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Z-Numbers-Based MCDM Approach for Personnel Selection at Institutions of Higher Education for Transportation

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Abstract: Personnel evaluation and selection is an essential part of modern business. Appropriate candidate selection can significantly contribute to companies in terms of increased profit, good culture, reputation, reduced costs, etc. This paper addresses the personnel evaluation and selection problem at the University of Pardubice, Faculty of Transport Engineering (UPCE). Since this is a typical ranking alternative problem where multiple criteria affect the decision, the Z-numbers-based Alternative Ranking Order Method Accounting for the two-step Normalization (AROMAN) is applied. Four Ph.D. candidates are assessed, and the most appropriate is selected to be employed by the UPCE. The Z-numbers fuzzy AROMAN method ranks Ph.D. candidate number four as the most appropriate alternative. To investigate the stability and sensitivity of the Z-numbers fuzzy AROMAN method, the values of parameters β and λ used in the mathematical calculations of the method were changed. The results of sensitivity analysis revealed that the obtained solution is stable. To confirm the robustness of the proposed approach, a comparative analysis is performed. Simple Additive Weighting (SAW), Weighted Product Model (WPM), and Z-number fuzzy TOPSIS were applied. Besides, we applied the fuzzy inferior ratio method as well. The results confirm the high robustness of the proposed Z-numbers fuzzy AROMAN method.

Keywords: fuzzy logic; Z-numbers; personnel evaluation; selection; multi-criteria; decision-making; transportation education

MSC: 03B52; 08A72; 90B50

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1. Introduction

Over the last few years, significant changes have affected the labor market. One of the explanations can undoubtedly be found in the phenomenon of globalization. It has affected businesses both in their macroeconomic and microeconomic environment [1,2]. In the macroeconomic environment, there are mainly changes concerning the demographic structure of job seekers. Nowadays, an increasing number of job seekers, especially in the environment of global corporations, come from all over the world. In this context, it is possible to argue that national borders have fallen. This fact leads to the necessity of respecting different cultural or religious customs [3,4]. In connection with the demographic structure, it is also useful to consider the age structure of people who are currently applying for jobs [5]. At present, and for the first time in history, representatives of all four generations, namely baby boomers, generation X, generation Y, and generation Z, are seeking employment. It is interesting to note that in a few years, representatives of the new generation, named Generation Alpha, will also be among job seekers. This fact places even greater demands on employers in terms of their personnel planning and subsequent recruitment of employees [6]. The age structure is then reflected in the microeconomic environment of the company. Specific examples relate to the selection of new employees among various job applicants, the formation of work teams, the motivation of employees/work teams, the management of employees' careers, etc. Departments of human resource management play a significant role in all these activities [7]. It is crucial because a poor selection of employees can lead to a disruption in the performance of work teams. This ultimately affects the value of the company's human capital, one of the most significant components influencing the overall value of the company [8].

Businesses, as well as institutions in the public sector, are currently also facing the impact of ever-faster technological progress. Interestingly, within personnel selection, technological development has a much greater impact on so-called soft skills than on hard skills, which are expected or even required from job applicants. This is mainly because most businesses do not require skills in operating technological solutions, but rather require knowledge that enables quality interpretation of information and data acquired through technological solutions [9].

The phenomenon of globalization and technological development undoubtedly affect the employee selection process, making it much more demanding. Human resource departments should consider a wide range of differences, specifications, and requirements for selecting quality employees [10]. On the other hand, modern technology provides possibilities for overcoming this challenge in the personnel selection process. Currently, it is possible to use software solutions that enable solving multicriteria decision-making problems. These solutions can be seen as decision-support tools in determining suitable employees based on the defined criteria, including cases where multiple criteria are characterized by different weights of importance [11].

This article aims to demonstrate the use of a multi-criteria decision-making (MCDM) approach through a specific case study and to propose the original methodology that would be applied for the first time in the literature. In this paper, we apply the Z-numbers fuzzy Alternative Ranking Order Method Accounting for the Two-Step Normalization (AROMAN) method for solving the personnel selection problem at the University of Pardubice, Faculty of Transport Engineering (UPCE). This method couples both linear and vector normalization techniques to obtain a precise data structure that is further used in the final ranking of alternatives. In the presented case study, the UPCE is looking for a new Ph.D. candidate to be engaged in the Management, Marketing, and Logistics department. During the competition, four of the most appropriate candidates were shortlisted. A decision about which candidate is the most adequate for the given position can be considered a challenging multicriteria task; therefore, the authors of this paper decided to propose the implementation of the mentioned MCDM method. We concluded that the MCDM approach based on Z-numbers would be particularly convenient in this case. A motive for such a conclusion lies in the fact that Z-numbers are based on the concept of reliability of information [12]. They are described by two components in the form of fuzzy numbers; the first describes a restriction on the values that a real-valued uncertain variable can take, and the second is a measure of certainty. The adequacy of this method choice for solving the personnel selection problem can be illustrated in the following way. One of the evaluation criteria in our case study is the time required to complete previous study levels. If this criterion would be considered just as an absolute, i.e., crisp value, such evaluation of candidates can be considered as superficial. Much better insight can be gained by discussing with a candidate, to find out the circumstances of her/his life during studies, such as the case of working and studying at the same time, or taking care of some family member, etc. In this way, the employer would much better assess the efficiency of the candidate; however, the achieved impression would be difficult to express by crisp values, but rather with fuzzy numbers. Besides, to contribute to higher reliability of the evaluation process, based on the concrete conversation, a recruitment consultant can assess the certainty of obtained answers, which is covered by the methodology based on fuzzy Z-numbers.

The main contributions of this paper can be structured as follows: (1) The original multicriteria approach based on Z-numbers fuzzy AROMAN is proposed for the first time in the literature; (2) The personnel selection problem is solved by applying a novel perspective considering the used criteria specifically designed for recruitment procedure in the field of transportation; (3) The implementation of the proposed methodology is illustrated in solving a real-life decision-making problem at the UPCE.

The rest of the paper is structured as follows: Section 2 is the overview of the existing literature about used methods for solving the personnel selection problem. Section 3 describes the Z-numbers fuzzy AROMAN method. Section 4 applies the Z-numbers fuzzy AROMAN method in the case of UPCE and discusses the results, while Section 5 concludes the paper and gives possible future directions.

2. Literature Review on MCDM Methods for Personnel Selection

The review of methods used for personnel selection was prepared using scientific outputs indexed in the Web of Science database. The review includes outputs that meet the following criteria: the title of the output contains "personnel selection" and in the other searching field, "MCDM" or "multicriteria" is indicated; the document type is an article or review article; the output was published between 2010–2023. A total of 41 outputs were identified, of which 5 were excluded because, despite matching in keywords, they did not correspond to the examined issue thematically.

The literature review focused primarily on identifying methods used for personnel selection in individual outputs from the Web of Science database. The number of methods used for personnel selection within each output and their overall frequency across all analyzed outputs were also analyzed. A total of 36 outputs were analyzed, within which 41 scientific methods were used for personnel selection either separately or in combination. In most outputs (25 out of 36), multiple methods were used for personnel selection. Only 11 outputs used a single method for personnel selection. The study conducted by Yalcin and Pehlivan [13] combined various methods for personnel selection, utilizing a total of six methods. The overview of the frequency of the methods used is presented in Table 1; however, only the methods used three or more times are listed.

An overview of the methods used for personnel selection is provided in Table 2. The majority of the used methods (22 out of 41) are based on the application of fuzzy logic. Furthermore, the conducted research shows that none of the analyzed studies utilized the AROMAN method, which is the subject of this article.

Based on the literature review considering the criteria used for personnel selection, it can be stated that there is no consensus in the scientific community on this issue. Different criteria are used in the selection of an employee for managing IT infrastructure, for the position of HR director, etc. The studies that deal with the issue of selection use various criteria, which are often interwoven across studies. These criteria are then evaluated by different weights, representing in this way the inputs for multicriteria decision-making.

For this article, outputs from the longitudinal study, The Job Outlook Survey, conducted by the National Association of Colleges and Employers (NACE), are utilized. Each year, NACE surveys its employer members about their hiring plans and other employment-related issues to project the market for new college graduates for the current class and to assess various conditions that may influence that market.

Throughout 2013–2022, ten studies from NACE were presented. To provide an overview of NACE study methodologies, the methodology for The Job Outlook Survey 2020 is presented. Data for the Job Outlook 2020 survey were collected from 1 August 2019, through 30 September 2019. This year's data collection not only surveyed 905 NACE employer members but also 2229 employer organizations that were non-members. A total of 150 surveys were returned, 115 were NACE members, and the remaining 35 were non-members. Table 3 displays the changes in criteria that were considered crucial by leading employers within the NACE survey for the selection process of employees.

Table 1. Frequency of use of particular scientific methods for personnel selection.

Method	Number of Papers	Authors
Fuzzy-TOPSIS	6	- Yalçin and Pehlivan [13] - Efe and Kurt [14] - Sang, Liu and Qin [15] - Afshari Yusuff and Derayatifar [16] - Boran, Genç and Akay [17] - Dursun and Karsak [18]
TOPSIS	5	- Danişan, Özcan and Eren [19] - Nabeeh, Smarandache, Abdel-Basset, El-Ghareeb and Aboelfetouh [20] - Jasemi and Ahmadi [21] - Chang [22] - Dağdeviren [23]
Fuzzy ARAS	4	- Mishra, Sisodia, Raj Pardasani and Sharma [24] - Yalçin and Pehlivan [13] - Keršuliene and Turskis [25] - Karabasevic, Zavadskas, Turskis and Stanujkic [26]
Fuzzy SWARA	4	- Karabasevic, Zavadskas, Stanujkic, Popovic and Brzakovic [27] - Heidary Dahooie, Beheshti Jazan Abadi, Vanaki and Firoozfar [28] - Yildirim and Inegol [29] - Karabasevic, Zavadskas, Turskis and Stanujkic [26]
AHP	3	- Danişan, Özcan and Eren [19] - Nabeeh, Smarandache, Abdel-Basset, El-Ghareeb and Aboelfetouh [20] - Bucak, Mollaoğlu and Dinçer [30]
Fuzzy DEMATEL	3	- Özgörmüş, Şenocak and Gören [31] - Kilic, Demirci and Delen [32] - Kabak [33]
Fuzzy VIKOR	3	- Krishankumar, Premaladha, Ravichandran, Sekar, Manikandan and Gao [34] - Liu, Qin, Mao and Zhang [35] - Alidrisi [36]
Fuzzy EDAS	3	- Yalçin and Pehlivan [13] - Karabasevic, Zavadskas, Stanujkic, Popovic and Brzakovic [27] - Phan and Nguyen [37]
OWA/IPA	3	- Wen, Chang and Lai [38] - Asan and Soyer [39] - Dursun and Karsak [18]

Note: TOPSIS—Technique for Order Preference by Similarity to Ideal Solution, ARAS—Additive Ratio Assessment, SWARA—Stepwise Weight Assessment Ratio Analysis, DEMATEL—DEcision-MAking Trial and Evaluation Laboratory, VIKOR—VlseKriterijumska Optimizacija I Kompromisno Resenje [Multi-Criteria Optimization and Compromise Solution], EDAS—Evaluation Based on Distance from Average Solution, OWA—Order Weighted Averaging operator, IPA—Importance-Performance Analysis, AHP—Analytic Hierarchy Process.

Table 2. Overview of the scientific methods used for personnel selection and the year of publication.

Method	Authors	Year of Publication
TOPSIS	Dağdeviren [23]; Chang [22]; Jasemi and Ahmadi [21]; Nabeeh, Smarandache, Abdel-Basset, El-Ghareeb and Aboelfetouh [20]; Danişan, Özcan and Eren [19]	2010; 2015; 2018; 2019; 2022
Fuzzy-TOPSIS	Dursun and Karsak [18]; Boran, Genç and Akay [17]; Afshari Yusuff and Derayatifar [16]; Sang, Liu and Qin [15]; Efe and Kurt [14]; Yalçin and Pehlivan [13]	2010; 2011; 2013; 2015; 2018; 2019
OWA/IPA	Dursun and Karsak [18]; Wen, Chang and Lai [38]; Asan and Soyer [39]	2010; 2018; 2022
ANP	Dağdeviren [23]	2010

Table 2. *Cont.*

Method	Authors	Year of Publication
Fuzzy-GRA	Zhang and Liu [40]; Özgörmüş, Şenocak and Gören [31]	2011; 2021
Fuzzy-MULTIMOORA	Baležentis, Baležentis and Brauers [41]	2012
CWW + Per-C + LWA	Safarzadegan Gilan, Sebt and Shahhosseini [42]	2012
SDV-MOORA	El-Santawy and Ahmed [43]	2013
Fuzzy-AHP	Afshari Yusuff and Derayatifar [16]	2013
SDW	El-Santawy and Ahmed [43]	2013
Fuzzy-ANP	Afshari Yusuff and Derayatifar [16]; Kabak [33]	2013; 2013
Fuzzy-DEMATEL	Kabak [33]; Kilic, Demirci and Delen [32]; Özgörmüş, Şenocak and Gören [31]	2013; 2020; 2021
Fuzzy-HDMSOW'S	Saad, Ahmad, Abu and Jusoh [44]	2014
Fuzzy-ARAS	Mishra, Sisodia, Raj Pardasani and Sharma [24]; Yalçin and Pehlivan [13]; Keršuliene and Turskis [25]; Karabasevic, Zavadskas, Turskis and Stanujkic [26]	2014; 2016; 2019; 2020
Fuzzy-DELPHI	Chang [22]	2015
Fuzzy-VIKOR	Liu, Qin, Mao and Zhang [35]	2015
KEMIRA	Kosareva, Zavadskas, Krylovas, Dadelo [45]	2016
Fuzzy-SWARA	Karabasevic, Zavadskas, Stanujkic, Popovic and Brzakovic [27]; Heidary Dahooie, Beheshti Jazan Abadi, Vanaki and Firoozfar [28]; Yildirim and Inegol [29]; Karabasevic, Zavadskas, Turskis and Stanujkic [26]	2016; 2018; 2018; 2023
Fuzzy-ARAS-G	Heidary Dahooie, Beheshti Jazan Abadi, Vanaki and Firoozfar [28]	2018
Fuzzy-ELECTRE	Jasemi and Ahmadi [21]	2018
Fuzzy-TODIM	Ji, Zhang and Wang [46]	2018
Fuzzy-EDAS	Karabasevic, Zavadskas, Stanujkic, Popovic and Brzakovic [27]; Yalçin and Pehlivan [13]; Phan and Nguyen [37]	2018; 2019; 2022
Fuzzy-WASPAS	Yalçin and Pehlivan [13]	2019
Fuzzy-COPRAS	Yalçin and Pehlivan [13]	2019
Fuzzy-CODAS	Yalçin and Pehlivan [13]	2019
AHP	Nabeeh, Smarandache, Abdel-Basset, El-Ghareeb and Aboelfetouh [20]; Danişan, Özcan and Eren [19]; Bucak, Mollaoğlu and Dinçer [30]	2019; 2022; 2023
ELECTRE	Kilic, Demirci and Delen [32]	2020
Fuzzy-PIPRECIA-G	Ulutaş, Popovic, Stanujkic, Karabasevic, Zavadskas and Turskis [47]	2020
Fuzzy-OCRA-G	Ulutaş, Popovic, Stanujkic, Karabasevic, Zavadskas and Turskis [47]	2020
Fuzzy-QFD	Özgörmüş, Şenocak and Gören [31]	2021
PROMETHEE	Danişan, Özcan and Eren [19]	2022
GA-GDEMATEL	Phan and Nguyen [37]	2022
PLEAS + DAAs + LGBWM	Li, He and Wang [11]	2022
Weighted Bonferroni-OWA-based CBD	Asan and Soyer [39]	2022
IFNs	Li, He and Wang [11]; Turk [48]	2022; 2022
Fuzzy-AROMAN	Our study	2023

Note: AHP—Analytic Hierarchy Process, ANP—Analytic Network Process, ARAS—Additive Ratio Assessment, ARAS-G—Grey Additive Ratio Assessment, CODAS—COmbinative Distance-based Assessment, COPRAS—COmplex PRoportional ASsessment, CWW—Computing With Words, DAAs—Data Analytics Algorithms, DEMATEL—DEcision-MAking Trial and Evaluation Laboratory, EDAS—Evaluation Based on Distance from Average Solution, ELECTRE—Elimination and Choice Expressing the Reality, GA-GDEMATEL—Hybrid Genetic Algorithm and Decision-Making Trial and Evaluation Laboratory, GRA—Grey Relationship Analysis, HDMSOW'S—Hamming Distance Method with Subjective and Objective Weights, IFNs—Intuitionistic Fuzzy Numbers, IPA—Importance-Performance Analysis, KEMIRA—KEmeny Median Indicator Rank Accordance, KM—Karnik-Mendel algorithm, LGBWM—Linear Group Best–Worst Method, LWA—Linguistic Weighted Average, MULTIMOORA—Multi-Objective Optimization based on Ratio Analysis, MULTIMOORA—Multi-Objective Optimization based on Ratio Analysis For Group decision making, OCRA-G—Grey Operational Competitiveness Rating, OWA—Order Weighted Averaging operator, Per-C—Perceptual Computer, PIPRECIA-G—Grey Pivot Pairwise Relative Criteria Importance Assessment, PLEAS—Personnel Evaluation And Selection system, PROMETHEE—Preference Ranking Organization Method For Enrichment Evaluation, QFD—Quality Function Deployment, SDW—Standard Deviation Weight method, SWARA—Stepwise Weight Assessment Ratio Analysis, TODIM—TOmada de Decisão Iterativa Multicrit'erio [Interactive Multi-criteria Decision Making], TOPSIS—Technique for Order Preference by Similarity to Ideal Solution, Weighted Bonferroni-OWA-based CBD—Weighted Bonferroni Order Weighted Averaging based on an extended cumulative belief degree.

Table 3. Weight Attributes (%) employers seek on a candidate's resume (2013–2022).

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Leadership	80.6	76.0	77.8	80.1	68.9	72.6	67.4	72.5	67.8	60.3
Problem-solving skills	75.3	70.3	70.9	70.2	77.3	82.9	80.9	91.2	79.0	85.5
Communication skills (written)	74.7	76.6	73.4	70.2	75.0	80.3	82.0	77.5	72.7	73.3
Ability to work in a team	74.2	71.4	77.8	78.9	78.0	82.9	78.7	86.3	81.0	76.3
Strong work ethic	73.1	72.0	70.4	68.9	72.0	68.4	70.8	80.4	65.4	71.0
Analytical/quantitative skills	72.0	73.1	68.0	62.7	64.4	67.5	71.9	79.4	76.1	78.6
Communication skills (verbal)	67.2	68.6	67.0	68.9	70.5	67.5	67.4	69.6	73.2	58.8
Initiative	66.7	68.6	66.5	65.8	65.9	67.5	74.2	69.6	67.8	72.5
Computer skills	64.5	62.9	62.6	55.3	49.2	48.7	55.1	54.9	59.0	52.7
Technical skills	64.0	61.1	67.5	59.6	56.8	59.8	59.6	65.7	67.8	64.9
Detail-oriented	57.5	65.7	57.6	52.8	62.1	64.1	59.6	67.6	56.1	62.6
Flexibility/adaptability	57.5	59.4	62.1	60.9	63.6	60.7	58.4	62.7	65.9	63.4
Interpersonal skills	57.0	58.3	60.6	58.4	58.3	54.7	52.8	62.7	57.6	56.5
Organizational ability	49.5	42.9	42.4	48.4	47.7	48.7	43.8	47.1	39.0	42.0
Friendly/outgoing personality	33.3	32.6	29.1	35.4	25.8	27.4	22.5	29.4	25.9	21.4
Strategic planning skills	32.8	33.7	35.0	26.7	37.9	39.3	38.2	45.1	28.3	38.2
Creativity	25.8	21.7	18.2	23.6	21.2	29.1	23.6	23.5	29.8	26.7
Entrepreneurial skills/risk-taker	25.8	23.4	25.1	18.6	19.7	19.7	16.9	24.5	19.5	14.5
Tactfulness	23.7	22.9	23.2	20.5	25.8	22.2	25.8	24.5	17.6	19.1
Foreign language fluency	XXX	XXX	XXX	XXX	4.5	4.3	11.2	2.9	3.4	5.3

For this research, the authors identified the following criteria as crucial in the concrete case: C1: Time required to complete previous study levels; C2: Ability to solve transportation problems; C3: Foreign language; C4: Computer skills, and C5: Communication and presentation skills.

By summarizing the results of the literature review, the following conclusions have been reached:

(1) Multi-criteria decision-making methods are used in a wide range of scientific articles across many research fields. There are numerous articles dealing with the use of multi-criteria decision-making methods in personnel selection published in the Web of Science database between the years 2010–2023.

(2) The Fuzzy-TOPSIS method was most used in personnel selection, specifically in six articles. The highest number of various MCDM methods applied in personnel selection was recorded in an article by Yalcin and Pehlivan [13]. In their article, the following methods were implemented: Fuzzy-TOPSIS, Fuzzy ARAS, Fuzzy EDAS, Fuzzy-CODAS, Fuzzy-WASPAS, and Fuzzy-COPRAS.

(3) Many authors in their articles use fuzzy logic-based methods for personnel selection. However, none of the authors have used the AROMAN method for personnel selection, to date. To date, the AROMAN method has only been used a few times in other fields [49–53]. However, none of these papers combine the AROMAN method with fuzzy Z-numbers, which is the methodology of this paper.

3. Methods

The developed MCDM model based on Z-numbers and its algorithm are presented in this section. In the following text, the preliminaries on the Z-numbers and the step-by-step procedure of the proposed approach are presented.

3.1. Z-Numbers

A Z-number indicates the degree of ambiguity in the data and the reliability of the data source. A set of fuzzy numbers that is ordered, $Z = (\widetilde{A}, \widetilde{B})$, is a common representation of the Z-numbers, where the fuzzy value for identifying a variable's state is represented by $\widetilde{A}$, and the second element is the fuzzy number $\widetilde{B}$ describing the reliability of $\widetilde{A}$ [54]. Based on the previous explanation, the mathematical formulation of the Z-number is presented as follows [55].

Definition 1. *Let $Z = (\widetilde{A}, \widetilde{B})$ be a Z-number. The membership function of Z, $\widetilde{A}$ is described in Equation (1).*

$$R(X): \ X \text{ is } \widetilde{A}. \tag{1}$$

where X is a restriction function and is represented as in Equation (2).

$$R(X): X \text{ is } \widetilde{A} \rightarrow \mathrm{Poss}(X = u) = \mu_{\widetilde{A}}(u) \tag{2}$$

where $\mu_{\widetilde{A}}$ is $\widetilde{A}$'s membership function, and u is a generic X value.

The reliability function of Z is a fuzzy number $\widetilde{B}$. It is described in Equations (3) and (4).

$$R(X) = \widetilde{B}: X \text{ is } p. \tag{3}$$

$$R(X) =: X \text{ is } p \rightarrow \mathrm{Prob}(u \leq X \leq u + du) = \mathrm{p}(u)du \tag{4}$$

where X is p, and p is the probability density function of X.

Through the implementation of Z-numbers, the ability to gather not only vagueness in the data but also the hesitancy source of data can be applied to the conducted methodology. Thus, they provide more applicable and flexible results than the ordinary fuzzy sets. Based on the advantages, we employed Z-number concepts within the AROMAN method for the given problem.

3.2. Z-Numbers Fuzzy AROMAN Technique

The AROMAN method was developed as MCDM for use in decision-making problems. This method combines the normalized data from the two-stage normalization and generates an average matrix from it [49,50]. The classical AROMAN method has been improved by extending it with ordinary fuzzy numbers to improve its applicability [51–53]. However, by integrating fuzzy sets into the model, it is not possible to reflect the hesitations of decision-makers when making their judgments. For this reason, the Fuzzy AROMAN method in the previous study has been taken one step further and extended with Z-numbers to include the hesitancy of decision-makers. As a result, the AROMAN method is integrated with Z-number fuzzy for the first time to solve the considered problem. The steps of the integrated method are described as follows.

Step 1. Create the initial decision-making matrix ($\widetilde{D}$) by using the input data, which are obtained by expert evaluation. Mathematical repression of $\widetilde{D}$ is presented in Equation (5).

$$\widetilde{D} = \begin{bmatrix} (\widetilde{x}_{ij}, \widetilde{r}_{ij}) & \cdots & (\widetilde{x}_{ij}, \widetilde{r}_{ij}) & \cdots & (\widetilde{x}_{ij}, \widetilde{r}_{ij}) \\ (\widetilde{x}_{ij}, \widetilde{r}_{ij}) & \cdots & (\widetilde{x}_{ij}, \widetilde{r}_{ij}) & \cdots & (\widetilde{x}_{ij}, \widetilde{r}_{ij}) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (\widetilde{x}_{ij}, \widetilde{r}_{ij}) & \cdots & (\widetilde{x}_{ij}, \widetilde{r}_{ij}) & \cdots & (\widetilde{x}_{ij}, \widetilde{r}_{ij}) \end{bmatrix}, \ (i = 1, 2, \ldots, m), \ (j = 1, 2, \ldots, n), \tag{5}$$

where m is the number of alternatives, n is number of criteria, $\widetilde{x}_{ij}$ is membership function, and $\widetilde{r}_{ij}$ is the reliability function.

To convert the expert's evaluations to fuzzy numbers, Table 4 is designed. It consists of linguistic terms and their corresponding fuzzy numbers [54,55]. These fuzzy numbers are used to represent linguistic terms in mathematical operations.

Table 4. Linguistic terms for assessment of the membership functions.

Linguistic Variable	Fuzzy Number
Very low (VL)	(1.0, 1.0, 2.0)
Low (L)	(1.0, 2.25, 3.5)
Medium-low (ML)	(2.25, 3.5, 4.75)
Medium (M)	(3.5, 4.75, 6.0)
Medium-high (MH)	(4.75, 6.0, 7.25)
High (H)	(6.0, 7.25, 8.5)
Very high (VH)	(8.5, 8.5, 10.0)

Moreover, for the assessment of the reliability of the membership functions, another scale is constructed, which is presented in Table 5.

Table 5. Linguistic terms for the assessment of reliability functions.

Linguistic Variable	Fuzzy Number
Very weakly reliable (VWR)	(0.3, 0.4, 0.5)
Weakly reliable (WR)	(0.4, 0.5, 0.6)
Moderately reliable (MR)	(0.5, 0.6, 0.7)
Strongly reliable (SR)	(0.6, 0.7, 0.8)
Very strongly reliable (VSR)	(0.7, 0.8, 0.9)
Absolutely reliable (AR)	(0.8, 0.9, 1.0)

Step 2. Convert linguistic terms to their corresponding values by using Tables 4 and 5.

Step 3. Fuse the membership and reliability functions by using Equation (6).

$$\tilde{A}_F\left(\tilde{f}_{ij}\right) = \mu_A^{\alpha}, \tag{6}$$

where $\alpha = \frac{\int x\mu_{\tilde{B}}(x)dx}{\int \mu_{\tilde{B}}(x)dx}$, and $\tilde{f}_{ij} = (\mu_{\tilde{f}}^L, \mu_{\tilde{f}}^M, \mu_{\tilde{f}}^U)$.

Following these steps, data normalization should be conducted. As mentioned in Steps 4 and 5, the Z-numbers fuzzy AROMAN approach applies two types of normalization techniques. During normalization, the type of criterion (benefit or cost) is not taken into account. This is solved in the further steps.

Step 4. Apply the min-max normalization by using Equation (7).

$$\tilde{t}_{ij} = \frac{\tilde{x}_{ij} - min_i\tilde{x}_{ij}}{max_i\tilde{x}_{ij} - min_i\tilde{x}_{ij}}, \tag{7}$$

where $\tilde{t}_{ij}$ is the result of the min-max normalization process.

Step 5. Apply the vector normalization by using Equation (8).

$$\tilde{t}^*_{ij} = \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^{m}\tilde{x}^2_{ij}}}, (i = 1,\ 2,\ \ldots, m), \tag{8}$$

where $\tilde{t}^*_{ij}$ is the result of the vector normalization process.

Step 6. Aggregate the results of normalization techniques by using Equation (9).

$$\tilde{t}^{norm}_{ij} = \frac{\beta\tilde{t}_{ij} + (1-\beta)\tilde{t}^*_{ij}}{2},\ (i = 1,\ 2,\ \ldots, m),\ (j = 1,\ 2,\ \ldots,\ n), \tag{9}$$

where $\tilde{t}_{ij}^{norm}$ is a parameter of the aggregated averaged normalization. β is the weighting factor ranging from 0 to 1.

Step 7. Obtain the weighted aggregated normalized decision-making matrix by using Equation (10). The sum of the weights should be equal to 1.

$$\widehat{\widetilde{t}}_{ij} = w_j \cdot \tilde{t}_{ij}^{norm} \;\; (i = 1,2,\ldots,m),\; (j = 1,2,\ldots,n), \tag{10}$$

where $\widehat{\widetilde{t}}_{ij}$ is the weighted aggregated normalization, and w_j is the weight of the criterion j.

Step 8. Summation of weighted aggregated normalized decision-making matrix per the criteria type by using Equations (11) and (12).

$$\left(\widetilde{L}_i = \sum_{j=1}^{n} \widehat{\widetilde{t}}_{ij}^{(min)^n}\right),\; (i = 1,2,\ldots,m),\; (j = 1,2,\ldots,n). \tag{11}$$

$$\left(\widetilde{A}_i = \sum_{j=1}^{n} \widehat{\widetilde{t}}_{ij}^{(max)^n}\right),\; (i = 1,2,\ldots,m),\; (j = 1,2,\ldots,n). \tag{12}$$

Step 9. Transform the obtained $\widetilde{L}_i$ and $\widetilde{A}_i$ values by adopting a λ value as in Equations (13) and (14).

$$\widehat{\widetilde{L}}_i = \widetilde{L}_i^{\lambda} = \left(\sum_{j=1}^{n} \widehat{\widetilde{t}}_{ij}^{(min)}\right)^{\lambda},\; (i = 1,2,\ldots,m),\; (j = 1,2,\ldots,n), \tag{13}$$

$$\widehat{\widetilde{A}}_i = \widetilde{A}_i^{1-\lambda} = \left(\sum_{j=1}^{n} \widehat{\widetilde{t}}_{ij}^{(max)}\right)^{1-\lambda},\; (i = 1,2,\ldots,m; j = 1,2,\ldots,n), \tag{14}$$

where λ indicates the criterion type's coefficient degree. If we denote the weights of the min type criteria by w_j^{min}, then the parameter is calculated by using Equation (15).

$$\lambda = \sum_{j=1}^{n} w_j^{min}, (\, j = 1,2,\ldots.,n). \tag{15}$$

Step 10. Calculate the final score of the alternatives (R_i) by using Equation (16). Then, the ranking of alternatives is obtained in descending order of the R_i.

$$R_i = e^{\widehat{\widetilde{A}}_i - \widehat{\widetilde{L}}_i} \tag{16}$$

4. Case Study and Results

This section is divided into four subsections. The first relates to the description of the considered case study. The second part is devoted to solving the problem of the most suitable Ph.D. candidate selection by the Z-numbers fuzzy AROMAN technique. Then, sensitivity analysis is performed in the third subsection. Finally, a comparative analysis is completed in the fourth part.

4.1. Description of Considered Multi-Criteria Problem

The problem that we are solving is related to the recruitment procedure, i.e., selection of the most appropriate Ph.D. candidate that would be hired by the Faculty of Transport Engineering, University of Pardubice, Czech Republic. Firstly, we will introduce the system of higher education in the considered case.

The fundamentals of Czech higher education date back to the fourteenth century. Emperor Charles IV founded a university in Prague in 1348. This was the oldest academic institution in Central Europe. Today, it is called the Charles University.

The University of Pardubice is a prominent institution of higher education and research located in the city of Pardubice, Czech Republic. The position is shown in Figure 1. It was established in 1950 as a college dedicated to chemical engineering due to the region's industrial importance in chemical production. Over the years, it has expanded into a comprehensive university with a range of faculties and fields of study. The University of Pardubice is organized into seven faculties: Faculty of Chemical Technology, Faculty of Economics and Administration, Faculty of Electrical Engineering and Informatics, Faculty of Arts and Philosophy, Faculty of Health Studies, Faculty of Transport Engineering, and Faculty of Restoration.

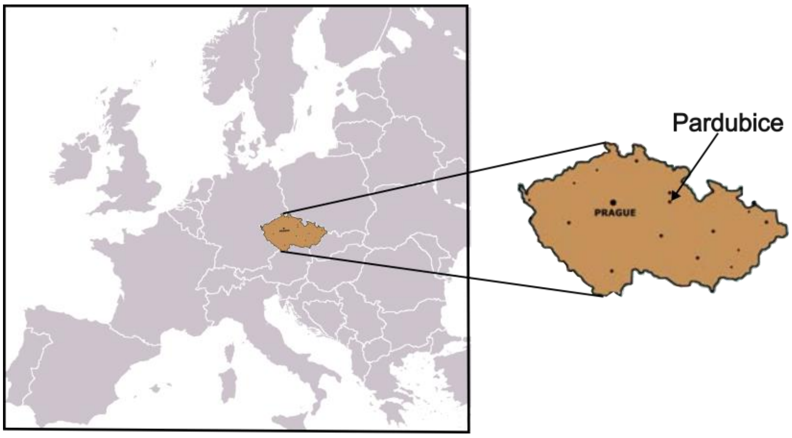

Figure 1. Position of the Czech Republic and Pardubice city.

The Faculty of Transport Engineering at the University of Pardubice specializes in the study and research of transportation systems, logistics, and technology. It is recognized for its comprehensive approach to transport education, encompassing rail, road, air, and water transport modes, as well as the interplay between them in multimodal transport systems.

The faculty offers a range of undergraduate, graduate, and postgraduate programs tailored to equip students with the necessary skills and knowledge for the transport industry. The programs typically cover subjects like transport infrastructure, vehicle engineering, transport safety, logistics, traffic modeling and management, and transport environmental impacts. Research is a pivotal component of the faculty's activities. It has established itself as a hub for innovation in transport technology and systems. The faculty conducts research in several key areas, such as transport infrastructure design and maintenance, intelligent transport systems, safety analysis, and sustainable transport development.

The Faculty of Transport Engineering employs a total of 94 academic staff and 4 scientific workers. The faculty has 1180 students enrolled in bachelor's, master's, and doctoral degree programs in various forms of study (full-time and part-time). In the bachelor's programs, there are 615 students in full-time study and 255 students in part-time study. In the master's programs, there are 135 students in full-time study and 130 students in part-time study. In the doctoral programs, there are 20 students in full-time study and 25 students in part-time study. The organization of the Faculty of Transport Engineering is presented in Figure 2.

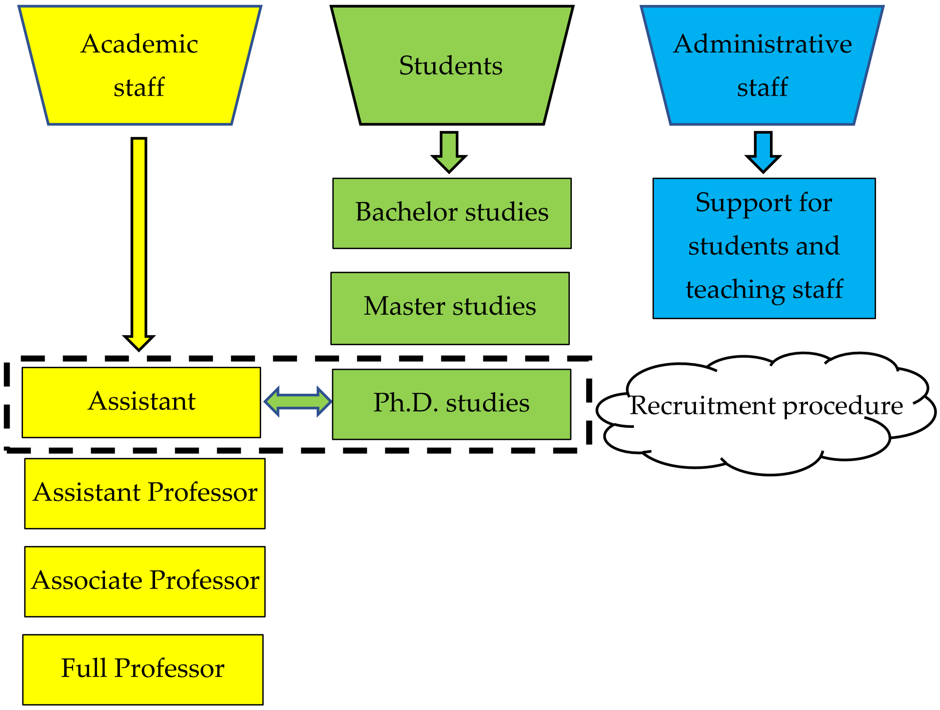

Figure 2. Organization of the Faculty of Transport Engineering considering employees.

As in any other institution that strives to achieve high goals in development, the issue of young academic staff employment is of crucial importance. This fact was a motive to demonstrate the proposed methodology application in such a case study. Therefore, the Faculty of Transport Engineering at the University of Pardubice is searching for the most suitable Ph.D. candidate to be employed as a new Faculty member. During the competition, four of the most appropriate candidates were shortlisted. Since the candidates can be evaluated by various criteria, the considered problem can be seen as a typical MCDM problem. One of the recently developed MCDM methods that will be applied to this case is the AROMAN method, i.e., its extension in the Z-numbers fuzzy environment. By integrating Z-numbers fuzzy sets into the model, it is possible to reflect the hesitations of decision-makers when making their judgments. This method couples both linear and vector normalization techniques to obtain precise data structure to finally rank the alternatives. The selection procedure is done according to the following criteria: time required to complete previous study levels, ability to solve transportation problems, foreign language fluency, computer skills, and communication and presentation skills. The schematic description of the problem is presented in Figure 3.

4.2. Results of Z-Number Fuzzy AROMAN Technique

The assessed candidates can be considered as alternatives marked by A1, A2, A3 and A4. The criteria for evaluation are identified as C1, C2, C3, C4 and C5.

The Z-numbers fuzzy AROMAN method to be applied for the identified problem was applied as in the steps mentioned above. The software used for the calculation purposes was MS Excel.

Step 1: Experts evaluate the alternatives using linguistic terms and we obtained the initial decision-making matrix as represented in Table 6 according to their responses. In the concrete case, the procedure of data collection was performed by three experts who are members of UPCE. However, it should be emphasized that these experts did not provide data for all criteria, but just for those that fall under their professional specialty. This approach is slightly different from the generally used approach in the MCDM field where experts provide answers for all considered criteria; however, the authors of this paper considered the division in responsibilities between experts per criteria as useful in the concrete case, leading to more objective results.

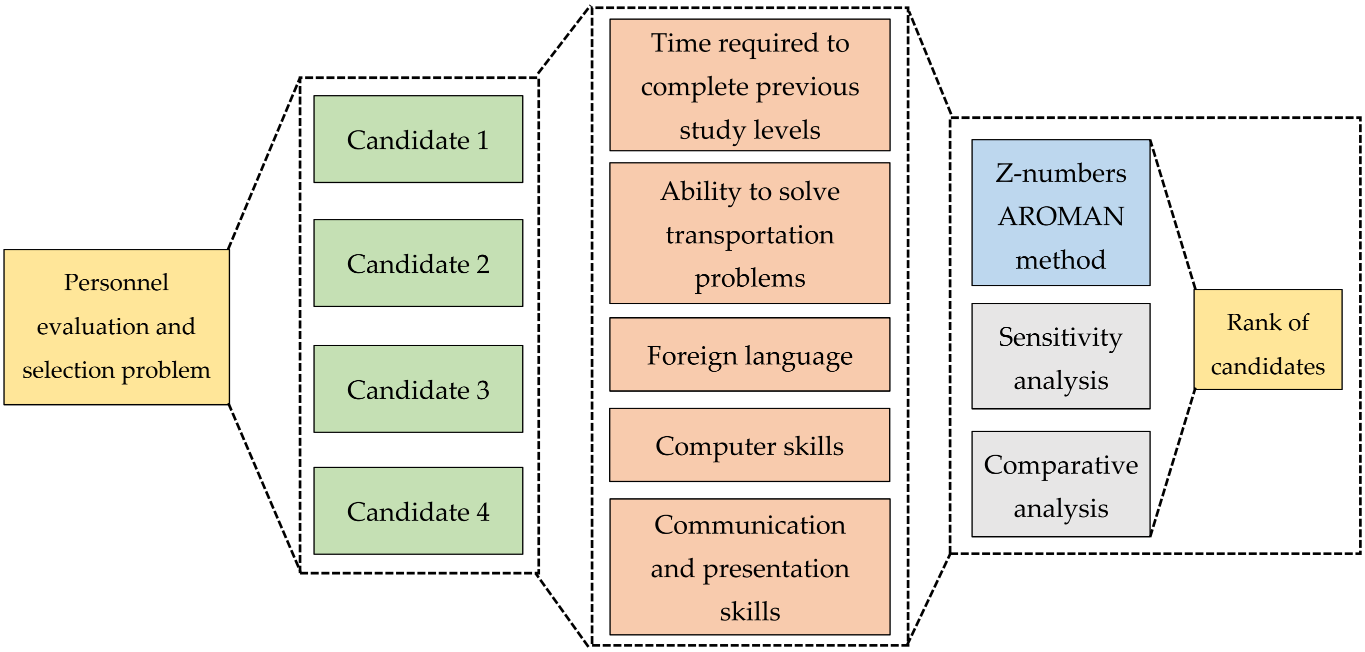

Figure 3. Configuration of the research.

Table 6. An initial decision-making matrix.

	C1	C2	C3	C4	C5
A1	(MH, AR)	(ML, MR)	(VL, AR)	(ML, SR)	(ML, VSR)
A2	(H, VSR)	(M, SR)	(ML, AR)	(M, WR)	(MH, VWR)
A3	(VH, SR)	(ML, VSR)	(VL, SR)	(M, AR)	(M, MR)
A4	(MH, MR)	(MH, SR)	(L, AR)	(MH, SR)	(M, SR)

The first expert was responsible for providing answers about all candidates considering two criteria: time required to complete previous study levels and communication and presentation skills. The expert combined official data about the candidates and information obtained in the interview with them. The aim was to assess the efficiency of candidates during the previous study levels by collecting a broader picture of their life during studies, their interests and accompanying activities such as working and studying, or taking care of some other persons, for example, children, parents, grandparents, etc. The criterion related to communication and presentation skills was assessed by listening to the presentation that each candidate prepared on the topic of their choice. The presentations were in the English language, which is the foreign language for these candidates.

The second expert evaluated the candidates by two additional criteria: the ability to solve transportation problems and computer skills. Since these two criteria are to some extent interconnected, the candidates received certain tasks to be solved on a computer. The expert assesses the time required for solving the problems, as well as the level of success in achieving the solution.

Finally, the third expert is a professor of foreign language, and accordingly in charge of the evaluation of this criterion. This expert also listened to the presentations prepared by the candidates and in further discussion concluded about their proficiency in foreign language knowledge. All collected answers from experts are shown in Table 6.

It should be mentioned here that the proposed Z-numbers AROMAN approach is also suitable for group decision-making in the case when all experts give opinions about all considered criteria. In this case, an initial decision-making matrix would be formed based on Equation (17), where $\overset{\sim m}{x_{ij}}$ is a fuzzy number representing fused membership and reliability functions of m-th expert and k is the number of experts participating in the research.

$$\tilde{x}_{ij} = \frac{1}{K}\left[\overset{\sim 1}{x_{ij}}\,(+)\,\overset{\sim 2}{x_{ij}}\,(+)\ldots(+)\,\overset{\sim K}{x_{ij}}\right] \tag{17}$$

Step 2: The rules listed in Tables 4 and 5 are used to convert the language inputs to fuzzy numbers.

Step 3: Fuse the membership and reliability degrees by using Equation (6) (Table 7).

Table 7. Z-numbers fuzzy decision matrix.

	C1	C2	C3	C4	C5
A1	(4.06, 5.02,5.95)	(1.63, 2.12, 2.55)	(1.00, 1.00, 1.87)	(1.76, 2.40, 2.98)	(1.91, 2.72, 3.48)
A2	(4.19, 4.88, 5.54)	(2.40, 2.98, 3.51)	(2.07, 3.09, 4.06)	(1.87, 2.18, 2.45)	(1.86, 2.05, 2.21)
A3	(4.47, 4.47, 5.01)	(1.91, 2.72, 3.48)	(1.00, 1.00, 1.62)	(3.09, 4.06, 5.02)	(2.12, 2.55, 2.93)
A4	(2.55, 2.93, 3.28)	(2.98, 3.51, 4.00)	(1.00, 2.07, 3.09)	(2.98, 3.51, 4.00)	(2.40, 2.98, 3.51)

Step 4: Perform Equation (7). Results are shown in Table 8.

Table 8. Min-max normalization of the Z-numbers fuzzy decision matrix.

	C1	C2	C3	C4	C5
A1	(0.45, 0.73, 1.00)	(0.00, 0.21, 0.39)	(0.00, 0.00, 0.28)	(0.00, 0.20, 0.37)	(0.03, 0.52, 0.98)
A2	(0.48, 0.69, 0.88)	(0.33, 0.57, 0.79)	(0.35, 0.68, 1.00)	(0.03, 0.13, 0.21)	(0.00, 0.11, 0.21)
A3	(0.57, 0.57, 0.72)	(0.12, 0.46, 0.78)	(0.00, 0.00, 0.20)	(0.41, 0.71, 1.00)	(0.16, 0.42, 0.65)
A4	(0.00, 0.11, 0.22)	(0.57, 0.79, 1.00)	(0.00, 0.35, 0.68)	(0.37, 0.54, 0.69)	(0.33, 0.68, 1.00)

Step 5. Perform Equation (8). Results are shown in Table 9.

Table 9. Vectoral normalization of the Z-numbers fuzzy decision matrix.

	C1	C2	C3	C4	C5
A1	(0.40, 0.57, 0.76)	(0.24, 0.37, 0.56)	(0.18, 0.25, 0.69)	(0.24, 0.38, 0.60)	(0.31, 0.52, 0.83)
A2	(0.42, 0.55, 0.71)	(0.35, 0.52, 0.77)	(0.37, 0.78, 1.50)	(0.25, 0.35, 0.49)	(0.30, 0.39, 0.53)
A3	(0.44, 0.51, 0.64)	(0.28, 0.47, 0.76)	(0.18, 0.25, 0.60)	(0.41, 0.65, 1.00)	(0.34, 0.49, 0.70)
A4	(0.25, 0.33, 0.42)	(0.43, 0.61, 0.87)	(0.18, 0.52, 1.14)	(0.40, 0.56, 0.80)	(0.39, 0.57, 0.84)

Step 6: Perform Equation (9) for aggregated normalization. The parameter β is considered to be 0.5. The results are shown in Table 10.

Table 10. Aggregated normalization of the Z-numbers fuzzy decision matrix.

	C1	C2	C3	C4	C5
A1	(0.21, 0.32, 0.44)	(0.06, 0.14, 0.24)	(0.04, 0.06, 0.24)	(0.06, 0.14, 0.24)	(0.09, 0.26, 0.45)
A2	(0.22, 0.31, 0.40)	(0.17, 0.27, 0.39)	(0.18, 0.36, 0.63)	(0.07, 0.12, 0.18)	(0.08, 0.13, 0.18)
A3	(0.25, 0.27, 0.34)	(0.10, 0.23, 0.38)	(0.04, 0.06, 0.20)	(0.20, 0.34, 0.50)	(0.13, 0.23, 0.34)
A4	(0.06, 0.11, 0.16)	(0.25, 0.35, 0.47)	(0.04, 0.22, 0.46)	(0.19, 0.27, 0.37)	(0.18, 0.31, 0.46)

Step 7: To obtain the weighted aggregated normalized Z-numbers fuzzy decision matrix, Equation (10) is applied. However, we need to get information about the criteria weights first. Various methods can be used for this purpose. In the literature, these methods are structured into subjective, objective and combinative approaches. In this paper, we applied a subjective method which means that the obtained weights were formed based on the experts' opinions. Two experts participated in the criteria assessment process. They

used a percentage scaling method. Each criterion is evaluated by assigning a certain percentage while respecting the condition that the sum of all percentages should be equal to 100%. Both experts are members of UPCE, which was the subject of the case study. When it comes to their reputations, Expert 1 has more than 6 years of experience in the field, while Expert 2 has around 20 years of professional experience. According to expert assessments, criterion number 3 is the one with the highest importance, followed by C4, C2, C5 and C1, respectively. The results are shown in Table 11. The weighted Z-numbers fuzzy decision matrix is shown in Table 12.

Table 11. The weights of the criteria.

Criteria	Expert 1 (%)	Expert 2 (%)	Average (%)	Weights
C1	10	10	10	0.10
C2	15	25	20	0.20
C3	40	20	30	0.30
C4	25	25	25	0.25
C5	10	20	15	0.15
Sum	100	100	100	1

Table 12. The weighted Z-numbers fuzzy decision matrix.

	C1	C2	C3	C4	C5
A1	(0.02,0.03,0.04)	(0.01, 0.03,0.05)	(0.01, 0.02,0.07)	(0.01, 0.04,0.06)	(0.01, 0.04,0.07)
A2	(0.02, 0.03,0.04)	(0.03, 0.05,0.08)	(0.05, 0.11,0.19)	(0.02, 0.03,0.04)	(0.01, 0.02,0.03)
A3	(0.03, 0.03,0.03)	(0.02, 0.05,0.08)	(0.01, 0.02,0.06)	(0.05, 0.08,0.13)	(0.02, 0.03,0.05)
A4	(0.01, 0.01,0.02)	(0.05,0.07, 0.09)	(0.01,0.07, 0.14)	(0.05, 0.07,0.09)	(0.03, 0.05,0.07)

Step 8: In this stage, the summation of the weighted aggregated normalized Z-numbers fuzzy decision matrix should be performed according to the criteria type. In the case study, C1 is a criterion of the minimum type, and C2, C3, C4, C5 are the maximum type criteria. This step is performed by Equations (11) and (12). The results are shown in Table 13.

Table 13. The summation of the weighted aggregated normalized Z-numbers fuzzy decision matrix.

	$\tilde{L}_i$	$\tilde{A}_i$
A1	(0.02, 0.03, 0.04)	(0.05, 0.12, 0.25)
A2	(0.02, 0.03, 0.04)	(0.12, 0.21, 0.34)
A3	(0.03, 0.03, 0.03)	(0.10, 0.18, 0.31)
A4	(0.01, 0.01, 0.02)	(0.14, 0.25, 0.39)

Step 9: The sums from Step 8 should be scaled by the degree of λ. This is performed by Equations (13) and (14). The results are shown in Table 14, where λ indicates the criteria type's coefficient degree. The parameter λ is calculated using Equation (15).

Table 14. The scaled summation of the weighted aggregated normalized Z-numbers fuzzy decision matrix.

	$\tilde{L}_i$	$\tilde{A}_i$
A1	(0.68, 0.71, 0.73)	(0.07, 0.15, 0.29)
A2	(0.68, 0.71, 0.72)	(0.14, 0.25, 0.38)
A3	(0.68, 0.70, 0.71)	(0.13, 0.22, 0.35)
A4	(0.60, 0.64, 0.66)	(0.17, 0.29, 0.43)

Step 10: In the final step, Equation (16) is applied to obtain the final ranking. According to the findings of the implemented approach, the best candidate is A4, followed by A2, A3 and A1. The results are shown in Table 15.

Table 15. Final Ranking.

	$\tilde{L}_i$
A1	0.59
A2	0.64
A3	0.63
A4	0.72

4.3. Sensitivity Analysis

Sensitivity analysis is applied to check the stability and sensitivity of the Z-numbers fuzzy AROMAN method. The parameters β and λ used in the mathematical calculations of the method are changed. By changing the values of these parameters, the Z-numbers fuzzy AROMAN method was run again. The model was evaluated using an increment value of 0.1 for all other scenarios.

First, the parameter β is changed gradually by 0.1 to check how different types of normalizations affect the final ranking of alternatives. The obtained results are shown in Figure 4.

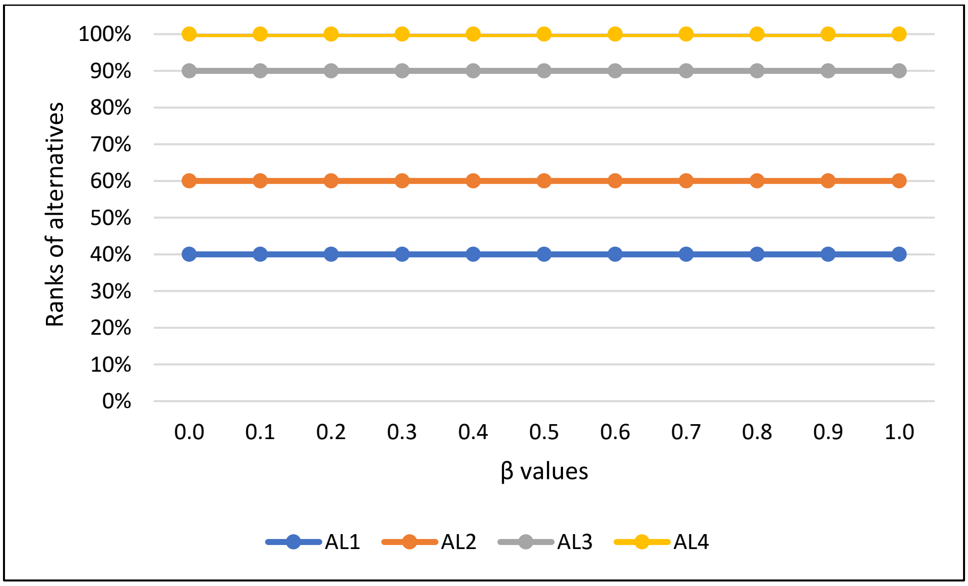

Figure 4. Ranks of the alternatives based on the β value changes.

Secondly, the parameter λ was also gradually varied to check how various importances assigned to the types of criteria (benefit or cost) impact the final ranking of alternatives. The differences in ranks of the alternatives based on the λ value changes are illustrated in Figure 5.

According to the analysis, the model is robust considering the change in β value. When different β values are analyzed, it is observed that the ranking does not change.

Change in ranking is observed for λ values of 0.8, 0.9 and 1.0. In this case, Alternative 2 is in the third position, while Alternative 3 is in the second. For other tested values of λ, Alternative 2 is ranked second and Alternative 3 is third. When it comes to Alternatives 1 and 4, their ranking is not changed for any λ values. Alternative 1 is always last-ranked and Alternative 4 is the most favorable solution in all scenarios.

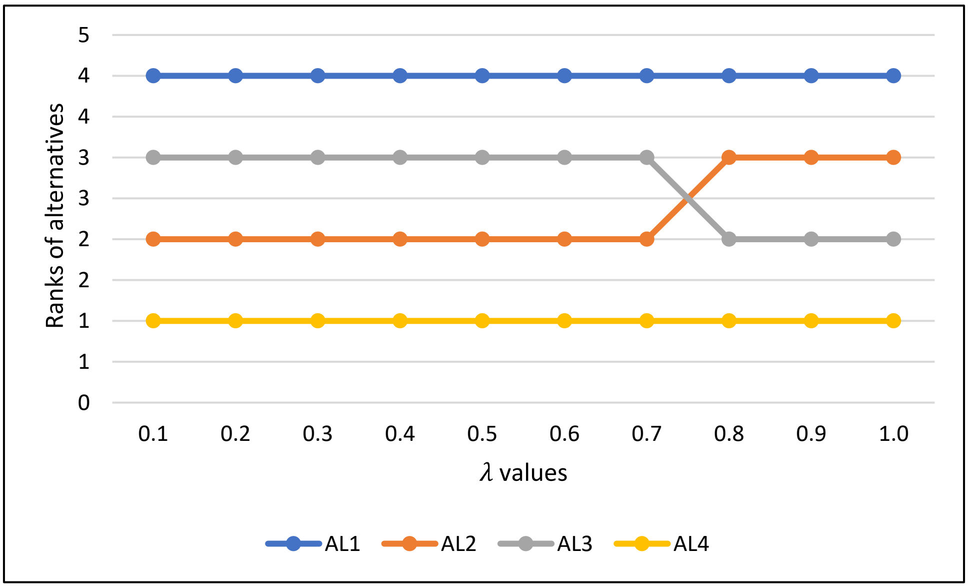

Figure 5. Ranks of the alternatives based on the λ value changes.

4.4. Comparative Analysis

A comparative analysis is performed to verify the proposed model's robustness. Frequently used MCDM models, Z-numbers fuzzy Simple Additive Weighting (SAW) [56], Z-numbers fuzzy Weighted Product Model (WPM) [57], Z-numbers fuzzy TOPSIS method [58], and Z-numbers fuzzy inferior ratio method [59] are applied in the comparative analysis. The same inputs (initial decision matrix, the parameters) as in the case of Z-number fuzzy AROMAN are used. The results obtained for the four mentioned methods are shown in Table 16. In the procedure of solving the Z-numbers fuzzy inferior ratio method, we tested the model by taking the following values of parameter p: 2, 3, 7 and 29. These values can be chosen randomly; however, we used the same as the authors Hadi-Vencheh and Mirjaberi [59].

Table 16. Comparative Analysis of Z-numbers fuzzy AROMAN and other MCDM methods.

Alternative		Results of Z-numbers fuzzy AROMAN	Results of Z-numbers fuzzy SAW
A1		0.59	0.49
A2		0.64	0.62
A3		0.63	0.59
A4		0.72	0.72
Alternative		**Results of Z-numbers fuzzy WPM**	**Results of Z-numbers fuzzy TOPSIS**
A1		60.70	0.16
A2		79.47	0.58
A3		71.58	0.37
A4		90.47	0.70
p	**Alternative**	**Results of Z-numbers Fuzzy Inferior Ratio Method**	
		$\zeta_i(A_i)$	$IR_p(i)$
$p = 2$	A1	−2.64	1.00
	A2	−0.60	0.27
	A3	−1.61	0.61
	A4	0.00	0.00
$p = 3$	A1	−2.58	1.00
	A2	−0.44	0.17
	A3	−1.58	0.61
	A4	0.00	0.00

Table 16. *Cont.*

p	Alternative	Results of Z-numbers Fuzzy Inferior Ratio Method	
$p = 7$	A1	−2.57	1.00
	A2	−0.44	0.17
	A3	−1.60	0.62
	A4	0.00	0.00
$p = 29$	A1	−2.56	1.00
	A2	−0.43	0.17
	A3	−1.59	0.62
	A4	0.00	0.00

As shown in Table 17, identical rankings are obtained between the method proposed in the article and other compared methods. As a result, it can be concluded that the proposed method is reliable.

Table 17. The final ranks of Z-numbers fuzzy AROMAN and other MCDM methods.

	Z-Numbers Fuzzy AROMAN	Z-Numbers Fuzzy SAW	Z-Numbers Fuzzy WPM	Z-Numbers Fuzzy TOPSIS	Z-Numbers Fuzzy Inferior Ratio Method
A1	4	4	4	4	4
A2	2	2	2	2	2
A3	3	3	3	3	3
A4	1	1	1	1	1

Spearman rank correlation coefficient was taken into account to check the reliability of the answers obtained in this study. Spearman rank correlation coefficient is useful to determine the measure of association between ranks obtained by different MCDM methods. The results are shown in Table 18.

Table 18. Spearman rank correlation coefficient values.

	Z-Numbers Fuzzy AROMAN	Z-Numbers Fuzzy SAW	Z-Numbers Fuzzy WPM	Z-Numbers Fuzzy TOPSIS	Z-Numbers Fuzzy Inferior Ratio Method
Z-numbers fuzzy AROMAN	1	1	1	1	1
Z-numbers fuzzy SAW	1	1	1	1	1
Z-numbers fuzzy WPM	1	1	1	1	1
Z-numbers fuzzy TOPSIS	1	1	1	1	1
Z-numbers fuzzy inferior ratio method	1	1	1	1	1

As shown in Table 18, due to identical rankings obtained between the method proposed in this article and other methods, the correlation coefficient has a value equal to one. Finally, the fact that Spearman's rank correlation coefficient equals one shows the validity and effectiveness of the Z-numbers fuzzy AROMAN method.

While comparing the Z-numbers fuzzy AROMAN with other MCDM approaches in this paper, it can be concluded that all the considered MCDM methods use only one type of data normalization and mostly differ in the final ranking formula. However, in the Z-numbers fuzzy AROMAN we use two types of data normalization with an assumption that such a procedure would lead to more objective conclusions while giving more space for sensitivity analysis at the same time. The procedure of the proposed approach is clearly defined through adequate steps, making it easily applicable to other researchers and professionals as well.

Based on the conclusions that the Z-numbers fuzzy AROMAN method is a stable and reliable approach for solving personnel selection problems, it can be stated that its application can lead to significant practical implications for companies. Speaking about institutions of higher education, the adequate selection of new employees contributes to a better overall reputation of the institution, through high-quality research results, modern educational processes and achievements in professional projects.

5. Conclusions

Personnel evaluation and selection is an essential part of modern business. The appropriate candidate selection can significantly contribute to companies in terms of increased profit, good culture, reputation, reduced costs, etc.

This paper addressed the personnel selection problem by using the MCDM methods. The personnel selection problem was solved in the context of the UPCE. Five criteria were identified as critical factors for personnel selection at the UPCE: time required to complete previous study levels, ability to solve transportation problems, foreign language fluency, computer skills, and communication and presentation skills. Four candidates were evaluated according to these criteria and the best candidate was selected. Regarding the methodology, the authors applied the recently developed method called the Alternative Ranking Order Method Accounting for the two-step Normalization (AROMAN) method in the Z-numbers fuzzy environment. The results of the applied method ranked the alternatives in the following order: Candidate 4 > Candidate 2 > Candidate 3 > Candidate 1. Besides the applied AROMAN method, a comparative analysis was performed to check the reliability of the obtained results. The same problem was solved by applying SAW, WPM and TOPSIS also in the Z-numbers fuzzy environment. The results of the comparative analysis confirmed that Candidate 4 is the best solution for the UPCE. In addition, sensitivity analysis was performed to check how the changes in adequate parameters affect the final ranking of alternatives. The results of the sensitivity analysis show the high stability level of the applied Z-numbers fuzzy AROMAN method. The main contributions of this paper are as follows: (i) The personnel selection problem is solved for the first time in the literature by applying the Z-numbers fuzzy AROMAN method; (ii) This paper solves a real-life decision-making problem at the University of Pardubice, and (iii) This method can be considered as a future decision-making tool at the University of Pardubice or in any other institution in the context of personnel selection.

It is useful to mention that this research has certain limitations. The proposed Z-numbers AROMAN approach is suitable only for solving MCDM problems that consist of both criteria types, cost and benefit. This limitation should not represent a huge obstacle to implementation in practice, because the vast majority of MCDM problems are characterized by many criteria, involving both types mentioned. In addition, we solved the problem of criteria weighting by a percentage scaling method. Since there are more sophisticated methods to be used for this purpose, such as AHP, SWARA, CRITIC, BWM, FullEX, FUCOM, CIMAS and others [60–62], it would be useful to integrate such methods in the proposed approach. This can be considered as a future research direction of this paper. The authors are particularly interested in integrating the FullEX method [63], as one of the most recently proposed methods for criteria importance assessment that includes the experts' reputations in the calculation process. Besides, further research direction can be related to the implementation of some other type of fuzzy numbers in the AROMAN-based MCDM [64].

The authors believe this research will inspire other authors to continue to develop and contribute to the personnel evaluation and selection issue since the productivity of any company depends on it.

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