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Evaluating Vehicle Energy Efficiency in Urban Transport Systems Based on Fuzzy Logic Models

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Abstract: This work solves the task of developing a fuzzy logic model for evaluating the energy efficiency of vehicles as part of the control unit of an intelligent transport system. Within the scope of this study, the previously obtained morphological model of the transport system was modified. A mathematical dependence is proposed to determine the vehicle energy efficiency indicator. This dependence characterizes the energy consumption of the vehicle in relation to the energy consumption of the vehicle under the reference operating conditions. Synthesis of system configurations was performed, and procedures were used to transform the morphological formulas of the received configurations into a base of logical derivation rules. Parameters of the membership functions of system parameters to fuzzy terms of the area of their definition are defined. Based on the results of the morphological analysis, two fuzzy derivation models were developed: the Mamdani type and the Sugeno type. The accuracy of the modeling was evaluated using different defuzzification algorithms in the control sample. The most accurate model is the fuzzy Mamdani model, with an accuracy value of 98.8%. Using the developed model, the nature of the mutual influence of the transport system parameters on the level of vehicle efficiency was assessed. The results of the study can be used to justify the choice of the vehicle under the specified operating conditions and in the settlement design of the road infrastructure.

Keywords: fuzzy logic model; membership function; morphological matrix; urban transport system; vehicle energy efficiency

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1. Introduction

The global trend of increasing motorization causes several problems, including those related to ensuring the rational functioning of city transport systems. Changes in one of the subsystems of the transport system require prompt adjustment of others. On the one hand, the renewal and growth of the car fleet require taking into account its characteristics when designing road infrastructure and implementing the latest traffic management tools. On the other hand, with the well-established structure of the already existing transport network, it is necessary to develop mechanisms for choosing the optimal type of transport depending on the operating conditions. In accordance with the goal of modernization, new technical and management solutions require the modernization of the knowledge base about system elements and states. In order to build the structure of the knowledge base and further determine the optimal solution to improve the technical system in the conceptualization phase, it is appropriate to use the method of morphological analysis, the stages of which are described in detail in the work [1]. At the same time, they build a morphological model (matrix) of the system. Based on the structure of the morphological matrix, the possible states of the system are synthesized. The disadvantage of the morphological model is the difficulty in transforming them into equivalent mathematical ones for further research.

Usually, the morphological features of the system are fully or partially represented by qualitative parameters. Therefore, when designing technical systems, it is convenient to use formal models: production, logical, network, and frame [2]. Thus, the authors of [1], based on the results of morphological analysis, built a base of production rules in the model of quality control of technological processes of car service systems. This model is based on the principles of fuzzy sets. The Sugeno fuzzy derivation algorithm used in [1] is shown to give a higher accuracy of the result compared to the Mamdani algorithm.

The paper [3] presents an intelligent method for controlling the movement of an electric vehicle. The method is based on the use of the Fuzzy Logic controller (FLC) as part of the driver model and the implementation of the genetic algorithm of swarm intelligence in the control design. This model allows for controlling the use of energy during movement and predicting the energy efficiency of the vehicle under the given conditions. The experimental results show that the use of the specified method provides energy savings while maintaining the performance of the electric vehicle.

The authors of [4] developed an intelligent system for preventing risky driving maneuvers based on soft computing technologies with the use of Mamdani-type fuzzy inference algorithms. The input parameters of the system are the structural properties of the road and the dynamic characteristics of the car, which are obtained using the inertial sensors of the smartphone, the GPS system, the accelerometer, and the gyroscope. The system is designed to work in real time and ensures an increase in the economy, environmental friendliness, and safety level of transport processes. However, among the multitude of input parameters, those that characterize settlement, weather conditions, and the peculiarities of driving during peak hours are missing. In the study [5], Soft Computing technology was used to design a classification system for two-lane roads. The work [6] is devoted to solving the problem of diagnosing driving skills in real conditions based on a fuzzy logic algorithm based on GPS data and video recordings. Fuzzy inference rules are built with traffic rules and expert driving criteria in mind.

The authors of [7] developed a fuzzy logic model for intelligent control and management of the behavior of electricity consumption of an electric car with battery power. The fuzzy model has two inputs: battery state and speed and three outputs according to the power consumption regulation functions of the car's auxiliary devices. The centroid method was used for the defuzzification of model outputs. Each of the parameters has only three implementation options. An optimal intelligent control strategy has been proven to make the engine operate in the high-efficiency zone most of the time, which can improve the energy recycling rate and reduce fuel consumption at a constant vehicle power. Experimental results show that when this energy consumption management system is used with auxiliary devices, it is possible to increase the battery range by 9.8–20.4%. Although the study was conducted for different driving cycles (European, Japanese), the control strategy was developed based on the technical characteristics of the LG-Proton IRIZ BEV and must be adjusted for other electric vehicle models.

In work [8], a simulation model of a hybrid tractor containing an optimization module was implemented to control energy consumption based on fuzzy logic. The optimal control strategy is determined by a genetic algorithm for Particle Swarm Optimization. The disadvantages of the classical algorithm for particle swarm optimization are given in [8], one of which is the probability of falling into a local extremum in the space of admissible solutions. To eliminate this shortcoming, the authors proposed a quantum modification of the classical algorithm. The simulation results of tractor operation in different work cycles show that the average fuel efficiency of the fuzzy logic control strategy after optimization improves by 6.9% compared to the strategy without optimization.

The results of the study [9] demonstrate the energy efficiency of multimode adaptive driving based on the use of fuzzy logic. The FLC controller contains one input (control loop) and three outputs: speed limit, β limit, and comfort level. The BEV battery electric vehicle model, which supports adaptive driving mode, has been tested for various weather conditions that are most typical for Malaysia throughout the year. In adaptive mode, the driving parameters change automatically depending on the driving speed.

The authors of [10] presented a model in the form of a multilayer neural network with direct communication for forecasting the concentration of $PM_{2.5}$ based on traffic parameters in the area of crossroads, meteorological data, and background concentration of PM_{10}. The network was trained using the gradient descent method. Only a third of the statistical sample participated in the training process. This model is designed to expand the functionality of the intelligent system for monitoring traffic and harmful emissions in the city of Bielsko-Biała, Poland. The paper [11] presents an adaptive neuro-fuzzy inference system (ANFIS-PSO) for predicting the intensity of traffic flows in the example of the South African transport system. Training of the neuro-fuzzy system is implemented using the algorithm of Particle Swarm Optimization. The results of the study showed that the period of the day is a significant parameter affecting the movement of vehicles on freeways. The authors of [12] proposed the deep convolutional neural network for use in the process of technical diagnostics. Network optimization is carried out using the minibatch gradient descent method.

The variety of tasks successfully solved in the field of transport by Soft Computing methods testifies to their universality and feasibility of use in models of transport systems of cities, taking into account the nature of variability, partial uncertainty, and vagueness of statistical information. Soft Computing technologies are based on the principles of theories of fuzzy sets and neural networks, operate with fuzzy logic, and implement genetic algorithms. The integration of fuzzy logic controllers into the control units of the specified systems increased the efficiency of their functional elements. Furthermore, the development of the FLC strategy does not require precise analytical models.

In the last stage of the morphological analysis, the most rational states of the technical system are selected according to the given criterion. In research on optimizing the operation of the urban transport system, it is relevant to determine its best configurations based on the highest values of energy efficiency, productivity, and environmental safety. The effectiveness of the entire system can be evaluated based on partial performance indicators of its partitive functional elements or on the basis of an indicator that reflects the synergistic effect of the interaction of their morphological attributes. Since the number of emissions of harmful substances into the air is directly proportional to fuel consumption, and separate algorithms for evaluating the energy efficiency of road transport contain procedures for determining the work performed, the criterion of energy efficiency of transport can be considered a basic condition in the process of evaluating the configurations of the transport system synthesized based on the results of morphological analysis.

Currently, scientists offer several methods to evaluate the energy efficiency of road transport and strategies to increase its level. In work [13], the evaluation of its fuel economy, which is defined as the ratio of mileage to fuel consumption, is taken as an indicator of the efficiency of a vehicle. However, this estimate does not characterize the impact of vehicle loading. Studies [14,15] are devoted to evaluating the energy efficiency of public passenger transport. These works are limited to a given class of buses; at the same time, the results of their research can be adapted to other specifications of buses with internal combustion engines. The authors of [14] proposed a set of indicators that reflect the dependence of the energy efficiency of a city bus on the length of the haul, the coefficient of static use of passenger capacity, and the maximum power of the engine. Models of the energy efficiency of vehicles require an adequate assessment of vehicle energy consumption during operation. According to the authors [15], the fuel consumption of a city bus is determined using the VSP method, which is based on the defined index, which is affected by aerodynamic resistance, rolling resistance, road gradient, speed, and variable load on the bus. Polynomial, logarithmic, and exponential forms of analytical dependences are used to estimate the fuel consumption of an arbitrary vehicle in works [16–18], taking into account its instantaneous speed and modes of movement.

The authors of [19] proposed a strategy for managing thermal comfort in an electric vehicle based on the criterion of minimizing energy consumption in moderate and hot climates. Within the specified strategy, the energy required for traction and the energy required to maintain thermal comfort is determined on the basis of navigation data. The total traction energy is calculated as the sum of the traction energies of individual sections of the route, taking into account the average speed of the vehicle, its standard deviation, and the slope of the road in the sections. However, the average relative error can reach 10% in sections with a negative value of the road slope. In [19], a mathematical model was built for forecasting the energy required to maintain the rational operation of the HVAC in the air conditioning and ventilation modes. The model uses information about weather conditions and a scale of thermal comfort indices. The implementation of the algorithm of the proposed strategy was carried out in the MATLAB environment under different weather conditions, traffic flow intensity values, and the initial level of the battery charge. In the process of research [20], innovative technologies were developed to increase the energy efficiency of vehicles by reducing the weight of individual components and systems of vehicles and optimizing their operation using the example of the demonstration model of the QUIET battery electric vehicle of the Horizon 2020 European Union project. In [20], the results of the study [19] were also used and further developed. It has been proven that the issue of HVAC energy efficiency is relevant for electric vehicles with relatively low movement resistance.

In research [21], the consumption of fuel with given properties is determined based on the mass of emissions of carbon-containing gaseous components in exhaust gases using the carbon balance method. Usually, fuel consumption indicators are based on test results in driving cycles. A critical description of driving cycles used in different countries has been made. Its own unique vehicle test procedures have been developed to control fuel consumption. It is noted that the main problem in the design of fuel consumption control systems is the difficulty of formalizing a large number of variants of driving conditions, driving behavior, and weather conditions.

Articles [22,23] provide methods for managing the energy resource efficiency of a car in its life cycle. The authors of [22] proposed a complex indicator of the technical and energy and transport energy efficiency of a car. The built mathematical model of this indicator contains the energy mileage coefficient, the method of determining which is based on the comparison of the energy efficiency of the specified and reference cars during the performance of test and reference transport operations. The complex indicator in the study [22] takes into account the structural and parametric organization of vehicle design and road properties. However, this efficiency indicator is based on the average (for the test operation) and constant set (for the reference operation) value of the movement speed and its individual components require the determination of coefficients in accordance with the specifics of different vehicles and types of test operations. In [23], the energy efficiency of a vehicle is determined by taking into account the aging of materials during the stages of manufacture and operation for a vehicle with an internal combustion engine (CV), an electric vehicle (EV), a hybrid vehicle (HV) and a fuel cell vehicle (FCV). In addition, in [23], an indicator of the overall national energy efficiency of a car was proposed. This indicator is determined by the method of additive aggregation. The essence of the method is to find the sum of the products of the values of the energy efficiency indicators of the vehicle types under study and the share of their annual sales. It is observed that the difference between the values of the energy efficiency indicators of different types of vehicles decreases with an increase in the duration of the operation.

Articles [24–26] are devoted to the study of the energy efficiency of electric vehicles. The authors of [24] evaluate the energy efficiency of the Edison II electric car manufactured at the University of Zilina, Slovakia. Three modes of operation of the car were studied: battery charging, mode of wheel driving, and recuperation. Analytical dependences for energy calculation at various measurement points are presented on the basis of experimental data. It is shown that 47% of the energy is lost during transmission from the socket to the electric motor shaft. It was determined that the amount of energy loss also depends on the design of the battery. The results of this study indicate that the formation of nitrogen oxides in the energy efficiency of Edison II will be greater than when using heavy trucks. The authors of [25] defined the energy efficiency index of the vehicle, which is the inverse of the energy load indicator Y_W [W/J]. In turn, the Y_W indicator depends on the maximum effective power of the engine, the total weight of the car, and the maximum speed of the car. It is shown that the energy load indicator Y_W compared to the specific engine power P_{sp} [kW/t], has a smaller variance. In paper [26], the energy efficiency of electric vehicles of seven categories was investigated. Separate linear regression dependences of the energy consumption of an electric vehicle on its mass, nominal engine power, and battery capacity were obtained, taking into account the modeling error. A multiple regression model was built to estimate energy consumption based on the specified indicators, year of manufacture, and vehicle category. The authors of [27] systematized the types of energy losses in vehicles and their elimination on the basis of improving the car design.

The results of the analysis of the results of recent studies are combined in Table 1.

Despite a significant number of studies in the direction of evaluating the energy efficiency of vehicles, the majority of them are aimed at optimizing this indicator by improving the design and operational characteristics of the vehicle. It remains relevant to identify potential external factors that, in combination with the technical and operational properties of the vehicle, affect its effectiveness, as well as the construction of generalized models that reflect the importance of this influence for research. In addition, among the latest studies, there is a lack of universal energy efficiency estimates for different categories of vehicles, which would take into account the parameters of all elements of the transport system and the changing conditions of its operation.

The purpose of the study is to evaluate the energy efficiency of vehicles taking into account the changing conditions of the transport system based on fuzzy output models. It is suggested that there is a close relationship between the results of the morphological analysis of the transport system and non-linear models for evaluating the energy efficiency of vehicles. The works discussed above reflected only separate stages of the morphological analysis of the studied systems. The formalization of the transition between the stages of morphological analysis and the construction of appropriate models will allow a comprehensive assessment of the level of energy efficiency of transport depending on the factors of all elements of the system.

Table 1. Generalized characteristics of the results of recent studies.

Methods and Technologies	Reference Number	Advantages	Disadvantages
Morphological analysis method	[1]	The principle of constructing a morphological matrix and morphological formulas is described	The transition to an equivalent mathematical model has not been formalized
	[2]	The stages of morphological analysis are described	The presented models only take into account the operational characteristics and design of the vehicle
Soft Computing Technologies (fuzzy logic)	[3]	A model for forecasting energy efficiency was built	The model is only adequate for electric vehicles
	[4]	The developed intelligent system ensures an increase in the efficiency of transport processes	Traffic environment parameters, weather conditions and hours of the day are not taken into account
	[5]	The results can be used to define the attributes of the element of the "Road" system	Only Two-Lane Roads are considered
	[6]	Real driving conditions are considered; traffic rules are taken into account	An intelligent system is not universal; the energy efficiency of the vehicle is not taken into account
	[7–9]	An intelligent system for controlling the energy consumption of vehicles has been developed, which allows to increase energy efficiency up to 20.4%	Only the vehicle parameters are taken into account (weather conditions are also taken into account in [8]); the system is intended for only one model of electric vehicle/hybrid vehicle; there is no argumentation for choosing the defuzzification method
Soft Computing Technologies (neural network)	[10,11]	Attributes of the functional element of the "Transport flow" system are defined; in [11] an adaptive fuzzy neural network is used	In [10], the training sample is only a third of the initial sample; the modeling error (Mean Absolute Percentage Error) is significant and amounts to 24%. In [11], not all categories of vehicles were taken into account
	[12]	Used deep convolutional neural networks ensured an increase in the productivity of the machine learning system; the method can be used to determine the structure of the traffic flow	It requires significant financial resources to identify traffic flows on the entire street network of the city

Table 1. *Cont.*

Methods and Technologies	Reference Number	Advantages	Disadvantages
Analytical and statistical methods of energy efficiency assessment	[13]	The indicator of energy efficiency of the vehicle was determined	The indicator does not take into account vehicle loading, environmental, traffic flow, roads parameters
	[14,15]	The indicator of energy efficiency of the vehicle was determined	Research is limited to a given class of bus
	[16–18]	Analytical estimates of the fuel consumption of arbitrary vehicle have been developed	The parameters of other (except vehicle) functional elements of the transport system are not taken into account
	[19,20]	models were built to forecast the energy required for efficient HVAC operation; the parameters of all functional elements of the system are taken into account	The average relative error can reach 10%; models are only adequate for electric vehicles
	[21]	Own unique vehicle test procedures for tracking fuel consumption have been developed	Dependence of the complexity of formalization of system parameters on their number
	[22,23]	Comprehensive indicators of energy efficiency of various categories of vehicles, taking into account their construction and road parameters, are proposed	Requires additional calculations in accordance with the specifics of various vehicles and types of test operations; in [23], the use of the indicator requires annual sales statistics
	[24–26]	Analytical dependencies of energy efficiency indicators were obtained; a comparison of the energy efficiency of different categories of electric vehicles was made	The energy efficiency of only electric cars was studied
	[27]	The types of energy losses in vehicles and methods of their elimination are systematized	Only the parameters of the "vehicle" functional element are taken into account

In order to achieve the goal, the following tasks must be solved:

- Formalize the mechanism of synthesis of transport system configurations;
- Synthesize various system configurations based on experimental data;
- Build a fuzzy inference model for evaluating the energy efficiency of the vehicle within the system;
- Determine rational modes of operation of the transport system.

According to the purpose of the research, the article consists of the following sections:

- The Section 1 provides a description of the results of the latest publications on the subject of the research and defines its purpose;
- In the Section 2, the morphological structure of the urban transport system with independent parameters is developed; its morphological model was built in the form of a morphological matrix; the criterion for evaluating the effectiveness of the vehicle is defined; a formalized transition from a morphological system model to a mathematical one is proposed;
- In the Section 3, the experimental part of the research is described, and its partial results are highlighted: the configurations of the transport system are synthesized, and the system of fuzzy rules of derivation is built for the evaluation of the energy efficiency of the vehicle under the given conditions of the transport system; the influence of the system parameters on the energy efficiency of the vehicle was investigated;
- The Section 4 presents the discussion and interpretation of the obtained results;
- The Section 5 summarizes the obtained results and outlines the vector of further research.

2. Materials and Methods

In order to ensure the rational operation of the urban transport system, it is necessary to have mechanisms and technologies to influence its essential parameters and focus on the problem of increasing the level of energy efficiency of vehicles (*LEE*). The algorithms of these mechanisms should be based on models characterizing the connection between system inputs and *LEE*. Such dependencies between parameters usually have a non-linear character.

This study is a continuation of the work [28] in which the functional elements of the intelligent transport energy efficiency management system (TrEECS) were identified on the basis of morphological analysis. The structure of the system is presented in Figure 1.

At the first level of the system, there are functional elements: vehicle (*V*), traffic flow (*TF*), road (*R*), and traffic environment (*Env*). At the second level, the morphological features (attributes) of these elements are defined. In the process of research [28], 10 independent parameters (the basis of the system) were selected from the set of 18 significant quantitative and qualitative parameters corresponding to morphological features. Figure 1 shows only the basic attributes. At the third level, for each attribute, its implementation options (domain, possible values) are listed. The method of determining the quantitative values of the limits of implementation options for each attribute is given in [28].

This hierarchy can be presented in the form of a morphological matrix (Table 2). Under each basic attribute (line 2 in Table 2), its implementation options x_{ij} (*i*—the attribute number; *j*—is the number the implementation option of the *i* -th attribute) are presented. All possible variants of one attribute make up its domain (cells of lines 3–8 of Table 2).

In Table 2, next to each verbal value of a qualitative characteristic, its quantitative counterpart is defined. For example, the attribute "1. Category" can take the following values: M1, M2, M3, N1, N2, N3. The first three categories correspond to passenger vehicles. M1 vehicles have no more than 8 seats. M2s have more than 8 seats, and the maximum weight does not exceed 5 tons. The maximum weight of M3 is more than 5 tons. Categories N1, N2, and N3 correspond to cargo vehicles. N1s have a maximum mass of less than 3.5 t. The maximum mass of N2 is more than 3.5 t but does not exceed 12 t. The maximum mass of N3 exceeds 12 t.

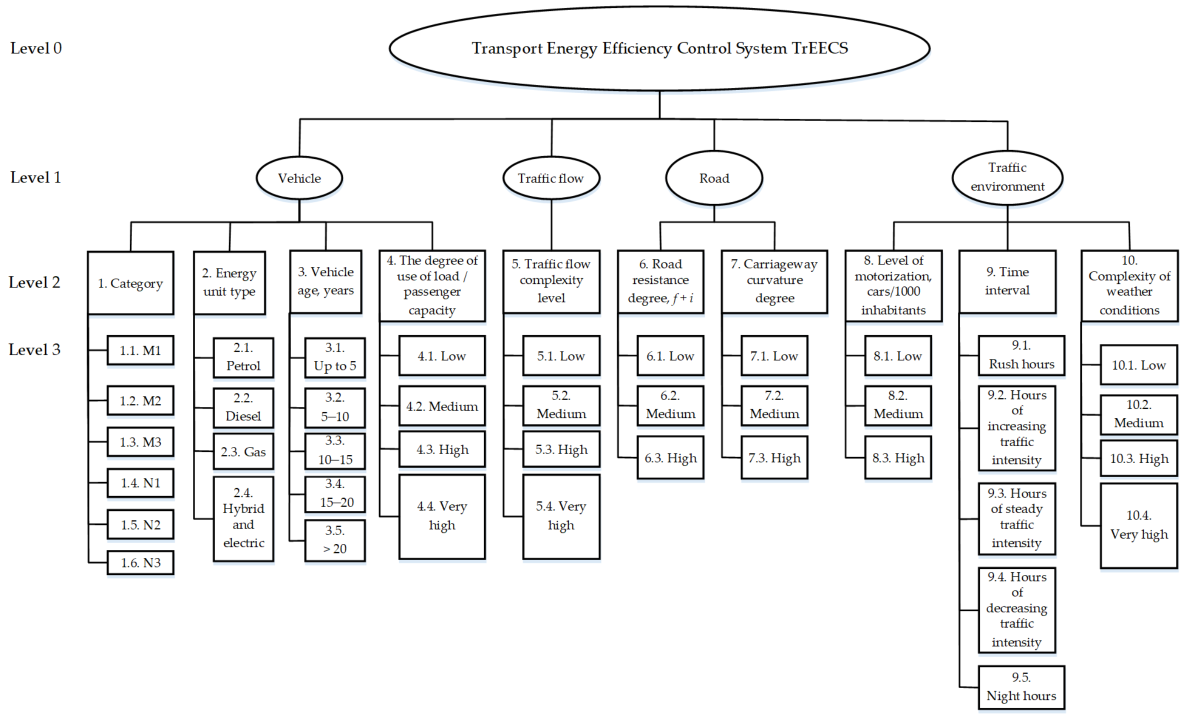


Figure 1. Structure of TrEECS.

This matrix (Table 2) is a modification of the matrix given in [28]. Dependent attributes were removed, and some value ranges were changed. Furthermore, based on the results of the [28], the order of implementation options for the separate attributes were inverted to reduce the number of negative correlations. Based on the real distribution of the values of the complexity level of the traffic flow, the ranges of its implementation options were changed compared to [28].

The synthesis of various configurations of the system takes place by combining various options for implementing its attributes. A separate configuration is given by a morphological formula. An example of a morphological formula is expression (1), which was constructed in the process of evaluating the energy efficiency of a SEAT Toledo passenger car (category M1 (x_{11}), gasoline (x_{21}), year of manufacture 2008 (x_{33}), the degree of use of passenger capacity—0.75 (x_{44}))—heading in a stream with a low level of complexity 0.03 (x_{51}) on a road with an average degree of road resistance—0.09 (x_{62})—and an average degree of curvature (x_{72}) in an urban environment (Zamkovy Uzviz Street, Cherkasy) with an average level of motorization (200–300 cars/1000 inhabitants) (x_{82}), in the hours of reduced traffic intensity (20:00–21:00) (x_{94}) under weather conditions of high complexity (x_{103}):

$$[(x_{11} - x_{21} - x_{33} - x_{44}) + (x_{51}) + (x_{62} - x_{72}) + (x_{82} - x_{94} - x_{103})] = Y \tag{1}$$

Table 2. Modified morphological matrix of the TrEECS system (built according to the results [28]).

Vehicle				Traffic Flow	Road		Traffic Environment		
1. Category	**2. Energy Unit Type**	**3. Vehicle Age**	**4. The Degree of Use of Load/Passenger Capacity**	**5. Traffic Flow Complexity Level**	**6. Road Resistance Degree, $f + i$**	**7. Carriageway Curvature Degree**	**8. Level of Motorization, Cars/1000 Inhabitants**	**9. Time Interval**	**10. Complexity of Weather Conditions**
1.1. M1 1	2.1. Petrol 1	3.1. Up to 5 years 1	4.1. Low 0–0.4	5.1. Low 0–0.2	6.1. Low 0.007–0.049	7.1. Low 2maxR/3-maxR 1	8.1. Low <200 1	9.1. Rush hours 1	10.1. Low 0–0.19
1.2. M2 2	2.2. Diesel 2	3.2. 5–10 years 2	4.2. Medium 0.41–0.5	5.2. Medium 0.21–0.4				9.2. Hours of increasing traffic intensity 2	10.2. Medium 0.2–0.39
1.3. M3 3	2.3. Gas 3	3.3. 10–15 years 3	4.3. High 0.51–0.7	5.3. High 0.41–0.7	6.2. Medium 0.05–0.099	7.2. Medium maxR/3–2maxR/3 2	8.2. Medium 200–300 2	9.3. Hours of steady traffic intensity 3	10.3. High 0.4–0.69
1.4. N1 4		3.4. 15–20 years 4							
1.5. N2 5	2.4. Hybrid and electric 4	3.5. More than 20 years 5	4.4. Very high 0.71–1	5.4. Very high 0.71–1	6.3. High 0.1–0.15	7.3. High 0-maxR/3 3	8.3. High > 300 3	9.4. Hours of decreasing traffic intensity 4	10.4. Very high 0.7–1
1.6. N3 6								9.5. Night hours 5	

In the general case, the output of system Y is a vector consisting of indicators of environmental safety, energy efficiency, safety of transport processes, etc. In this study, the level of energy efficiency *LEE* is considered as the output of the TrEECS system, which for a given configuration is proposed to be determined as follows:

$$LEE = \frac{E_{basis}}{E_{fact}} = \frac{E_{basis}}{E_{basis}(1 + 0.01 \cdot K_e)} = \frac{1}{1 + 0.01 \cdot \left(\sum_{i=1}^{n} K_i - \sum_{j=n+1}^{n+m} K_j \right)} \tag{2}$$

where E_{basis}—energy consumed by the engine under ideal operating conditions, MJ; is determined according to the basic norms of fuel/energy consumption for a given vehicle model;

E_{fact}—energy actually consumed by the engine, MJ;

K_e—complex correction coefficient, %;

K_i—i-th correction factor that increases fuel consumption norms ($1 \le i \le n$), %;

K_j—j-th correction factor that reduces fuel consumption norms ($1 \le j \le m$), %.

The work [28] gives the values of the main correction coefficients used in the conditions of urban mobility.

Analytical dependence (2) is a universal formula that can be used to determine the energy efficiency of vehicles of different classes with a given type of power plant.

Thus, the selection of the best system configuration from a set of already synthesized ones is carried out according to the following criterion:

$$LEE = f(K_1, K_2, \cdots K_n, K_{n+1}, K_{n+2}, \cdots, K_{n+m}) \to max \tag{3}$$

However, the number of all possible TrEECS configurations, calculated using the combinatorics product rule, is 1.0368×10^6. Processing such a volume of information requires significant resources and is not possible. In addition, the values of the correction coefficients are not known for all configurations. Therefore, the development of a mathematical fuzzy model with the possibility of further integration into the intelligent system of the control of energy efficiency of transport is relevant.

The fuzzy model of logical derivation represents a base of logical derivation rules (deduction rules) built on the results of the TrEECS morphological analysis. At the same time, each morphological formula of synthesized TrEECS configurations is uniquely matched by one logical derivation rule. System (4) characterizes the mechanism of transformation of a morphological formula into a rule as part of the model:

$$\begin{cases} \Omega_{X_i} = \cup_{j=1}^{m_i} A_i^j, \textit{under the condition} \cap_{j=1}^{m_i} A_i^j = \varnothing \\ A_i^j = \Psi_{x_{ij}} \\ \Theta_{LEE} = \cup_{s=1}^{p} B^s, \textit{under the condition} \cap_{s=1}^{p} B^s = \varnothing \\ Left(F) \to \textit{rule condition} \\ Right(F) \to \textit{the rule conclusion} \end{cases} \tag{4}$$

where Ω_{X_i}—area of determination of values of parameter X_i;

A_i^j—j-th term (interval of definition area division) of i-th parameter;

m_i—the number of implementation options for the i-th feature;

$\Psi_{x_{ij}}$—area of definition of the j-th variant of the implementation of the i-th feature;

Θ_{LEE}—area of definition of the *LEE* values;

B^s—s-th term of the resulting parameter *LEE*;

$Left(F)$—the left part of the morphological formula;

$Right(F)$—the right part of the morphological formula.

In the next step, membership functions mf_j of system parameter values to fuzzy terms (intervals) of their definition area are constructed (Table 3).

Table 3. Parameters of the membership functions of the system input and output terms.

Inputs	Term A_i^j	Membership Function *mf* Parameters				Inputs/ Output	Term A_i^j	Membership Function *mf* Parameters			
		a	**b**	**c**	**d**			**a**	**b**	**c**	**d**
X_1	A_1^1	0	0.5	1.5	7	X_6	A_6^1	0	0.007	0.049	0.151
	A_1^2	0	1.5	2.5	7		A_6^2	0	0.05	0.099	0.151
	A_1^3	0	2.5	3.5	7		A_6^3	0	0.1	0.15	0.151
	A_1^4	0	3.5	4.5	7	X_7	A_7^1	0	0.5	1.5	4
	A_1^5	0	4.5	5.5	7		A_7^2	0	1.5	2.5	4
	A_1^6	0	5.5	6.5	7		A_7^3	0	2.5	3.5	4
X_2	A_2^1	0	0.5	1.5	5	X_8	A_8^1	0	0.5	1.5	4
	A_2^2	0	1.5	2.5	5		A_8^2	0	1.5	2.5	4
	A_2^3	0	2.5	3.5	5		A_8^3	0	2.5	3.5	4
	A_2^4	0	3.5	4.5	5	X_9	A_9^1	0	0.5	1.5	6
X_3	A_3^1	0	0.5	1.5	6		A_9^2	0	1.5	2.5	6
	A_3^2	0	1.5	2.5	6		A_9^3	0	2.5	3.5	6
	A_3^3	0	2.5	3.5	6		A_9^4	0	3.5	4.5	6
	A_3^4	0	3.5	4.5	6		A_9^5	0	4.5	5.5	6
	A_3^5	0	4.5	5.5	6	X_{10}	A_{10}^1	0	0.05	0.19	1.01
X_4	A_4^1	0	0.01	0.4	1.01		A_{10}^2	0	0.2	0.39	1.01
	A_4^2	0	0.41	0.5	1.01		A_{10}^3	0	0.4	0.69	1.01
	A_4^3	0	0.51	0.7	1.01		A_{10}^4	0	0.7	1	1.01
	A_4^4	0	0.71	1	1.01	*LEE*	B^1	0	0.01	0.2	1.01
X_5	A_5^1	0	0.01	0.2	1.01		B^2	0	0.21	0.4	1.01
	A_5^2	0	0.21	0.4	1.01		B^3	0	0.41	0.6	1.01
	A_5^3	0	0.41	0.7	1.01		B^4	0	0.61	0.8	1.01
	A_5^4	0	0.71	1	1.01		B^5	0	0.81	1	1.01

In most of the fuzzy inference systems considered in the first section, triangular and trapezoidal membership functions of the terms to the parameter definition area of the fuzzy model are accepted. In some cases, Gaussian functions are used. The results of the study, which will be described in the next section, proved the feasibility of using the trapezoidal form of the membership function, given by the vector of parameters (a, b, c, d, h), height h = 1 [29]. On the basis of the implementation options values of the morphological features (Table 2) and system (4), parameters of the membership functions of the input and output values of the TrEECS are determined, which are presented in Table 3. When determining the parameters of the membership functions, the experience of experts in the field of organization and provision of road safety, including specialists of the civil service "Ukrtransbezpeka", was taken into account. The parameters of the membership functions were adjusted according to the criterion of the smallest modeling error.

The general appearance of the logical derivation models of the Mamdani and Sugeno types of the TrEECS system is given by expressions (5), (6), respectively:

$$Rules_{Mamdani} = \left\{ rule_i \ : \ \&_{i=1}^{10} \left(X_i \in A_{ik}^j \right) \Rightarrow \ LEE_k \in \ B_k^s, \ i = \overline{1, m} \right\} \quad (5)$$

where X_i—value of the i-th TrEECS parameter;

A_{ik}^j—j-th term of the i-th parameter for the k-th system configuration;

LEE_k—level of energy efficiency of the vehicle in the k-th configuration;
B_k^s—s-th term of the LEE_k value, m—number of TrEECS configurations.

$$Rules_{Sugeno} = \left\{ rule_i \ : \ \&_{i=1}^{10} \left(X_i \in A_{ik}^j \right) \Rightarrow \ LEE_k = LEE_{tabl}, \ i = \overline{1, m} \ \right\} \tag{6}$$

where LEE_{tabl}—LEE value obtained experimentally.

Thus, Formula (1) will be transformed into the following rule of logical derivation according to the Mamdani algorithm:

$$rule : \left(x_1 \in A_1^1\right) \& \left(x_2 \in A_2^1\right) \& \left(x_3 \in A_3^3\right) \& \left(x_4 \in A_4^4\right) \& \left(x_5 \in A_5^1\right) \& \left(x_6 \in A_6^2\right) \& \left(x_7 \in A_7^2\right) \& \left(x_8 \in A_8^2\right) \& \left(x_9 \in A_9^4\right) \& \left(x_{10} \in A_{10}^3\right) \Rightarrow LEE \in B^4 \tag{7}$$

Thus, the transition from the conceptual model of the system to the corresponding mathematical model can be represented by the following algorithm (Figure 2).

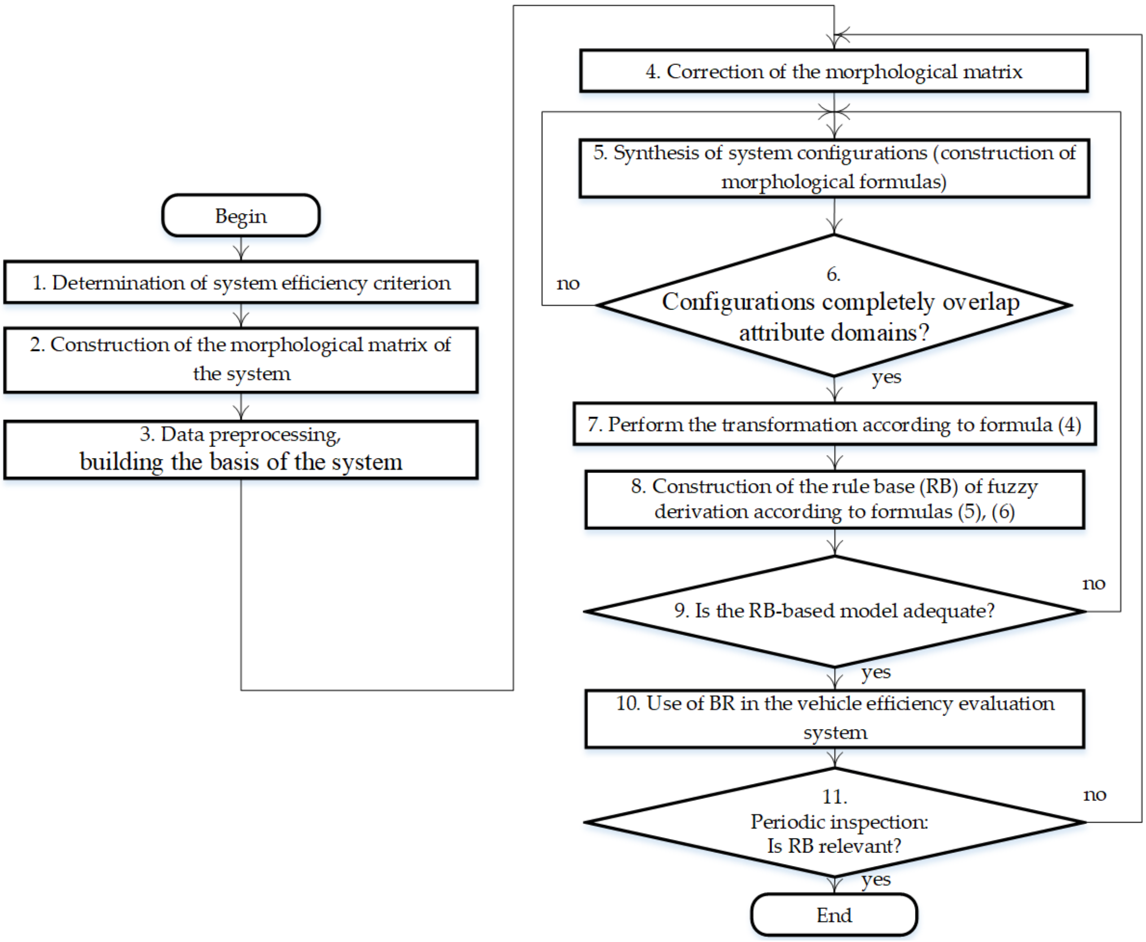


Figure 2. Scheme of the proposed approach.

The data preprocessing procedure (block 3 in Figure 2) is presented in [28].

The main condition for the completeness of statistical data is that they overlap all intervals of the area of definition of system attributes (the presence of all possible variants of their implementation). Therefore, loops 5–6 will be repeated until the condition of block 6 is met.

A sufficient number of statistical values of the resulting LEE parameter can be determined by Formulas (8) and (9):

$$N_{LEE} = \frac{t_\alpha^2 \cdot \sigma^2}{\eta^2} \tag{8}$$

where t_α—confidence probability function, for confidence probability θ = 0.95 function of confidence probability t_α = 1.96;

σ—standard deviation;

η—extreme error allowed.

$$\eta = \Delta \cdot LEE_{avg} \tag{9}$$

where Δ—relative accuracy of accounting, assume Δ = 0.05;

LEE_{avg}—average value of energy efficiency of vehicles.

In the next section, it is noted that for the initial sample, the examination of 25 transport system states, that is, 25 TrEECS configurations, proved to be sufficient. If as a result of the study, high accuracy of the modeling will not be achieved, then the study of other states of the system (synthesis of configurations) will be continued (loop 5–9 in Figure 2).

3. Results

3.1. Synthesis of System Configurations

Monitoring of the TrEECS states was carried out on the example of fragments of street and road networks in Kyiv, Lviv, Odesa, Cherkasy, Kaniv, Boryspil, Smila, Cherkasy Region, Zolotonosha, Cherkasy District (Ukraine) and the city of Rzeszów (Poland) under different time periods and weather conditions. The functional element "Vehicle" within the TrEECS was represented by the following car models: Renault Logan 1.2, Skoda Octavia A7 1.8, SEAT Toledo 1.6, ZAZ Lanos T150, Nissan Micra 1.2, Volkswagen Passat B5 GP 2.0, PAZ-4234, Ataman A092G6, Mercedes -Benz O530, Bogdan T70117, Mercedes Sprinter 214, IVECO Daily 35S170, FORD Transit 2.4D, MAN L 8.220, MAN TGL 8.180, VOLVO FH 460, which provided a complete set of options for the implementation of the three morphological attributes of the specified functional element. The methods for determining the TrEECS input parameters are given in [28].

In the process of researching TrEECS states, the specifics of traffic organization in different settlements are taken into account. Differences were recorded regarding the distribution of "peak" periods during the day and the level of passenger capacity utilization of public transport in Poland and Ukraine.

Based on the results of the TrEECS state monitoring in the sections of the investigated networks [28], 25 system configurations were synthesized, the morphological formulas of which are presented in Table 4. The left parts of the morphological formulas are constructed similarly to (1). The options for implementing the attributes of a separate functional element are listed in round brackets. It can be seen from the constructed 25 morphological formulas that the implementation options written in them completely overlap the areas of defining the attributes of the functional elements of the system. In addition, the required number of *LEE* values with a confidence probability θ = 0.95 and relative accuracy of accounting Δ = 0.05 is determined taking into account (8) by Formula (10):

$$N = \frac{1.96^2 \cdot 0.08^2}{(0.05 \cdot 0.657)^2} \approx 23 < 25. \tag{10}$$

Thus, 25 TrEECS configurations ensure the reliability of the initial statistical data sample.

System configurations with the lowest value of the sample variance were selected for the control sample [29]. The training sample was used for learning the constructed fuzzy logic models (Mamdani and Sugeno). The control sample was used to assess the accuracy of the developed models. The sample type is indicated in the last column of Table 4. The experimental values of the energy efficiency level *LEE* for the synthesized configurations were obtained using Formula (2). According to this method of calculating the output parameter, its scope is in a narrow range of values [0.5, 0.8]. To be consistent with the area corresponding to the terms B^s (Table 3), the range of experimental *LEE* values is converted to a more acceptable interval [0, 1] by expression (11):

$$LEE_{tabl} = (LEE - a)/(b - a) = (LEE - 0.5)/0.3 \quad (11)$$

where *LEE* and LEE_{tabl}—experimental and reduced value of the energy efficiency level of the system, respectively;

a, b—the left and right boundaries of the *LEE* definition area, respectively.

The converted (tabular) output values of the system (LEE_{tabl}) are given in Table 4.

Table 4. Input data for building a fuzzy inference model.

Configuration Number	Left Part of the Morphological Formula	LEE_{tabl}	Sample Type
1	$[(x_{11} - x_{21} - x_{33} - x_{44}) + (x_{51}) + (x_{62} - x_{72}) + (x_{82} - x_{94} - x_{10\,3})]$	0.648	training
2	$[(x_{11} - x_{23} - x_{35} - x_{42}) + (x_{51}) + (x_{62} - x_{72}) + (x_{82} - x_{94} - x_{10\,2})]$	0.632	training
3	$[(x_{15} - x_{22} - x_{32} - x_{43}) + (x_{52}) + (x_{61} - x_{71}) + (x_{82} - x_{93} - x_{10\,1})]$	0.556	training
4	$[(x_{13} - x_{22} - x_{34} - x_{44}) + (x_{52}) + (x_{61} - x_{71}) + (x_{82} - x_{93} - x_{10\,1})]$	0.227	control
5	$[(x_{11} - x_{21} - x_{34} - x_{43}) + (x_{53}) + (x_{61} - x_{71}) + (x_{82} - x_{92} - x_{10\,3})]$	0.632	control
6	$[(x_{13} - x_{24} - x_{32} - x_{44}) + (x_{51}) + (x_{61} - x_{71}) + (x_{83} - x_{91} - x_{10\,2})]$	0.060	training
7	$[(x_{11} - x_{23} - x_{35} - x_{41}) + (x_{51}) + (x_{61} - x_{71}) + (x_{83} - x_{92} - x_{10\,2})]$	0.681	training
8	$[(x_{11} - x_{21} - x_{31} - x_{41}) + (x_{52}) + (x_{62} - x_{71}) + (x_{81} - x_{93} - x_{10\,1})]$	0.958	training
9	$[(x_{11} - x_{21} - x_{33} - x_{41}) + (x_{51}) + (x_{61} - x_{72}) + (x_{82} - x_{95} - x_{10\,4})]$	0.859	training
10	$[(x_{12} - x_{22} - x_{33} - x_{44}) + (x_{51}) + (x_{61} - x_{72}) + (x_{82} - x_{93} - x_{10\,2})]$	0.329	control
11	$[(x_{16} - x_{22} - x_{33} - x_{44}) + (x_{52}) + (x_{61} - x_{71}) + (x_{82} - x_{92} - x_{10\,3})]$	0.017	training
12	$[(x_{14} - x_{22} - x_{34} - x_{43}) + (x_{52}) + (x_{61} - x_{71}) + (x_{81} - x_{91} - x_{10\,1})]$	0.601	training
13	$[(x_{14} - x_{22} - x_{32} - x_{44}) + (x_{52}) + (x_{61} - x_{71}) + (x_{81} - x_{91} - x_{10\,3})]$	0.430	training
14	$[(x_{13} - x_{22} - x_{35} - x_{42}) + (x_{51}) + (x_{61} - x_{71}) + (x_{81} - x_{94} - x_{10\,3})]$	0.556	training
15	$[(x_{15} - x_{22} - x_{34} - x_{44}) + (x_{52}) + (x_{62} - x_{71}) + (x_{81} - x_{93} - x_{10\,2})]$	0.175	training
16	$[(x_{11} - x_{23} - x_{35} - x_{41}) + (x_{52}) + (x_{62} - x_{71}) + (x_{81} - x_{94} - x_{10\,2})]$	0.802	training
17	$[(x_{11} - x_{22} - x_{35} - x_{41}) + (x_{53}) + (x_{62} - x_{71}) + (x_{82} - x_{91} - x_{10\,1})]$	0.632	training
18	$[(x_{11} - x_{21} - x_{33} - x_{42}) + (x_{52}) + (x_{62} - x_{71}) + (x_{82} - x_{94} - x_{10\,1})]$	0.859	training
19	$[(x_{14} - x_{23} - x_{35} - x_{41}) + (x_{51}) + (x_{62} - x_{71}) + (x_{82} - x_{95} - x_{10\,1})]$	0.897	training
20	$[(x_{14} - x_{22} - x_{34} - x_{44}) + (x_{53}) + (x_{61} - x_{71}) + (x_{82} - x_{93} - x_{10\,2})]$	0.366	control
21	$[(x_{13} - x_{22} - x_{33} - x_{44}) + (x_{54}) + (x_{61} - x_{71}) + (x_{82} - x_{92} - x_{10\,1})]$	0.145	control
22	$[(x_{11} - x_{21} - x_{33} - x_{41}) + (x_{54}) + (x_{61} - x_{73}) + (x_{82} - x_{93} - x_{10\,1})]$	0.681	training
23	$[(x_{11} - x_{21} - x_{31} - x_{41}) + (x_{51}) + (x_{61} - x_{71}) + (x_{83} - x_{91} - x_{10\,2})]$	0.714	training
24	$[(x_{14} - x_{22} - x_{32} - x_{43}) + (x_{51}) + (x_{63} - x_{73}) + (x_{82} - x_{93} - x_{10\,4})]$	0.271	training
25	$[(x_{12} - x_{22} - x_{32} - x_{43}) + (x_{51}) + (x_{62} - x_{73}) + (x_{82} - x_{92} - x_{10\,2})]$	0.329	training

3.2. Construction of TrEECS Nonlinear Models

In order to evaluate the *LEE* indicator, the TrEECS fuzzy control module has been developed, which consists of a rule base and blocks: Fuzzifier, The Inference Engine, and De-fuzzifier. The fuzzy control module was implemented in the Fuzzy Logic Toolbox environment of the Matlab package.

Based on the fuzzy logic models of Mamdani and Sugeno, two versions of the control unit were developed. The terms of the input parameters are given by trapezoidal membership functions. Model variants differ in the form of presentation of the area of the definition of the resulting parameter, presentation of the inference rules, and defuzzification algorithms. In Mamdani's model, the membership functions of the *LEE* value ranges are used (Table 4). The type and parameters of the membership functions were experimentally selected. The Sugeno model uses an array of *LEE* values in the training sample. The view of the membership functions of the resulting parameter terms in the Mamdani model is shown in Figure 3.

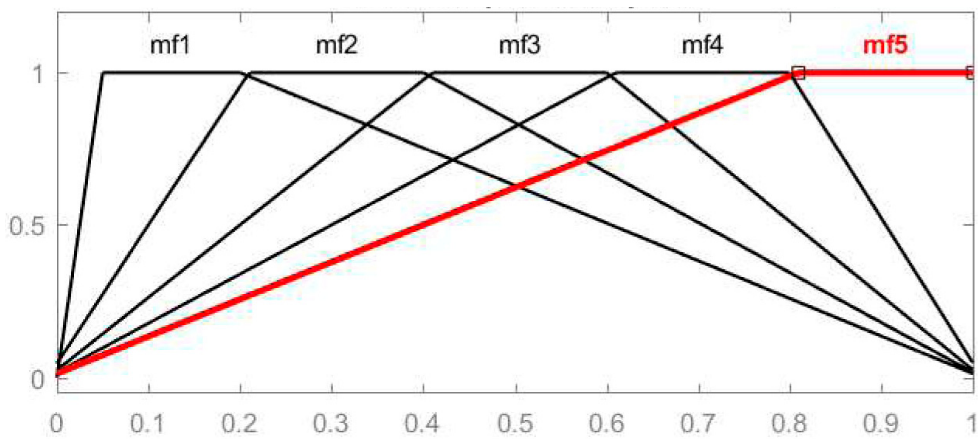


Figure 3. *LEE* membership functions in the Mamdani model.

The membership functions of the terms of the *LEE* parameter correspond to the following ranges of its values:

- Very low (mf1)—from 0 to 0.2;
- Low (mf2)—from 0.21 to 0.4;
- Middle (mf3)—from 0.41 to 0.6;
- High (mf4)—from 0.61 to 0.8;
- Very high (mf5)—from 0.81 to 1.

In order to achieve more accurate simulation results, the experimental data were divided into training and control samples in a ratio of 80:20, respectively. Accordingly, five configurations of the system were included in the control sample.

Based on the results of the morphological analysis, rule bases were built, which contain 20 derivation rules according to the size of the training sample. Since there are no repetitions in the rule bases, the weight of each rule is equal to 1. To determine the best model, the following defuzzification algorithms were implemented: bisector, centroid, the smallest of maximums, the mean of maximums, the weighted average, and the weighted sum. Evaluation of the simulation results was carried out for the values of the output parameter to which the inverse transformation of (11) was applied. The outputs of the system (*LEE*) in the control sample, the model values of the energy efficiency level (LEE_{model}) obtained by different algorithms, and their accuracy estimates are shown in Table 5.

The higher the level of overlap between the theoretically and practically obtained energy efficiency estimates, the higher the validity of the methodology. The level of agreement between the specified estimates can be analyzed by the value of the relative root-mean-square error of modeling (the last line in Table 5). According to Table 5, the relative root mean square error of model values of energy efficiency in the Sugeno system is achieved by the defuzzification method "the weighted average" and is 0.019 (1.9%).

The simulation results prove that the Mamdani model with the defuzzification algorithm "the smallest of maximums" is more adapted to the real operating conditions of the investigated transport systems. The relative standard deviation is 0.012 (1.2%). At the same time, the standard deviation of the model values from the experimental values is equal to 0.005. The specified model should be used to predict the level of vehicle energy efficiency.

Table 5. Simulation results using different defuzzification algorithms.

Configuration Number	Control Output Value *LEE*	Defuzzification Methods					
		Mamdani Type Model				Sugeno-Model	
		Bisector	Centroid	The Smallest of Maximums	The Mean of Maximums	The Weighted Average	The Weighted Sum
		Model Output Value LEE_{model}					
4	0.568	0.668	0.665	0.623	0.691	0.691	0.727
5	0.690	0.659	0.658	0.584	0.692	0.688	0.706
10	0.599	0.635	0.640	0.509	0.586	0.650	0.682
20	0.610	0.656	0.654	0.623	0.691	0.643	0.768
21	0.543	0.650	0.651	0.506	0.641	0.650	0.604
Average value	0.60197	0.6536	0.65354	0.569	0.6599	0.66446	0.69722
		Standard deviation σ					
4		0.009964	0.009374	0.003005	0.014962	0.015183	0.02535
5		0.000940	0.001034	0.011163	0.000005	0.000005	0.000251
10		0.001310	0.001705	0.008064	0.000177	0.002591	0.006839
20		0.002138	0.001975	0.000175	0.006520	0.001132	0.024915
21		0.011347	0.011539	0.001405	0.009510	0.011411	0.003675
Average value		0.00514	0.005126	0.004763	0.006235	0.006064	0.012206
		Relative standard deviation *Sr*					
4		0.03086	0.02904	0.00931	0.04635	0.04703	0.07853
5		0.00198	0.00217	0.02347	0.00001	0.00001	0.00053
10		0.00365	0.00476	0.02249	0.00049	0.00722	0.01907
20		0.00575	0.00531	0.00047	0.01754	0.00304	0.06701
21		0.03842	0.03907	0.00476	0.03220	0.03863	0.01244
Average value		0.016132	0.016069	0.012099	0.019317	0.019188	0.035516

3.3. The Influence of TrEECS Parameters on the Vehicle Energy Efficiency

In order to study vehicle dynamics of changes in energy efficiency, it is advisable to use the mode of visualization of logical inference.

Analysis of the joint influence of the input parameters of the system on the indicator *LEE* was performed using a graphical method. At the same time, it is convenient to use the Sugeno model, which also showed a high accuracy of the model values of the energy efficiency level. According to the results of the previous study, it can be stated that the most significant factor in evaluating vehicle energy efficiency is the parameter x_4 − the degree of use of load/passenger capacity. Therefore, it is advisable to study the dynamics of the influence of combinations of the specified parameters and parameters of various functional elements of the system on the level of vehicle energy efficiency. Figure 4 shows the influence of the degree of use of load capacity of cars and the complexity of the traffic flow on the indicator *LEE*.

The dependence of $LEE(x_4,x_5)$ is non-linear. Figure 5 shows the projection of LEE(x_4,x_5) onto the $x_4 \times x_5$ plane for buses (a) and trucks (b). The arrows in Figure 5 (gradient) point to the point (x_4^*, x_5^*) where the maximum value of LEE energy efficiency is reached. The maximum value of LEE(x_4,x_5) is reached within the average level of its arguments (see Table 2): $x_4 \in [0.41,\ 0.5]$ and $x_5 \in [0.2,\ 0.4]$ regardless of the vehicle category (Figure 5).

When the vehicle category changes from a smaller value to a larger value (see Table 2), the gradient of the $LEE(x_4,x_5)$ decreases, and the area of *LEE* values close to the maximum narrows (Figure 4). Therefore, changing these system parameters has a greater effect on the energy efficiency of a bus than of a truck.

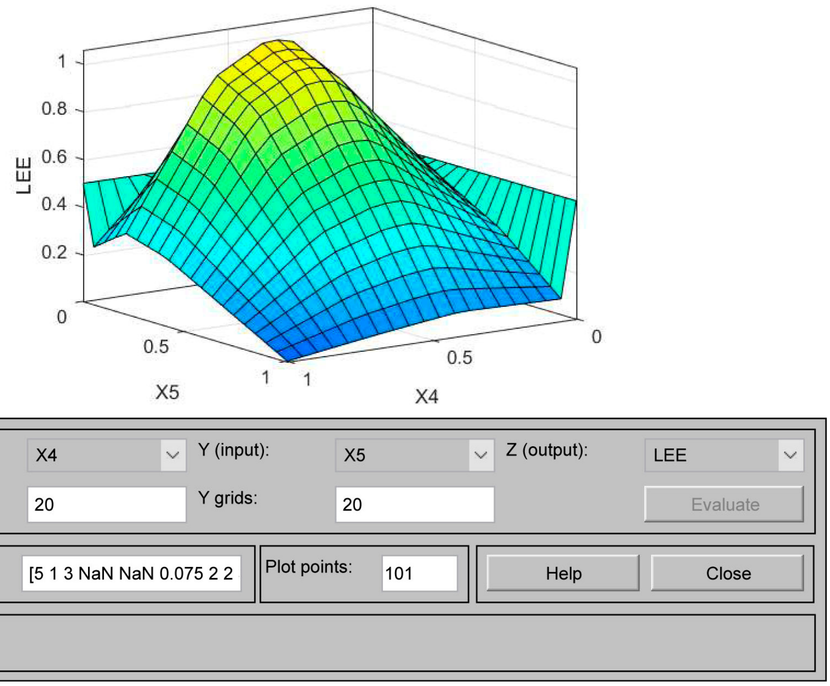
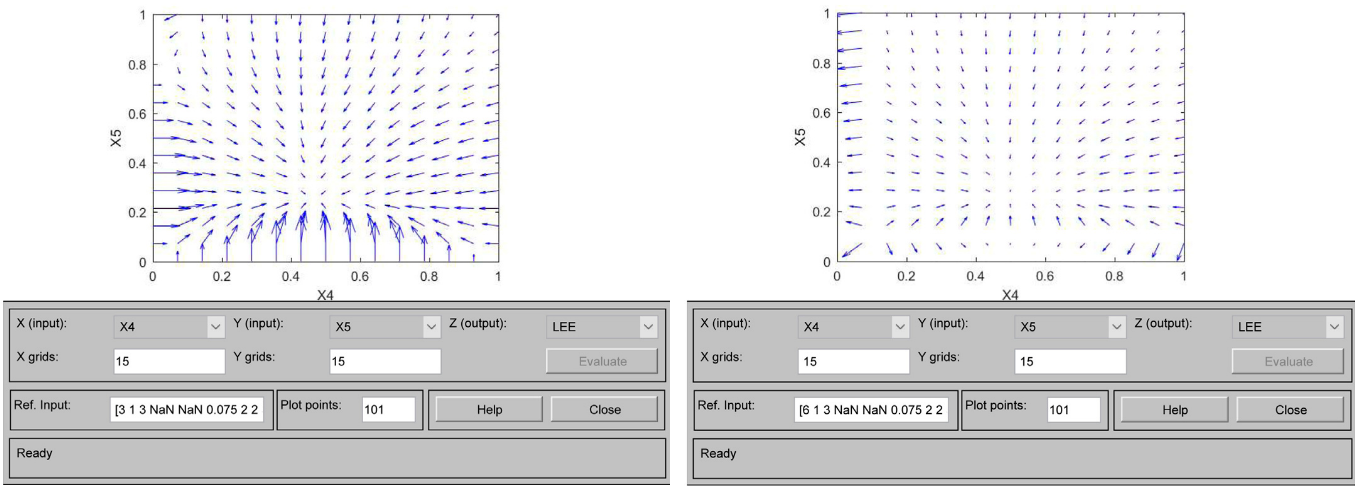


Figure 4. Dependence of $LEE(x_4,x_5)$ on the degree of use of load capacity (x_4) and traffic flow complexity level (x_5).



(**a**) (**b**)

Figure 5. Optimal values of the $LEE(x_4,x_5)$: (**a**) bus, (**b**) truck.

The described trends regarding the dependence gradient $LEE(x_4,x_j)$, $1 \leq j \leq 9$, are preserved for other combinations of x_4 with the parameters of the functional elements of the transport system. Thus, the decrease in the $LEE(x_4,x_9)$ gradient reflects a decrease in the level of energy efficiency when the parameter $x_1 = 5$ (category N2) is changed to the value $x_1 = 6$ (category N3), provided that other parameters are the same (Figures 6 and 7).

As can be seen in Figures 6 and 7, the optimal value is $LEE_{N2}^* > LEE_{N3}^*$. The highest values of the vehicle energy efficiency level are observed in hours of constant intensity ($x_9 = 3$) and in hours of decreasing traffic intensity ($x_9 = 4$).

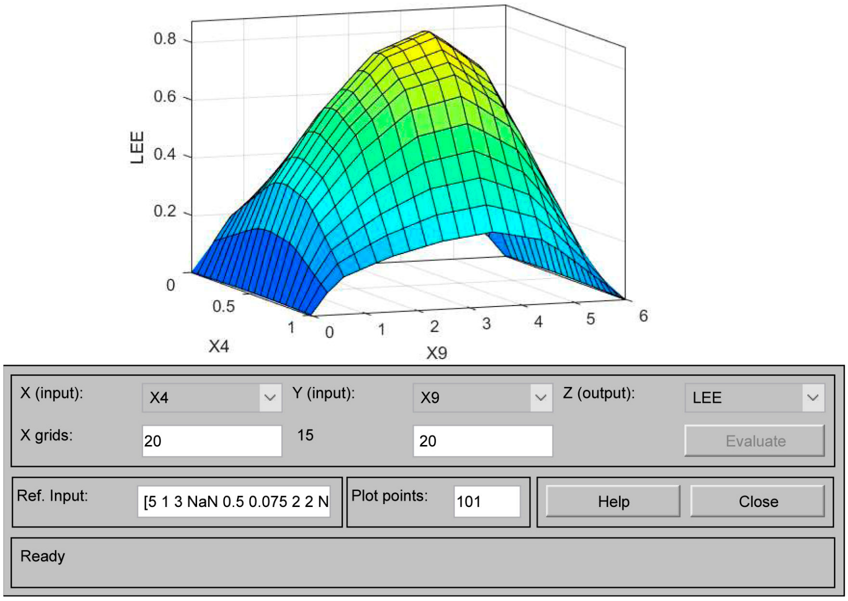


Figure 6. Dependence of $LEE(x_4,x_9)$ on the degree of use of load capacity (x_4) and time interval (x_9) for vehicle of category N2.

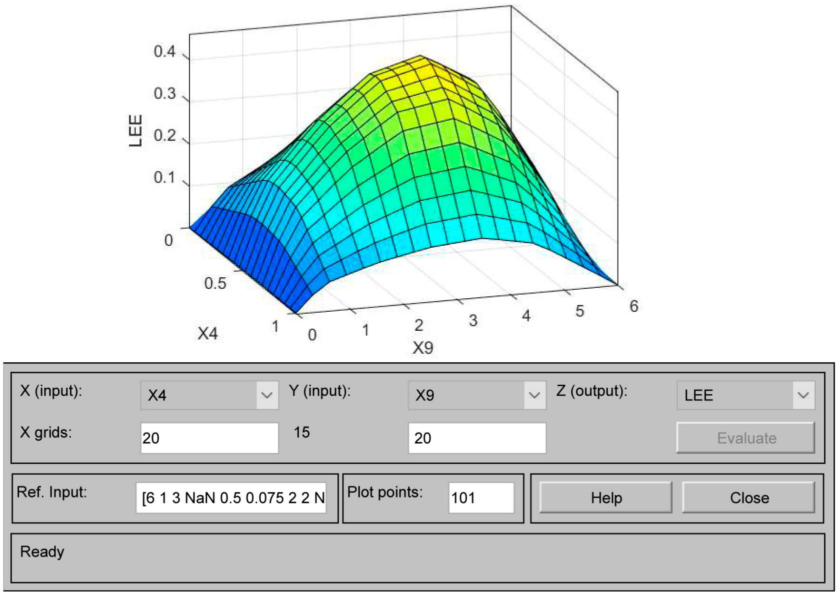


Figure 7. Dependence of $LEE(x_4,x_9)$ on the degree of use of load capacity (x_4) and time interval (x_9) for vehicle of category N3.

4. Discussion

Intelligent management of the urban transport system according to the selected criterion requires evaluation and formalization of the characteristics of the influence of the system on the components of the performance indicator. Estimating the energy efficiency of the vehicle is a basic subtask that is solved within the scope of implementing a significant number of methods to improve its environmental friendliness and productivity. In contrast to existing methods, determining the vehicle efficiency in the proposed way does not require a direct assessment of the energy consumption of the vehicle under study, but it can give a large error in the result. For the application of this method, additional studies are needed in the direction of clarification and completeness of the vector of correction coefficients, taking into account the peculiarities of the operation of the vehicle in different regions.

The results of the morphological analysis of the TrEECS system form the basis for the procedures for building a base of logical rules as part of the transport system control module. The construction and implementation of logical inference models partially smooth out the negative impact of the vague nature of the experimental data. The terms of the domains of each parameter are given by trapezoidal membership functions, the form of which is selected experimentally according to the criterion of the smallest modeling error. The developed system of Mamdani determines the value of the energy efficiency of the vehicle with an error of 1.2%, and the system of Sugeno—with an error of 1.9%—indicates the adequacy of the built models. The largest error is obtained for TrEECS configurations with a low level of energy efficiency. In the future, it is planned to adjust the obtained membership functions to ensure the accuracy of the model results within the given configurations.

On the developed models, it became possible to investigate the influence of transport system parameters on vehicle energy efficiency. It was determined that the parameter x_4—the degree of use of load/passenger capacity—has the greatest weight in the evaluation of the indicator *LEE*. The results of the analysis of the level of dependence of the energy efficiency on the combination of this parameter and the level of complexity of the traffic flow showed that the weight of their total impact on *LEE* depends on the category of vehicle. The energy efficiency of buses is more affected by the combination (x_4,x_5) than that of trucks.

The initial sample was represented by a small number of new hybrid and electric cars and did not reflect their properties under the studied conditions. In the future, it is planned to expand the obtained base of rules of logical derivation, having previously checked that the new configurations do not affect the structure of the system base.

The aging of the vehicle park imposes certain limitations on the duration of the life cycle of the TrEECS model and requires periodic updating of the existing rule base by adjusting the vehicle age in the statistical sample and the values of the transition of the corresponding parameters to the next fuzzy term. The formalized stages of morphological analysis can be repeated to maintain an up-to-date base of derivatives. An up-to-date database will provide an assessment and forecast of the energy efficiency of vehicles in changing system conditions.

5. Conclusions

To evaluate the energy efficiency of vehicles of the TrEECS transport system, a morphological model of this system was built. The structure of the model contains four functional elements, 10 independent attributes of functional elements, and domains of their possible values. For the first time, a formalized mechanism of transition from the morphological model of the system to the corresponding fuzzy model of derivation is proposed. This will make it possible to periodically update the base of the intelligent transport system to maintain its relevance, taking into account new elements and factors.

The criterion of energy efficiency of vehicles based on dimensionless coefficients is determined. The proposed energy efficiency indicator characterizes the increase in energy consumption of vehicles relative to energy consumption under standard operating conditions. Unlike existing methods, this indicator is universal for vehicles of various categories and types, and its definition does not require a direct assessment of energy consumption.

On the basis of experimental data on the state of the TrEECS system, a synthesis of 25 system configurations was carried out on the example of nine settlements in Ukraine and Poland. Observation of the state of the relevant transport systems was carried out with the involvement of 16 units of equipment in different time and weather conditions. Mamdani and Sugeno, fuzzy derivation systems, were built for comprehensive evaluation of the energy efficiency of vehicles under given conditions. These systems are based on fuzzy models that take into account ten attributes of the vehicle, traffic flow, road, and traffic environment. At the same time, six defuzzification algorithms were used. The accuracy of the obtained models confirms their adequacy. The Mamdani system was the most adapted to real conditions, with an energy efficiency estimation error of 1.2%. It is advisable to use this system in the control module of intelligent transport systems.

The impact of the TrEECS system parameters on the energy efficiency of the vehicle for the configurations of the control sample was evaluated. The degree of utilization of cargo/passenger capacity has the greatest influence. It was established that the total effect of combinations of this parameter with others depends on the vehicle category.

Further, it is planned to refine the correction coefficients for determining the energy efficiency indicator and expand the base of the transport system control module due to the study of new TrEECS configurations for electric vehicles. Further research also will be aimed at determining rational configurations of the TrEECS system based on multi-criteria optimization. The outputs of the corresponding model will be components of the complex efficiency criterion. The results of the study should be used in the design of effective mechanisms to manage the transport infrastructure of cities and road traffic in intelligent transport systems.

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