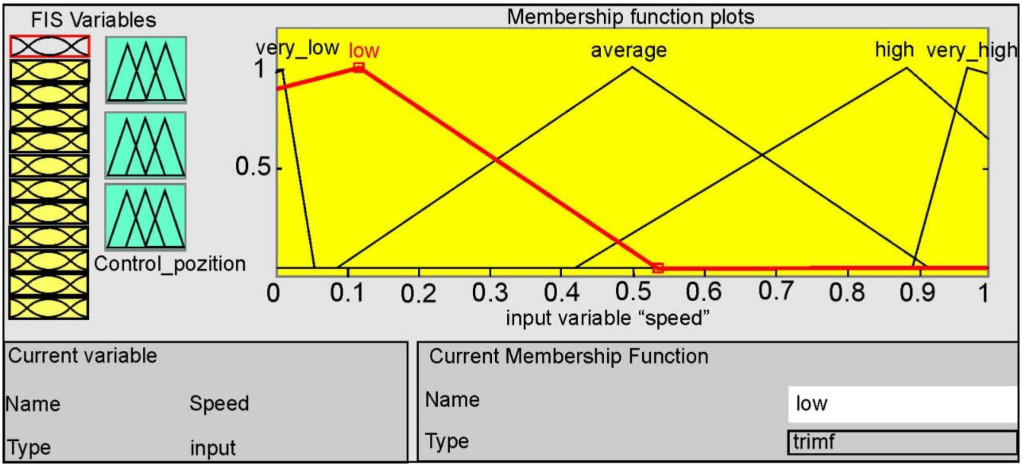

Fig. 4. "Train speed" fuzzy variable

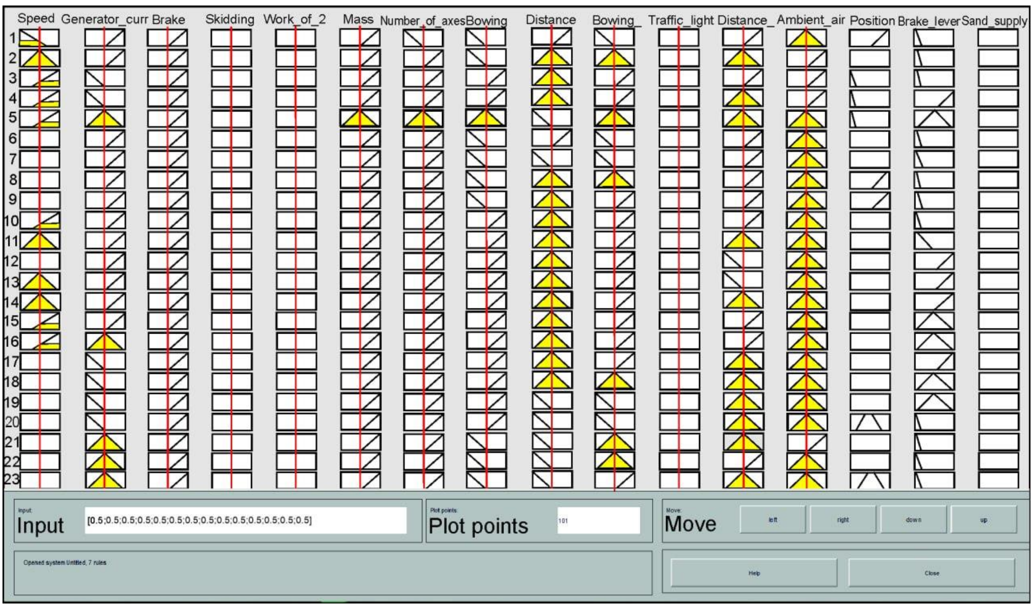

Fig. 5. General view of the rules in the knowledge base

Additionally, from May to June 2024, experimental studies were conducted on operating locomotives running between the "Kyiv-Passenger" station to the "Hrebinka" station. Eight locomotive crews were involved, completing 16 trips. During each trip, all control actions taken by the locomotive driver were tracked and systematized under all conditions, including movement on intermediate station tracks, night-time travel, travel in adverse weather conditions (3 trips), movement under prohibitive signal aspects, and more. The DSS program incorporated all train operation conditions on the section from "Kyiv-Passenger" to "Hrebinka," and automated train operation recommendations were obtained. After collecting data from the actual trips and modeling these trips using the DSS, a comparison was made, the results of which are presented below.

When analyzing the decisions made by drivers on the simulator complex, up to 4% of the decisions made by the system and the human did not coincide. Figure 6 shows the distribution of the time deviations in decision-making by the intelligent system compared to the human for those control decisions that did match.

Analyzing the data from real trips and comparing them with the train operation system's recommendations, the deviation of the system's decisions from the driver's decisions amounted to 6%.

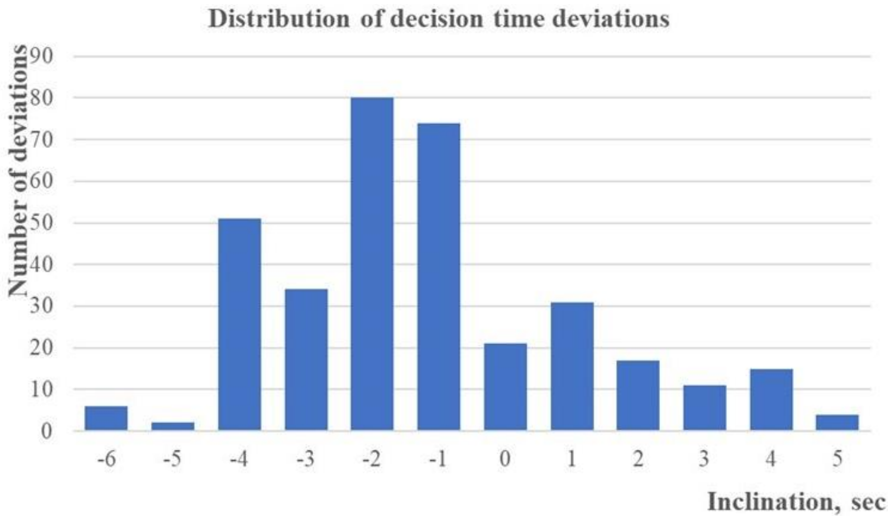

Fig. 6. Distribution of deviations of the decision-making time of an intelligent system in comparison with a person (based on simulator trip data)

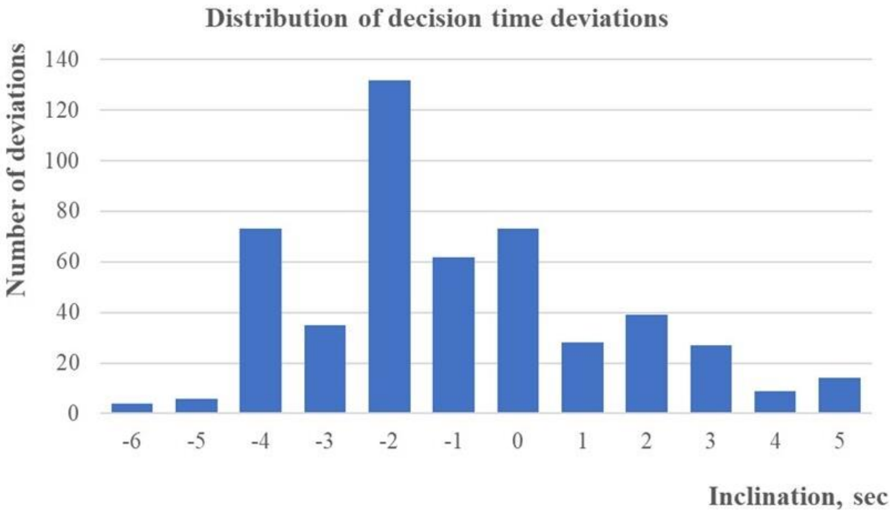

Fig. 7. Distribution of deviations of the decision-making time of an intelligent system in comparison with a person (based on real locomotive trip data)

The analysis of experimental data presented in Figures 6 and 7 provides grounds to assert that the intelligent system generally generates control decisions for locomotive operation faster than the driver does. The mathematical expectation of the sample shown in the figures is determined by the following formula:

$$M(\Delta t) = \sum_{i=-6}^{5} p(\Delta t_i) \cdot \Delta t_i \tag{20}$$

whereΔt_i – deviation of the decision-making time between the person and the system;
$p(\Delta t_i)$– deviation probability.

Calculations show that the mathematical expectation of the decision-making time deviation by the automated system compared to the human during the simulator study is $M(\Delta t) = -1.18$ seconds. This parameter for real trip data in operation is $M(\Delta t) = -0.96$ seconds, which is less than the simulator trip data but generally confirms the overall effectiveness of using intelligent DSS for locomotive control.
In the course of the research, a list of factors influencing the decision-making process of train control was determined (listed in Table 1). But this list is not exhaustive. In the process of developing decision-making support systems for specific types of traction rolling stock, this list must be expanded and specified depending on the capabilities of automated control systems installed on locomotives. The latest locomotives have the ability to control, process and transmit information of dozens of parameters. Taking them into account (perhaps with the introduction of ranking according to the degree of influence on the train movement process) is a necessary condition for the high-quality operation of intelligent control systems. In addition, when making decisions, the driver is also guided by additional information about the train situation (the condition of the track ahead, radio dispatcher commands, existing speed limits when moving along separate sections, etc.). All of this operational information needs to be taken into account. For this, it is necessary to develop an interface part that would allow to submit this information to the intelligent system in an automated mode. It is also necessary to make appropriate changes to the knowledge base to take into account this expanded list of informational signals.

When conducting an experiment on a training complex, it is possible to accurately reproduce the conditions of driving a train several times. This is an advantage for evaluating and adjusting the model of intelligent DSS. But in order to transfer these results to operating locomotives, it is necessary to conduct additional studies in real operating conditions, as there is a possibility of the occurrence of additional, not taken into account factors and events during movement.
The model of intelligent DSS demonstrates positive results in the presented form. Characteristic functions of triangular and trapezoidal shapes are mainly used for fuzzification of values. In order to increase the accuracy of the model in the future, it is necessary to conduct a study on the selection and justification of each membership function for each type of signal at the input to the system. Also, in order to improve the work, it is necessary to justify the number of elements in the set of membership functions, that is, to expand the range of concepts from simple [small, average, big] to, for example, [very small, small, not big, average, above average, not small, big, extra big]. This will add flexibility to the knowledge base model, although it will increase the complexity of its structure.
The paper presents the theoretical rationale for the development of a knowledge base for intelligent locomotive control systems. 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 defines a fuzzy image of the current train situation. Also, the knowledge base has the possibility of constant self-improvement. This happens in two ways. The first is by adding new rules to the knowledge base in case the current situation does not match the existing ones in the base, in which case an additional rule is created and checked for adequacy. The second way is a mechanism for ranking rules in the knowledge base. If the control action of the locomotive driver coincided with the DSS recommendation in the current situation, then the rating of this recommendation (rule) increases, and in the future, the rule selection algorithm will choose one or another control action for the current situation that has the highest rating (that is, it has already been verified several times person).

The presented model was tested on a driver's simulator. The experiment has shown that the use of intelligent DSS has positive results. On average, the DSS made the correct train control decisions faster than the locomotive driver, the mathematical expectation of the deviation of the decision-making time between the intelligent DSS and the locomotive driver is $M(\Delta t) = -1.18$ seconds. This means that the proposed system makes decisions one second faster on average than a human operator.
Improving the performance of this model is proposed by improving the selection of functions of belonging to fuzzy values and by expanding the list of informative factors processed by the intelligent system.

Acknowledgment
The work was carried out with the support of the National Research Fund of Ukraine within the framework of the development of the project 2022.01/0224 on the topic "Development of scientific foundations of comprehensive improvement of safety, efficiency of operation and management of critical objects of railway transport in the conditions of post-war development of Ukraine"

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