

Article

# Model of Evaluation and Selection of Expert Group Members for Smart Cities, Green Transportation and Mobility: From Safe Times to Pandemic Times

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**Abstract:** This paper presents the development of technologies to support the decision-making of local government executives and smart city concept managers in selecting and evaluating the competencies of new members for advisory groups for solving problems that are implemented in safe times in individual areas or in crises, such as pandemics. The reason for developing effective urban transformation strategies and for the transparent selection of independent experts (non-politicians) for policymaking, decision-making, and implementation teams is not only the heterogeneity of smart city dimensions together with the necessary complexity and systems approach, but also the nature of the capacities and tools needed for smart city concepts. The innovative hybrid competency assessment model is based on fuzzy logic and a network for neuro-fuzzy assessment. It is a technological model for evaluating the competencies of specialists, taking into account the influence of human factors on the processes of personnel selection and system management. An innovative web platform named “Smart City Concept Personnel Selection” has been designed, which can be adapted to various users of municipalities or regional institutions for the transparent selection of qualified personnel for effective decision-making and the use of public funds during safe times or emergencies, such as the COVID-19 pandemic.

**Keywords:** expert group; neuro-fuzzy assessment; evaluation of specialists; smart city; assessment risk; smart transport; mobility; transparent selection; public financial resources; recovery plan

## 1. Introduction

The success or failure of an organization is directly related to how its human resources are used and maintained. Due to increased competition and globalization and rapid technological improvements, global markets require high-quality and professional human resources. This can only be achieved by hiring potentially adequate staff. This also applies to the management of a smart city, which seeks to improve traditional methods of recruiting staff to achieve ideal solutions. By achieving ideal solutions, a smart city, as a community–government–business system, will improve resource management, which will lead to achieving the goals of the smart city concept and increasing capital for its development.

To implement projects within the concept of a smart city in order to create new value for services and customer satisfaction, it is necessary to implement the following tasks:

form a project team, generate service ideas, test the service ideas, select a development concept, design and develop the concept, and test the services and commercialize and improve the quality of the services. In this study, we will focus on the task of evaluating and selecting members of a smart city and green transportation and mobility expert group. Here, it is necessary to select a group of specialists (experts) to evaluate and recommend projects aimed at reducing congestion in the smart city and improving the environment. The target function of any project is to use minimal resources and deliver the maximal effect. Appropriate specialists are needed for a systematic understanding of the implementation processes of the presented projects. They must have both general and special competencies. The superstructure of the evaluation criteria is entrusted to a systems analyst, depending on the target needs of evaluation.

The main goal of the study was to develop technologies to support the decision-making processes of municipal managers and managers of smart city concepts in transparently evaluating the competencies of new specialists (experts, non-politicians) and selecting them for special or innovative tasks within advisory commissions at the local or regional level.

Innovative software in the form of the Smart City Concept Personnel Selection web platform was designed as a tool for this purpose. This tool was approved within the research on the evaluation and selection of an advisory group of experts for an intelligent city and ecological transport and mobility as members of the Commission for Transport and Construction of the City of Košice with 250,000 inhabitants. The innovative web platform “Smart City Concept Personnel Selection” can be adapted to various users of municipalities or regional institutions for the transparent selection of qualified personnel for effective decision-making and use of public funds during safe times or emergencies, such as a global pandemic.

The study provides an answer to a basic research question: what tool can be used to support the right and coordinated decisions of municipal leaders and responsible smart city concept managers in the transparent selection of independent experts for advisory commissions to make beneficial decisions for the public and use public resources effectively to implement measures in times of safety but also in emergencies, such as the COVID-19 pandemic, which endanger people’s lives?

#### *Overview of Domestic and Foreign Research Studies*

The reason for developing effective urban transformation strategies and transparent selection of independent experts for policy teams for decision-making and implementation is not only due to the heterogeneity of smart city dimensions together with the necessary complexity and systems approach, but also the nature of the capacities and tools needed for smart city concepts. Their development is complex due to the diverse structure of the systems within which the decision-making processes take place, as well as the risks arising from the challenging quantification of some of the assumptions that the decision-making processes are based on. There is a lack of studies aimed at developing a methodological platform for the decision-making processes influenced by the pandemic (as in the work of Abebe et al. [1]; Gavril et al. [2]; Rathore and Khanna [3]; Wójcik and Ioannou [4]; or Waiho et al. [5]). We have seen the emergence of numerous research studies whose research trajectories have been linked to policymaking, but which have been largely compensatory (e.g., Åslund [6]; Hudson [7]; ILO, International Labour Office [8]; Juergensen et al. [9]; UNCTAD, United Nations Conference on Trade and Development [10,11]).

The relevance of this study is evidenced by significant global research, scientific publications, and the COVID-19 pandemic. At present, many publications and conferences are being devoted to the smart city concept, and startups and innovative projects are being developed to improve and stimulate the development of such cities [12,13].

While obtaining and processing intellectual knowledge on the concept of the smart city, there is a problem of formalizing the opinions of experts on the object of study. There

are no general approaches to transforming experienced human expert knowledge into a knowledge base.

Hybrid models of multiple-criteria decision-making (MCDM) are rapidly emerging as alternative methods of information modeling [14,15]. Fuzzy or hybrid decision-making methods are widely used in many areas that require effective information management when evaluating alternative decisions and making optimal decisions [16,17]. The human experience uses fuzzy systems and, on their basis, a fuzzy initial estimate is obtained [18,19]. Current approaches and advantages of using fuzzy mathematics in decision support systems are investigated in [20,21]. For example, the applied application of fuzzy mathematics in various fields has been studied in [22,23]. In [24], a narrowly specialized approach to evaluating startup project developers using fuzzy networks is presented. In [25], an innovative fuzzy model for assessing expert knowledge is proposed to increase the security of decision-making. Unfortunately, the last two works are not suitable for evaluation by experts in different fields.

Many researchers around the world are working on selecting the best choice of specialists for vacant positions. In [26], Gungor et al. considered quantitative and qualitative factors using a vague analytical hierarchical process to solve the problem of personnel selection. Some researchers have used an object-oriented programming model and a machine learning method to solve the problem of recruitment for the project team [27,28]. Zhang and Liu [29] combined fuzzy numbers with a gray relational approach to select software engineers. In [30], Afshari used a fuzzy integral to recruit staff when the recruitment criteria were interdependent. In [31], a fuzzy number is used to assess the weight of each criterion and the performance of the evaluated specialists. Heidary Dahooie et al. [32] developed a system of competencies with five criteria to select the best IT expert. Researchers in [33] used vague linguistic terms to express the opinions of experts to solve the problem of recruitment. Ozdemir and Nalbant [34] evaluated the applicants using the method of fuzzy analytic hierarchy, based on five criteria and their pairwise comparison. As a result, a ranking number of applicants was built. In [35], a method of multi-criteria decision-making for the selection of suitable people for vacant positions is developed, taking into account quantitative and qualitative factors. In [36], a hybrid gray model of multiple-criteria decision-making methods for personnel selection is proposed, which allows for eliminating the vagueness of the input information. Only [37,38] solve the task of supporting decision-making for the management of a smart city regarding the evaluation and selection of experts. The aim of [37] was to develop a methodology for assessing and selecting instructor pilots for smart city UAM Urban Air Mobility, based on the principles of fuzzy mathematics and using different information criteria and competency models. A feature of [38] is the general fuzzy model of evaluation and selection of a group of experts (teams) for smart urban transport and mobility. Such experts are selected for various tasks of smart city management.

However, there is no comprehensive study assessing the competencies of advisory commissions' experts and their selection to solve special or innovative tasks within the functioning and smart city concept in safe and pandemic times.

This paper is systematized as follows: in Section 2, we define the formal problem statement and fuzzy, hybrid, and neuro-fuzzy models for assessing the competence of smart city specialists. The criteria were based on the experts' knowledge, their skills, and at least 15 years of practical experience in municipality management and personnel selection processes. In Section 3, we outline the results of the experiment. The model algorithm was used to create a web application to support municipal management decisions for the above-mentioned agenda, from safe times to a pandemic. In Section 4, we discuss the results of the hybrid fuzzy model and the SW developed in the study. In Section 5, we conclude the paper and present the main results. We also discuss ideas for future work and improvements.

## 2. Materials and Methods

### 2.1. Formal Problem Statement

In the study of the smart city as a complex system, there is a need to understand and influence the controllability of the processes to achieve its goals. In addition to many different factors, the controllability of the smart city system depends on the specialists [39]. Such entities may include the following:

- Decision makers (DM) at a certain stage of the smart city system development and at some point in time;
- Experts/system analysts who provide information on the performance indicators of the smart city system;
- Managers who are directly responsible for achieving the goals in the concept of the smart city system;
- Members of the City Council commission as experts who make management decisions within their competences, etc.

The subject of management is an expert (specialist) who is endowed with certain competencies and powers that allow for implementing their will in the form of management decisions, which management teams are required to perform.

Depending on the applied task, it is necessary to evaluate managers and their competencies. The level of controllability of processes in the complex systems of a smart city depends on the competence of the specialists. In the future, without reducing the generality, the subjects of management of such complex systems will be named specialists.

Adequate solutions of the problem of evaluation and selection of smart city specialists, taking into account their competencies, directly affect the achievement of goals by the functioning systems of the smart city.

To assess the competencies of specialists, there are tasks through which we can clearly understand what the ideal combination of knowledge and practical skills should be, as well as the ways of thinking; professional, ideological, and civic qualities; and moral and ethical values, which determine a person's ability to successfully pursue professional activities in this system of functioning. Examples of such tasks for a smart city include the evaluation and selection of instructor pilots for Smart City Urban Air Mobility to operate drones for the delivery of parcels or for the prospective operation of drone taxis (VTOL—Vertical Take Off and Landing); assessment of experts' knowledge with the implementation of IT tools; assessment of the competencies of infectious disease experts for staffing situations and others. Such tasks simulate linear processes of assessing the competencies of specialists.

On the other hand, there are tasks where, when innovative goals are achieved, a new task is created. It does not clearly articulate and investigate what properties the subject must have to in order to achieve the goal of the system. Therefore, to build an information model of criteria for assessing the competencies of specialists, managers use practical experience and intuitive knowledge. At the same time, managers predict that these competencies of specialists can achieve the target needs of the system of functioning of the smart city. Examples of such tasks include evaluating a team of experts to select a project aimed at reducing congestion in a smart city and improving the environment; evaluation and selection of an expert group for smart city and green transportation and mobility, as members of the Transport and Construction Commission; assessment of the competencies of a group of specialists for innovation, development, grant work and implementation of new research. In such problems, we cannot talk about the linearity of the processes of assessing the competencies of specialists.

Given the above, the task of assessing the competencies of specialists can be classified as modeling linear and nonlinear processes.

To adequately determine the impact of human factors on the controllability of the processes of smart city systems, we propose assessing the competencies of the system managers using the following approaches. Additionally, taking into account any type of data, there is a need and relevance to present fuzzy knowledge on the application of fuzzy sets to build information models. Information modeling of the presentation of

fuzzy knowledge will provide an opportunity to adequately approach the evaluation of alternative decisions, while increasing the degree of validity of decision-making. When modeling linear processes, use the apparatus of fuzzy sets [19,22]. This will reveal the uncertainties of information and works with different scales of input data. Additionally, to assess the competencies of specialists in innovative tasks, when modeling nonlinear processes, we propose to use neuro-fuzzy models [24]. Fuzzy neural networks have the following advantages: the ability to work with fuzzy and high-quality information; the possibility of using expert knowledge in the form of fuzzy inference rules. Rationality and adequacy of the use of neuro-fuzzy models are proved in [19–23].

The model of technology for assessing the competencies of specialists in the system of functioning of the smart city, taking into account the influence of human factors on the processes of control, is presented as follows:

$$\{E, K, LP | Y\}, \quad (1)$$

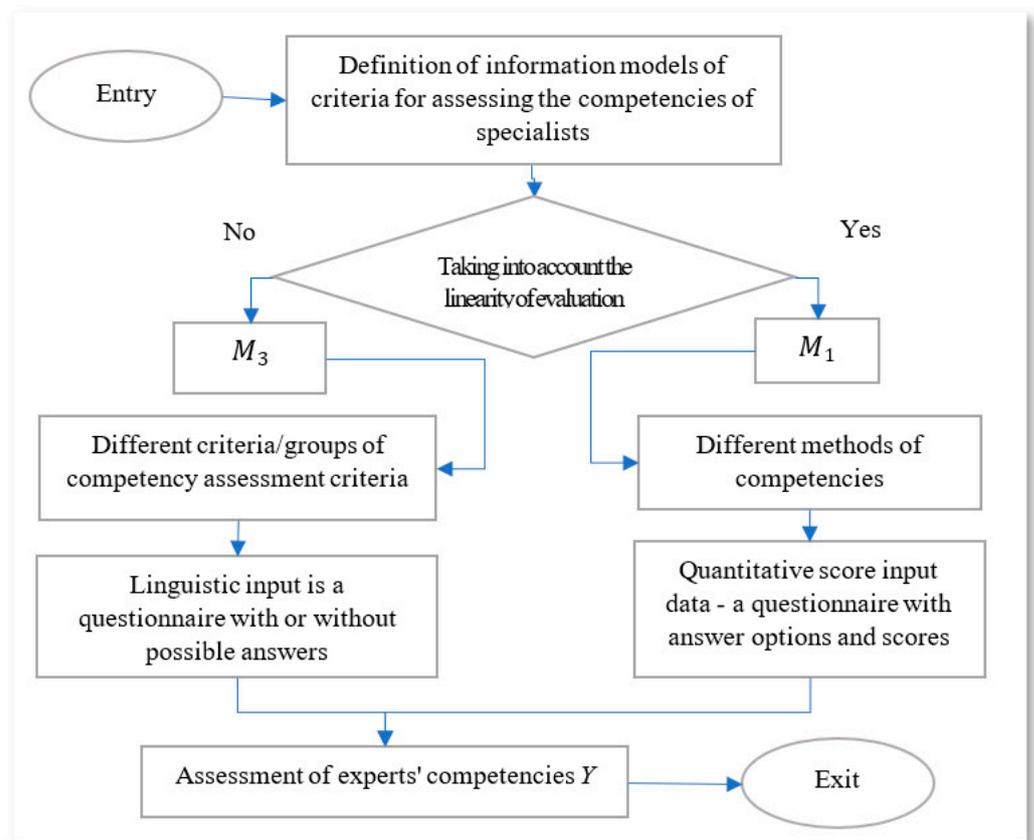
where  $E$  is a set of specialists in some subject area in the smart city system;  $K$  is the information model of the criteria (groups of criteria) for assessing the competencies of the specialists, taking into account the human impact on the control processes of the smart city system;  $LP = \{M_1; M_2; M_3\}$  is a type of model for assessing the competencies of experts. As part of our study, we offer the following models:  $M_1$ —a fuzzy model for the assessment of the competence of specialists, taking into account different models of competencies for linear assessment tasks;  $M_2$ —a hybrid fuzzy model that takes into account the experience of managers;  $M_3$ —a neuro-fuzzy network for modeling nonlinear evaluation processes.

As a result, we obtain an initial assessment of  $Y$  competencies of specialists, on the basis of which we make decisions on the selection of specialists. The algorithm for selecting the model for assessing the competencies of smart city specialists, taking into account the linearity of the assessment processes, is given as follows in Figure 1.

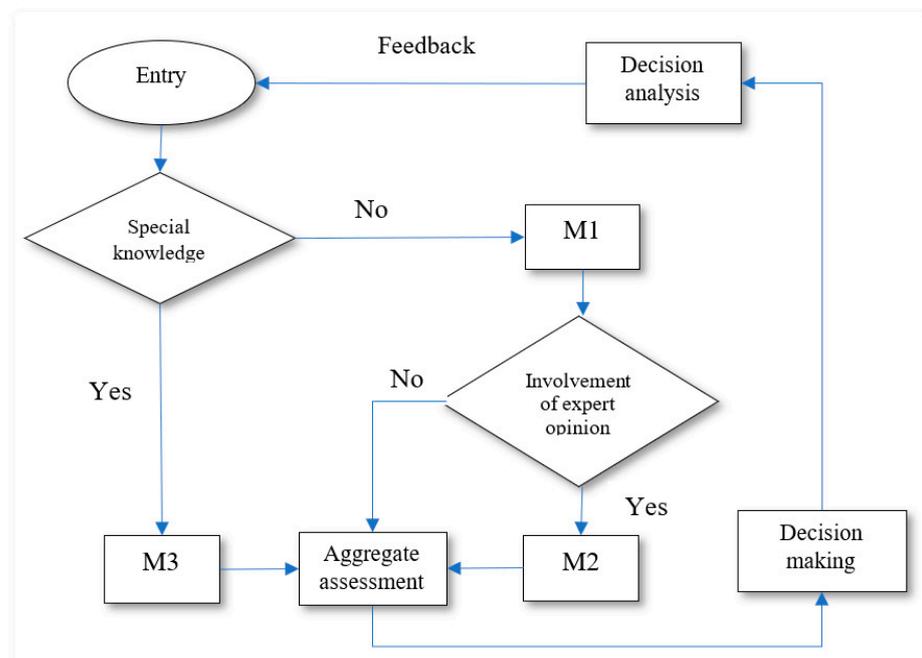
Let a set of specialists be given,  $E = \{e_1, e_2, \dots, e_n\}$ , for a smart city. Specialists need to be evaluated according to different methods of competencies, which, in turn, consist of evaluation indicators (criteria). After that, specialists need to be organized according to a certain rule to select the most competent ones or determine their assessments. Different methods of assessing the knowledge, skills, abilities, or psychophysiological properties of specialists are used in the smart city system for different target tasks. For example, within this study, consider the following methods:  $m_1$ —evaluation of ways of thinking;  $m_2$ —assessment of theoretical knowledge;  $m_3$ —assessment of practical knowledge;  $m_4$ —assessment of knowledge in the theory of pedagogy, psychology, and communicative competence;  $m_5$ —assessment of narrowly specialized skills. For the fuzzy model of assessment of the competence of specialists, we use the methods  $m_1$ – $m_4$ , and for the neuro-fuzzy network of assessment— $m_5$ .

Take the set of criteria  $K_d = \{K_{d1}, K_{d2}, \dots, K_{dm}\}$ ,  $d = \overline{1, \omega}$  for the corresponding methods of competence  $m_d$ . Each criterion is a question to which the answer must be chosen that is close to the truth. The answers to the question are denoted by  $Z_{djk}$ ,  $d = \overline{1, \omega}$ ,  $j = \overline{1, m}$  and  $k = \overline{1, l}$ , where  $d$  is the evaluation method,  $j$  is the number of the criterion (question) in the corresponding model, and  $k$  is the number of the answer to the question. According to each criterion, the specialist chooses one of the answer options, which is assigned the appropriate score  $b_{djk}$  or some linguistic term, such as  $L = \{H; HC; C; B\}$ : H—“low level of the indicator”; HC—“level of the indicator below average”; C—“average level of the indicator”; B—“high level of the indicator”.

Next, based on the experience of the authors and significant experiments on the evaluation of specialists in various fields, we present a block diagram of the technology for the evaluation and selection of specialists of the smart city, shown in Figure 2. According to this scheme, software support was developed in the form of a web platform, where there is a choice for special knowledge of specialists and involvement of managers’ opinions.



**Figure 1.** Algorithm for choosing a model for assessing the competencies of smart city specialists, taking into account the linearity of assessment processes:  $M_1$ —fuzzy model for assessment of the competence of specialists;  $M_3$ —neuro-fuzzy network.



**Figure 2.** Block diagram of the technology for the assessment and selection of specialists of the smart city:  $M_1$ —fuzzy model for assessment of competence of specialists;  $M_2$ —hybrid fuzzy model;  $M_3$ —neuro-fuzzy network.

The choice of evaluation model depends on the specialist's need for special knowledge, skills, and abilities, the ability to attract expert opinion on the evaluated professionals, their competence, ability, and potential to adequately perform the task to achieve the target needs of the system. For this purpose, three models are proposed, which will give an aggregate assessment of specialists of the smart city.

The choice of the method  $M_1$ —a fuzzy model for the assessment of the competence of specialists, taking into account different models of competency tasks—follows from the fact that knowledge about the subject area is incomplete, subjective, and not always reliable. The use of accurate methods does not allow taking into account the verbal inaccuracy and subjectivity of expert information, which in turn imposes restrictions on the quality of knowledge for decision-making.

To apply the knowledge and experience of smart city managers in the evaluation process, the  $M_2$  model is proposed—a hybrid fuzzy model that takes into account the experience of managers, which is able to derive a normalized assessment of the quality of selection of specialists. Its feature is that it combines different types of data in one structure.

The correctness of the choice of the method  $M_3$ —neuro-fuzzy network, for the studied problems—the authors prove in [24].  $M_3$  is based on Takagi–Sugeno–Kang (TSK) and determined that among neural networks, the TSK network gives more accurate results than the Adaptive-Network-Based Fuzzy Inference System (ANFIS). In addition, the change in the number of rules in the training sample does not have a significant effect on the forecasting results.

After that, the decision-maker analyzes and selects the decision, followed by approval of the decision. If over time the solution does not meet the target needs of the system, or new conditions appear, then there is feedback and evaluation occur first.

## 2.2. Fuzzy, Hybrid, and Neuro-Fuzzy Models for Assessing the Competence of Smart City Specialists

We present a fuzzy model for assessing the competence of specialists,  $M_1$  [37,38].

At the first stage, it is necessary to select evaluation models and calculate the number of points scored.

To reveal the quality of the evaluated specialists in a specific applied task, it is necessary to adequately build methods and criteria of competencies. After that, we proceed to the survey of experts on the relevant models of competencies  $g(M_d) = \{s_{d1}, s_{d2}, \dots, s_{dn}\}$  and summarize the number of points scored.

Next, we phase the input data. Since the input data are presented in the form of questionnaires, with score points that are subjective in nature, there is a need to reveal the uncertainty of the input data [40]. As a result, the obtained numerical variables  $\{s_{d1}, s_{d2}, \dots, s_{dn}\}$  take different numerical values, and to compare them, the values need to be normalized. For this, we propose using the modeling of fuzzy knowledge using the apparatus of fuzzy sets and membership functions [41]. The procedure for transferring fuzzy data does not depend on the type of membership functions. Therefore, in fuzzy set theory, it is assumed that experts may have different representations of the types of membership functions and the base sets on which they are defined, and this does not affect the final result [42]. For example, the membership function of a harmonic S-spline is given by formula (2):

$$\partial_{di}(s_{di}, a, b) = \begin{cases} 0, & s_{di} < a; \\ \frac{1}{2} + \frac{1}{2} \cos \left( \frac{s_{di}-b}{b-a} \cdot \pi \right), & a \leq s_{di} \leq b; \\ 1, & s_{di} > b. \end{cases}, \quad (i = \overline{1, n}; d = \overline{1, \omega}). \quad (2)$$

where  $a$  is the convolution of the sum of the minimum points,  $b$  is the convolution of the sum of the maximum points of the grading scale according to the criteria in the methods  $m_d$ , and  $s_{di}$  is the convolution of the sum of points of the  $i$ -th specialist in the competency model  $m_d$ . Thus, the obtained input data will be normalized and comparative.

In addition, fuzzification of the “desired values” is necessary [43]. For each competency model, the decision-maker (manager) has his own considerations, which should be the “desired values”—that is, the sum of the scores for each method  $m_d$ . We denote them by the respective vector  $T = (t_1, t_2, \dots, t_\omega)$  of the models  $m_d$ , ( $d = \overline{1, \omega}$ ). To compare the “desired values”, we calculate the value of the constructed membership function of the quadratic S-spline:

$$\delta_d(t_d, a, b) = \begin{cases} 0, & t_d \leq a; \\ 2\left(\frac{t_d - a}{b - a}\right)^2, & a < t_d \leq \frac{a+b}{2}; \\ 1 - 2\left(\frac{b - t_d}{b - a}\right)^2, & \frac{a+b}{2} < t_d < b; \\ 1, & t_d \geq b. \end{cases}, \quad (d = \overline{1, \omega}). \tag{3}$$

For the model  $m_1$ , the DM chooses one of the values of the thinking strategies of the specialist, or a combination thereof, according to the proposed characteristic function [37]:

$$\delta_1 = \begin{cases} 0.2 & \text{if } \textit{synthesiser}, \\ 0.3 & \text{if } \textit{synthesiser / idealist}, \\ 0.4 & \text{if } \textit{idealist}, \\ 0.5 & \text{if } \textit{idealist / pragmatist}, \\ 0.6 & \text{if } \textit{pragmatist}, \\ 0.7 & \text{if } \textit{pragmatist / analyst}, \\ 0.8 & \text{if } \textit{analyst}, \\ 0.9 & \text{if } \textit{analyst / realist}, \\ 1 & \text{if } \textit{realist}, \end{cases} \tag{4}$$

Next, we polarize the input data and “desired values”. To do this, define a set of quantities that are a relative estimate of the proximity of the elements  $\mu_{di}$  to the corresponding element of the “desired values”  $\delta_d$  [44]:

$$z_{di} = 1 - \frac{|\delta_d - \mu_{di}|}{\max\left\{\delta_d - \min_i \mu_{di}; \max_i \mu_{di} - \delta_d\right\}}, \quad d = \overline{1, \omega}; \quad i = \overline{1, n}. \tag{5}$$

The matrix  $Z = (z_{di})$ , defined in this way, characterizes the relative estimates of the proximity of the corresponding specialist  $e_i$  to the “desired values”  $\delta_d$  by the methods of assessing competencies.

If we have more than one method of assessing competencies, then they will have different levels of importance. In this regard, the DM sets the weight for each method of assessing the competence of specialists  $\{p_1, p_2, \dots, p_\omega\}$ , for example, from the interval [12,21]. If there is no need to set weights, then we accept them as equally important. For further calculations, we carry out their rationing [37]:

$$w_d = \frac{p_d}{\sum_{d=1}^{\omega} p_d}, \quad d = \overline{1, \omega}; \quad w_d \in [0, 1]. \tag{6}$$

where the condition  $\sum_{d=1}^{\omega} w_d = 1$  is met.

To defuzzify the data, an aggregate estimate is constructed using the convolution model. For example, take a weighted average convolution:

$$\mu(e_i) = \sum_{d=1}^{\omega} w_d \cdot z_{di}, \quad i = \overline{1, n}. \tag{7}$$

Based on the obtained estimates  $\mu(e_i)$ , we can build a ranking of specialists in terms of competency in the assessment methods—for example, to select a team:  $A =$

$\{\mu(e_1), \mu(e_2), \dots, \mu(e_n)\}$ . Depending on the needs, a combination of the most competent specialists is chosen.

Next, consider a hybrid fuzzy model— $M_2$ .

When choosing a specialist, there is a need to analyze their competency, work experience, and other additional indicators that are not taken into account in the methods of assessing competency. In this case, we offer a formalized toolkit that will allow managers of the municipality of a smart city to take into account their own opinions about the specialists in question.

Suppose that we have the calculated aggregate assessments of all specialists (7) assessed according to a fuzzy model. We present a hybrid fuzzy evaluation model in the following formal form:

$$M(\mu(e); E) \rightarrow \varphi(e). \tag{8}$$

where  $\mu(e)$  is the aggregate assessment of the specialist  $e$  based on the methods of assessing competencies;  $E$ —expert assessment of the specialists by the managers of the smart city. At the output of the model, we have  $\varphi(e)$ —a normalized assessment of the quality of the selection of specialists.

We will introduce the concept of “risk trend” in the selection of specialists. To do so, we project the estimates of  $\mu(e)$  on the “risk trend” of the evaluation and selection of specialists as well as considering the dependence in the form of the S-linear membership function:

$$\mu(e_i) = \begin{cases} 0, & P_i < \tau_1; \\ \frac{P_i - \tau_1}{\tau_2 - \tau_1}, & \tau_1 \leq P_i \leq \tau_2; \\ 1, & P_i > \tau_2. \end{cases} \quad i = \overline{1, n}. \tag{9}$$

where  $\tau_1, \tau_2$  are numerical values that we consider in the percentage scale— $\tau_1 = 0, \tau_2 = 100$ . For example, when it comes to risk, 100% is associated with the most critical risk. Since the values of the membership function are known  $\mu(e_i)$  and are known numerical values, we express the following from formula (9)  $P_i: P_i = \mu(e_i) \cdot 100$ . The obtained value of  $P$  characterizes the assessment of the projection of the “risk trend” of specialist selection.

Let the reasoning of smart city managers regarding the evaluated specialists be presented in the form of linguistic variables—for example, G {the specialist is very well suited to perform the task}; H {the specialist suitable for the task}; S {the specialist is poorly suited to perform the task}. To adequately interpret the dependence of the aggregate assessment of the specialist on the projection of the “risk trend” of the selection and consideration of the opinions of the managers of the smart city, we construct the following membership function:

$$\varphi(e_i) = \begin{cases} 0, & P_i < 0; \\ (\mu(e_i))^k, & 0 \leq P_i \leq 100; \\ 1, & P_i > 100. \end{cases} \tag{10}$$

where  $k$  is the degree of compliance of the specialist to perform tasks. For example, let us say that one specialist is very well suited to perform the task  $k = 1/3$ , one specialist is suitable for the task  $k = 1$ , and one specialist is poorly suited to perform the task  $k = 5/3$ .

The obtained value of  $\varphi(e_i)$  is an aggregate assessment of the quality of the selection of specialists.

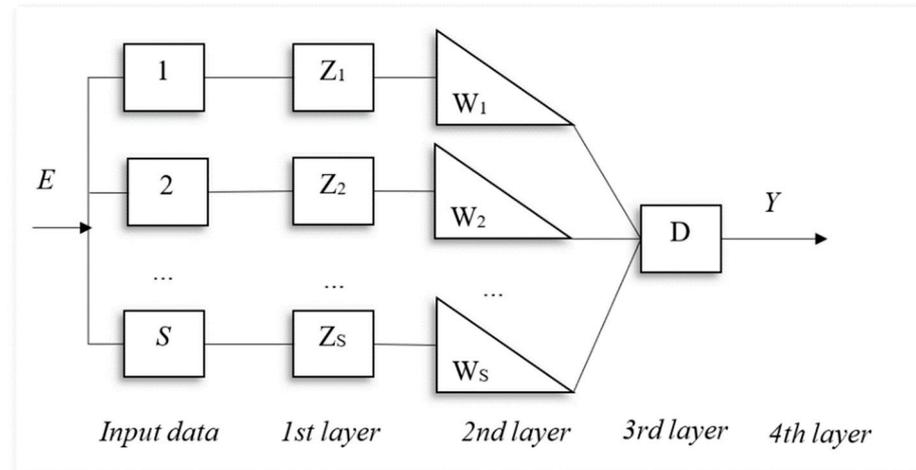
Thus, the presented fuzzy hybrid model for assessing the competence of specialists, which is able to derive a normalized assessment of the quality of the selection of specialists, uses the analysis of the reasoning of smart city managers, reveals the vagueness of the input assessments, and increases the validity of further management decisions based on the results.

To assess narrowly specialized skills, we offer a neuro-fuzzy assessment network [24,40].

Suppose that a set of specialists  $E = \{e_1, e_2, \dots, e_n\}$  is given for the smart city, which we will evaluate using many indicators (criteria) grouped into  $S$  groups. Specialists need to be organized according to a certain rule and derive a linguistic rating of  $Y$ .

Each criterion for evaluating specialists is expertly evaluated using one of the terms—for example, the next term set of linguistic variables  $L = \{H; HC; C; B\}$ , where H is “low level”; HC—“below average”; C—“average level of the indicator”; B—“high level of the indicator” [32]. Additionally, for each assessment, the specialist receives a “coefficient of confidence”  $d$  [24] in assigning an assessment, from the interval  $[0; 1]$ .

Obtaining an aggregate assessment of the competencies of specialists can be represented in the form of a four-layer neuro-fuzzy network, based on Takagi–Sugeno–Kang (TSK) [20]; Figure 3.



**Figure 3.** The structure of the neural fuzzy network, where  $E$ —a set of specialists;  $S$ —number of groups of criteria;  $Z$ —neurons;  $W$ —functions of postsynaptic potential;  $D$ —data defuzzification;  $Y$ —output assessment of competencies of specialists.

Next, we consider in more detail what happens on each layer of the neural network.

First layer: Fuzzification of input data

In the neurons of the first layer, the operation of fuzzification is performed—that is, the construction of the membership rule to obtain a normalized estimate of the input data  $(L_{lji}; d_{lji})$ , where  $l$  is a group of evaluation criteria  $l = \overline{1, S}$ ,  $j$  is the number of criteria groups  $j = \overline{1, m}$ , and  $i$  is the number of the evaluated specialist  $i = \overline{1, n}$ . Let the term set of linguistic variables  $L = \{H; HC; C; B\}$  be represented in some numerical interval  $[a_1; a_5]$ , where  $H \in [a_1; a_2]$ ,  $HC \in [a_2; a_3]$ ,  $C \in [a_3; a_4]$  and  $B \in [a_4; a_5]$ . The values of the partitioning of the intervals can be determined in the process of learning the neural network.

Next, we present the rule of belonging by modeling fuzzy knowledge. The membership function is chosen on the basis of “ $x$  is greater than”; for example, this type is a linear S-shaped membership function:

$$\mu(O_{lji}) = \begin{cases} 0, & O_{lji} \leq a_1; \\ \frac{O_{lji}-a_1}{a_5-a_1}, & a_1 < O_{lji} \leq a_5; \\ 1, & O_{lji} \geq a_5. \end{cases} \text{ where } O_{lji} = \begin{cases} a_2 \cdot d_{lji}, & \text{if } L_{lji} \in H; \\ a_3 \cdot d_{lji}, & \text{if } L_{lji} \in HC; \\ a_4 \cdot d_{lji}, & \text{if } L_{lji} \in C; \\ a_5 \cdot d_{lji}, & \text{if } L_{lji} \in B. \end{cases} \quad (11)$$

The membership function constructed in this way means that the obtained value of  $\mu(O_{lji})$  will be 1 if the specialist has high scores.

Thus, in the neurons of the first layer, we reveal the subjectivity of the opinions of specialists and move from linguistic assessments and confidence in their assignment to normalized comparable data [24].

Second layer: Aggregation of values of activation conditions



Thus, a fuzzy model for assessing the competence of specialists, a hybrid fuzzy model, and a neuro-fuzzy network have been developed as components of decision support technologies for smart city managers in assessing the competencies of specialists and choosing them to solve special or innovative tasks.

### 2.3. The Information Model for Evaluation and Selection of the Expert Group as Members of the Transport and Construction Commission

Here, the criteria for assessing narrowly specialized skills ( $m_5$ ) are presented, which allow for assessing specialists as members of the Transport and Construction Commission of the city of Košice using  $M_3$ , the neuro-fuzzy assessment network.

The City Councils of Košice have 14 commissions [45]: the Commission for the Protection of the Public Interest in the Performance of the Functions of Public Officials; Legislative and Legal Commission; Culture Commission; Commission of National Minorities; Finance Commission; Commission for Education; Commission for Sport and Active Recreation; Commission for Regional Development and Tourism; Transport and Construction Commission; Commission for the Environment, Public Order and Health; Social and Housing Commission; Property Commission; Church Commission; Temporary Commission for the Organization of Relations between the City of Košice and EEI Ltd. (canceled).

The city commissions are made up of deputies of the City Parliament and experts, without a parliamentary mandate. The deputies of the City Parliament are elected by the citizens, who cannot influence in which city commission the deputies will work, but can help in the selection of experts without a parliamentary mandate [46].

In our study, we present an information model for the evaluation and selection of the expert group members (who are not deputies of the City Council) of the Transport and Construction Commission to evaluate and oversee the implementation of innovative projects. The Transport and Construction Commission consists of nine politicians (commission chair and eight city deputies) and eleven experts (non-politicians). The work of the Commission follows [46]:

- (a) Assesses and gives recommendations on drafts of the city's zoning plans, its amendments and the Košice Development Program, as well as on the proposals of city-wide concepts for the development of individual areas of city life and urban areas from the point of view of spatial development, construction, and transport;
- (b) Comments on the concepts, the design of preparation, and the method of implementation of construction projects in the city, which significantly affect the lives of the city's people from the point of view of transport;
- (c) Expresses its opinion on fundamental conceptual proposals for the development of urban public transport and passenger, bicycle, and pedestrian transport in the city;
- (d) Comments on changes in the public transport tariffs in the city of Košice;
- (e) Comments on proposals for the preparation and implementation of transport constructions in the city and on decisive constructions of a city-wide characteristic;
- (f) Comments on the concept and solutions of urban static transport;
- (g) Takes a position on activities in the field of administration and maintenance of roads in the city pursuant to the Road Act;
- (h) Gives opinions on individual points of City Council meetings, which are substantively related to the issues of construction and transport, as well as on points that are related to the actual activity of the commission.

Under the new Program for Economic Development and Social Development for 2022–2027, which is part of the Integrated Territorial Strategy for Sustainable Urban Development of the Functional Area of Košice [47], certain specific objectives are planned with regard to transport, such as the following:

Priority no. 1: green area—SMART Integrated Transport System (EUR 9.615 million); low-emission vehicle fleet for public passenger transport (EUR 164.197 million); modernized transport infrastructure for public passenger transport (EUR 190.955 million); comprehensive network of transport cycle routes in the UMR (EUR 24.57 million);

Priority no. 2: quality public services—safety of the population (EUR 27.683 million, of which public lighting in the city requires EUR 24.12 million and safe pedestrian crossings require EUR 2.0 million); active leisure (EUR 28.827 million).

For these intentions, the great importance of selecting quality experts (external analysts, members of commissions—non-deputies) can already be seen in order to effectively use public funds, not only “according to political and populist proposals of regional and city politicians”.

Thus, for the information model, we present the following set of evaluation criteria for experts of the Transport and Construction Commission of the city of Košice, which is classified into three groups.

The first group of criteria  $K_1$  includes professional competence and experience in spatial development, construction, and transport. For this group, we offer the following indicators and answer options:

$K_{11}$ —Possession of professional knowledge, skills, and abilities in the transport and/or construction industry, which is confirmed by education: 1. Bachelor’s degree in technical/managerial direction; 2. Master’s degree in technical/managerial direction; 3. Master’s degree in technical/managerial orientation and availability of various advanced training certificates; 4. Available scientific degree.

$K_{12}$ —Successful experience in working on various tasks related to the concept of transport in the city, control over the implementation of transport solutions, reduction in environmental impact, and traffic assessment to reduce accidents: 1. Absent; 2. Available for one or two tasks; 3. Available for two or three tasks; 4. Available for all tasks.

$K_{13}$ —Successful experience of working on investment, innovative, or scientific projects, programs and development strategies aimed at transport and construction: 1. Absent; 2. Project executor; 3. Expert in the project; 4. Project manager.

$K_{14}$ —Ability to anticipate risks related to the implementation of transport solutions with reduced environmental impact and accidents: 1. Available; 2. Average; 3. High; 4. Very high.

$K_{15}$ —Understanding of pricing of passenger transportation services on public transport: 1. Available; 2. Project participant on this topic; 3. Bachelor’s degree in economics; 4. Master’s degree or Ph.D. in economics.

The second group of criteria  $K_2$  includes the professional activity and sociality of experts.

$K_{21}$ —Communication ability, openness and ability to cooperate with different partners: 1. Insignificant; 2. Average; 3. Significant; 4. Intensive.

$K_{22}$ —Availability of publications on the issues of analysis, development, innovations in the field of transport and the concept of smart city: 1. Absent; 2. Available publication; 3. Available articles of a scientific nature; 4. Numerous articles.

$K_{23}$ —Teamwork skills: 1. No experience; 2. Experience of project work in a team; 3. Middle manager; 4. Senior manager.

$K_{24}$ —Ability to manage people, set tasks, delegate authority, and desire to compete in the struggle for supremacy and authority: 1. Absent; 2. Available experience in people management; 3. The middle manager or teaching experience; 4. Senior manager.

$K_{25}$ —Focus on winning and maintaining their own reputation, recognition, and the achievement of goals and respect among people: 1. Low dynamics; 2. Average dynamics; 3. High dynamics; 4. Very high dynamics.

The third group of criteria  $K_3$  includes the creativity and psycho-physiology of experts.

$K_{31}$ —Openness to new ideas, constant movement forward, growth and focus on innovative changes to achieve the most effective result: 1. Insignificant; 2. Average; 3. Significant; 4. Intensive.

$K_{32}$ —The correct assessment of their strengths and weaknesses, the constant development of professional and personal qualities, the desire to solve complex professional problems for self-development, and accumulation of knowledge and experience: 1. Available; 2. Average; 3. High; 4. Very high.

$K_{33}$ —Ability to acquire knowledge and its implementation in practice: 1. Available; 2. Average; 3. High; 4. Very high.

$K_{34}$ —Efficiency and systematic thinking: 1. Available; 2. Average; 3. High; 4. Very high.

$K_{35}$ —Stress resistance and emotional balance: 1. Available; 2. Average; 3. High; 4. Very high.

### 3. Results

We tested the study on the example of the evaluation of experts for smart city and green transportation and mobility as members of the Transport and Construction Commission of the city of Košice, using a neural network. For the evaluation, we had five candidate experts for the position of member of the Transport and Construction Commission [46]. The input data were the answers of the applicants to the questions given in the form of the term set of linguistic variables,  $L = \{H; HC; C; B\}$ , proposed in the study, and estimates of the “coefficient of confidence”  $d$ ; see Table 1.

Table 1. Input data.

Group of Criteria	The Name of the Criterion	Weight Criterion	$e_1$		$e_2$		$e_3$		$e_4$		$e_5$	
$K_1$	$K_{11}$	10	HC	0.5	HC	0.6	C	0.9	C	0.9	B	0.8
	$K_{12}$	8	HC	0.9	HC	0.6	HC	0.8	C	0.8	C	0.7
	$K_{13}$	10	C	0.7	HC	0.5	C	0.8	C	0.7	B	0.9
	$K_{14}$	9	C	0.8	HC	0.8	C	0.7	C	0.9	HC	0.8
	$K_{15}$	8	HC	0.6	B	0.8	B	0.9	B	0.9	C	0.9
$K_2$	$K_{21}$	9	C	0.8	C	0.8	C	0.9	B	0.8	B	0.9
	$K_{22}$	7	B	0.7	C	0.9	C	0.7	C	0.7	B	0.8
	$K_{23}$	8	C	0.8	C	0.8	B	0.8	B	0.9	C	0.9
	$K_{24}$	7	HC	0.9	HC	0.8	B	0.6	B	0.9	B	0.8
	$K_{25}$	7	C	0.9	C	0.9	C	0.7	C	0.6	C	0.9
$K_3$	$K_{31}$	8	C	0.8	HC	0.8	C	0.8	HC	0.8	C	0.9
	$K_{32}$	8	HC	0.9	HC	0.9	B	0.9	HC	0.8	C	0.9
	$K_{33}$	8	C	0.7	HC	0.8	C	0.6	C	0.9	B	0.8
	$K_{34}$	9	HC	0.7	B	0.9	B	0.7	B	0.8	C	0.9
	$K_{35}$	7	B	0.8	HC	0.8	C	0.7	C	0.8	B	0.8

We next show the process of obtaining an aggregate assessment of the competencies of the specialists using the proposed four-layer neural network. To fuzzify the input data, we defined the membership function in the numerical interval  $[0; 10]$ , where  $H \in [0; 2]$ ,  $HC \in [2; 5]$ ,  $C \in [5; 8]$  and  $B \in [8; 10]$ .

The value of  $\mu(O_{lji})$  was calculated using formula (11); Figure 4.

Next, to aggregate the values of the activation conditions, we calculated the value of the level of excitation of neurons using formula (12). To aggregate the values of the weights of the groups of criteria, the manager of the municipality had his own considerations about the synaptic weights according to the groups of criteria:  $K_1$ —the most important effect ( $\alpha_1 = 10$ );  $K_2$ —significant effect ( $\alpha_3 = 8$ );  $K_3$ —average effect ( $\alpha_2 = 6$ ). Then, we calculated the functions of the postsynaptic potential of the neurons of the third layer using formula (13). The results of the calculations are shown in Figure 5.

Next, we defuzzified the data and compared the levels of decision-making on the linguistic interpretation of the competencies of specialists using the activation function (14):  $Z(e_1) = 0.5424$ ;  $Z(e_2) = 0.5048$ ;  $Z(e_3) = 0.6524$ ;  $Z(e_4) = 0.687$ ;  $Z(e_5) = 0.7371$ . We built a ranking of the specialists using the obtained values:  $e_5; e_4; e_3; e_1; e_2$ . We compared the quantitative result with the original variable  $Y$  and found that the specialists  $e_5$  and  $e_4$  had a “specialist rating above average” and all the others had a “specialist rating—average”.

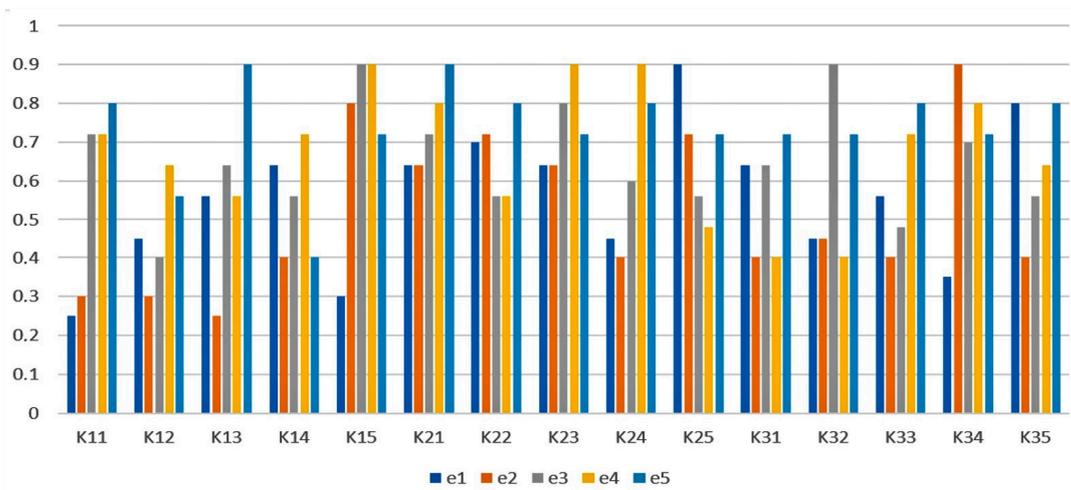


Figure 4. Fuzzification of input data.

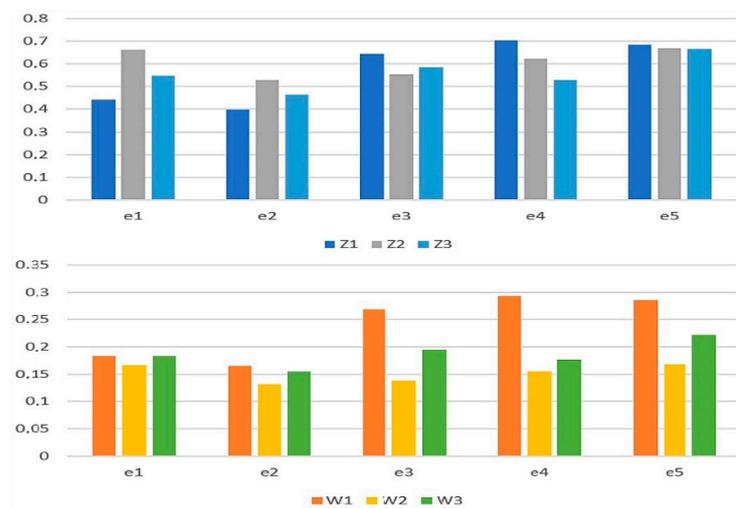


Figure 5. Values of neuronal excitation level ( $Z_1; Z_2; Z_3$ ) and postsynaptic potential function ( $W_1; W_2; W_3$ ).

As part of the study, an innovative web platform named Smart City Concept Personnel Selection [48] was developed on the basis of the proposed technology for the evaluation and selection of specialists, as shown in Figure 6.

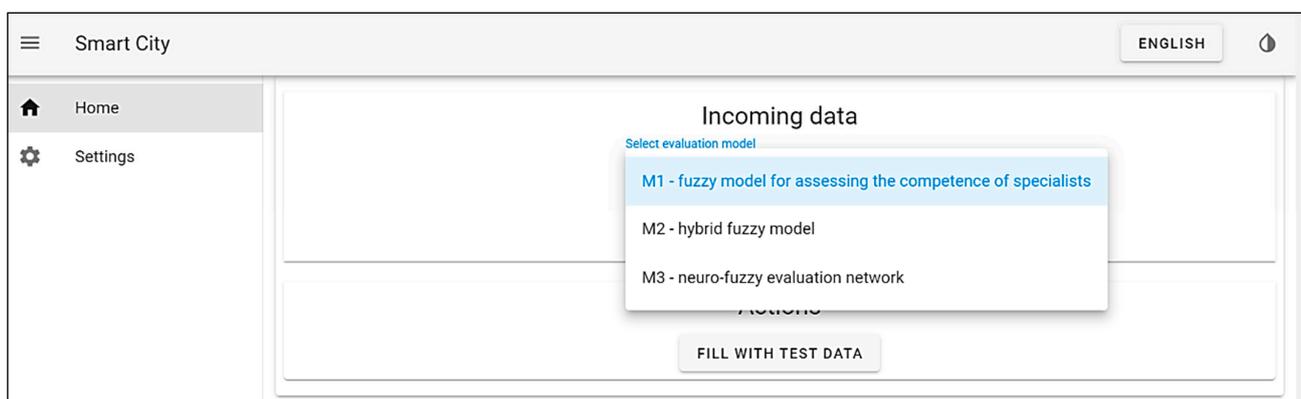


Figure 6. Head screen of the Smart City Concept Personnel Selection web platform.

All of the important components on which the technology of decision support for assessing the competencies of specialists and their selection is based were placed in the settings (Figure 7).

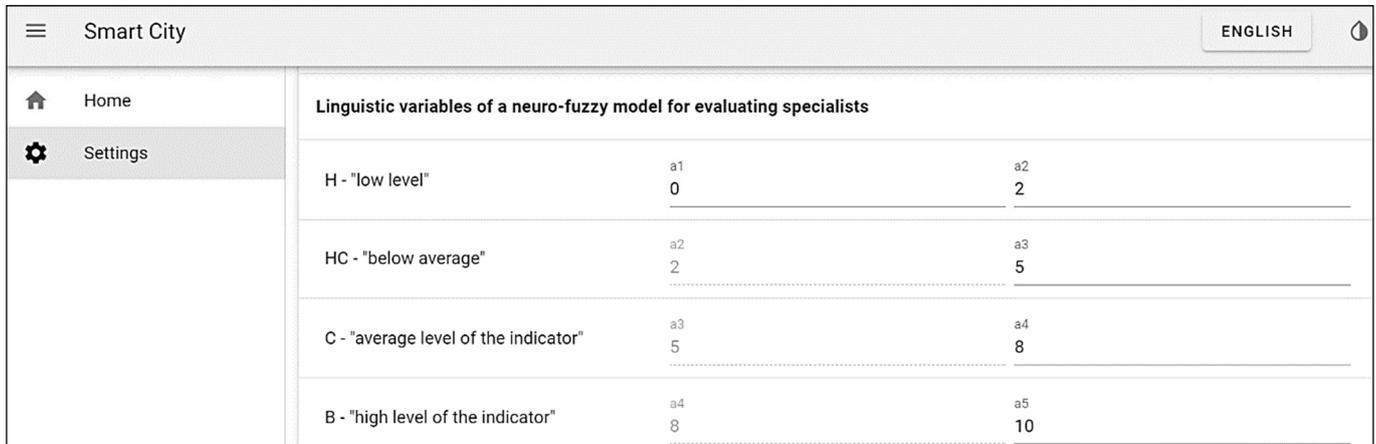


Figure 7. Smart City Concept Personnel Selection web platform setup screen.

In addition, in the setup, it is easy for system analysts to build information evaluation models for various experts, such as members of other commissions. Thus, using the identifier (ID), it is possible to store and protect the adjusted information models on the server for the assessment of various experts and various users (Figure 8).

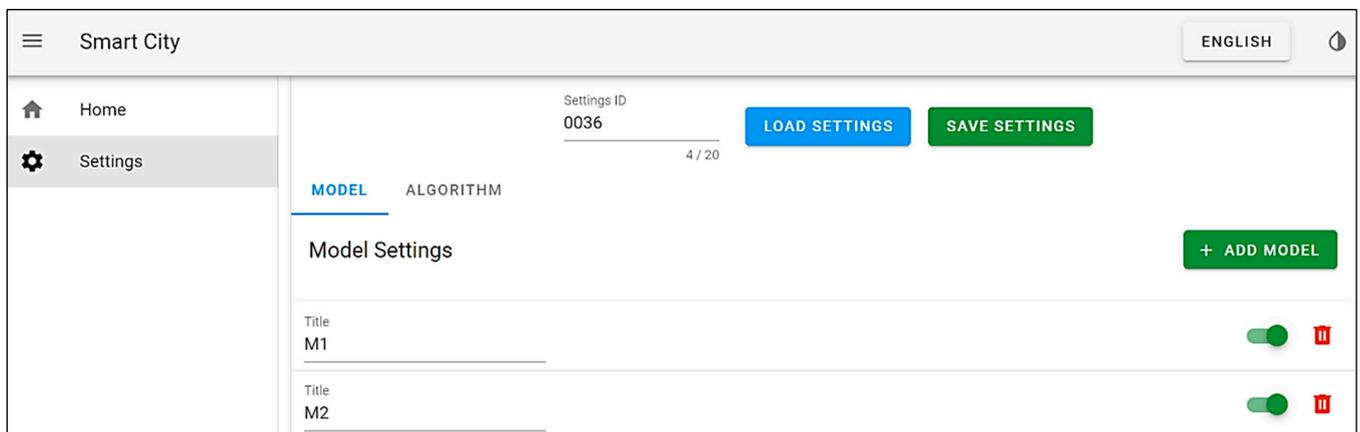


Figure 8. ID for the evaluation information model members of the Transport and Construction Commission.

After selecting the model for assessing the competencies of smart city specialists and entering the input data, we proceeded to the calculations. Based on the initial assessment of the competencies of specialists and the level of rating, further decisions could be made.

The developed technology and web platform is a useful innovative tool for managers in the concept of a smart city when assessing the competencies of specialists and choosing them to solve special or innovative tasks, which reveals the vagueness of input assessments, increases the validity of further management solutions, and uses the analysis of reasoning, experience, and knowledge of managers.

#### 4. Discussion

The result of the study is technology providing decision support for the managers of smart cities for the estimation of the competencies of experts and their selection for special or innovative tasks. For this purpose, a fuzzy model for assessing the competencies of specialists, a hybrid fuzzy model, and a neuro-fuzzy network were developed. The models

are able to assess the levels of competencies of specialists and derive their ranking based on many subjects of management (specialists) of a subject area in the system of a smart city, information models of criteria (groups of criteria) for assessing the competencies of specialists that take into account human impact on the controllability of the smart city system, and a kind of competency assessment model. At the same time, the tools of intellectual analysis of knowledge, a system approach, processing of fuzzy data, and a neuro-fuzzy network are used. The models developed in the work reveal the vagueness of the input estimates and increase the degree of validity of further management decisions by the managers of the municipality regarding the selection of specialists to perform innovative tasks. The output of the models is an assessment of the competencies of specialists and their rating.

Depending on the requirements for the choice of specialists, information methods are proposed that allow to obtain a set of input data for the work of the developed models, namely evaluation of ways of thinking; assessment of theoretical knowledge; assessment of practical knowledge; assessment of knowledge in the theory of pedagogy, psychology and communicative competence; and assessment of narrowly specialized skills. For the proposed information methods, it is necessary to define a set of evaluation criteria for specialists, which will allow assessing their competencies depending on the tasks assigned to them.

The paper proposes an information model for evaluation and selection of an expert group as members of the Transport and Construction Commission. Innovative software support in the form of a web platform has been constructed, which implements the developed methods, algorithms, and information models for application by smart city managers in the evaluation and selection of specialists. The toolkit allows smart city analysts to change decision-making levels, synaptic weights, and the degree of suitability of the specialist to perform tasks in the context of reasoning by municipal managers and to set different sets of criteria for evaluating specialists within the proposed information methods. All of this allows for maximizing the adaptation process and supports decision-making for specific professionals within the functioning of the smart city system. In addition, the study was tested on the example of the evaluation of experts for smart city and green transportation and mobility as members of the Transport and Construction Commission of the city of Košice, using a neuro-fuzzy network.

The advantages of technology to support decision-making by smart city managers in the selection of specialists (management entities) stem from the advantages of the developed models in particular. The model of assessing the competence of specialists is based on different methods of competence assessment of specialists, which uses not only the skills of specialists but also different qualitative properties, and can be used for different inputs and different methods of competencies and criteria, taking into account the wishes of the manager and importance assessment competency methods. The advantage of the fuzzy hybrid model is its ability to take into account the own opinions of municipal managers regarding the specialists in question—if necessary, taking into account other additional indicators. The advantages of a neuro-fuzzy assessment network are the objectivity of expert assessments using input linguistic variables and the “coefficient of confidence” of the specialist’s reasoning regarding their assignment; it is based on a neuro-fuzzy network, which has the ability to change the settings of synaptic scales; upon receipt of experimental data, it is possible to conduct training of the neural network.

The disadvantages of this technology for supporting decision-making include the fact that it is necessary to adequately select membership functions for the criteria of competency models. The membership function in a fuzzy network corresponds to the stage of rough debugging, and this process depends on the partitioning of the interval  $[a_1; a_5]$ , which requires the sampling of reliable experimental data. Additionally, the use of different types of convolutions can lead to ambiguity of the final results.

The mathematical substantiation of the models has already been described in more detail by the authors in [24,25,37,38]. Determining the effectiveness of the developed

models  $M_1$ —fuzzy model, for assessment of the competence of specialists, and  $M_2$ —hybrid fuzzy model, was performed by the number of comparison operations. The number of operations of comparison of alternatives decreases, in comparison with methods using the technology of pairwise comparisons (analytic hierarchy process), by  $100 \cdot (n - 3) / (n - 1)$  percent or in  $(n - 1) / 2$  times ( $n$ —number of evaluation specialists) [22,23]. Thus, at  $n = 4$  by 33.3%, at  $n = 5$  by 50%, at  $n = 11$  by 80%, etc.

The proposed model  $M_3$ —neuro-fuzzy network was tested for different data sets [24,25] and compared with known, widely used artificial neural networks and teaching methods, forming a knowledge base by generating new production rules that do not contradict the rules of the knowledge base of the system, based on the analysis of experimental data. The method of teaching corresponds to a simplified method of fuzzy inference, but it differs in that the knowledge base is not fixed, but supplemented by the receipt of experimental data [24]. The consistency of the new production rule is guaranteed by the procedure of replenishment of the knowledge base.

The rationality of the research results is proved by the advantages of the developed technology. The reliability of the obtained results is ensured by the correct use of the apparatus of fuzzy sets, system approach, and neural-fuzzy networks, which is confirmed by the research results.

## 5. Conclusions

In this study, we researched the actual task of developing technology to support decision-making by the managers of smart cities in assessing the competencies of specialists (management entities) and their selection to solve special or innovative tasks. The following results were obtained:

- For the first time, a model of technology for assessing the competencies of specialists in the system of functioning of a smart city was constructed that takes into account the influence of human factors on the processes of controllability of the system. This technology uses a fuzzy model for assessing the competence of specialists to take into account different models of competencies for linear assessment tasks, a hybrid fuzzy model that takes into account the experience of managers, and a neuro-fuzzy network in modeling nonlinear assessment processes.
- For the first time, a hybrid fuzzy model for assessing the competencies of specialists in the smart city system was developed. The peculiarity of the model is that it is able to derive a normalized assessment of the quality of selection of specialists; uses the analysis of reasoning, experience, and knowledge of smart city managers; reveals the vagueness of input assessments; and increases the validity of further management decisions based on results.
- A fuzzy model of assessment of the competence of specialists and a neuro-fuzzy network were further developed. The fuzzy model is adapted to evaluate different specialists on different indicators, including both quantitative and qualitative properties. The neuro-fuzzy network is adapted to assess the narrowly specialized skills of specialists. For each group of criteria, scales in the form of a linguistically effective assessment were used.
- For the first time, an information model was presented for evaluation and selection of an expert group as members of the Transport and Construction Commission. To do this, we proposed 15 evaluation criteria (divided into three groups) of narrowly specialized skills to evaluate members of the Transport and Construction Commission using the neuro-fuzzy network.
- An example evaluation of five candidate experts for smart city and green transportation and mobility, as potential members of the Transport and Construction Commission of the city of Košice, was conducted using real data.
- An innovative web platform was constructed, which implements the developed methods, algorithms, and information models for application by smart city managers in the evaluation and selection of specialists.

The individual components of the smart city concept will form future work on the separate application areas for innovative modeling and evaluation of measures with an impact on public funds. As we have emphasized, the innovative web platform “Smart City Concept Personnel Selection” can be adapted to different users of municipalities or regional institutions for the transparent selection of qualified personnel for effective decision-making and use of public funds. The innovative web platform will respect local conditions and national law regulations and standards. The importance of innovative solutions to support transparent decision-making and the efficient use of public resources is growing in the context of current European Union support for the development and implementation of country-specific recovery and resilience plans, primarily for the recovery of member states and regions in 2021–2027 after the global COVID-19 pandemic.

Among other things, we also see further research in ablation experiments aimed at extending scientific validation of developed technological models to support the decisions of smart city managers, with this method. According to other researchers, we respect that although an ablation study is of course usually not sufficient to conclude the contributions of different modules, when coupled with other empirical and statistical methods, it can provide valuable insights to practitioners and researchers [49].

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