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Oleksandr Gorobchenko[1], Denys Zaika[2*], Sergiy Maliuk[3], Oleksander Arkhypov[4], Oleksandr Nevedrov[5]

[1]Professor, Electromechanics and Rolling Stock of Railways Department, National Transport University, 1, M. Omelianovycha-Pavlenka str., Kyiv, 01010, Ukraine. ORCID: https://orcid.org/0000-0002-9868-3852.
[2]Assistant, Electromechanics and Rolling Stock of Railways Department, National Transport University, 1, M. Omelianovycha-Pavlenka str., Kyiv, 01010, Ukraine. ORCID: https://orcid.org/0000-0003-0693-9580.
[3]Senior Lecturer, Electromechanics and Rolling Stock of Railways Department, National Transport University, 1, M. Omelianovycha-Pavlenka str., Kyiv, 01010, Ukraine. ORCID: https://orcid.org/0000-0003-1777-2384.
[4]Postgraduate student, Electromechanics and Rolling Stock of Railways Department, National Transport University, 1, M. Omelianovycha-Pavlenka str., Kyiv, 01010, Ukraine. ORCID: https://orcid.org/0009-0009-8873-8643.
[5]Senior Lecturer, Electromechanics and Rolling Stock of Railways Department, National Transport University, 1, M. Omelianovycha-Pavlenka str., Kyiv, 01010, Ukraine. ORCID: https://orcid.org/0000-0001-9347-0973.

***Corresponding author:** zaika_do@gsuite.duit.edu.ua.

Research of theoretical basis of implementation of intelligent control systems for locomotive traction transmission

The paper presents an analysis of existing automated control systems based on artificial intelligence theory. These systems employ methods such as fuzzy logic, artificial neural networks, and genetic algorithms. The application of these techniques enables the development of more adaptive and efficient control systems compared to traditional approaches. The main areas of artificial intelligence application in railway transport are identified, particularly in locomotive control systems and optimization of operational modes. The fundamental stages of artificial intelligence-based model development are outlined, including data collection and model training. Key directions for modeling intelligent systems are established. A generalized approach is proposed for the development of an intelligent traction transmission control system for shunting locomotives, taking into account the rolling stock characteristics and operational conditions. For solving control tasks, the use of a production model is proposed, which integrates elements of both logical and network-based approaches. A production model is proposed for solving control tasks.

Keywords: *railway transport, rolling stock, control, artificial intelligence, Mamdani method, risk, traction electric transmission, safety*

Introduction. Modern intelligent control systems have recently undergone significant progress in many areas of human development [1-3]. These systems are distinguished by their ability to “understand” and learn, adapting to the characteristics of the control object, its operating conditions and environmental influences. Their main difference is the presence of mechanisms for complex knowledge processing. The architectural feature that distinguishes intelligent systems from traditional ones is the ability to accumulate, store and analyze knowledge for the effective performance of control functions. Increasingly, such systems that use fuzzy logic methods, artificial neural networks and genetic algorithms are being introduced into various areas, including railway transport. Thanks to these technologies, adaptive, reliable and efficient systems have been created that cope better with changing conditions and uncertainty compared to traditional control approaches [4,5].

Analysis of recent research and problem statement. According to A. Bayen's research, artificial intelligence can control a vehicle in a way that is not intuitive to humans, but is generally more efficient. F. You's work explores the combination of quantum computing with artificial intelligence to solve complex optimization problems in energy systems. A multi-level optimization framework combined with machine learning is presented for planning the transition of energy systems, such an approach allows for detailed planning of energy capacities with hourly accuracy.

Innovative projects for the implementation of intelligent systems in rail transport can be conditionally divided into implemented ones, as well as promising technologies with a implementation period of up to 2030 [6]. The implemented ones include "Smart Locomotive" – a system that combines artificial intelligence, the Internet of Things (IoT) and big data analysis for monitoring the technical condition of locomotives, predicting faults and optimizing routes [7]; "Smart train" refers to intelligent trains, such as the Chinese Yiqun from CRRC, equipped with autonomous control modules, energy-efficient systems and adaptive interfaces for passengers [8]; "Smart depot" refers to depots that use robotic systems and AI to diagnose, maintain and repair rolling stock, which allows to reduce downtime and increase service efficiency [9]. In the metros of Santiago, Paris, Hong Kong and Beijing, Alstom is implementing its development based on implemented projects. An additional example of the implementation of such technologies is the Copenhagen metro. It is unique in that there is no driver in the metro trains, and control is carried out thanks to the fully automated ATC (Automatic Train Control) system [10]. This system is designed to eliminate the possibility of human error, as well as to more accurately control the distance between trains (thanks to the precisely set value of braking and acceleration). The ATC system consists of three subsystems:

- ATS (Automatic Train Supervisory) subsystem – a system for monitoring and controlling train routes and directions. It is this system that selects the train route. The ATS subsystem, depending on the situation, selects a scenario for movement. For example, there are different scenarios: normal movement, movement at night, movement during track maintenance. Information about train movement and routes is displayed on the monitors of the control center. The ATS also stores information about errors and malfunctions, repair and maintenance activities.
- ATO (Automatic Train Operation) subsystem – a system for controlling movement at stations, namely train stops, opening doors, waiting for a certain period of time, closing doors, and continuing movement. This part of the system is an analogue of an autopilot and performs the physical function of a train driver. The ATO subsystem operates at a very high level and cannot independently change its parameters, such as braking speed or waiting interval at the station.
- ATP (Automatic Train Protection) subsystem – a system for protecting subway passengers and personnel from accidents (in particular, derailments, train collisions, opening doors during movement). The system checks and controls the speed limit (three speed switch positions: start of movement or acceleration, movement and braking), the distance between trains, the switch and the free path (presence of foreign objects on the path, repair work or maintenance work).

The development of unmanned train movement in rail transport is actively implemented thanks to intelligent systems such as Cognitive Rail Pilot, which use artificial intelligence to improve safety and efficiency of transportation [11]. These systems are aimed at achieving high levels of automation, in particular GoA 3 (control without a driver, but with the presence of personnel on board) and GoA 4 (fully autonomous control without personnel on board). Cognitive Rail Pilot, a system developed by Cognitive Pilot, is designed to help drivers prevent dangerous errors that can lead to accidents. It uses artificial intelligence to analyze the environment and make decisions in real time. Promising technologies with an implementation deadline of 2030 include the GoA 4 automation level, which requires not only technical improvements, but also adaptation of the regulatory framework. New standards such as ANSI/UL 4600 are considered as the basis for certification of autonomous control systems based on artificial intelligence methods [12]. Additionally, Knorr-Bremse and Rail Vision are currently testing an obstacle recognition system for shunting locomotives in Switzerland [13]. This system includes optical sensors, artificial intelligence and machine learning elements, and is capable of recognizing switches, traffic light readings and track obstacles at a distance of up to 200 meters, classifying objects in real time and issuing warnings to the driver. Research is also being conducted on the use of SLAM technologies (lidar and visual) to obtain additional data on the location of locomotives [14]. Obstacle detection is carried out using lidar data, stereo vision and neural networks, which allows to increase the accuracy and reliability of the system. In [15], the pragmatic and neurobiotic approaches to the use of artificial intelligence were analyzed. In [16], the creation of a knowledge base for intelligent locomotive DSS was theoretically substantiated. The authors proposed an approach and structure of a self-learning system for intelligent DSS, the main advantage of which is the use of a fuzzy classifier. This classifier operates according to specified criteria and forms a fuzzy image of the current situation during train movement. In article [17], the main control algorithms of an automated train control system are analyzed. In particular, control based on artificial neural network algorithms is considered, as well as fuzzy control using a fuzzy controller. The latter plays a key role in the system, which includes the stages of fuzzification, defuzzification, a knowledge base and a fuzzy logical inference unit. In article [18], the development of the structure of an intelligent decision support system for locomotives is presented. Formal indicators of the efficiency of the train control process are determined. The method of establishing weight coefficients for each individual control quality criterion is also theoretically justified. In work [19], a mathematical model of an automated traction control system for a shunting locomotive is presented. Using fuzzy logic methods, a fuzzy knowledge base of the system was formed and theoretically substantiated. A scheme of an automated system for controlling the traction transmission of a shunting locomotive with the possibility of self-learning was developed. The obtained results of the system operation allow implementing quite diverse modes of controlling the traction transmission of a shunting locomotive, which differ from those adopted in traction calculations and indicated in the mode maps.

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 basis for creating intelligent control systems. Each work investigates the factors that affect the movement of the locomotive and the control signals necessary for individual elements of the control system. The disadvantages include: the lack of consideration of the operation of each of the locomotive elements separately.

The purpose and tasks of the study. The main purpose of this work is to analyze existing methods and approaches to the development of automated control systems based on the theory of artificial intelligence, as well as to conduct applied research on the development of an intelligent locomotive traction control system.

To solve this problem, the main directions of using artificial intelligence methods in railway transport have been formed. The main stages of developing a model based on artificial intelligence have been identified and the main directions of modeling intelligent systems have been formed. It is proposed to use production models for rolling stock management tasks, and the Mamdani Algorithm to build a model of automated control of the traction transmission of shunting locomotives.

The main tasks.

1. To analyze the current state of development of intelligent technologies in railway transport and determine the main areas of application of artificial intelligence.
2. To study the theoretical foundations of existing decision-making methods by the intelligent control system of traction rolling stock.
3. To develop a generalized approach to the development of an intelligent control system for the traction transmission of shunting locomotives.

Materials and methods of research. The analysis of existing works devoted to the development of digital technologies in railway transport allows to systematize the areas of application of intelligent technologies and form Table 1 [15].

Table 1 **Main areas of use of artificial intelligence in railway transport**

Conversational artificial intelligence, automation of manual processing of typical applications, appeals	Infrastructure and rolling stock	Traction rolling stock	Automation of routine operations
Interactive artificial intelligence, capable of conducting a dialogue in natural language, as well as automating the processing of standard requests, applications and appeals. Such a system significantly reduces the workload on staff, increases the speed of response and provides 24/7 user support. In addition, it can learn based on the history of interactions, gradually improving the accuracy of responses and adapting to the specifics of tasks.	Predictive diagnostics. Maintenance and repair	Locomotive control using artificial intelligence methods	Technical support. Reporting. Maintaining regulatory information

The first in the field of implementing AI-based systems were A. Simon and A. Newell, who argue that research in the field of AI is like a heuristic search in the state space. Each node represents a task, and each path in the graph is a project aimed at solving this task. Based on this, it is possible to distinguish the main stages of developing any AI model (Fig. 1.).

The AI concept is quite multifaceted and sometimes even contradictory, but based on them, two basic directions in modeling intelligent systems can be distinguished (Fig. 2.).

The pragmatic or informational approach consists in the optional copying of all the principles of natural intelligence, data can be represented only in symbolic, not in numerical form. The solution algorithm in the general case is presented as a "black box", which in turn may be inapplicable in the light of a certain set of constraints. The objective function in these tasks is either complex or not formalized at all. All this does not allow the use of existing methods and algorithms when solving problems. The informational approach allows modeling only the properties of intelligence associated with information processing and heuristic analysis.

Neurobionics is based on the mandatory computer implementation of problem-solving processes by natural intelligence, and the adequacy of using AI theory to define them. The main idea of this approach is that successful reproduction of intellectual processes is impossible without reproducing their material carriers, that is, the creation of AI is inextricably linked with the modeling of brain processes. The key direction in this approach is the analysis of decision-making, formalization of tasks and parameters, which closely connects neurobionics with psychology, as a result of which psychonics emerged.

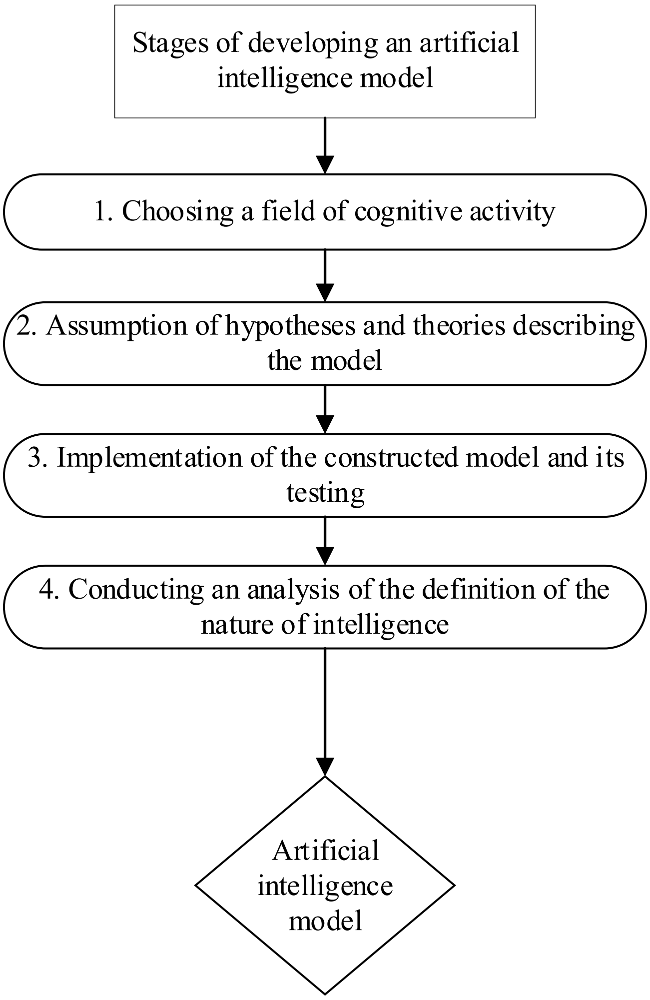

Fig. 1. **Stages of developing an artificial intelligence model**

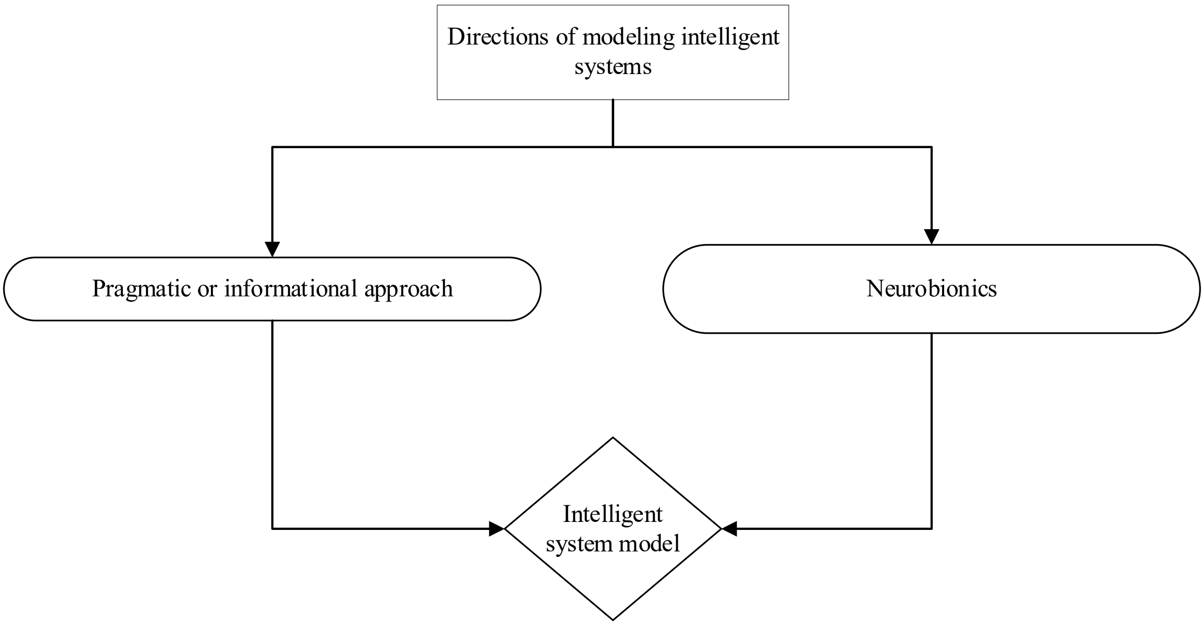

Fig. 2. **Directions of modeling intelligent systems**

The study [20] presents a structural diagram of the application of artificial intelligence on high-speed railways. The structural diagram includes the following blocks:

1) Mechanical and electrical system. This block includes intelligent manufacturing of trains and key components; forecasting of railway maintenance using artificial intelligence; optimization of energy consumption on railways and trains using artificial intelligence.

2) Communication and signal control. This block includes communication security using artificial intelligence methods; reliability of information exchange using artificial intelligence; modeling and evaluation of communication channels using artificial intelligence.

3) Railway transport management. This block includes passenger traffic planning based on artificial intelligence; traffic flow forecasting based on artificial intelligence. "Smart" platform for high-speed railway based on artificial intelligence.

To create intelligent systems based on artificial intelligence methods, a database and a knowledge base are required. To formalize and represent knowledge in the memory of information systems, a number of models are used, which can be structured as follows:

- Logical models – use formal logical systems, where knowledge is represented in the form of facts and rules, with the help of which conclusions are drawn. 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 the connections between them reflect relationships. An example is a semantic network, which illustrates the relationships between concepts.
- Frame models – knowledge is organized in the form of frames, which are data structures for representing stereotypical situations. A frame contains slots corresponding to the attributes of an 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-then” rules (productions) that determine what actions should be performed under certain conditions. These rules allow to make inferences and make decisions based on the available information.

Each of the models of knowledge representation in artificial intelligence has its limitations and shortcomings. Let's consider the main shortcomings of logical, network, frame and production models:

Logical models:
- Difficulty in scaling.
- Lack of flexibility.
- Sensitivity to incomplete data.

Network models:
- Difficulty in building and maintaining.
- Limited expression of complex concepts.
- Performance problems:

Frame models:
- Rigidity of structure.
- Problems with uncertainty handling.
- Problems with frame interaction.

Production models:
- Complexity of managing a large number of rules.
- Problems with efficiency.
- Maintenance and updating.

For the rolling stock management problem, it is proposed to use a production model that combines elements of logical and network approaches. The concept of inference rules, called products, is borrowed from logical models, and the representation of knowledge in the form of a semantic network is borrowed from network models.

One of the most convenient programming tools in the field of fuzzy logic is the Fuzzy Logic environment of the Matlab application package [21-26]. The main advantage of this method is visual modeling, when it is possible to create quite complex programs without writing program code. To create simulation programs in Matlab (Fuzzy Logic), Mamdani or Sugeno algorithms [27] are used.

The Sugeno algorithm [28] formalizes decision-making processes under uncertainty when the input data are imprecise or fuzzy (Fig. 3).

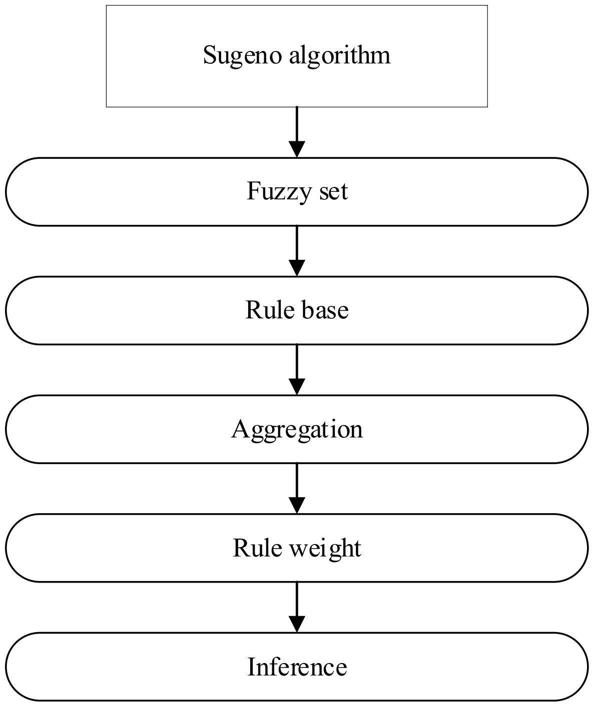

Fig. 3. **Class diagram of the Sugeno algorithm**

All input variables are converted into degrees of membership in fuzzy sets (fuzzification):

$$\begin{aligned} x_1 &= high(0.8),\ medium(0.2) \\ x_2 &= low(1.0) \end{aligned} \tag{1}$$

Кожне правило має вигляд:

$$If\ \mathrm{x}_1 \in A_1\ \mathrm{i}\ \mathrm{x}_2 \in A_2, then\ \mathrm{y}{=}f(\mathrm{x}_1,\mathrm{x}_2), \tag{2}$$

where x_1, x_2 – the input variables of the system;
A_1, A_2 – the fuzzy set that describes the linguistic values of these variables (for example, “High”, “Medium”, “Low”;
$f(\mathrm{x}_1,\mathrm{x}_2)$ – the consequence function (linear or constant).

For example, there is the variable “Engine Temperature (x1)”. A1= “Low” is a fuzzy set with a certain membership function:

$$\mu_{A_1}(x_1) = \max(0, \min(1, (\frac{30 - x_1}{10}))), \tag{3}$$

where μ_{A_1} – the membership function of the element x to the fuzzy set A.

That is, the lower the temperature, the higher the degree of membership to "Low". Unlike Mamdani Algorithm, Sugeno conclusion is not a fuzzy concept, but is usually a linear or constant function.

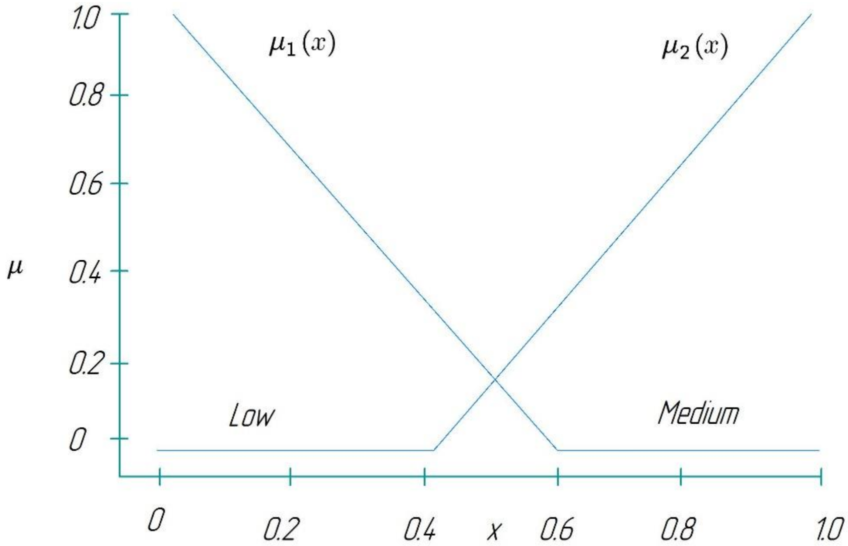

Fig. 4. **Diagram of the membership function A_1, A_2**

Instead of weight cents, as in Mamdani, a weighted average is used:

$$y = \frac{\sum_{i=1}^{n} w_i \cdot f_i(x)}{\sum_{i=1}^{n} w_i}, \tag{4}$$

where w_i – the degree of activation (weight) of the rule;
$f_i(x)$ – the result of the consequence function of the rule.

Mamdani algorithm [29-32] describes several stages that are executed sequentially. At the same time, each subsequent stage receives the values obtained at the previous step as input. The algorithm works according to the "black box" principle [33]. At the intermediate stages, the fuzzy logic apparatus and the theory of fuzzy sets are used. To implement the algorithm, the diagram shown in Fig. 5 is used, which indicates the most significant connections and relationships between the classes involved in the algorithm.

Rules consist of conditions and conclusions, which in turn are fuzzy statements. A fuzzy statement includes a linguistic variable and a term represented by a fuzzy set. A membership function is defined on the fuzzy set, the value of which can be obtained using the get Value method. This method is defined in the FuzzySetlface interface. When executing the algorithm, it will be necessary to use an "activated" fuzzy set (ActivatedFuzzySet), which in some way redefines the membership function of the fuzzy set (FuzzySet). The algorithm also uses the union of fuzzy sets (UnionOfFuzzySets). The union is also a fuzzy set, and therefore has a membership function (defined by FuzzySetlface). Mamdani Algorithm includes all stages and uses a rule base (List<Rule>) as input data. The algorithm also involves the use of "activated" fuzzy sets (ActivatedFuzzySet) and their unions (UnionOfFuzzySets).

Formation of a rule base. A rule base is a set of rules, where each subconclusion corresponds to a certain weight coefficient.

A rule base can have the following form (for example, rules of different constructions are used):

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);

RULE_n: IF «Condition_k» THEN «Conclusion_(q-1)» (Fq-1) AND «Conclusion_q» (Fq),

Fi - are weight coefficients, which denote the degree of confidence in the truth of the obtained subconclusion (i = 1..q). By default, the weight coefficient is taken equal to 1. Linguistic variables present in the conditions are called input, and in the conclusions - output.

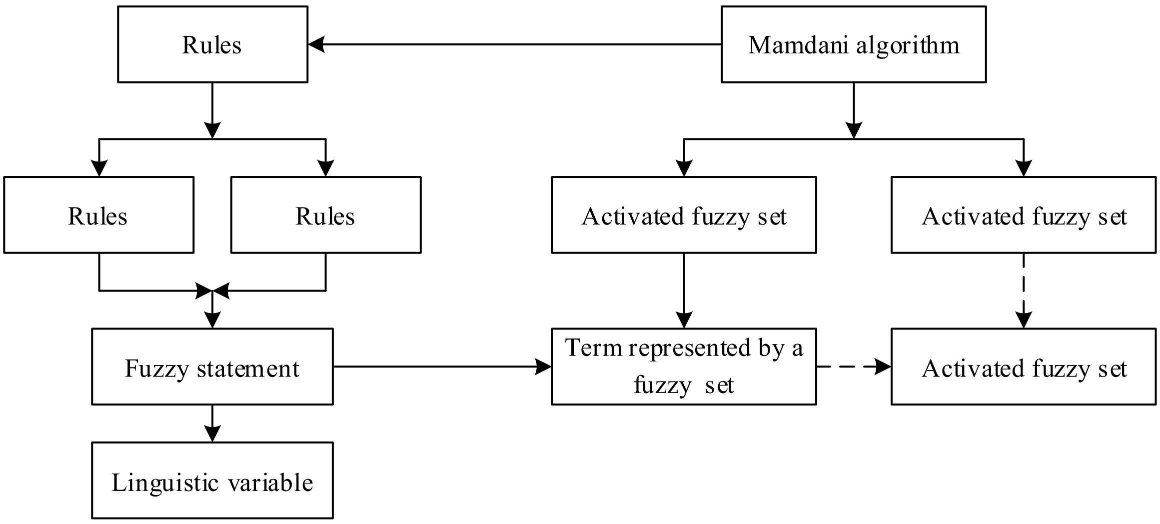

Fig. 5. **Mamdani algorithm implementation class diagram**

Aggregation of subconclusions. The purpose of this stage is to determine the degree of truth of the conditions for each rule of the fuzzy inference system [19]. Formally, it looks like this:

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

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

Activation of subconclusions. 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 membership function of the term;
d_i – the degree of truth of the i-th subconclusion.

Accumulation of conclusions. The purpose of this stage is to obtain fuzzy sets (or their union) for each of the output variables [10]. 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 $\mu_1(x)$, $\mu_{12}(x)$ – 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 output linguistic variables [19]. This implementation of the algorithm uses the center of gravity method, according to which the value of the i-th output variable is calculated by 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.

For a simple interpretation, close to human logic, in the process of controlling the traction transmission of shunting locomotives, it is proposed to use the Mamdani Algorithm, which will allow obtaining a clearer graphical representation.

In work [19], an intelligent model of controlling the traction transmission of shunting locomotives is proposed, the basis of which is the Mamdani Algorithm. To create a knowledge base, rules in the form of logical products "If condition, then action" were used. The number of connected TEDs at partial loads was chosen as actions. All input signals were normalized in the interval [0;1]. To represent them in the form of fuzzy values, a set of characteristic functions was assigned to each input signal. Fig. 6 and 7 show the fuzzification of the values "Speed", "Traction generator current", "They are represented by the following fuzzy values: "very_low", "low", "middle", "high", "very_high".

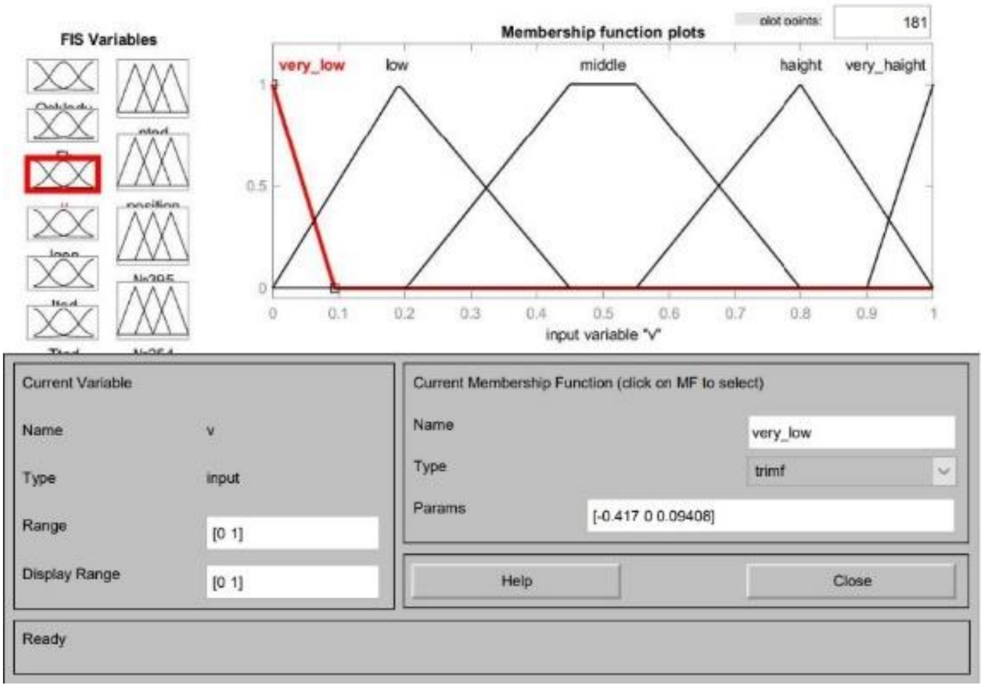

Fig. 6. **Fuzzification of the "Speed" value**

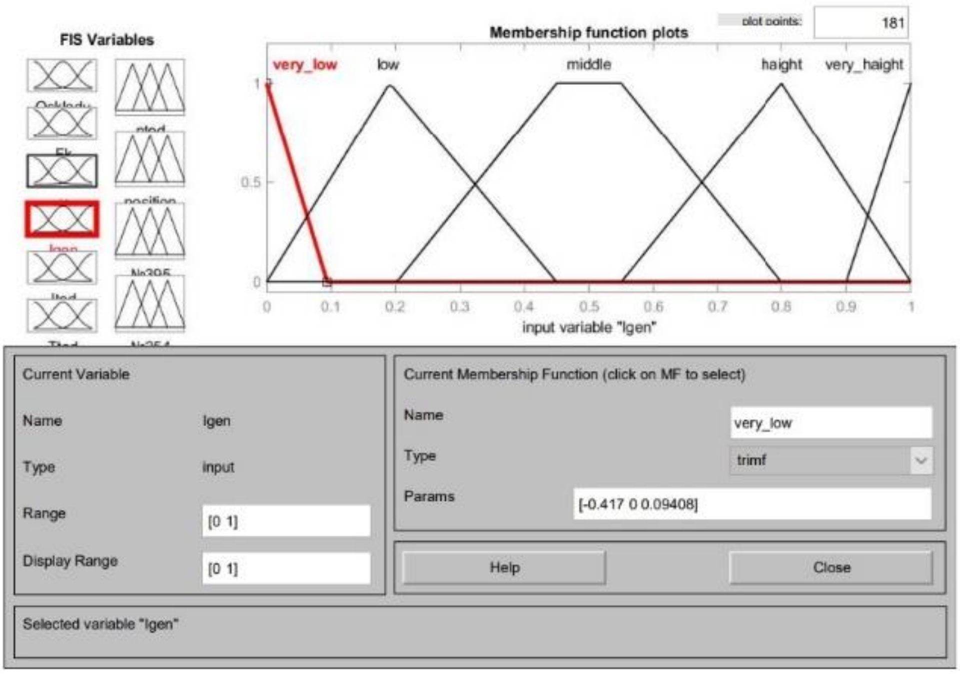

Fig. 7. **Fuzzification of the "Traction generator current" value**

Fig. 8 and 9 present the defuzzification of the "Number of connected TEM" and "Position of the driver's controller handle No. 254" output values

Fig. 8. **Defuzzification of the "Number of connected TEM" value**

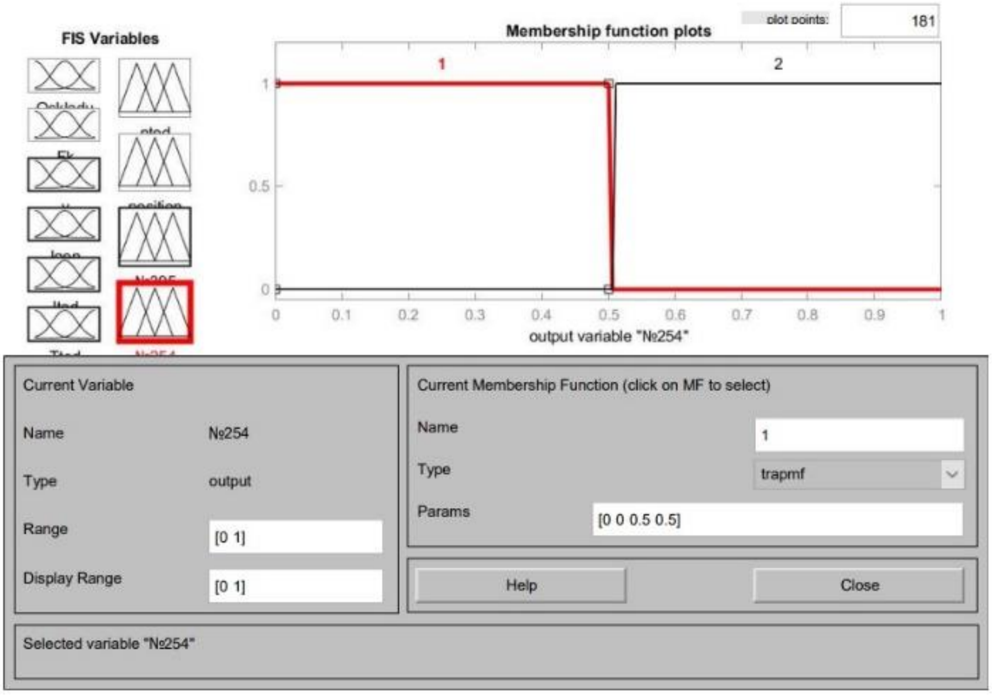

Fig. 9. **Defuzzification of the "Position of the driver's controller handle No. 254" value**

Using the method of expert assessments and traction rolling stock control logic, a list of logical rules for this control system has been developed. For example, one variant of the developed logical rules is shown, which has the following form:

If(IF) (Qskladu(Train mass) is very_low) and(I) (Fk(Traction force) is very_high) and(I) (v(Speed) is very_high) and(I) (Igen(Generator current) is high) and(I) (Ited(Traction electric motor current) is high) and(I) (Tted(Temperature above ambient for TED Д) is low) then(then) (nted(Number of connected TEMs is 6ted)(position(Locomotive position is 5ps) (№395(Driver's controller position No.395) is 2)(№254(Driver's controller position No 254) is 2) (1);

The results of modeling the automated traction control system of shunting locomotives based on a mathematical model allow to analyze the relationship between the input parameters and the output variable of the system. This approach allows to identify patterns in the behavior of the system under different operating modes. In particular, using the Fuzzy Logic Surface Viewer tool, it is possible to construct three-dimensional dependencies that clearly reflect the nature of changes in the output signal depending on variations in the input variables. This allows to:

- visualize fuzzy dependencies between parameters;
- identify critical areas of operation;
- optimize control based on graphical analysis;
- compare the effectiveness of different traction control strategies.

Thus, the use of fuzzy logic in modeling provides flexibility, adaptability and more accurate accounting for uncertainties in the operation of the locomotive, which is especially important for shunting modes.

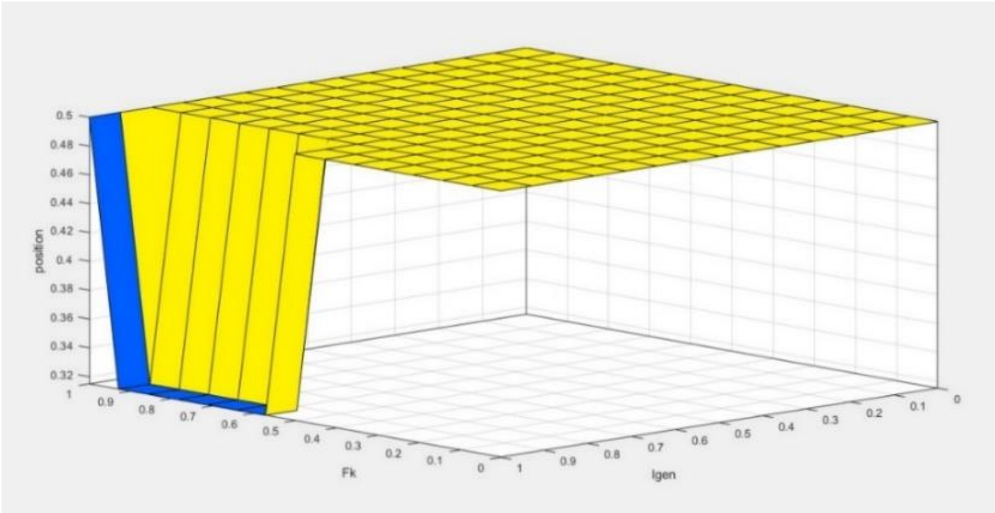

Fig. 10. **Three-dimensional surface of the dependence of the "Driver's controller position" output variable on the "Traction force" and "Traction generator current" inputs**

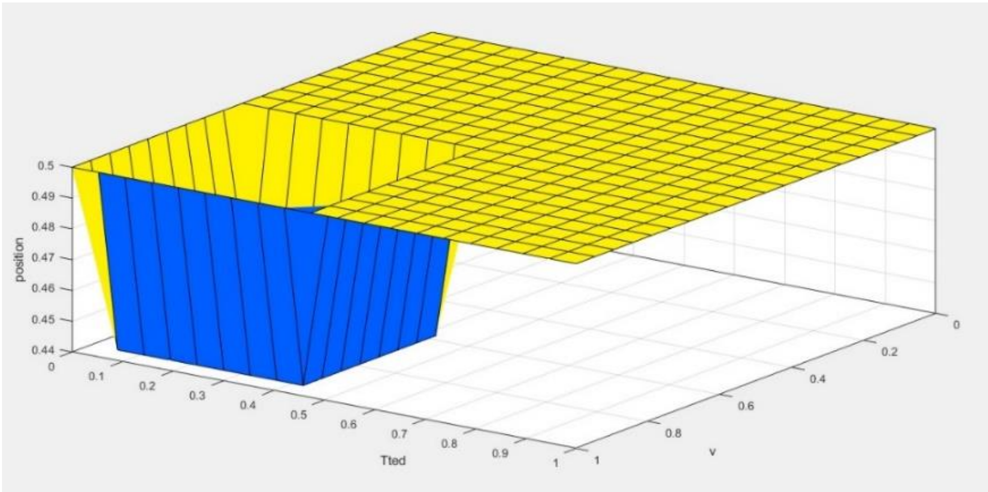

Fig. 11. **Three-dimensional surface of the dependence of the "Driver's controller position" output variable on the "Temperature above ambient for TED" and "Speed" inputs**

Assessment of shortcomings and prospects for the development of the above research. In the process of analyzing existing automated rolling stock control systems based on artificial intelligence methods, the main shortcomings can be identified, such as limited consideration of locomotive components, existing works have created effective models for controlling individual nodes, but do not take into account the interaction with other key subsystems of the locomotive (braking, cooling system, electrical network, etc.), which reduces the complexity of the model. An additional disadvantage is the complexity of scaling and maintenance. With an increase in the number of rules and variables, the system becomes more complicated, becomes difficult to administer, and the possibility of conflicts between rules increases. The works lack a clear description of experimental testing of the model on real equipment or in simulation conditions, which makes it difficult to assess its practical effectiveness. In addition, there is a problem with providing an analysis of the time delay in the operation of the control system, which is critical in real conditions of railway transport. In further research, the models should be expanded to a full digital twin of the locomotive, combining the developed models with other digital modules, which will allow the implementation of the "Smart Locomotive" concept. Additionally, integration with machine learning and reinforcement learning is required, which will allow the use of self-learning models for automatic generation or correction of production rules, and the creation of a dynamic knowledge base that will adapt to new train situations.

Conclusions. The conducted analysis allowed to form the main directions of application of artificial intelligence in railway transport, to highlight the main stages of developing a vehicle control model based on artificial intelligence. Based on the analysis conducted, it is proposed to use a production model for traction rolling stock control tasks. The conducted analysis of the theoretical foundations of existing decision-making methods demonstrates the effective application of the Mamdani algorithm, which is closest to human logic, but has the potential for significant development – both in the direction of expanding functionality and in improving adaptability and practical application. Based on the conducted research, a generalized approach to creating an intelligent traction control system for shunting locomotives is presented. The model has demonstrated its adequacy and effectiveness, it has significant potential for further development.

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Олександр Горобченко[1], Денис Заіка[2], Сергій Малюк[3], Олександр Архипов[4], Олександр Неведров[5]

[1]Професор, Кафедра електромеханіки та рухомого складу залізниць, Національний транспортний університет, М. Омеляновича-Павленка, 1, м. Київ, 01010, Україна. ORCID: https://orcid.org/0000-0002-9868-3852.

[2]Асистент, Кафедра електромеханіки та рухомого складу залізниць, Національний транспортний університет, М. Омеляновича-Павленка, 1, м. Київ, 01010, Україна. ORCID: https://orcid.org/0000-0003-0693-9580.

[3]Старший викладач, Кафедра електромеханіки та рухомого складу залізниць, Національний транспортний університет, М. Омеляновича-Павленка, 1, м. Київ, 01010, Україна. ORCID: https://orcid.org/0000-0003-1777-2384.

[4]Аспірант, Кафедра електромеханіки та рухомого складу залізниць, Національний транспортний університет, М. Омеляновича-Павленка, 1, м. Київ, 01010, Україна. ORCID: https://orcid.org/0009-0009-8873-8643.

[5]Старший викладач, Кафедра електромеханіки та рухомого складу залізниць, Національний транспортний університет, М. Омеляновича-Павленка, 1, м. Київ, 01010, Україна. ORCID: https://orcid.org/0000-0001-9347-0973.

Дослідження теоретичних основ впровадження інтелектуальних систем управління тяговою передачею локомотивів

В роботі виконано аналіз існуючих систем автоматизованого управління на основі теорії штучного інтелекту. Дані системи використовують методи нечіткої логіки, штучні нейроні мережі та генетичні алгоритми. Використання даних методів дозволяє створювати більш адаптивні та ефективні системи управління в порівнянні з традиційними методами. Сформовано основні напрямки застосування методів штучного інтелекту на залізничному транспорті, зокрема в системах управління локомотивами, та оптимізації режимів руху. Виділено основні етапи розробки моделей на основі штучного інтелекту, включаючи збір даних та навчання моделей. Сформовано основі напрямки моделювання інтелектуальних систем. Представлено узагальнений підхід для розробки інтелектуальної системи управління тяговою передачею маневрових локомотивів, який враховує характеристики рухомого складу та умови експлуатації. Для задачі управління пропонується використовувати продукційну модель.

Keywords: *залізничний транспорт, рухомий склад, управління, штучний інтелект, метод Мамдані, ризик, тягова електрична передача, безпека.*