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The theoretical basis of the choice of new locomotives for Ukraine in the post-war period

In the case of the research of promising locomotives, we are dealing with a complex event – "choosing a locomotive for implementation". To effectively solve this problem, it is suggested to decompose this event. Therefore, the purpose of this work is to develop a methodology for modeling the evaluation process according to objective criteria of various options of new traction rolling stock. The Saaty method has been developed by transforming the hierarchy into an artificial neural network. The training of this network occurs automatically when analyzing the matrices of pairwise comparisons, and at the output we have a generalized criterion – the rating of the locomotive R, the value of which varies from 0 (the worst indicator) to 1. This allowed, unlike the existing approach, not to compare locomotives by compiling a matrix of comparisons at the last stage. Instead, a matrix of comparisons of the most important criteria by which traction rolling stock is evaluated has been compiled. The developed method has the ability to support various strategies for the operation of the locomotive park. This is implemented at the stage of drawing up the second-level criteria comparison matrix. Depending on the tasks facing the railways, it is also possible to adjust the degree of preference of one criterion over another. This provides even greater flexibility in using the proposed method.

Keywords: *rolling stock, diesel locomotive, transport system, the Saaty method, artificial neural network.*

Introduction. Updating the locomotive park of Ukraine is a priority task in the post-war development of the state. Over the past decades, the structure of the fleet of freight and passenger locomotives has practically not changed. The most significant implementation was the acquisition of new TE33AS diesel locomotives manufactured by General Electric. But this implementation has not yet received further development and these diesel locomotives make up a small part of the operational fleet of railways. In addition, some difficulties arose during the commissioning of these locomotives, which could have been avoided with a more detailed analysis of their characteristics and operating conditions.

Analysis of recent research and problem statement. Currently, the theoretical provisions describing the choice between existing alternatives and management decision-making are sufficiently developed. They are based on the pattern recognition theory presented in works [1-4]. Direct use of approaches given in similar sources is not always possible. It is necessary to carry out sufficiently extensive preparation of initial data, adaptation of physical quantities and characteristics of the rolling stock to the conditions of theoretical calculations. The use of neural networks is also a promising method for solving selection tasks [5,6]. This allows to conduct network training in an automated mode and obtain reliable selection results. But this method is limited by the need to have a training sample. In our case, it is necessary to have all the parameters of an "ideal locomotive" for training a neural network according to classical algorithms [7]. This is usually impossible, as the choice is made from a limited number of competing models. In addition, within one series of the locomotive, the characteristics may deviate significantly within the established norms [8]. And if it is possible to conditionally set the "ideal" values of individual parameters, then it is difficult to create a complex of such values under the condition of their most optimal ratio, which can reduce the adequacy of the final result of the neural network.

Considering the above, the most promising is the use of the method of analysis of hierarchies [9] to solve the task of choosing new locomotives. The Saaty method allows to evaluate several competing series of locomotives based on a combination of their technical characteristics, operating conditions and expert opinion.

The purpose and tasks of the study. Currently, there is no complete theoretical justification for the selection of new locomotives among several competing series, which would take into account a wide range of criteria and operational factors inherent in the operating conditions of Ukrainian railways.

In the process of planning the introduction of new equipment, railway transport specialists determine a list of promising objects planned for implementation and evaluate the advantages and disadvantages of each of them according to various criteria [10–12]. In the case of the research of promising locomotives, we are dealing with a complex event – "choosing a locomotive for implementation". To effectively solve this problem, it is suggested to decompose this event. Although the decompositions carried out by different people may differ from each other [13], experience shows that experts get close estimates at the operational level when describing and defining this or that option for implementing new technology on railways. Therefore, it is necessary to obtain a formalized model to describe this complex procedure, which would allow taking into account a wide range of factors influencing the final choice of a locomotive and obtain quantitative indicators of this choice. Therefore, the purpose of this study is to develop a methodology for modeling the evaluation process according to objective criteria of various options of new traction rolling stock.

Materials and methods of research. Building a hierarchy of locomotive selection.

Let's introduce some notation. Under the terms of the locomotive selection task, let's obtain a set of locomotives

$$L \in (l_1, l_2, ..., l_n) \tag{1}$$

where де L – set of all locomotives intended for selection;
l_n – a separate locomotive series from the set L.

When comparing locomotives, let's use the plural

$$C \in (c_1, c_2, c_3, ..., c_n) \tag{2}$$

where C – the set of all significant criteria for choosing a locomotive;
c_n – a separate criterion from the set C by which locomotives are compared.

If the set L is known and defined, then the set C needs clarification and structuring. This is due to the fact that there is a very wide range of characteristics of locomotives. Different experts determine the number of significant elements of the set C from 10 to 60, depending on the approaches and selection tasks. In connection with such a large number of evaluation criteria, this work proposes to create a hierarchy of criteria for the selection of locomotives, which will ensure the structuredness, logic and visibility of the representation of the set C.

According to the Regulation on the State Administration of Railway Transport of Ukraine [14], the main tasks of Ukrzaliznytsia are:

1) organization of the coordinated work of railways and enterprises in order to meet the needs of public production and the population in transportation;

2) ensuring effective operation of railway rolling stock, its repair and renewal;

3) development of railway transport development concepts;

4) taking measures to ensure the safety of railway transport, its infrastructure and the reliability of its work.

In addition, there are three main regulatory documents that affect the strategy of using traction rolling stock: the rules of technical operation of railways of Ukraine, the manual for the operation of a separate series of rolling stock, and the financial plan of Ukrzaliznytsia. Therefore, it is considered appropriate to combine all criteria for the selection of locomotives according to the following three groups: "economic criterion", "operational criterion" and "safety criterion".

As a result of the analysis, a list of all significant criteria that influence the decision to choose a new locomotive was obtained. The resulting set C consists of both individual elements (criteria) and subsets (formula 3)

$$C \in (c_1, c_2, c_3, c_4(), c_5(), c_6, c_7, c_8, c_9, c_{10}(), c_{11}, c_{12}) \tag{3}$$

where c_1 –"price of the locomotive" criterion;
c_2 –"relative consumption of fuel and lubricants" criterion;
c_3 –"life cycle of the locomotive" criterion;
$c_4()$ – a subset of criteria "costs for service maintenance and repair";
$c_5()$ – a subset of "reliability" criteria;
c_6 – "coefficient of useful action of the locomotive" criterion
c_7 – "coefficient of useful use of power of the internal combustion engine" criterion;
c_8 – "design speed" criterion;
c_9 – "power of the locomotive" criterion;
$c_{10}()$ – a subset of criteria "permissible influence on the track of a typical design" [15];
c_{11} – "modernity (year of commissioning of the series)" criterion;
c_{12} – "working conditions of the locomotive brigade" criterion.

Subsets of criteria include the following criteria for evaluating locomotives.

$$c_4() \in (c_{41}, c_{42}, c_{43}) \tag{4}$$

where c_{41} – "depot conversion costs" criterion;
c_{42} –"maintenance costs" criterion;
c_{43} –"expenses for current repairs" criterion.

$$c_5() \in (c_{51}, c_{52}, c_{53}, c_{54}, c_{55}) \tag{5}$$

where c_{51} – "quality of the on-board diagnostic system" criterion;
c_{52} –"longevity of the locomotive" criterion;
c_{53} – "repairability of the locomotive" criterion;
c_{54} – "locomotive reliability" criterion;
c_{55} – "locomotive maintainability" criterion.

$$c_{10}() \in (c_{101}, c_{102}, c_{103}, c_{104}) \tag{6}$$

where c_{101} – "axle load" criterion;
c_{102} – "lateral force" criterion;
c_{103} –"dynamic running load on the track from the cart" criterion;
c_{104} – "the ratio of the maximum horizontal load to the average vertical load from the rail to the sleeper" criterion.

The resulting hierarchy of locomotive selection criteria is presented in Fig. 1.

In this way, a general four-level hierarchy was obtained, at the top of which there is the goal – to choose for purchase the most suitable locomotive for the existing conditions. For the practical use of the Saaty method, it is necessary to obtain an algorithm that will ensure the achievement of the goal when entering the initial data. The initial data are the values of all the criteria of the fourth (lower) level and the values of the criteria belonging to the set C, with the exception of the subsets $c_4()$, $c_5()$ and $c_{10}()$. These subsets represent the results of processing the fourth level criteria.

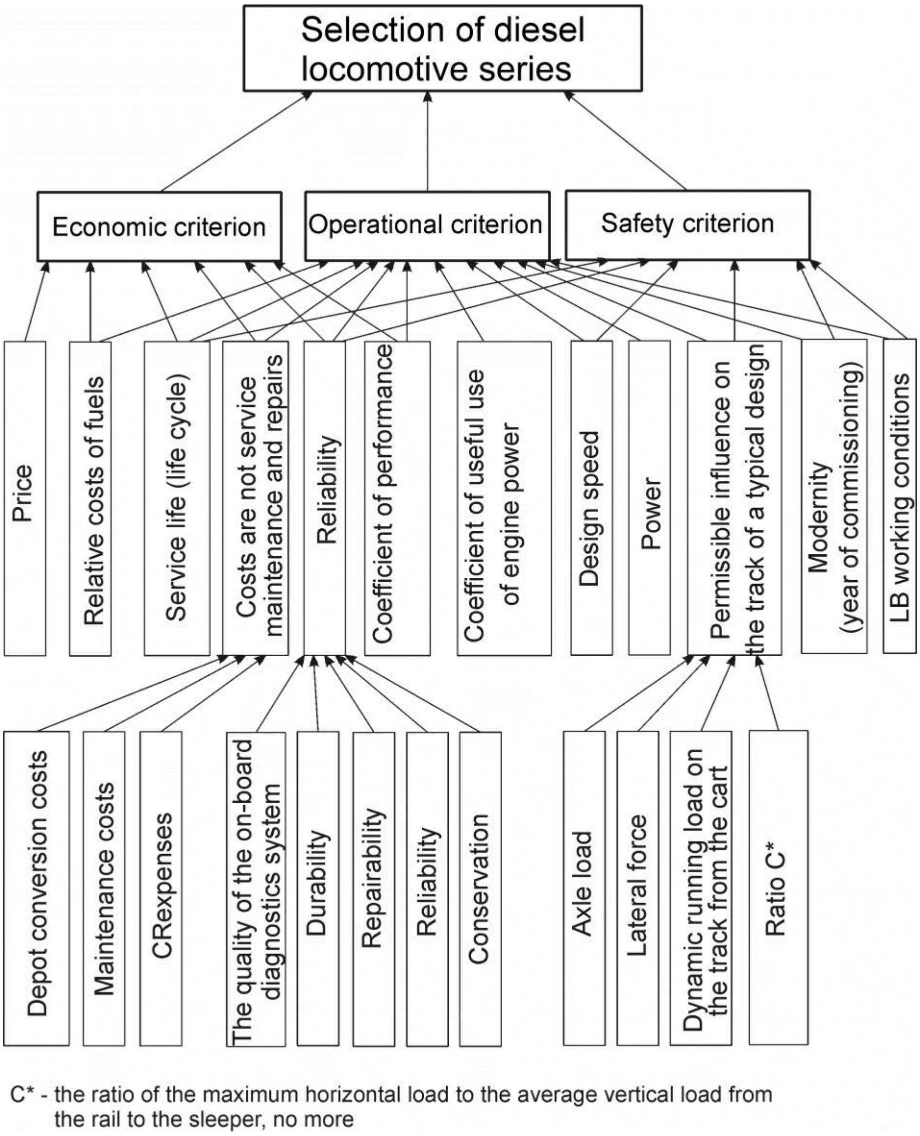

Fig. 1. **Structure of the hierarchy of significant criteria for choosing a new locomotive**.

At each level of the hierarchy, elements of this level are compared with each other [16]. Moreover, the comparison is performed several times: as many elements as are contained at the highest level. Each comparison is made "from the position" of one of the elements of the higher level, which acts as a criterion by which the elements of the current level are compared pairwise.

All groups of criteria, actually criteria and options are compared with each other according to the classic scale 1..9 according to the scheme "each with each", the results of the comparison are presented in the form of a matrix of paired comparisons. A vector of weighting coefficients is formed for each matrix of pairwise comparisons. For greater scientificity of the method, Saaty recommends calculating the weighting coefficients as an eigenvector of the matrix of pairwise comparisons, which corresponds to the largest eigenvalue of this matrix. There is no problem of calculating this eigenvector, but there is no particular need for its calculation either: if to normalize the elements of the columns of the matrix of pairwise comparisons by their sums, and then average the results obtained in each row, the result will be very close to the Saaty eigenvector.

The construction of the matrix of pairwise comparisons is as follows. Let’s set a qualitative pairwise comparison scale with the following conversion into points:

exactly, don't care = 1
slightly superior (worse) = 3 (1/3)
better (worse) = 5 (1/5)
much more preferable (worse) = 7 (1/7)
fundamentally preferable (worse) = 9 (1/9)
They are used in the case of an intermediate opinion
intermediate points 2, 4, 6, 8.

Next, using the given scale, let’s build a matrix of pairwise comparisons of the criteria of the second level of the hierarchy. The purpose of this is to establish which criterion has the greatest influence when choosing a locomotive. According to the survey of 26 experts (specialists in the fields of operation and repair of locomotives, managers of locomotive depots, representatives of railway management), the following matrix was obtained (Table 1).

Using the scale and terms given above, it is possible to say that the economic criterion is "slightly more important" (3 on the scale) than the operational one.

Table 1. **Matrix of pairwise comparisons of criteria of the second level**

Criterion name	Economic criterion	Operational criterion	Safety criterion
Economic criterion	1	3	1/5
Operational criterion	1/3	1	1/2
Safety criterion	5	2	1

Let's analyze the matrix in Table 1. To do this, let’s normalize the matrix: find the sum of the elements of each column (7) and divide all the elements of the matrix by the sum of the elements of the corresponding column (8):

$$S_j = a_{1j} + a_{2j} + a_{3j} \tag{7}$$

$$A_{ij} = \frac{a_{ij}}{S_j} \tag{8}$$

As a result, let’s get a matrix of weighted average ratios between the criteria. By adding the average values of each row to the tabular representation of this matrix, let’s get the weight column of the criteria according to the goal (Table 2.)

Table 2. **Normalized mean values of ratios between criteria**

Criterion name	Economic criterion	Operational criterion	Safety criterion	Criterion weight
Economic criterion	0,1579	0,5000	0,1176	**0,2585**
Operational criterion	0,0526	0,1667	0,2941	**0,1711**
Safety criterion	0,7895	0,3333	0,5882	**0,5703**

In practice, the "Weight of criteria" column allows to evaluate individual criteria according to their importance and rank them. In our case, priority is given to the safety criterion when choosing locomotives. It should be noted that in this way, the weight of the criteria based on the opinion of the expert community is obtained. But an approach is also possible, when the railway management, when making a decision to update the locomotive park, is guided by a given development strategy. This strategy could theoretically involve prioritizing cost minimization or minimizing the time to process and deliver cargo. Then, according to the goals, the decision-maker can manually assign weights to individual criteria. Also, in the future, when carrying out specific calculations, it is possible to obtain the relative cost of increasing the weight of safety or operational priorities, or evaluate the impact of an operational criterion on the safety of transportation, etc.

The next step is the analysis of the third level criteria (Fig. 1). For example, let's give this process for establishing the relative weight of sub-criteria related to the "Economic criterion". the matrix of comparisons in this case will be presented in the form of a Table 3.

Table 3. **Matrix of paired comparisons of the third-level criteria in relation to the "Economic criterion"**

	Subcriterion name	1	2	3	4	5	6
1	Price	1	3	6	1/5	3	5
2	Relative costs of fuels	1/3	1	7	2	1/3	3
3	Term of operation	1/6	1/7	1	1/6	1/3	4
4	Service and repair costs	5	1/2	6	1	6	8
5	Reliability	1/3	3	3	1/6	1	3
6	Efficiency coefficient (Efficiency)	1/5	1/3	1/4	1/8	1/3	1

Let's determine the average values of the relationships between the economic subcriteria and obtain their weights (Table 4)

Table 4. **Normalized average values of relations between economic subcriteria**

	Subcriterion name	1	2	3	4	5	6	Criterion weight
1	Price	0,14	0,38	0,26	0,05	0,27	0,21	**0,22**
2	Relative costs of fuels	0,05	0,13	0,30	0,55	0,03	0,13	**0,20**
3	Term of operation	0,02	0,02	0,04	0,05	0,03	0,17	**0,05**
4	Service and repair costs	0,71	0,06	0,26	0,27	0,55	0,33	**0,36**
5	Reliability	0,05	0,38	0,13	0,05	0,09	0,13	**0,14**
6	Efficiency coefficient (Efficiency)	0,03	0,04	0,01	0,03	0,03	0,04	**0,03**

Using the example in Tables 2 and 3, tables of normalized average values of relations between other sub-criteria of the third level, as well as between sub-criteria of the fourth level (Fig. 1) are prepared.

The next stage is the preparation of the initial data for the calculation of the selection of the locomotive. Based on the physical meaning of the criteria of the third and fourth level, they all have different dimensions and values. For the possibility of their processing, it is proposed to normalize the initial data, that is, to present them in the form of numbers in the interval $0 > w_{Ci} \geq 1$, and the minimum values are the least acceptable, and the maximum values are, respectively, the most acceptable for the selection of the locomotive. Let's also note that it is not desirable to obtain a normalized value of the criterion equal to 0, since this automatically excludes the criterion in the calculation of the higher-level criterion in further calculations. This can lead to a distortion of the final result.

When carrying out normalization, it is necessary to take into account the logic of each indicator in the general structure of the hierarchy. There are values whose increase has a positive effect on the choice of a locomotive (efficiency coefficient, service life, power utilization factor, etc.), and there are values whose increase has a negative effect on the choice (the price of the locomotive, the cost of its maintenance, fuel consumption). Based on this, the formula for normalization of input values will have the following form:

$$\left| \begin{array}{l} \chi_{Ci} = \dfrac{c_{i\text{present}}}{c_{i\max}}, \text{ if } c_i \to \max \\ \chi_{Ci} = 1 - \dfrac{c_{i\text{present}} - c_{i\min}}{c_{i\max}}, \text{ if } c_i \to \min \end{array} \right. \tag{9}$$

where χ_{Ci} – the normalized value of the criterion;
$c_i \to \max$ ($c_i \to \min$) – an increase (decrease) in the value of the criterion increases the probability of choosing a locomotive;
$c_{i\max}$ –the maximum value of the criterion value from all locomotives selected for inspection;
$c_{i\min}$ – the minimum value of the criterion value from all locomotives selected for inspection;
$c_{i\text{present}}$ – the current value of the criterion value of the locomotive being checked at the moment.

Using formula (9) will approximate the normalized value of the criterion to 1 for all types of criteria, provided that this value contributes to the final selection of the current locomotive being calculated.

From the lower level of the hierarchy to the upper level, information is transferred according to the following expression:

$$\chi_{zi} = \sum_{i=1}^{k} w_{C(z-1)i} \cdot \chi_{C(z-1)i} \tag{10}$$

where - the normalized value of the i-th criterion of the z-th level of the hierarchy
k – the number of criteria at the hierarchy level (z-1).
wC(z-1)I – the weight of criterion si, calculated based on the results of the analysis of the matrix of pairwise comparisons of the criteria of the (z-1)-th level of the hierarchy.

An artificial neural network can be built based on the hierarchy shown in Figure 1 [17] (Figure 2).

A set of analytical expressions describing the one shown in Fig. 2 neural network, offered in the following form:

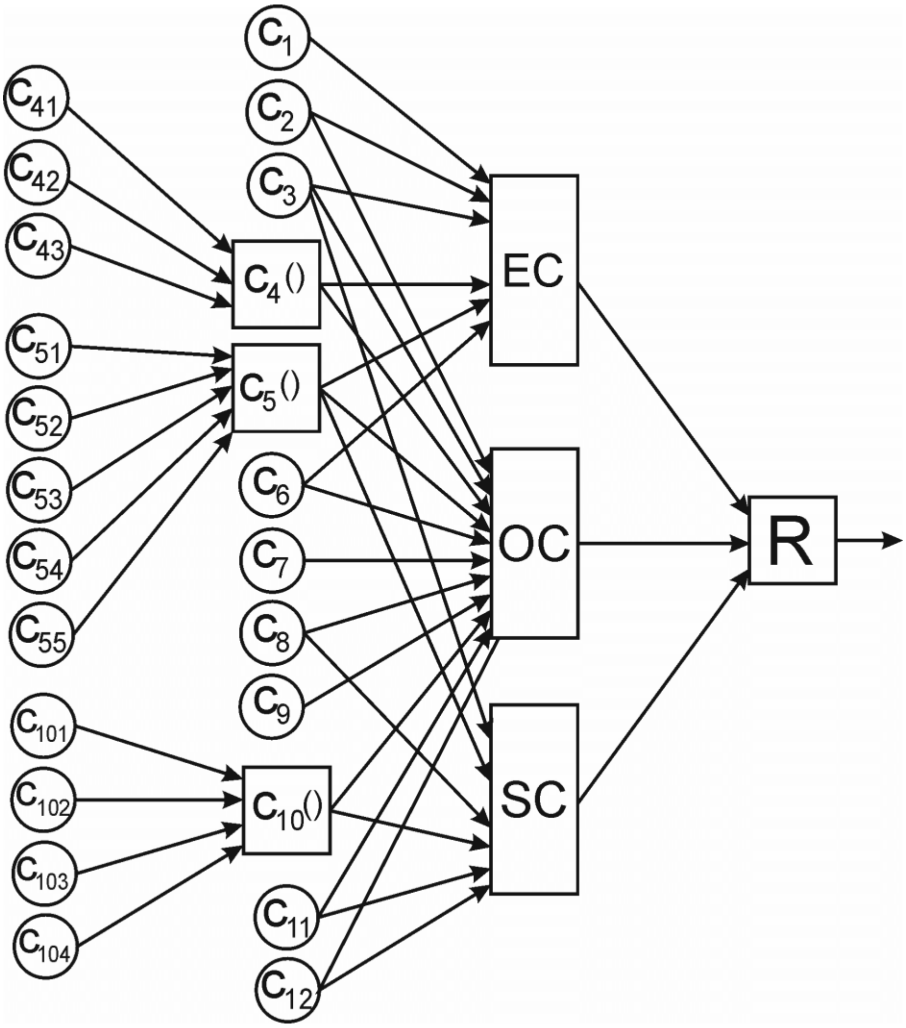

Fig. 2. **Artificial neural network for locomotive selection**

$$\begin{cases} c_4() = \sum_{i=1}^{3} w_{c4()i} \cdot \chi_{c4()i} \\ c_5() = \sum_{i=1}^{5} w_{c5()i} \cdot \chi_{c5()i} \\ c_{10}() = \sum_{i=1}^{4} w_{c10()i} \cdot \chi_{c10()i} \\ EC = w_{c1}\chi_{c1} + w_{c2}\chi_{c2} + w_{c3}\chi_{c3} + w_{c4}c_4() + w_{c5}c_5() + w_{c6}\chi_{c6} \\ OC = w_{c2}\chi_{c2} + w_{c3}\chi_{c3} + w_{c4}c_4() + w_{c5}c_5() + w_{c6}\chi_{c6} + w_{c7}\chi_{c7} + \\ +w_{c8}\chi_{c8} + w_{c9}\chi_{c9} + w_{c10}c_{10}() + w_{c11}\chi_{c11} + w_{c12}\chi_{c12} \\ SC = w_{c3}\chi_{c3} + w_{c5}c_5() + w_{c8}\chi_{c8} + w_{c10}c_{10}() + w_{c11}\chi_{c11} + w_{c12}\chi_{c12} \\ R = w_{EC} \cdot EC + w_{OC} \cdot OC + w_{SC} \cdot SC \end{cases} \tag{11}$$

where c – the parameters of the locomotive (input data of the neural network) contained in the set (3);
w – the weight of the relevant criteria, which was obtained during the analysis of the comparison matrices;
χ - normalized values entering the input of the neural network from the set (3);
EC, OS, SC – values of economic, operational and safety criteria, respectively;
R – the value of the final rating of the locomotive from the set (1).

The presented neural network for locomotive selection has three layers: input neurons (marked by circles), an inner layer (marked by squares) and an output layer consisting of one neuron R. The activation function of the neural network is a simple linear function f(x)=x. In our case, the neural network is already trained, using the method of hierarchy analysis we obtained the criteria weights, which for the neural network are the synapse weights. The output neuron R at the output gives the value [0;1], which characterizes a specific locomotive, represents its rating in comparison with other locomotives. The maximum value of the rating makes it possible to choose the most suitable locomotive from all presented for comparison.

Conclusions. When planning the introduction of new series of locomotives, railway management faces a complex multi-criteria task. Obtaining a mathematical apparatus that will allow to objectively evaluate each locomotive and predict the consequences of its operation will significantly speed up and formalize this process. The method of analyzing hierarchies has already proven itself sufficiently and in this case gives quite adequate results. This article develops the Saaty method by transforming the hierarchy into an artificial neural network. The training of this network occurs automatically when analyzing the matrices of pairwise comparisons, and at the output we have a generalized criterion - the rating of the locomotive R, the value of which varies from 0 (the worst indicator) to 1. This allowed, unlike the existing approach, not to compare locomotives by compiling a matrix of comparisons at the last stage. Instead, a matrix of comparisons of the most important criteria by which traction rolling stock is evaluated has been compiled. In this case, it is possible to enter input data for any locomotive and get its general rating for the conditions embedded in the neural network. To retrain the network for other conditions of operation of promising locomotives, it is only necessary to change the priorities of the criteria in the matrices of their comparisons (for example, in the matrices of Table 1 and Table 3)

In addition, the developed method has the ability to support various strategies for the operation of the locomotive fleet. This is implemented at the stage of drawing up the second-level criteria comparison matrix. If the strategy of railway development is the preference of operational indicators over economic ones, then this can be easily implemented by adjusting pairwise comparisons within the given scale, i.e. giving greater preference to the "Operational Criterion". Depending on the tasks facing the railways, it is also possible to adjust the degree of preference of one criterion over another. This provides even greater flexibility in using the proposed method.

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Теоретичне підґрунтя вибору нових локомотивів для україни у післявоєнний час

У випадку з дослідженням перспективних локомотивів ми маємо справу зі складним заходом – «вибір локомотива для впровадження». Для ефективного вирішення цієї проблеми пропонується розкласти цю подію. Тому метою даної роботи є розробка методології моделювання процесу оцінки за об'єктивними критеріями різних варіантів нового тягового рухомого складу. Метод Saaty був удосконалений шляхом перетворення ієрархії в штучну *нейронну мережу. Навчання цієї мережі відбувається автоматично при аналізі матриць попарних порівнянь, а на виході маємо узагальнений критерій – рейтинг локомотива R, значення якого змінюється від 0 (найгірший показник) до 1. Це дозволило, на відміну від існуючого підходу, не порівнювати локомотиви шляхом складання матриці порівнянь на останньому етапі. Натомість складено матрицю порівнянь найважливіших критеріїв, за якими оцінюється тяговий рухомий склад. Розроблений метод має можливість підтримувати різні стратегії функціонування локомотивного парку. Це реалізується на етапі складання матриці порівняння критеріїв другого рівня. Залежно від завдань, які стоять перед залізницею, також можна регулювати ступінь переваги одного критерію над іншим. Це забезпечує ще більшу гнучкість використання запропонованого методу.*

Ключові слова: *рухомий склад, дизельний локомотив, транспортна система, метод* Saaty*, штучна нейронна мережа.*