http://doi.org/10.35784/iapgos.8276 *received: 21.08.2025 | revised: 03.12.2025 | accepted: 11.12.2025 | available online: 20.12.2025*

INTELLIGENT MODEL FOR RELIABILITY CONTROL AND SAFETY IN URBAN TRANSPORT SYSTEMS

Anastasiia Kashkanova[1], Alexander Rotshtein[2,3], Andrii Kashkanov[1], Denis Katelnikov[1]
[1]Vinnytsia Technical National University, Vinnytsia, Ukraine, [2]Jerusalem College of Technology, Jerusalem, Israel, [3]Vasyl Stus Donetsk National University, Vinnytsia, Ukraine

Abstract. *This paper proposes an intelligent model for controlling the reliability and safety of urban transport systems, integrating fuzzy cognitive maps (FCMs) with the Bellman-Zadeh decision-making principle. This approach enables the consideration of complex interactions between evaluation criteria and controllable variables, which are characteristic of modern urban environments. To harmonise the modelling outcomes, a membership function to the ideal solution is introduced, allowing for the aggregation of the criteria vector through the intersection of corresponding fuzzy sets. A generalised algorithm is developed for forecasting reliability and safety parameters under the influence of multiple factors, facilitating multi-criteria selection of alternatives in dynamic and uncertain conditions. Special attention is given to the model's applicability in road safety audits, where both technical and behavioural risk factors must be considered. The proposed framework supports scenario analysis, enabling the simulation of various event developments, the assessment of their implications for transport safety, and the formulation of adaptive response strategies. The integration of FCMs with the Bellman-Zadeh principle formalises the evaluation of safety scenarios, ranks critical factors, and supports decision-making for the optimisation of transport infrastructure. The approach can be adapted to various types of transport systems and utilised to enhance risk management, environmental safety, and strategic planning in urban contexts.*

Keywords: fuzzy cognitive maps, Bellman-Zadeh principle, reliability control, risk assessment, scenario analysis, urban transport systems

INTELIGENTNY MODEL STEROWANIA NIEZAWODNOŚCIĄ I BEZPIECZEŃSTWEM W SYSTEMACH TRANSPORTU MIEJSKIEGO

Streszczenie. *W artykule zaproponowano inteligentny model sterowania niezawodnością i bezpieczeństwem systemów transportu miejskiego, oparty na integracji rozmytych map poznawczych (RMP) z zasadą podejmowania decyzji Bellmana-Zadeha. Przedstawione podejście umożliwia uwzględnienie złożonych interakcji pomiędzy kryteriami oceny a zmiennymi sterowalnymi, które są typowe dla współczesnych środowisk miejskich. W celu ujednolicenia wyników modelowania wprowadzono funkcję przynależności do rozwiązania idealnego, co pozwala na agregację wektora kryteriów poprzez przecięcie odpowiadających mu zbiorów rozmytych. Opracowano uogólniony algorytm prognozowania parametrów niezawodności i bezpieczeństwa pod wpływem wielu czynników, wspierający wielokryterialny wybór alternatyw w warunkach dynamicznych i niepewnych. Szczególną uwagę poświęcono zastosowaniu modelu w audytach bezpieczeństwa ruchu drogowego, gdzie uwzględniane są zarówno czynniki techniczne, jak i behawioralne. Zaproponowane rozwiązanie wspiera analizę scenariuszową, umożliwiając symulację różnych przebiegów zdarzeń, ocenę ich wpływu na bezpieczeństwo transportu oraz opracowanie adaptacyjnych strategii reagowania. Integracja RMP z zasadą Bellmana-Zadeha formalizuje ocenę scenariuszy bezpieczeństwa, umożliwia rangowanie czynników krytycznych oraz wspiera proces decyzyjny w zakresie optymalizacji infrastruktury transportowej. Proponowane podejście może być dostosowane do różnych typów systemów transportowych i wykorzystane w celu usprawnienia zarządzania ryzykiem, bezpieczeństwa środowiskowego oraz planowania strategicznego w kontekście miejskim.*

Słowa kluczowe: rozmyte mapy poznawcze, zasada Bellmana-Zadeha, sterowanie niezawodności, ocena ryzyka, analiza scenariuszowa, systemy transportu miejskiego

Introduction

Modern urban transport systems face increasing complexity and vulnerability due to infrastructural degradation, behavioral unpredictability, and environmental stressors. These risks compromise system reliability and demand adaptive, data-driven approaches to safety and control. Conventional audit methods often lack the capacity to model dynamic interdependencies and uncertainty, limiting their effectiveness in real-time decision-making.

Recent studies indexed in Scopus emphasize the need for hybrid modeling frameworks that integrate expert knowledge, fuzzy logic, and scenario-based analysis. Bibliometric analysis by İnce [8] reveals that over 2000 articles from 617 journals emphasize sustainable mobility, smart infrastructure, and hybrid decision-making frameworks.

Several studies have advanced the use of fuzzy cognitive maps (FCMs) for behavioral modeling and transport control:

- León et al. [14] applied FCMs to simulate travel behavior and policy impact, integrating clustering and optimization techniques for decision support.
- Zhao et al. [25] used FCMs to model intelligent transport construction, identifying key causal dimensions such as policy support and technical infrastructure.
- Rotshtein et al. [19] proposed a fuzzy cognitive approach to ranking reliability factors in man–machine systems, demonstrating its relevance for transport safety modeling.

In parallel, the Bellman-Zadeh principle has been revisited for fuzzy optimization in transport planning:

- Keshavarz et al. [12] formulated a fuzzy transportation model using Bellman-Zadeh's max-min criterion to handle uncertainty in shipping costs and route selection.
- Poonia & Sharma [17] critically reviewed multi-objective fuzzy linear programming, comparing Bellman-Zadeh with other fuzzy decision methods.

Scenario-based risk assessment is also gaining traction:

- Gu et al. [6] evaluated maritime transport resilience under port congestion and labor shortages using fuzzy multi-criteria methods.
- SAE researchers [15] proposed a Bayesian scenario-based framework for quantifying residual risk in autonomous vehicles.

Complementing these modelling approaches, Kashkanov et al. [10] investigated the braking dynamics of M1 category vehicles under accident conditions, revealing nonlinear deceleration patterns and the influence of automated braking systems on manoeuvrability. Additionally, in [11], the authors developed a method for assessing object visibility in automotive lighting, which is critical for nighttime accident reconstruction and driver response modelling. The findings of these investigations underscore the importance of integrating both behavioural and technical parameters into risk models.

This paper builds upon these insights by proposing an integrated methodology combining fuzzy cognitive maps (FCMs), Bellman-Zadeh optimization, and scenario analysis to assess and control reliability in urban transport systems. The approach enables:

- Identification of critical risk factors across technical, behavioral, and environmental domains;
- Modeling of causal interdependencies and system dynamics;
- Multi-criteria evaluation of mitigation strategies under uncertainty.

The proposed framework contributes to intelligent transport planning by enhancing risk visualization, decision support, and adaptive control.

1. Methodological and theoretical justification

Evaluating the reliability and safety of an urban transport system constitutes a critical stage in the development of integrated mobility management strategies. System reliability refers to the ability of its components to operate without failure under specified load conditions, whereas safety implies the minimisation of road traffic accident risks through infrastructural, behavioural, and organisational interventions.

To ensure a comprehensive assessment of reliability and safety, it is essential to consider key performance indicators (Table 1), grouped into thematic categories reflecting the multidimensional nature of urban transport operations.

Table 1. Key performance indicators for urban transport system assessment

Category	Representative indicators
Technical	Equipment reliability, failure frequency, component wear and degradation
Safety-related	Number of traffic accidents, injury rates, conflict-prone locations
Environmental	Emission levels, energy efficiency, noise pollution
Social	Accessibility, user comfort, inclusiveness of the transport environment
Economic	Maintenance costs, route profitability

From an integrated perspective, the urban transport system should be conceptualised as a complex, generalised, and dynamic entity that requires analysis through the lens of systems theory. In systems analysis, generalised dynamic systems – according to the conceptual framework proposed by V. M. Glushkov [5] – are interpreted as sets of interrelated processes and entities that evolve over time. Typical examples of such systems include urban infrastructure, the human body, industrial complexes, international conflicts, and geopolitical conditions.

The application of classical optimisation approaches to the management of such systems encounters a range of complexities arising from inherent uncertainty, which manifests in the following aspects:

- A high number of variables and interdependencies, most of which are described through expert judgement rather than precise measurements;
- The presence of multiple, often conflicting criteria, making it difficult to identify a dominant objective that could serve as a reference for constructing the target function;
- A lack of accurate data regarding constraints on controllable parameters, which complicates the formulation of the problem within the framework of mathematical programming;
- Interdependence between criteria and controllable variables, where parameters influence both the criteria and each other, while the criteria themselves exert reciprocal effects on the variables.

According to [5], the synthesis of managerial decisions for generalised dynamic systems is grounded in the gradual refinement of an initial solution, implemented through either a trial-and-error approach or scenario-based modelling aimed at answering "what-if" questions. In this context, a scenario is understood as a set of parameters (a vector of variables) that determine the system's performance quality, while a set of alternative scenarios for comparative analysis is constructed based on expert evaluation.

In the context of decision-making under uncertainty, the Bellman–Zadeh concept [2] is widely applied. According to this framework, the optimal scenario is determined as follows:

- Each criterion is formalised as a fuzzy set, constructed over the universe of all feasible alternatives.
- The intersection of these fuzzy sets – representing individual criteria – results in a new fuzzy set, which defines the set of potentially acceptable decisions.
- The element with the highest degree of membership within this resulting set is selected as the optimal choice.

The Bellman–Zadeh principle [2] can be integrated with the Analytic Hierarchy Process (AHP) proposed by Saaty [20] to compute membership degrees underlying fuzzy sets of criteria [9]. However, neither of these approaches' accounts for the interdependencies between membership degrees and the mutual influence of controllable variables and evaluative criteria.

This study proposes a methodology for comparing managerial scenarios within an urban transport system, taking into account the interrelations between controllable parameters and evaluative criteria. The approach is grounded in the integration of the Bellman–Zadeh principle with the concept of a FCM [13]. The development and calibration of the FCM are based on the findings of prior studies [19], adapted for modelling complex systems with multiple inputs and outputs.

The implementation of the proposed approach involves addressing a sequential set of tasks, including:

- Constructing a generalised mathematical model that captures the interaction between evaluative criteria and controllable variables.
- Developing an algorithm for identifying the most appropriate scenario from a set of potential decision alternatives.
- Validating the effectiveness of the proposed solutions through a case study focused on managing the reliability and safety of an urban transport system.

According to the concept proposed by Kosko [13], a FCM is a directed graph in which the relationships between elements are represented by weighted arcs that reflect fuzzy linguistic terms [9]. The nodes of this graph, referred to as concepts, represent the variables involved in the model, while the arc weights illustrate the strength of influence exerted by one variable (cause) on another (effect). The term "cognitive" indicates that the modelling process is based on expert assessments expressed in the form of verbal statements such as "increases" or "decreases". The term "fuzzy" implies that the FCM allows for varying degrees of such changes – e.g., weak, moderate, or strong increases or decreases – which are quantified using numerical values within the intervals [0,1] and [−1,0], in accordance with the principles of fuzzy set theory [24].

Let $C = \{C_1, C_2, \dots, C_n\}$ denote the set of concepts – i.e., variables involved in the modelling process. Each element of this set, denoted as $C_i \in C$, is treated as a linguistic variable [9], defined over the universal interval [−1, 1], where −1 corresponds to the minimum feasible value and 1 to the maximum admissible value of the given concept C_i. To provide a quantitative description of C_i, the fuzzy term "perfectness", introduced in [19], is employed and formalised through a membership function

$$\pi_i = \frac{x_i + 1}{2} \quad (1)$$

which illustrates the correspondence between the value of the concept $x_i \in [-1,1]$ and its degree of perfectness $\pi_i \in [0,1]$, as shown in Fig. 1.

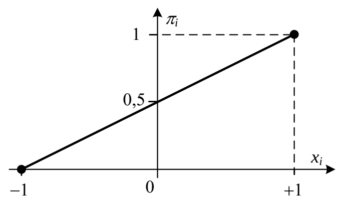

Fig. 1. Membership function of elements with respect to the degree of perfectness

The weight w_{ij}, which characterises the arc between concepts C_i and c_j, reflects both the strength and direction of their mutual influence – i.e., the extent to which a change in one concept affects the other. Assuming that the variables x_i and x_j represent the concepts C_i and c_j, respectively, and that a functional relationship $x_j = f(x_i)$ exists between them, the weight w_{ij} can be defined as the derivative $w_{ij} = \frac{dx_j}{dx_i}$.

The type of influence depends on the sign of this derivative:

- $w_{ij} > 0$: an increase or decrease in x_i leads to a corresponding change in x_j, indicating a positive influence of C_i on c_j.

- $w_{ij} < 0$: an increase or decrease in x_i causes an opposite change in x_j, interpreted as a negative influence.
- $w_{ij} = 0$: the parameter x_j remains unaffected by changes in x_i, implying no influence between the respective concepts.

The magnitude of w_{ij} is assessed through expert evaluation using qualitative linguistic descriptors, arranged along a graduated scale analogous to a thermometric scale (see Table 2).

Table 2. Thermometric scale of linguistic evaluations and corresponding numerical values

Influence category	Linguistic descriptor	Numerical value	
Strong positive	Positive maximum	+1.00	1 — 1
Moderate positive	Positive above average	+0.75	
	Positive average	+0.50	
	Positive below average	+0.25	
Neutral	No influence	0.00	0 — 0
Moderate negative	Negative below average	−0.25	
	Negative average	−0.50	
	Negative above average	−0.75	
Strong negative	Negative maximum	−1.00	−1 — −1

To characterise oscillatory behaviour within the framework of a FCM, an $n \times n$ dimensional matrix is employed, containing values that represent the intensity of mutual influence between concepts C_i. A distinctive feature of this matrix is that its diagonal elements are equal to zero, indicating the absence of self-influence – i.e., a concept does not exert an effect on itself.

$$W_0 = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & 0 \end{bmatrix} \quad (2)$$

The initial configuration of a FCM is defined by the vector

$$X^0 = [x_1^0, x_2^0, \dots, x_n^0] \quad (3)$$

whose components represent the actual values of the concepts at the initial step $k = 0$.

The stationary configuration of a FCM is represented by the state vector

$$X^l = [x_1^l, x_2^l, \dots, x_n^l] \quad (4)$$

at a step l, at which the system reaches a steady-state regime due to the interactions among concepts. This regime is characterised by the condition $\left|x_i^l - x_i^{l-1}\right| < \varepsilon$, where ε is a small positive number and $i = 1,2,\dots,n$.

To describe the evolution of concept values across successive modelling steps $k = 1,2,\dots$, a recurrence equation based on variable increments $x_i^{k+1} = x_i^k + \sum_{j=1}^{n}\left(x_j^k - x_j^{k-1}\right)w_{ji}$ is applied. In matrix form, this equation is expressed as

$$X^{k+1} = X^k \oplus (X^k \ominus X^{k-1})W_0, \quad (5)$$

where the "$\oplus$" and "$\ominus$" operations denote component-wise addition and subtraction of vector quantities, performed according to the specified procedure

$$[a,b] \oplus [c,d] = [a + c, b + d]$$
$$[a,b] \ominus [c,d] = [a - c, b - d]$$

In equation (5), it is assumed that under the condition $k = 0$, the value $X^1 = X^0 \oplus X^0 W_0$.

To formalize the model, the concept set $C = \{C_1, C_2, \dots, C_n\}$ is divided into controllable inputs $U = \{C_1, C_2, \dots, C_q\}$ and goal-oriented criteria $G = \{C_{q+1}, C_{q+2}, \dots, C_n\}$, forming the structure $C = U \cup G$. Their interdependencies are depicted in the generalized FCM framework in Fig. 2.

To evaluate the degree of perfectness of criteria from the set G, which correlate with controllable variables from the set U, the following algorithmic approach should be implemented:

Step 1. Initialise the FCM in accordance with equation (3), using the initial state vector

$$X^0 = \left[x_1^0, x_2^0, \dots, x_q^0, x_{q+1}^0 = x_{q+2}^0 = \dots = x_n^0 = 0\right] \quad (6)$$

Step 2. Using the recursive equation (5), determine the vector defined in equation (4), which represents the values of the concepts in the stabilised (stationary) state of the system

$$X^l = \left[x_1^l, x_2^l, \dots, x_q^l, x_{q+1}^l, x_{q+2}^l, \dots, x_n^l\right] \quad (7)$$

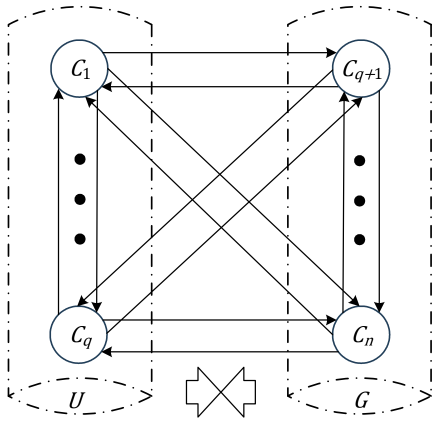

Fig. 2. The universal FCM model that captures the interconnections between controllable variables and evaluation criteria

Step 3. Perform normalisation of the components of the vector defined in equation (7), resulting in the formation of a new vector

$$\hat{X} = [\hat{x}_1, \hat{x}_2, \dots, \hat{x}_q, \hat{x}_{q+1}, \hat{x}_{q+2}, \dots, \hat{x}_n] \quad (8)$$

where $\hat{x}_i = \begin{cases} \frac{x_i^l}{\overline{x}_i}, \text{ if } x_i^l > 0 \\ -\frac{x_i^l}{\underline{x}_i}, \text{ if } x_i^l < 0 \end{cases}$

Here, $\underline{x}_i$ and $\overline{x}_i$ denote the minimum and maximum values, respectively, of the concept C_i at the stage when the stationary state is reached.

Step 4. Construct the criterion vector

$$\hat{X}_G = [\hat{x}_{q+1}, \hat{x}_{q+2}, \dots, \hat{x}_n] \quad (9)$$

with normalised values by extracting the components from vector (8) that correspond to the relevant concepts $G = \{C_{q+1}, C_{q+2}, \dots, C_n\}$.

Step 5. Based on vector (9), construct a value vector that reflects the levels of criterion perfection in the context of the specified parameters of the controlled variables

$$\Pi_G = [\pi_{q+1}, \pi_{q+2}, \dots, \pi_n] \quad (10)$$

where $\pi_j = \frac{\hat{x}_j + 1}{2}$, $j = q+1, q+2, \dots, n$.

Let us assume a set of scenarios $S = \{s_1, s_2, \dots, s_m\}$ to be compared according to a defined set of criteria belonging to a separate set $G = \{C_{q+1}, C_{q+2}, \dots, C_n\}$. Each scenario $s_r \in S$ is associated with a vector of controllable variable values X_U, which belong to the specified set $U = \{C_1, C_2, \dots, C_q\}$, i.e.

$$X_U = \left[x_1^{(r)}, x_2^{(r)}, \dots, x_q^{(r)}\right], r = 1,2,\dots,m \quad (11)$$

Based on vector (11), in conjunction with the algorithmic procedure outlined above, it is possible to construct a corresponding vector of criterion perfection scores (10) for each scenario $s_r \in S$

$$\Pi_G^{(r)} = \left[\pi_{q+1}^{(r)}, \pi_{q+2}^{(r)}, \dots, \pi_n^{(r)}\right], r = 1,2,\dots,m \quad (12)$$

Using the Bellman–Zadeh approach [1], each criterion $C_j \in G = \{C_{q+1}, C_{q+2}, \dots, C_n\}$ is treated as a fuzzy set representing the degree of its perfection. This set is defined over the universal space of scenarios $S = \{s_1, s_2, \dots, s_m\}$ by means of membership values presented in vector (12)

$$C_{q+1} = \left\{\frac{\pi_{q+1}^{(1)}}{s_1}, \frac{\pi_{q+1}^{(2)}}{s_2}, \dots, \frac{\pi_{q+1}^{(m)}}{s_m}\right\}, C_{q+2} = \left\{\frac{\pi_{q+2}^{(1)}}{s_1}, \frac{\pi_{q+2}^{(2)}}{s_2}, \dots, \frac{\pi_{q+2}^{(m)}}{s_m}\right\}, \dots$$

$$C_n = \left\{\frac{\pi_n^{(1)}}{s_1}, \frac{\pi_n^{(2)}}{s_2}, \dots, \frac{\pi_n^{(m)}}{s_m}\right\}$$

where $\pi_j^{(r)}$ denotes the degree of membership of scenario $s_r \in S = \{s_1, s_2, \dots, s_m\}$ to the conceptual category of "perfection," as determined by the corresponding criterion $C_j \in G = \{C_{q+1}, C_{q+2}, \dots, C_n\}$.

Within the Bellman–Zadeh framework [2], the search for the most acceptable scenario s_{opt} is carried out within the intersection domain ($\cap$) of fuzzy sets corresponding to individual criteria (see Fig. 3), i.e. $s_{opt} \in D = C_{q+1} \cap C_{q+2} \cap C_n$.

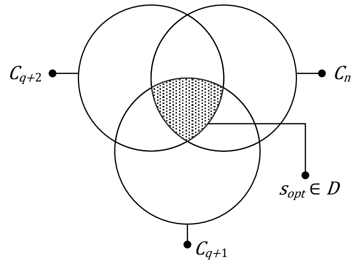

Fig. 3. The set of decisions that may be considered acceptable according to the specified criteria

Within the framework of fuzzy set theory [24], a transformation of the basic operations ($\cap \to \min$) occurs, resulting in a derived decision set

$$D = \left\{ \begin{array}{c} \frac{\min\left(\pi_{q+1}^{(1)},\dots,\pi_n^{(1)}\right)}{s_1}, \frac{\min\left(\pi_{q+1}^{(2)},\dots,\pi_n^{(2)}\right)}{s_2}, \dots, \\ \frac{\min\left(\pi_{q+1}^{(m)},\dots,\pi_n^{(m)}\right)}{s_m} \end{array} \right\}$$

The most acceptable alternative is considered to be the scenario $s_{opt} \in D$, which possesses the highest level of perfection

$$\pi(s_{opt}) = \max \left\{ \begin{array}{l} \min\left(\pi_{q+1}^{(1)}, \dots, \pi_n^{(1)}\right) \\ \dots, \\ \min\left(\pi_{q+1}^{(m)}, \dots, \pi_n^{(m)}\right) \end{array} \right.$$

2. Model configuration and calibration

The urban transport system represents a non-linear, multi-agent environment, where infrastructure, behaviour, and regulation co-evolve over time. The reliability and safety of an urban transport system are determined by its ability to operate consistently within a dynamic urban environment, ensuring efficient, timely, and accident-free mobility.

In the context of road safety auditing, particular attention is given to the system's capacity to respond to risks, anticipate conflict situations, and adapt to changes in user behaviour or the technical condition of infrastructure. This necessitates the application of methodologically coherent approaches to analysis, among which one of the most effective tools is the fuzzy cognitive map – a conceptual model that enables the consideration of multifactorial interdependencies among system elements, incorporating uncertainty and expert judgement.

According to [5], the model of any complex system should reflect its structure (elements, objects), behaviour (interactions, processes), management objectives, and resources. These components form the basis for the classification of concepts within a FCM. Such classification ensures a systemic coverage of technical, behavioural [1], institutional, and infrastructural aspects that influence safety and reliability.

The set of possible concepts within each class is flexible – it can be extended or modified depending on the city's specific context, audit objectives, or identified risks. However, the set of concept classes remains fixed, as it reflects the fundamental characteristics of the system.

Table 3 presents potential FCM concepts in the context of the driver–vehicle–road–environment (DVRE) system, used for analysing the reliability and safety of urban transport systems.

The list of potential concepts within the FCM of the DVRE system, presented in Table 3, should be extended by incorporating three additional types of potential concepts – process-oriented, goal-oriented, and resource-oriented – as shown in Table 4. This extension aligns with the conceptual framework for describing complex dynamic systems [5, 22].

These additional concept types are critically important for the comprehensive modelling of reliability and safety in urban transport systems (UTS) [21]. Their inclusion enables a more holistic representation of system behaviour, facilitating scenario analysis, adaptive control, and strategic decision-making under uncertainty.

Table 3. Classification of potential FCM concepts in the DVRE system

Object	Concept	Function description in the safety system
Driver	Driving experience	Influences the likelihood of operational errors
	Behavioural patterns	Represents response models to road events and stress
	Psychophysiological condition	Determines the ability to react promptly
	Knowledge of traffic regulations	Defines the alignment of driver actions with legal norms
	Adaptability	Reflects the ability to navigate changing environments
	Communicative interaction	Indicator of social cohesion in traffic
Vehicle	Technical condition	Determines the risk posed by mechanical failures
	Vehicle type	Affects interaction with infrastructure
	Availability of safety systems	Reduces accident risk in critical situations
	Environmental characteristics	Related to the vehicle's impact on the surrounding environment
	Manoeuvrability	Determines the effectiveness of conflict avoidance
	Vehicle age	Indicator of technical obsolescence and associated risks
Road	Pavement condition	Influences movement stability and hazard levels
	Road geometry	Determines risks associated with limited visibility
	Safety infrastructure	Shapes protection mechanisms for road users
	Conflict zones	Localises areas with elevated risk levels
	Accessibility for reduced mobility	Indicator of road environment inclusiveness
	Lighting	Affects visibility during nighttime conditions
Environment	Weather conditions	External factor influencing transport behaviour
	Traffic dynamics	Determines flow density and load levels
	Driving culture	Linked to social norms and ethical behaviour
	Accident statistics	Enables identification of critical trends
	Environmental constraints	Define permissible operating modes for vehicles
	Institutional support	Shapes the conditions for implementing management decisions

Table 4. Concept typology for FCM urban transport safety model

Concept type	Concept name	Functional description
Goal-Oriented	Road traffic safety level	Core objective reflecting the system's safety performance
	Transport accessibility	Indicator of inclusivity and population coverage
	Route network efficiency	Reflects planning quality and ease of urban mobility
	Environmental sustainability	Target for minimizing ecological impact
	Passenger delivery timeliness	Measures intra-urban travel time and punctuality
Process-Oriented	Route planning	Defines the logic of network configuration
	Vehicle technical inspections	Ensures operational reliability of transport units
	Risk scenario development	Anticipates critical situations and system vulnerabilities
	Conflict zone analysis	Identifies spatial threats and high-risk areas
	Road safety audit implementation	Provides systematic evaluation and validation of safety measures
	System response to complaints/incidents	Indicates adaptability and responsiveness to disruptions
Resource-Oriented	Financial provision	Enables implementation of safety-enhancing interventions
	Human resources	Availability of specialists for engineering and operational tasks
	IT infrastructure (GIS, IoT)	Digital tools for monitoring, modelling, and decision support
	Vehicle fleet	Physical assets for transport service delivery
	Accident data	Empirical base for modelling and risk assessment
	Regulatory and legal support	Legal framework enabling policy enforcement and system upgrades

By integrating the key concepts from Tables 3 and 4 and evaluating the influence of one concept on another – on a scale from 0 (no influence) to 5 (critical influence) – a relationship matrix is obtained, as presented in Table 5.

Table 5. Interrelationship matrix of causal and target concepts in UTS evaluation

Target concept / causal concept	Road traffic safety	Environmental sustainability	Transport accessibility	Delivery timeliness	Economic efficiency of UTS
Technical condition of vehicles	5	3	2	4	2
Condition of road surface	5	2	3	4	3
Weather conditions	4	2	2	3	2
Driver behavioural patterns	5	1	2	4	2
Vehicle inspection process	4	2	1	3	1
Funding (resource availability)	3	4	5	3	4
IT Infrastructure	3	2	4	3	5
Route planning process	2	1	3	3	5
Conflict zone analysis process	5	1	2	2	2
Institutional support (environment)	4	3	4	3	3

All values presented in Table 5 represent expert assessments, which may be refined using the Delphi method [7] or regression analysis techniques [16]. The matrix illustrates the interrelationships between controllable parameters and target functions within the urban transport system. Based on the data from Tables 3–5, the resulting FCM is visualised in Fig. 4.

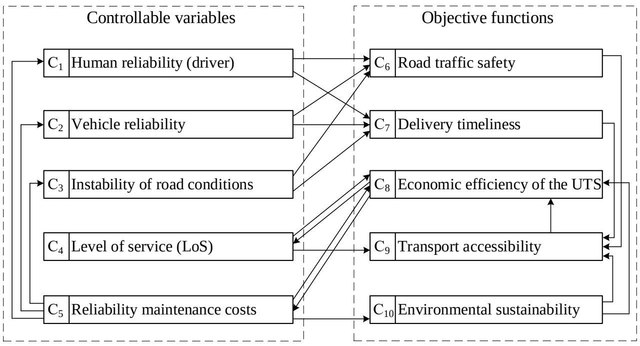

Fig. 4. FCM for reliability and safety management in UTS

The intensity of influence between individual concepts is formalised in the form of an evaluation matrix (Table 6). The values in this matrix are derived from expert judgements, subsequently refined through the application of the least squares method [3] to a training dataset composed of expert-derived inputs.

The training dataset was constructed by experts in the form of seven observation pairs of the type "input parameters $(x_1, x_2, \dots, x_5)$ – output parameters $(x_6, x_7, \dots, x_{10})$", as presented in Table 7. To generate Table 7, the experts applied linguistic assessments, which were subsequently transformed into numerical values using a thermometric scale (see Table 2).

The optimisation task required for calibrating the arc weights of the FCM graph is formulated as follows: to identify the elements of the matrix W_0 that minimise the expression

$$S(W_0) = \sum_{p=1}^{7} \sum_{i=6}^{10} \left(x_{i,p} - \hat{x}_{i,p}\right)^2 \to min \quad (13)$$

subject to the condition $w_{ij} \in [\underline{w}_{ij}, \overline{w}_{ij}]$, where: $\underline{w}_{ij}, (\overline{w}_{ij})$ are the arc weights subject to optimisation, constrained by their permissible lower and upper bounds, $w_{ij} \in W_0$; $x_{i,p}$ denotes the observed value of the i-th criterion (where $i = 6, 7, \dots, 10$) in the p-th observation (where $p = 6, 7, \dots, 10$), as presented in Table 7; $\hat{x}_{i,p}$ represents the predicted value of the i-th criterion (where $i = 6, 7, \dots, 10$) in the p-th observation (where $p = 6, 7, \dots, 10$), generated by the algorithm described in Section 1.

Table 6. FCM arc weights before and after calibration

$w_{i,j}$	Before calibration	Acceptable intervals		After calibration
		$\underline{w}_{i,j}$	$\overline{w}_{i,j}$	
$w_{1,6}$	0.5	0.2	0.8	0.7806
$w_{1,7}$	0.8	0.5	0.95	0.587
$w_{2,6}$	0.5	0.2	0.8	0.3076
$w_{2,7}$	0.6	0.3	0.9	0.5034
$w_{3,6}$	-0.7	-0.95	-0.4	-0.9175
$w_{3,7}$	-0.5	-0.8	-0.2	-0.4691
$w_{4,8}$	0.4	0.1	0.7	0.1723
$w_{4,9}$	0.4	0.1	0.7	0.2398
$w_{5,1}$	0.4	0.1	0.7	0.1845
$w_{5,2}$	0.6	0.3	0.9	0.4082
$w_{5,3}$	-0.5	-0.8	-0.2	-0.2369
$w_{5,8}$	-0.3	-0.6	-0.05	-0.4672
$w_{5,10}$	0.3	0.05	0.6	0.4617
$w_{6,9}$	0.8	0.5	0.95	0.8527
$w_{7,9}$	0.8	0.5	0.95	0.9481
$w_{8,4}$	0.2	0.05	0.5	0.4704
$w_{8,5}$	0.5	0.2	0.8	0.7707
$w_{9,8}$	0.6	0.3	0.9	0.8873
$w_{10,8}$	-0.3	-0.6	-0.05	-0.4898
$w_{10,9}$	0.2	0.05	0.5	0.4407

Table 7. Training dataset

No	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
1	-0.4	-0.6	0.4	-0.8	-0.6	-0.6	-0.6	-0.4	-0.8	-0.6
2	-0.2	-0.4	0.2	-0.6	-0.2	-0.3	-0.2	-0.1	-0.4	-0.4
3	0	-0.2	0	-0.4	0.1	-0.1	0	0.2	-0.1	-0.2
4	0.2	0.2	-0.2	-0.2	0.4	0.2	0.2	0.4	0.2	0.2
5	0.4	0.4	-0.4	0.2	0.6	0.4	0.4	0.6	0.4	0.4
6	0.6	0.6	-0.6	0.4	0.7	0.6	0.6	0.8	0.6	0.6
7	0.7	0.8	-0.8	0.6	0.8	0.8	0.8	0.9	0.7	0.8

Based on the data in Table 6, a matrix is constructed to represent the strength of influence between individual concepts

$$W_0 = \begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \\ C_7 \\ C_8 \\ C_9 \\ C_{10} \end{array} \begin{array}{|c|c|c|c|c|c|c|c|c|c|} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} \\ \hline 0 & 0 & 0 & 0 & 0 & 0.78 & 0.59 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.31 & 0.50 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -0.92 & -0.47 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.17 & 0.24 & 0 \\ 0.18 & 0.41 & -0.24 & 0 & 0 & 0 & 0 & -0.47 & 0 & 0.46 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.85 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.95 & 0 \\ 0 & 0 & 0 & 0.47 & 0.77 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.89 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.49 & 0.44 & 0 \\ \hline \end{array} \quad (14)$$

The use of matrix (14) enables the observation of stepwise dynamics in concept values. The example illustrated in Fig. 5 demonstrates that the FCM reaches a stationary state at iteration $l = 43$. The predicted criterion values prior to calibration (expression 7) and after calibration (expression 8) are presented in Tables 8 and 9, respectively. The values of controllable variables at which the maximum and minimum criterion values are achieved – required for normalisation – are provided in Table 10.

The proximity between the modelled results and expert assessments is characterised by the mean absolute deviation (MAD) and the mean squared error (MSE), which amount to

$$MSE = \frac{1}{7} \sum_{p=1}^{7} \sum_{i=6}^{10} \left(x_{i,p} - \hat{x}_{i,p}\right)^2 = \begin{cases} 0.239 \text{ before tuning} \\ 0.004 \text{ after tuning} \end{cases}$$

$$MAD = \frac{1}{7} \sum_{p=1}^{7} \sum_{i=6}^{10} \left|x_{i,p} - \hat{x}_{i,p}\right| = \begin{cases} 0.896 \text{ before tuning} \\ 0.115 \text{ after tuning} \end{cases}$$

The optimisation problem (13) was solved using a genetic algorithm [4]. The step-by-step dynamics of criterion $S(W_0)$ minimisation are illustrated in Figure 6.

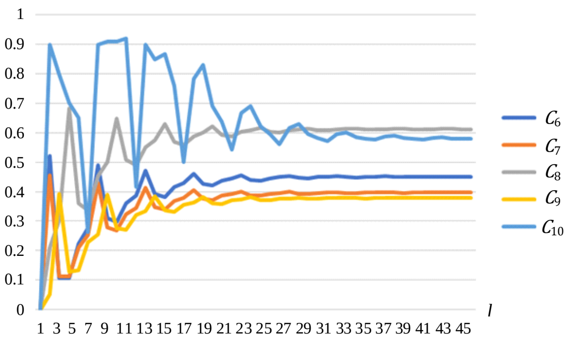

Fig. 5. Stepwise change of target concepts for the input vector $X^0 = [0.2, 0.8, -0.2, 0.4, -0.6, 0, 0, 0, 0, 0]$

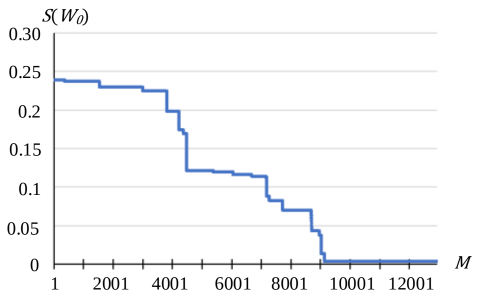

Fig. 6. Optimisation dynamics of the criterion $S(W_0)$ during the arc weight calibration process in the UTS graph

Table 8. Criterion values computed prior to model calibration

No	x_6^l	x_7^l	x_8^l	x_9^l	x_{10}^l
1	0.252	0.285	0.356	0.309	0.369
2	0.559	0.549	0.556	0.556	0.570
3	0.720	0.710	0.694	0.709	0.726
4	0.123	0.130	0.215	0.139	-0.031
5	0.111	0.126	0.167	0.158	0.328
6	0.117	0.129	0.151	0.151	0.287
7	0.307	0.312	0.288	0.304	0.322

Table 9. Criterion values computed after model calibration

No	$\hat{x}_6$	$\hat{x}_7$	$\hat{x}_8$	$\hat{x}_9$	$\hat{x}_{10}$
1	0.209	-0.028	0.236	0.239	0.239
2	0.642	0.631	0.81	0.608	0.677
3	0.674	0.793	0.871	0.81	0.893
4	0.451	0.397	0.612	0.379	0.579
5	0.045	-0.183	0.19	0.008	0.167
6	-0.207	0.039	0.283	-0.202	0.025
7	0.464	0.23	0.437	0.243	0.395

Table 10. Input variable values corresponding to min ($\underline{x}$) and max ($\overline{x}$) of output variables for matrix (14)

x_1	x_2	x_3	x_4	x_5	Extremal values (minimum and maximum)
-1	-1	1	-1	-1	$\underline{x}_6$ =-4.511
1	1	-1	1	1	$\overline{x}_6$ =4.511
-1	-1	1	-1	-1	$\underline{x}_7$ =-4.975
1	1	-1	1	1	$\overline{x}_7$ =4.975
-1	-1	1	-1	-1	$\underline{x}_8$ =-4.613
1	1	-1	1	1	$\overline{x}_8$ =4.613
-1	-1	1	-1	-1	$\underline{x}_9$ =-8.556
1	1	-1	1	1	$\overline{x}_9$ =8.556
-1	-1	1	-1	-1	$\underline{x}_{10}$ =-0.992
1	1	-1	1	1	$\overline{x}_{10}$ =0.992

3. Scenario analysis: results and discussion

Seven alternative scenarios were analysed within the scope of this study. The parameters of the controllable and target variables for each scenario are presented in Tables 11 and 12, respectively. For each scenario, the corresponding levels of criterion perfection were determined using the algorithm described in Section 1, and are structured in Table 13.

Table 11. Values of controllable variables across different scenarios

Scenario	x_1	x_2	x_3	x_4	x_5
s_1	0.8	-0.6	0	1.0	0.4
s_2	0.4	0.6	-0.6	0.6	0.6
s_3	0.6	0.7	-0.8	0.6	0.8
s_4	0.2	0.8	-0.2	0.4	-0.6
s_5	-0.4	0.4	0.6	0.8	0.7
s_6	-0.2	0.2	0.4	0.6	0.6
s_7	0.6	-0.2	-0.4	0.2	0.4

Table 12. Values of target variables across different scenarios

Scenario	x_6	x_7	x_8	x_9	x_{10}
s_1	0.209	-0.028	0.236	0.239	0.239
s_2	0.642	0.631	0.810	0.608	0.677
s_3	0.674	0.793	0.871	0.810	0.893
s_4	0.451	0.397	0.612	0.379	0.579
s_5	0.045	-0.183	0.190	0.008	0.167
s_6	-0.207	0.039	0.283	-0.202	0.025
s_7	0.464	0.230	0.437	0.243	0.395

Table 13. Levels of criterion perfection across different scenarios

Scenario	π_6	π_7	π_8	π_9	π_{10}
s_1	0.605	0.486	0.618	0.620	0.620
s_2	0.821	0.816	0.905	0.804	0.839
s_3	0.837	0.897	0.936	0.905	0.947
s_4	0.726	0.699	0.806	0.690	0.790
s_5	0.523	0.398	0.595	0.504	0.584
s_6	0.397	0.520	0.642	0.399	0.513
s_7	0.732	0.615	0.719	0.622	0.698

Within the universal set of scenarios, the criteria are interpreted as fuzzy sets represented in the following form:

$$C_6 = \left\{\frac{0.605}{s_1}, \frac{0.821}{s_2}, \frac{0.837}{s_3}, \frac{0.726}{s_4}, \frac{0.523}{s_5}, \frac{0.397}{s_6}, \frac{0.732}{s_7}\right\}$$
$$C_7 = \left\{\frac{0.486}{s_1}, \frac{0.816}{s_2}, \frac{0.897}{s_3}, \frac{0.699}{s_4}, \frac{0.398}{s_5}, \frac{0.520}{s_6}, \frac{0.615}{s_7}\right\}$$
$$C_8 = \left\{\frac{0.618}{s_1}, \frac{0.905}{s_2}, \frac{0.936}{s_3}, \frac{0.806}{s_4}, \frac{0.595}{s_5}, \frac{0.642}{s_6}, \frac{0.719}{s_7}\right\}$$
$$C_9 = \left\{\frac{0.620}{s_1}, \frac{0.804}{s_2}, \frac{0.905}{s_3}, \frac{0.690}{s_4}, \frac{0.504}{s_5}, \frac{0.399}{s_6}, \frac{0.622}{s_7}\right\}$$
$$C_{10} = \left\{\frac{0.620}{s_1}, \frac{0.839}{s_2}, \frac{0.947}{s_3}, \frac{0.790}{s_4}, \frac{0.584}{s_5}, \frac{0.513}{s_6}, \frac{0.698}{s_7}\right\}$$

The intersection of the given fuzzy sets results in the formation of a fuzzy set of alternative decisions

$$D = \left\{\frac{0.486}{s_1}, \frac{0.804}{s_2}, \frac{0.837}{s_3}, \frac{0.690}{s_4}, \frac{0.398}{s_5}, \frac{0.397}{s_6}, \frac{0.615}{s_7}\right\} \quad (15)$$

In the process of selecting the optimal scenario for solving transport safety problems, fuzzy logic methods play a crucial role, as they allow for the incorporation of uncertainty in the evaluation of alternatives. According to expression (15), the highest membership degree is observed for scenario s_3, which is considered the most acceptable among the others. Scenario s_2 ranks second, while scenarios s_5 and s_6 are identified as the least effective.

The fuzzy set formed in accordance with expression (15) is constructed under the assumption of equal importance of all criteria. However, in real-world conditions, the significance of individual parameters may vary considerably. To adjust the influence of perfection level on the overall evaluation of alternatives, it is proposed to raise these values to a power corresponding to the weight coefficient of the respective criterion [9, 23].

To determine the criteria weights, the best-worst method [18] is recommended. This method is based on comparing all indicators with the important criterion using Saaty's nine-point scale [20]. At the same time, it is necessary to ensure that the sum of all weights equals the total number of criteria.

As a result of applying the weighting method [18], the weights of the target criteria (C_6, C_7, ..., C_{10}) were determined: $\mu_6 = 1.8$, $\mu_7 = 1.4$, $\mu_8 = 0.2$, $\mu_9 = 1$ and $\mu_{10} = 0.6$.

The fuzzy sets of criteria are then modified as follows:

$$C_6 = \left\{\frac{[0.605]^{1.8}}{s_1}, \frac{[0.821]^{1.8}}{s_2}, \frac{[0.837]^{1.8}}{s_3}, \frac{[0.726]^{1.8}}{s_4}, \frac{[0.523]^{1.8}}{s_5}, \frac{[0.397]^{1.8}}{s_6}, \frac{[0.732]^{1.8}}{s_7}\right\}$$

$$C_7 = \left\{\frac{[0.486]^{1.4}}{s_1}, \frac{[0.816]^{1.4}}{s_2}, \frac{[0.897]^{1.4}}{s_3}, \frac{[0.699]^{1.4}}{s_4}, \frac{[0.398]^{1.4}}{s_5}, \frac{[0.520]^{1.4}}{s_6}, \frac{[0.615]^{1.4}}{s_7}\right\}$$

$$C_8 = \left\{\frac{[0.618]^{0.2}}{s_1}, \frac{[0.905]^{0.2}}{s_2}, \frac{[0.936]^{0.2}}{s_3}, \frac{[0.806]^{0.2}}{s_4}, \frac{[0.595]^{0.2}}{s_5}, \frac{[0.642]^{0.2}}{s_6}, \frac{[0.719]^{0.2}}{s_7}\right\}$$

$$C_9 = \left\{\frac{[0.620]^{1.0}}{s_1}, \frac{[0.804]^{1.0}}{s_2}, \frac{[0.905]^{1.0}}{s_3}, \frac{[0.690]^{1.0}}{s_4}, \frac{[0.504]^{1.0}}{s_5}, \frac{[0.399]^{1.0}}{s_6}, \frac{[0.622]^{1.0}}{s_7}\right\}$$

$$C_{10} = \left\{\frac{[0.620]^{0.6}}{s_1}, \frac{[0.839]^{0.6}}{s_2}, \frac{[0.947]^{0.6}}{s_3}, \frac{[0.790]^{0.6}}{s_4}, \frac{[0.584]^{0.6}}{s_5}, \frac{[0.513]^{0.6}}{s_6}, \frac{[0.698]^{0.6}}{s_7}\right\}$$

As a result of aggregating (intersecting) the constructed fuzzy sets representing different evaluation criteria, a generalised fuzzy set $D = \left\{\frac{0.364}{s_1}, \frac{0.701}{s_2}, \frac{0.726}{s_3}, \frac{0.561}{s_4}, \frac{0.275}{s_5}, \frac{0.189}{s_6}, \frac{0.506}{s_7}\right\}$ of feasible decisions was obtained.

Based on this set, and taking into account the significance of each criterion, it was established that scenario s_3 demonstrates the highest preference and is considered the most appropriate for implementation. Scenario s_2 ranks next in terms of conformity, whereas s_6 proved to be the least optimal among the evaluated alternatives.

To develop management strategies aimed at improving the functional characteristics of the system, it is essential to determine the sensitivity of evaluation criteria to variations in controllable variables. For the purpose of ordering concepts C_1, C_2, ..., C_5 according to the strength of their influence on concepts C_6, C_7, ..., C_{10}, a methodological approach described in [19] was applied. The computational results, obtained using the algorithm presented in subsection 2, are summarised in Table 14.

Table 14. Semantic values of concepts for ranking controllable variables

Controllable variables					Objective functions				
x_1	x_2	x_3	x_4	x_5	$\hat{x}_6$	$\hat{x}_7$	$\hat{x}_8$	$\hat{x}_9$	$\hat{x}_{10}$
+1	-1	-1	-1	-1	0.473	0.548	0.520	0.486	0.389
-1	+1	-1	-1	-1	0.382	0.426	0.411	0.385	0.308
-1	-1	+1	-1	-1	-0.500	-0.448	-0.482	-0.451	-0.361
-1	-1	-1	+1	-1	0.115	0.121	0.210	0.153	0.157
-1	-1	-1	-1	+1	0.294	0.309	0.200	0.295	0.401

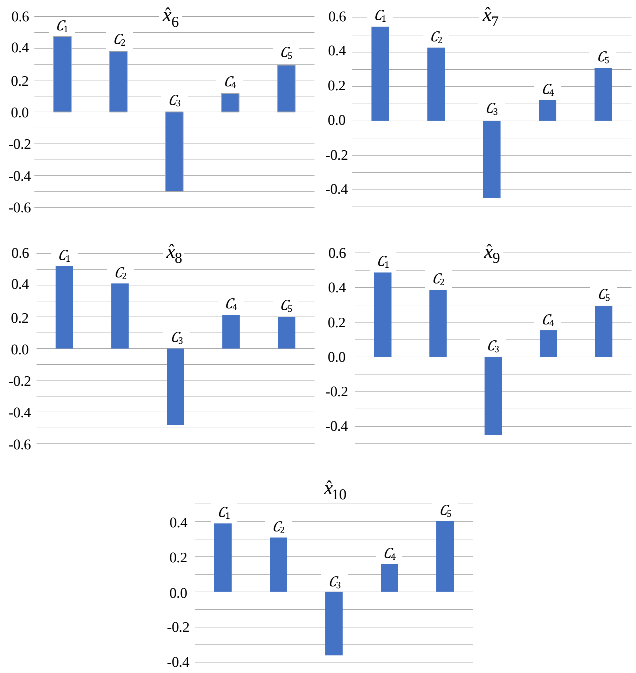

Fig. 7. Impact diagrams of controllable variables across evaluation criteria

Each row in the table represents the normalised values of the criteria for different configurations of controllable variable vectors, where only one variable assumes its maximum value (+1), while all others remain at the minimum level (–1). The values in columns $\hat{x}_6$, $\hat{x}_7$,...,$\hat{x}_{10}$ (from top to bottom) indicate the ranking of variables C_1, C_2, ..., C_5 according to their influence on individual criteria C_6, C_7, ..., C_{10}. This interdependence was also visualised using a graphical scheme (Fig. 7), which provides a clear representation of the variable impact structure.

The results of the analysis presented in Fig. 7 indicate that concept C_3, associated with road condition uncertainty, exerts the most significant negative impact on the performance indicators of the UTS Model (C_6, C_7, ..., C_{10}). To achieve an optimal level of safety and reliability in the functioning of the transport system, it is essential to comprehensively account for the combination of reliability parameters and socio-psychological factors represented by concepts C_1, C_2, ..., C_5, within the framework of an interdisciplinary risk management paradigm.

The approach proposed in this study demonstrates a high level of applicability for solving tasks related to the optimization of transport system management, particularly in situations where decisions must be made under conditions of uncertainty.

4. Conclusions

Effective design of transport systems requires modelling the relationship between system reliability, safety, and controllable variables that represent available redundancy mechanisms. Classical reliability engineering methods show limited applicability in cases where statistical failure data are incomplete and input information is imprecise or uncertain.

The integration of fuzzy cognitive maps with the Bellman–Zadeh decision-making principle provides a powerful tool for selecting reliability and safety management strategies in transport system modelling. This approach enables the consideration of interdependencies between evaluation criteria and controllable variables, thereby enhancing the system's adaptability under uncertainty and supporting well-informed decision-making.

Future research should focus on:

- empirical validation of the proposed model using real-world transport systems;
- expansion of the cognitive structure by incorporating dynamic risk scenarios;
- integration of multi-criteria evaluation methods with fuzzy logic to support regulatory recommendations;
- development of software tools for automated analysis and visualization of redundancy strategies.

References

[1] Aju Kumar V. N., Gandhi, M. S., & Gandhi, O. P.: Identification and assessment of factors influencing human reliability in maintenance using fuzzy cognitive maps. Quality and Reliability Engineering International, 31(2), 2015, 169–181. [https://doi.org/10.1002/qre.1569].

[2] Bellman R. E., Zadeh L. A.: Decision Making in Fuzzy Environment. Management Science 17(4), 1970, B141–B164 [https://doi.org/10.1287/mnsc.17.4.B141].

[3] Christodoulides C., Christodoulides G.: The Method of Least Squares. Analysis and Presentation of Experimental Results. Undergraduate Lecture Notes in Physics. Springer, Cham 2017 [https://doi.org/10.1007/978-3-319-53345-2_11].

[4] Gen M., Cheng R.: Genetic Algorithms and Engineering Design. Wiley Series in Engineering Design and Automation. John Wiley & Sons, Inc., New York, USA, 1997.

[5] Glushkov V. M.: On Systems Optimization. Laxenburg: International institute for applied systems analysis, 1981.

[6] Gu B., Liu J., Chen J.: Scenario-based strategies evaluation for the maritime supply chain resilience. Transportation Research Part D: Transport and Environment 124, 2023, 103948 [https://doi.org/10.3390/s22010271].

[7] Hasson F., Keeney S., McKenna H.: Revisiting the Delphi technique-research thinking and practice: a discussion paper. International Journal of Nursing Studies 168, 2025, 105119 [https://doi.org/10.1016/j.ijnurstu.2025.105119].

[8] İnce E. C.: Mapping the Path to Sustainable Urban Mobility: A Bibliometric Analysis of Global Trends and Innovations in Transportation Research. Sustainability 17(4), 2025, 1480 [https://doi.org/10.3390/su17041480].
[9] Kasabov N.: Foundations of neural networks, fuzzy systems, and knowledge engineering. MIT Press, London 1998.
[10] Kashkanov A. et al.: Estimation parameters of braking of vehicles category M1 at definition of circumstances road accidents. SAE Technical Paper 2022-01-1166, 2022 [https://doi.org/10.4271/2022-01-1166].
[11] Kashkanov A. et al.: Automotive lighting: Method of assessing the visibility of objects in the light of car headlights. Przegląd Elektrotechniczny 96(9), 2020, 90–94 [https://doi.org/10.15199/48.2020.09.19].
[12] Keshavarz E., Mahmoodirad A., Niroomand S.: A Transportation Problem Considering Fixed Charge and Fuzzy Shipping Costs. Decision Making Advances 1(1), 2023, 115–122 [https://doi.org/10.31181/dma11202313].
[13] Kosko B.: Fuzzy cognitive maps. International Journal of Man-Machine Studies. 24, 1986, 65-75.
[14] León M. et al.: Tackling Travel Behaviour: An approach based on Fuzzy Cognitive Maps. International Journal of Computational Intelligence Systems. 6(6), 2013, 1012-1039 [https://doi.org/10.1080/18756891.2013.816025].
[15] Madala K., Solmaz M.: Scenario-Based Risk Quantification Approach for Assuring Safety in Autonomous Vehicles. SAE Technical Paper 2023-01-0584. 2023 [https://doi.org/10.4271/2023-01-0584].
[16] Morris A. S., Langari R.: Measurement and Instrumentation: Theory and Application. Academic Press, 2021. [https://doi.org/10.1016/C2018-0-01451-6].
[17] Poonia H., Sharma A.: Multi-objective fuzzy linear programming techniques: A critical review. International Journal of Statistics and Applied Mathematics. 8(5), 2023, 224-229.
[18] Rezaei J.: Best-worst multi-criteria decision-making method. Omega, 53, 2015, 49–57. [https://doi.org/10.1016/j.omega.2014.11.009].
[19] Rotshtein A., Katielnikov D., Kashkanov A.: A fuzzy cognitive approach to ranking of factors affecting the reliability of man-machine systems. Cybernetics and Systems Analysis 55(6), 2019, 958–966 [https://doi.org/10.1007/s10559-019-00206-8].
[20] Saaty T. L.: The Analytic Hierarchy Process. McGraw-Hill, New York 1980.
[21] Safarpour H. et al.: Vision Zero: Evolution History and Developing Trend in Road Safety: A Scoping Review. Trauma Monthly 25(6), 2020, 275–286 [https://doi.org/10.30491/tm.2020.244740.1166].
[22] Vinnakota T.: A conceptual framework for complex system design and design management. Annual IEEE Systems Conference (SysCon). 2016, 16 [https://doi.org/10.1109/SYSCON.2016.7490575].
[23] Yager R.: Multiple objective decision-making using fuzzy sets. International Journal of Man-Machine Studies 9(4), 1977, 375–382 [https://doi.org/10.1016/S0020-7373(77)80008-4].
[24] Zadeh L.: Fuzzy sets. Information and Control 8(3), 1965, 338–353 [https://doi.org/10.1016/S0019-9958(65)90241-X].
[25] Zhao L., Wang Q., Hwang B.-G.: How to Promote Urban Intelligent Transportation: A Fuzzy Cognitive Map Study. Frontiers in Neuroscience 16, 2022, 919914 [https://doi.org/10.3389/fnins.2022.919914].

M.Sc. Anastasiia Kashkanova
e-mail: kashkanov9a@gmail.com

Anastasiia Kashkanova is a Ph.D. student in Transport Technologies at the Department of Automobiles and Transport Management, Vinnytsia National Technical University, Vinnytsia, Ukraine.
Research interests: urban and city safety in transport systems, operational properties and performance of motor vehicles, forensic examination and evaluation of road traffic accidents

https://orcid.org/0000-0003-4268-0000

Prof. Andrii Kashkanov
e-mail: a.kashkanov@vntu.edu.ua

Andrii Kashkanov is a Doctor of Technical Sciences, professor at the Department of Automobiles and Transport Management, Vinnytsia National Technical University, Vinnytsia, Ukraine.
Research interests: simulation and analysis of vehicle performance characteristics in operational conditions, road accident analysis, design and optimization of transport systems and technologies

https://orcid.org/0000-0003-3294-6135

Prof. Alexander Rotshtein
e-mail: rothstei@g.jct.ac.il

Alexander Rotshtein is a Doctor of Technical Sciences, professor at the Lev Academic Center, Jerusalem College of Technology, Israel. Professor at the Department of Computer Science and Information Technology at Vasyl Stus Donetsk National University, Vinnytsia, Ukraine.
Research interests: fuzzy logic and uncertainty modeling, neural networks, genetic algorithms, system reliability, machine learning

https://orcid.org/0000-0002-4048-3014

Ph.D. Denis Katelnikov
e-mail: fuzzy2dik@gmail.com

Denis Katelnikov is associate professor at the Department of Software Engineering, Vinnytsia National Technical University, Vinnytsia, Ukraine.
Research interests: computer science, fuzzy sets theory, genetic algorithms and evolutionary computation, chaos theory and complex dynamic processes, decision-making models, fuzzy cognitive systems

https://orcid.org/0000-0002-4150-9650