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Development of a complementary fuzzy decision support system for employees' performance evaluation

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ABSTRACT

This study aims to improve employee evaluation system in one of the leading automobile manufacturers in Iran by designing a fuzzy decision support system (F.D.S.S.). Since this manufacturer is a large-sized company with over 35,000 employees, the number of managers regularly evaluated requires too much capacity from the human resource team and hence increases the rate of possible misjudgements. However, the proposed F.D.S.S. can reduce the rate of unfair or inconsistent assessments by converting qualitative assessments of the panel to linguistic variables. This action increases the precision of assessment and improves the quality of evaluations. The proposed F.D.S.S. is compared with a fuzzy TOPSIS method to confirm its reliability and validity in which the results show consistency with fuzzy TOPSIS. As a result, the F.D.S.S. is implemented for evaluation of managers in this automobile company instead of the traditional method.

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1. Introduction

Nowadays, organisations are more aware that an employee's capability, knowledge and skills play a significant role in their overall success (Neluheni, Pretorius, & Ukpere, 2014). Therefore, the significance of change plans regarding human resource topics such as employee evaluation is noticeably increased among strategic goals (Billsberry, 2007). Such change plans are implemented to optimise the quality of outcomes and productivity, and reduce the inefficiencies, costs and redundancies of organisational processes. Most of these plans end in new methods designed to replace traditional methods practised for many years in these organisations. As a result, it is not possible to implement such changes with ease. The initial step is critical to prove that the change both can work and make improvements.

Employee evaluation is one of the soft topics that play a chief role in the total efficiency of human resource management. In large-sized companies, the urgency to

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enhance employee evaluation is higher due to the substantial number of repetitions. Managerial level appraisals are also challenging in these organisations because the human resource team should assess a more comprehensive set of criteria for each person, making the evaluation process more time-consuming and sensitive. In contrast, for non-managerial jobs the criteria are few and mostly there is no need for evaluation sessions.

To solve the problem of personnel evaluation at the managerial level of one of the biggest companies in the automotive industry of the Middle East, i.e., IKCO (formerly called Iran National before the Islamic revolution), a new approach is designed and tested by using linguistic criteria to improve the evaluation of managers. IKCO was established in 1963 and is now Iran's largest motor vehicle producer and industrial conglomerate. The number of staff at IKCO is more than 35,000. Since IKCO is a large-sized company, it is proposed to this company to design a fuzzy decision support system (F.D.S.S.) to facilitate the process of manager evaluation and reduce the inaccuracies observed. This F.D.S.S. is developed in MATLAB software (Matrix Laboratory). In order to test the F.D.S.S., a comparative test with a fuzzy TOPSIS is run for three candidates in the middle managerial positions who are considered as well qualified for this test by the human resource department.

2. Literature review

2.1. Employee evaluation

The fundamental specifics of any human resource management system include the principles of employee evaluation. These principles have a leading role in organisational development practice since they indirectly affect the other systems of human resources by introducing appraisal criteria for each layer of the organisation. The employees and managers consider improvements in their work based on these criteria. If the criteria are not comprehensive or well designed, the process of employee evaluation might harm the goals of human resource management. Also, even if the process is not consistent or fair, employees perceive the results as non-constrictive. All of which makes employee evaluation one of the most sensitive tasks in human resource management. Another application of employee evaluation is training or coaching. Organisations know the strategic value of employees; therefor they attempt to implement policies that improve their knowledge and skills. However, to design these policies they need to find the critical issues. Employee evaluation can help in this regard by showing the major weak spots of a group or team (Hennman & Schwab, 1985).

Thus, the human resource department must ensure that the results of employee evaluation are accurate, consistent and fair in the short and long term, because results of employee evaluation are not just an input for identifying the amount of salaries or benefits but rather an input for other parts of the human resource management system. Employee evaluation might look like a simple task at first. However, it is indeed a complicated matter that requires dynamic and constant planning and improvement (Hennman & Schwab, 1985).

2.2. Multi-criteria decision-making

In order to enhance the employee evaluation process, new techniques are implemented. Most of these techniques use multi-criteria decision-making (M.C.D.M.) due to the multi-dimensional advantages that they bring to managerial decision-making. For example, they can increase the speed and precision of assessment. Also, they can provide a full span of options to make sure that each company can find the best choice concerning the circumstance of its operation.

By definition, the problem of measuring according to a set of criteria is known as M.C.D.M.. Different authors have introduced various areas of applications for M.C.D.M. These methods can be used at national, organisational and project levels (Yousefi et al., 2018; Zavadskas et al., 2014). Most of these methods seek to find how to make the best decisions in terms of productivity (Sivilevičius, Zavadskas, & Turskis, 2008).

In managerial decisions also M.C.D.M. methods can be made by taking into account the priorities and objectives of different stakeholder's groups. In the hiring process or personnel evaluation at companies, decision makers can use most methods of M.C.D.M.. For instance, Keršulienė and Turskis (2014) focused on a fuzzy M.C.D.M. algorithm, which integrates the principles of fusion of fuzzy information such as additive ratio assessment method with fuzzy numbers (A.R.A.S.), fuzzy weighted-product model and analytic hierarchy process (A.H.P.). The proposed method is appropriate to manage information assessed using both linguistic and numerical scales in a decision-making problem with a group of information sources. In another example, Karabasevic, Zavadskas, Turskis and Stanujkic (2016) designed a framework for the selection of candidates during the process of the recruitment and selection of personnel based on the stepwise weight assessment ratio analysis (S.W.A.R.A.) and A.R.A.S. methods under uncertainties (Keršulienė & Turskis, 2012).

An appropriate mechanism concerning supporting personnel management practices can contribute to value over scope, time and total investment (Šaparauskas, Kazimieras Zavadskas, & Turskis, 2011). A high number of works applying M.C.D.M. techniques for assessment problems are published recently. Hybrid M.C.D.M. approaches, due to their abilities in integrating different techniques assist in handling miscellaneous information taking into account stakeholder's preferences when making decisions in management (Zavadskas, Govindan, Antucheviciene, & Turskis, 2016, Turskis, Zavadskas, Antucheviciene, & Kosareva, 2015).

Selection among alternatives like employee evaluation depends on a set of different conflicting criteria that have different optimisation directions. Turskis and Juodagalvienė (2016) presented a novel and original hybrid M.C.D.M. model, which was based on ten different M.C.D.M. methods: game theory, A.H.P., simple additive weighting, multiplicative exponential weighting, TOPSIS, evaluation based on distance from average solution (E.D.A.S.), A.R.A.S., full multiplicative form, Laplace rule and Bayes rule; this method is used to solve complicated problems. In another case, Zavadskas et al. (2013) integrated ELECTRE IV, MULTIMOORA, S.W.A.R.A.-TOPSIS, S.W.A.R.A.-ELECTRE III, S.W.A.R.A. and VIKOR to assess, rank and select the best alternatives. In addition, Štreimikienė, Šliogerienė and Turskis (2016) presented the process of choosing from such multiple criteria decision-making methods

Table 1. Steps of research method.

Step 1	Constructing decision model hierarchy (determining criteria and sub-criteria)
Step 2	Computing significant sub-criteria deducted from Friedman test
Step 3	Applying fuzzy TOPSIS for ranking
Step 4	Designing a fuzzy decision support system (F.D.S.S.) for employee evaluation
Step 5	Comparing results to confirm the validity and reliability of proposed F.D.S.S.

Source: authors.

by A.H.P. and A.R.A.S. Stanujkic, Zavadskas, Ghorabaee and Turskis (2017) recently proposed using the E.D.A.S. method with grey numbers for this objective too. TOPSIS is also one the most used M.C.D.M.s like A.H.P. regarding managerial decisions (Keršuliene, Zavadskas, & Turskis, 2010).

3. Methodology

3.1. Criteria for employee evaluation

In this paper, we design an F.D.S.S. to improve evaluation process. Then we use fuzzy TOPSIS to test our proposed F.D.S.S. With the comparison of two mentioned methods, we approve the reliability and validity of F.D.S.S. The steps of this research are shown in Table 1.

The framework of the current paper is based on the criteria of employee evaluation used in IKCO, as shown in Tables 2 and 3. The human resource team has developed this pool through many years of experience and constant improvements by their experts at the time. Based on the pool, 51 different items are categorised into eight different main skills.

The 51 sub-criteria constrain us to design a questionnaire for pairwise comparison in order to reduce the number of sub-criteria and solve this problem. The main goal of this reduction is to remove those factors that have a shared meaning and are making the ranking ambiguous. Reducing the criteria helps decision makers to more wisely evaluate the candidates since afterwards they only need to consider a few factors.

To make a pairwise comparison, a panel of experts are called including 40 professionals and academics from different deputies of human resources from all branches of IKCO. The questionnaire for this test is confirmed and distributed among the panel. Friedman test is applied to rank the results, which is a non-parametric statistical test used when the dependent variable is ordinal. The results of reduction are shown in Table 4, which categorises 12 sub-criteria in five main criteria.

3.2. Fuzzy numbers

In this part, some primal definitions of fuzzy sets, fuzzy numbers and linguistic variables are explained based on Klir and Yuan (1995), Kaufmann and Gupta (1991), Negi (1989), Buckley (1985) and Zadeh (1975). The basic definitions and notations mentioned below are used throughout this paper until otherwise stated.

Definition 1. A fuzzy set $\tilde{A}$ in a universe of discourse X is characterised by a membership function $\mu\tilde{A}(x)$ which associates with each element x in X a real number in the interval [0,1]. The function value $\mu\tilde{A}(x)$ is termed the grade of membership of x in $\tilde{A}$.

Table 2. Major criteria for employee evaluation 1.

Leadership (attention to factors concerning employees)	Leadership (attention to factors concerning organisation)	Employee's empowerment	Performance management
Paying attention to psychological needs	Providing work environment discipline	Providing necessary facilities for employees	Evaluating employees regularly
Contribution to decision-making and programming	Creating enthusiasm for reaching goals	Introducing appropriate education courses	Emphasis on fair employees evaluation
Making influence on employees under control	Observing organisational rules	Propagation of co-working culture	Clarification in declaring the results
Providing employees satisfaction	Making emphasis on administrative hierarchy	Giving feedback to employees about their strength & weakness	Emphasising correct use of time
Implementing incentives	Controlling employee's duties	Emphasising employee and job rotation	Paying attention to job's details
Delegation	Emphasising doing things accurately	Improving knowledge management	Classifying task fairly among employees
Improving trust among employees	Implementing better ways of doing jobs		Implementing fair rules in employees evaluation
Creating coherence and empathy among employees			Making coordination between available facilities and resources

Source: authors.

Table 3. Major criteria for employee evaluation 2.

Communication skills	Technical skills	Analysis skills	Creativity skills
Communicating with co-workers	Ability to use technical knowledge	Ability to understand technical and professional of employees	Applying ideas and suggestions of employees
Emphasis on friendship	Having good information about related specific fields	Ability to analyse complicated matters of organisation	Encouraging employees to provide new ideas
Transparency with co-workers	Harmony of education with job	Ability to program task schedule of job department	Emphasis on personal abilities development and personal knowledge
Respect for other employees	Dominance on co-workers' jobs	Using systemic view in decision-making	Providing a suitable situation for improving creativity
Providing an environment suitable for expression of opinions	Ability to direct and guide co-workers		Attention to creative co-workers
High criticism ability	Attention to redesign job processes to make them better		

Source: authors.

Definition 2. A fuzzy set $\tilde{A}$ in the universe of discourse X is convex if and only if:

$$\mu\tilde{A}(\lambda x1 + (1 + \lambda)x2 \geq \min(\mu\tilde{A}(x1), \mu\tilde{A}(x2))$$

for all x1; x2 in X and all $\lambda \in [0, 1]$ where min denotes the minimum operator (Klir & Yuan, 1995).

Definition 3. The height of a fuzzy set is the largest membership grade attained by any element in that set. A fuzzy set $\tilde{A}$ in the universe of discourse X is called normalised when the height of $\tilde{A}$ is equal to 1 (Klir & Yuan, 1995).

Table 4. Finalised criteria and sub-criteria.

Technical skills	Employee empowerment	Communication skills	Leadership skills	Analytical skills
Harmony of education with job	Knowledge management (transferring knowledge to employees)	Providing an environment suitable for expression of opinions	Contribution in decision-making and programming Paying attention to employees' psychological needs	Ability to program Task schedule of job department
Attention to redesign job processes to make them better	Propagation of co-working culture	High criticism ability	Observing organisation rules	Using systemic view in decision-making

Source: authors.

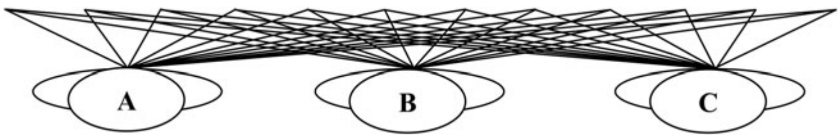

Figure 1. Employee evaluation hierarchical structure. Source: authors.

Definition 4. A fuzzy number is a fuzzy subset of the universe of discourse X that is both convex and normal. Figure 1 shows a fuzzy number Ñ in the universe of discourse X that conforms to this definition (Kaufmann & Gupta, 1991).

Definition 5. The α-cut of fuzzy number Ñ is defined as

$$\tilde{N}\alpha = \{xi\text{: } \mu\tilde{N}(xi) \geq \alpha,\ xi \in x\} \text{ where } \alpha \in [0\ 1]$$

The symbol $\tilde{N}\alpha$ represents a non-empty bounded interval contained in X, which can be denoted by $\tilde{N}\alpha = [\tilde{N}l\alpha, \tilde{N}u\alpha]$; $\tilde{N}l\alpha$ and $\tilde{N}u\alpha$ are the lower and upper bounds of the closed interval respectively (Kaufmann & Gupta, 1991). For a fuzzy number Ñ, if $\tilde{N}l\alpha > 0$ and $\tilde{N}u\alpha \leq 1$ for all $\alpha \in [0, 1]$, then Ñ is called a standardised (normalised) positive fuzzy number (Negi, 1989).

Definition 6. Trapezoid fuzzy numbers: let, $n1 < n2 < n3 < n4$ be a fuzzy set. It is called a fuzzy trapezoid number, if its membership function is (Kaufmann & Gupta, 1991)

$$\mu_{\tilde{A}}(x) = 4\begin{cases} \dfrac{x-n1}{n2-n1}, & if\ n1 \leq x \leq n2 \\ 1, & if\ n2 \leq x \leq n3 \\ \dfrac{n4-x}{n4-n3}, & if\ n3 \leq x \leq n4 \\ 0, & otherwise \end{cases}$$

Definition 7. While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric linguistic variables are often used to facilitate the expression of rules and facts. A linguistic variable is a variable whose values are expressed in linguistic terms. The concept of a linguistic variable is very useful in dealing with situations which are too complex or not well defined to be reasonably described in conventional quantitative expressions.

Figure 2. The status of candidate A. Source: authors.

Table 5. Approval status.

Assessment status	Closeness coefficient (CC_i)
Do not recommend	CC_i [0,0.2)
Recommend with high risk	CC_i [0.2,0.4)
Recommend with low risk	CC_i [0.4,0.6)
Approved	CC_i [0.6,0.8)
Approved and preferred	CC_i [0.8,1)

Source: authors.

3.3. Fuzzy TOPSIS

Employee evaluation is a group M.C.D.M. (G.M.C.D.M.) problem, which can be described by means of the following sets:

I. a set of k decision makers called E = {D1; D2; …; DK};
II. a set of m candidates called F = {A; B; …}
III. a set of n criteria, C = {C1; C2; …; Cn}
IV. a set of s sub-criteria, s = {C1; C12; …; C21; C22; … .; C31;C32 … .}

Assume that a decision group has K decision makers and the fuzzy rating of each decision maker can be represented as a positive trapezoidal fuzzy number. Let the fuzzy ratings of all decision makers be trapezoidal fuzzy numbers:

$\tilde{U}k$ = (ak; bk; ck; dk), k = 1; 2; …; K. Then the aggregated fuzzy rating can be defined as:

$$\tilde{U} = (a; b; c; d); k = 1; 2; \ldots; \text{ where } a = \min\{ak\}; b = \frac{1}{k}; c = \frac{1}{k}\ \frac{1}{K}; d = \max\{dk\}$$

Table 6. Pairwise comparisons among main criteria of employee evaluation hierarchical structure.

Analytical skills	Leadership skills	Communication skills	Employee empowerment skills	Technical skills
Ability to program task schedule of job department **C11**	Contribution in decision-making and programming **C21** Paying attention to employees' psychological needs **C22**	Providing an environment suitable for expression of opinions **C31**	Knowledge management (transferring knowledge to employees) **C41**	Harmony of education with job **C51**
Using systemic view in decision-making **C12**	Observing organisation rules **C23** Controlling employees' duties **C24**	High criticism ability **C32**	Propagation of co-working culture **C42**	Attention to redesign job processes to make them better **C52**

Source: authors.

From the practical point of view, there are many different membership functions available to choose, but the selection of membership function should be based on the expert's views because matching the data with a suitable membership function is extremely important. In general, the trapezoidal and triangular membership functions are the most used functions. It is believed the trapezoidal membership function generally works very well in different applications (Barua, Mudunuri, & Kosheleva, 2014). However, it is observed that the trapezoidal membership function is usually more effective than using a triangular membership function (Bouchon-Meunier, Dotoli, & Maione, 1996). The trapezoidal membership function is applied to develop the employee evaluation model as the initial model in this paper, and its development can be investigated and compared with other linear and nonlinear membership functions and if required replaced with more optimised ones. In order to describe the assessment status, the closeness coefficient is divided into five equal sub-intervals to cover 0 to 1. For each sub-interval, a linguistic variable is defined to divide the assessment status of candidates, as shown in Table 5.

In the following, every eight steps of fuzzy TOPSIS is delineated, and their related results are shown accordingly.

Step 1: The first step of fuzzy TOPSIS is to develop a hierarchical structure of the assessment problem, which is shown in Figure 1. After developing the hierarchy, decision makers have to determine the relative weights of each criterion and sub-criterion shown in Table 6. Weights are determined by using a pairwise comparison between each pair of criteria. Four decision makers are asked to make pairwise comparisons to determine relative weights, using a one to five preference scale based on the criteria shown in Table 6. All pairwise comparisons are made by four decision makers who based on the norms must attend all interview sessions held in an interactive face to face sessions. Tables 7 and 8 show the average weights of decision makers. The result of another pairwise comparison among sub-criteria is shown in Table 9.

In Tables 7 and 8, the geometric mean for each c1, c2, c3, c4 and c5 is calculated based on the following formula:

$$\left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}} = \sqrt[n]{x_1\ x_2 \ldots x_n}$$

After this step, the normal weight of each item is calculated based on its weight in the total geometric mean. The total normalised weight of each sub-criteria is shown

Table 7. Normalised weight of each criterion by geometric mean.

C1	2.88	0.78	3.89	3.86	1.00
C2	1.23	0.33	1.45	1.00	0.26
C3	0.48	0.25	1.00	0.83	0.16
C4	3.96	1.00	3.69	4.77	1.77
C5	1.00	0.28	2.22	0.88	0.33

Source: authors.

Table 8. Normalised weight of each criterion by geometric mean.

Pairwise comparison mean of four managers' viewpoints	Geometric mean	Normalised weight
C1	1.97	0.20
C2	0.70	0.15
C3	0.44	0.07
C4	2.49	0.39
C5	0.69	0.19
Sum	**6.98**	**1.00**

Source: authors.

in the last column of Table 9. For example, C1 has two sub-criteria which have their own weights. Each of them is multiplied by the C1-weight, and the final results are inserted in the last column.

Step 2: The assessment of three candidates was done by four decision makers. This assessment was based on linguistic variables. Table 10 shows the fuzzy number which corresponds to each linguistic variable. For example, candidate A was assessed by D1 for C11 being reported as 'very good' hence the correspondent trapezoidal fuzzy number in Table 11 is '(8, 9, 9, and 10)'.

Step 3: The normalised weight of each sub-criterion is converted to the trapezoidal fuzzy number; Table 12 shows the fuzzy weight of each candidate.

Step 4: In this step, the decision matrix of fuzzy TOPSIS is confirmed and shown in Table 13.

Step 5: In this step, normalised decision matrix of fuzzy TOPSIS is shown in Table 14.

Step 6: Determining the F.P.I.S. (fuzzy positive ideal solution and F.N.I.S. (fuzzy negative ideal solution is done and shown in Table 15.

Step 7: Distances between A, B, C and A − and A + with respect to each criterion are shown in Tables 16 and 17.

Step 8: The closeness coefficient (CC_i) is shown in Table 18.

Based on Table 18 all candidates are approved, and candidate A stands as the best candidate for employee evaluation. Candidates C and B are respectively in the subsequent rankings.

In Table 10, to calculate the average trapezoidal fuzzy number we have used the following logic:

- For the first number the minimum is used.
- For the last number the maximum is used.
- For the two numbers in the middle the average is calculated then rounded.

Table 9. Total normalised weight of each sub-criteria by geometric mean.

Criteria	Sub-criteria	Weight of criteria	Weight of sub-criteria	Total weight of each criterion (rounded after multiplication of criteria and sub-criteria)
C1	C11	0.20	0.35	0.070
	C12		0.65	0.130
C2	C21	0.15	0.33	0.050
	C22		0.17	0.025
	C23		0.20	0.030
	C24		0.30	0.045
C3	C31	0.07	0.53	0.030
	C32		0.47	0.030
C4	C41	0.39	0.32	0.120
	C42		0.68	0.250
C5	C51	0.19	0.20	0.030
	C52		0.80	0.150
TOTAL				1

Source: authors.

We can calculate CC_i by using the formula below; the results are shown in Table 18.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}$$

Based on the results shown in Table 18, candidate A is selected as best with the highest performance. Candidate C stands second, while candidate B has the worst performance.

5. Proposed F.D.S.S. to evaluate employees

The F.D.S.S. is run to determine the validity and reliability of corresponding results. This step requires building fuzzy inference defined as the process of mapping from a given input to output using fuzzy logic. This mapping provides a basis from which decisions can be made, and patterns discerned. The process of fuzzy inference involves all of the pieces that are described in the previous sections: membership functions, logical operations and if–then rules. Two types of fuzzy inference systems are implemented in the toolbox of MATLAB: Mamdani-type and Sugeno-type. These two types of inference systems vary in the way their outputs are determined (Jang, Sun, & Mizutani, 1997).

Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems and computer vision. Due to their multidisciplinary nature, fuzzy inference systems are linked with other names such as fuzzy-rule-based-systems. One of the major applications of F.D.S.S. is to enhance qualitative decision-making. As was mentioned before, employee evaluation problems should be attached to linguistic area since the human judgements are not consistent when the numbers are too many.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani (Mamdani & Assilian, 1975) as an attempt

Table 10. Average of trapezoidal fuzzy number for each candidate by assessment of decision maker.

Criteria	Sub-criteria	Candidates	Decision makers D1	D2	D3	D4	Average of trapezoidal fuzzy number
C1	C11	A	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)	(7, 8.3, 8.7, 10)
		B	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(5, 7.8, 8.2, 10)
		C	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8, 9, 9, 10)
	C12	A	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7, 8.3, 8.7, 10)
		B	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4, 6.7, 7, 9)
		C	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(7,8,8,9)	(7, 8.5, 9, 10)
C2	C21	A	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7, 8.5, 9, 10)
		B	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7, 8.3, 8.7, 10)
		C	(8,9,9,10)	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5, 8, 8.3, 10)
	C22	A	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,6,7,8)	(5, 7.3, 7.8, 10)
		B	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(4,5,5,6)	(4, 7.8, 8.2, 10)
		C	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7, 8.3, 8.7, 10)
	C23	A	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(4,5,5,6)	(4, 7.8, 8.2, 10)
		B	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(4,5,5,6)	(4, 7.8, 8.2, 10)
		C	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7, 8.3, 8.7, 10)
	C24	A	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4, 6.8, 7, 9)
		B	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7, 8.3, 8.7, 10)
		C	(8,9,9,10)	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5, 8, 8.3, 10)
C3	C31	A	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(5, 7.8, 8.2, 10)
		B	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8, 9, 9, 10)
		C	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7, 8.3, 8.7, 10)
	C32	A	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4, 6.7, 7, 9)
		B	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(7,8,8,9)	(7,8.5,9,10)
		C	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7, 8.5, 9, 10)
C4	C41	A	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7, 8.3, 8.7, 10)
		B	(8,9,9,10)	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5, 8, 8.3, 10)
		C	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(5,6,7,8)	(5, 7.3, 7.8, 10)
	C42	A	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(4,5,5,6)	(4, 7.8, 8.2, 10)
		B	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7,8.3,8.7,10)
		C	(5,6,7,8)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(5, 7.8, 8.2, 10)
C5	C43	A	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8,9,9,10)	(8, 9, 9, 10)
		B	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(7, 8.3, 8.7, 10)
		C	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(5,6,7,8)	(4, 6.8, 7, 9)
	C44	A	(7,8,8,9)	(8,9,9,10)	(8,9,9,10)	(7,8,8,9)	(7, 8.5, 9, 10)
		B	(8,9,9,10)	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7, 8.5, 9, 10)
		C	(7,8,8,9)	(7,8,8,9)	(8,9,9,10)	(7,8,8,9)	(7, 8.3, 8.7, 10)

Source: authors.

Table 11. Fuzzy numbers.

Fuzzy number	Linguistic variables
(0,1,1,2)	Very poor
(1,2,2,3)	Poor
(2,3,4,5)	Medium poor
(4,5,5,6)	Fair
(5,6,7,8)	Medium good
(7,8,8,9)	Good
(8,9,9,10)	Very good

Source: authors.

to control a steam engine and boiler combination by synthesising a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's paper on fuzzy algorithms for complex systems and decision processes (Zadeh, 1973). Sugeno, Takagi–Sugeno–Kang, is another method of fuzzy inference

Table 12. Fuzzy weight of candidates comparably to sub-criteria.

Criteria	Sub-criteria	Candidates	Average of trapezoidal fuzzy number	Normalised weight (trapezoidal fuzzy number) of each sub-criteria	Multiplication of average fuzzy number and normalised weight			
C1	C11	A	(7,8.3,8.7,10)	(0.07, 0.07, 0.07, 0.07)	0.49	0.581	0.609	0.7
		B	(5,7.8,8.2,10)	(0.07, 0.07, 0.07, 0.07)	0.35	0.546	0.574	0.7
		C	(8,9,9,10)	(0.07, 0.07, 0.07, 0.07)	0.56	0.63	0.63	0.7
	C12	A	(7,8.3,8.7,10)	(0.13, 0.13, 0.13, 0.13)	0.91	1.079	1.131	1.3
		B	(4,6.7,7,9)	(0.13, 0.13, 0.13, 0.13)	0.52	0.871	0.91	1.17
		C	(7,8.5,9,10)	(0.13, 0.13, 0.13, 0.13)	0.91	1.105	1.17	1.3
C2	C21	A	(7,8.5,9,10)	(0.09, 0.09, 0.09, 0.09)	0.63	0.765	0.81	0.9
		B	(7,8.3,8.7,10)	(0.09, 0.09, 0.09, 0.09)	0.63	0.747	0.783	0.9
		C	(5,8,8.3,10)	(0.09, 0.09, 0.09, 0.09)	0.45	0.72	0.747	0.9
	C22	A	(5,7.3,7.8,10)	(0.05, 0.05, 0.05, 0.05)	0.25	0.365	0.39	0.5
		B	(4,7.8,8.2,10)	(0.05, 0.05, 0.05, 0.05)	0.20	0.39	0.41	0.5
		C	(7,8.3,8.7,10)	(0.05, 0.05, 0.05, 0.05)	0.35	0.415	0.435	0.5
	C23	A	(4,7.8,8.2,10)	(0.05, 0.05, 0.05, 0.05)	0.20	0.44	0.41	0.5
		B	(4,7.8,8.2,10)	(0.05, 0.05, 0.05, 0.05)	0.20	0.44	0.41	0.5
		C	(7,8.3,8.7,10)	(0.05, 0.05, 0.05, 0.05)	0.35	0.415	0.435	0.5
	C24	A	(4,6.8,7,9)	(0.05, 0.05, 0.05, 0.05)	0.20	0.34	0.435	0.45
		B	(7,8.3,8.7,10)	(0.05, 0.05, 0.05, 0.05)	0.35	0.415	0.435	0.5
		C	(5,8,8.3,10)	(0.05, 0.05, 0.05, 0.05)	0.25	0.440	0.435	0.5
C3	C31	A	(5,7.8,8.2,10)	(0.03, 0.03, 0.03, 0.03)	0.15	0.234	0.246	0.3
		B	(8,9,9,10)	(0.03, 0.03, 0.03, 0.03)	0.24	0.27	0.27	0.3
		C	(7,8.3,8.7,10)	(0.03, 0.03, 0.03, 0.03)	0.21	0.249	0.261	0.3
	C32	A	(4,6.7,7,9)	(0.03, 0.03, 0.03, 0.03)	0.12	0.201	0.21	0.27
		B	(7,8.5,9,10)	(0.03, 0.03, 0.03, 0.03)	0.21	0.255	0.27	0.3
		C	(7,8.5,9,10)	(0.03, 0.03, 0.03, 0.03)	0.21	0.255	0.27	0.3
C4	C41	A	(7,8.3,8.7,10)	(0.12, 0.12, 0.12, 0.12)	0.84	0.996	1.044	1.2
		B	(5,8,8.3,10)	(0.12, 0.12, 0.12, 0.12)	0.6	0.96	0.996	1.2
		C	(5,7.3,7.8,10)	(0.12, 0.12, 0.12, 0.12)	0.6	0.876	0.936	1.2
	C42	A	(4,7.8,8.2,10)	(0.25, 0.25, 0.25, 0.25)	1	1.95	2.05	2.5
		B	(7,8.3,8.7,10)	(0.25, 0.25, 0.25, 0.25)	1.75	2.075	2.175	2.5
		C	(5,7.8,8.2,10)	(0.25, 0.25, 0.25, 0.25)	1.25	1.95	2.05	2.5
C5	C51	A	(8,9,9,10)	(0.03, 0.03, 0.03, 0.03)	0.24	0.27	0.27	0.3
		B	(7,8.3,8.7,10)	(0.03, 0.03, 0.03, 0.03)	0.21	0.249	0.261	0.3
		C	(4,6.8,7,9)	(0.03, 0.03, 0.03, 0.03)	0.12	0.204	0.21	0.27
	C52	A	(7,8.5,9,10)	(0.15, 0.15, 0.15, 0.15)	1.05	1.275	1.35	1.5
		B	(7,8.5,9,10)	(0.15, 0.15, 0.15, 0.15)	1.05	1.275	1.35	1.5
		C	(7,8.3,8.7,10)	(0.15, 0.15, 0.15, 0.15)	1.05	1.245	1.305	1.5

Source: authors.

which was introduced in 1985 (Sugeno, 1985). It is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. A typical rule in a Sugeno fuzzy model has the formula like $z = ax + by + c$. Based on mentioned method of fuzzy inference, we have used the Sugeno method. According to points of decision makers at IKCO company we have coded 12 sub-criteria with seven segments of fuzzy membership in MATLAB, we have used five main criteria with three segments of fuzzy membership.

Step 1: We have designed the decision matrix as the input of MATLAB software. The average fuzzy numbers are converted from linguistic variables which are obtained from four decision makers interviewing three candidates.

Step 2: We have to defuzzify Table 19 as the inputting of MATLAB software. There are lots of defuzzification methods. We have used Mean Value method for defuzzification. Table 19 shows the defuzzified matrix.

Table 13. Decision matrix of fuzzy TOPSIS.

	C11	C12	C21	C22	C23	C24	C31	C32	C41	C42	C51	C52
A	(0.49,0.581,-0.609,0.7)	(0.91,1.079,-1.131,1.3)	(0.63,0.765,-0.81,0.9)	(0.25,0.365,-0.39,0.5)	(0.20,0.44,0.-41,0.5)	(0.20,0.34,0.-435,0.45)	(0.15,0.234,-0.246,0.3)	(0.12,0.201,-0.21,0.27)	(0.84,0.996,-1.044,1.2)	(1,1.95,2.05,-2.5)	(0.24,0.27,0.-27,0.3)	(1.05,1.275,-1.35,1.5)
B	(0.35,0.546,-0.574,0.7)	(0.52,0.871,-0.91,1.17)	(0.63,0.747,-0.783,0.9)	(0.2,0.39,0.4-1,0.5)	(0.20, 0.44,0.41-,0.5)	(0.35,0.41,0.-435,0.5)	(0.24,0.27,0.-27,0.3)	(0.21,0.255,-0.27,0.3)	(0.6,0.96,0.9-96,1.2)	(1.75,2.075,-2.175,2.5)	(0.21,0.249,-0.261,0.3)	(1.05,1.275,-1.35,1.5)
C	(0.56,0.63,0.-63,0.7)	(0.91,1.105,-1.17,1.3)	(0.45,0.72,0.-747,0.9)	(0.35,0.415,-0.435,0.5)	(0.35,0.415,-0.435,0.5)	(0.25,0.44,0.-43,0.5)	(0.21,0.249,-0.261,0.3)	(0.21,0.255,-0.27,0.3)	(0.6,0.876,0.-936,1.2)	(1.25,1.95,2.-05,2.5)	(0.12,0.204,-0.21,0.27)	(1.05,1.245,-1.305,1.5)

Source: authors.

Table 14. Normalised decision matrix of fuzzy TOPSIS.

C11	A	(0.5958, 0.5717, 0.5813, 0.5773)
	B	(0.4256, 0.5373, 0.5479, 0.5773)
	C	(0.6810, 0.6199, 0.6014, 0.5773)
C12	A	(0.6556, 0.6085, 0.6066, 0.5965)
	B	(0.3746, 0.4912, 0.4880, 0.5368)
	C	(0.6556, 0.6231, 0.6275, 0.5965)
C21	A	(0.6311, 0.5934, 0.5992, 0.5773)
	B	(0.6311, 0.5794, 0.5792, 0.5773)
	C	(0.4508, 0.5585, 0.5526, 0.5773)
C23	A	(0.4444, 0.6113, 0.5656, 0.5773)
	B	(0.4444, 0.5882, 0.5656, 0.5773)
	C	(0.7777, 0.5548, 0.6001, 0.5773)
C24	A	(0.4444, 0.4900, 0.5884, 0.5368)
	B	(0.6556, 0.6118, 0.5773, 0.5965)
	C	(0.5270, 0.6341, 0.5773, 0.5965)
C22	A	(0.5270, 0.5396, 0.5464, 0.5773)
	B	(0.4216, 0.5765, 0.5744, 0.5773)
	C	(0.7378, 0.6135, 0.6094, 0.5773)
C31	A	(0.4256, 0.5373, 0.5479, 0.5773)
	B	(0.6810, 0.6199, 0.6014, 0.5773)
	C	(0.5958, 0.5717, 0.5813, 0.5773)
C32	A	(0.3746, 0.4868, 0.4818, 0.5368)
	B	(0.6556, 0.6176, 0.6195, 0.5965)
	C	(0.6556, 0.6176, 0.6195, 0.5965)
C41	A	(0.7035, 0.6082, 0.6070, 0.5773)
	B	(0.5025, 0.5863, 0.5791, 0.5773)
	C	(0.5025, 0.5350, 0.5442, 0.5773)
C42	A	(0.4216, 0.5650, 0.5656, 0.5773)
	B	(0.7378, 0.6012, 0.6001, 0.5773)
C51	C	(0.5270, 0.5650, 0.5656, 0.5773)
	A	(0.7043, 0.6426, 0.6275, 0.5965)
	B	(0.6163, 0.5926, 0.6060, 0.5965)
C52	C	(0.3521, 0.4855, 0.4880, 0.5368)
	A	(0.5773, 0.5818, 0.5837, 0.5773)
	B	(0.5773, 0.5818, 0.5837, 0.5773)

Source: authors.

Table 15. Determining F.P.I.S. and F.N.I.S.

	A+	A−
C11	(0.6810, 0.6200, 0.6014, 0.5774)	(0.4256, 0.5373, 0.5480, 0.5774)
C12	(0.6556, 0.4912, 0.6275, 0.5965)	(0.3746, 0.4912, 0.4881, 0.5369)
C21	(0.6312, 0.5935, 0.5992, 0.5774)	(0.4508, 0.5586, 0.5526, 0.5774)
C22	(0.7379, 0.6135, 0.6095, 0.5774)	(0.4216, 0.5396, 0.5464, 0.5774)
C23	(0.7778, 0.6114, 0.6001, 0.5774)	(0.7778, 0.6114, 0.6001, 0.5774)
C24	(0.6556, 0.6341, 0.5884, 0.5965)	(0.4444, 0.4900, 0.5774, 0.5369)
C31	(0.6810, 0.6200, 0.6014, 0.5774)	(0.4256, 0.5373, 0.5480, 0.5774)
C32	(0.6556, 0.6176, 0.6196, 0.5965)	(0.3746, 0.4869, 0.4819, 0.5369)
C41	(0.7035, 0.6083, 0.6070, 0.5774)	(0.5025, 0.5350, 0.5442, 0.5774)
C42	(0.7379, 0.6012, 0.6001, 0.5774)	(0.4216, 0.5650, 0.5656, 0.5774)
C51	(0.7044, 0.6426, 0.6275, 0.5965)	(0.3522, 0.4856, 0.4881, 0.5369)
C52	(0.5774, 0.5819, 0.5838, 0.5774)	(0.5774, 0.5682, 0.5643, 0.5774)

Source: authors.

Step 3: We have coded fuzzy logic in MATLAB. It was based on three linguistic variables with sixteen rules which are determined by experts at IKCO company. We have defined the function of the Sugeno model. The weights in the function are obtained from the TOPSIS model.

Table 16. Distances between A, B, C and D^{-} with respect to each criterion.

D^{-}	C11	C12	C21	C22	C23	C24	C31	C32	C41	C42	C51	C52
A	0.17691	0.2520	0.30428	0.11015	0.10010	0.10010	1.05046	0.88022	1.12677	1.05128	1.20219	1.14119
B	0.09976	0.09976	0.29243	0.14895	0.10010	0.17275	1.15479	1.13320	1.02555	1.20374	1.12409	1.14119
C	0.2432	0.2588	0.0574	0.17275	0.17275	0.17175	1.11552	1.19592	0.97973	1.05616	1.18593	1.13295

Source: authors.

Table 17. Distances between A, B, C and D^{+} with respect to each criterion.

D^{+}	C11	C12	C21	C22	C23	C24	C31	C32	C41	C42	C51	C52
A	0.09987	0.08468	0.04429	0.22613	0.24313	0.24313	1.05046	0.92669	1.22897	0.99881	1.20539	1.11515
B	0.24841	0.35345	0.06359	0.29580	0.24313	0.16555	1.19044	1.20300	1.10563	1.14753	1.12409	1.06524
C	0.05645	0.04129	0.26319	0.16555	0.16555	0.17555	1.05782	1.10116	1.05280	1.01291	1.21034	1.16878

Source: authors.

Table 18. Computations of D^{+} and D^{-} and CCi.

Computations of CC_i	$\sum D^{+}$	$\sum D^{-}$	CC_i
A	6.98044	7.29545	0.5105
B	7.79718	7.33319	0.4846
C	7.13029	7.39836	0.5095

Source: authors.

Table 19. Defuzzified matrix.

Decision matrix as the input Of MATLAB	C1	C2	C3	C4	C5	Employee evaluation
A	8	6.75	8	8	6.75	8.75
C	6.75	6.5	6.75	6.5	8	7.53
B	6.5	6.5	6.75	6.5	6.75	7.21

Source: authors.

$$Y = 0.2\ C_1 + 0.15\ C_2 + 0.07\ C_3 + 0.39\ C_4 + 0.19\ C_5$$

Step 4: We have run the software. Figure 2 shows the status of candidate A, Figure 3 shows the status of candidate C, and Figure 4 shows the status of candidate B. Based on software calculations the candidate A with value of 8.75 is the first priority in evaluation and candidates C and B are in other ranks with values of 7.53 and 7.21.

6. Conclusion

In this paper, a fuzzy decision support system (F.D.S.S.) is proposed for employee evaluation. The performance of the proposed method is compared with fuzzy TOPSIS, which confirms the reliability and validity of proposed F.D.S.S. VIKOR and fuzzy axiomatic design (Cevikcan, Cebi, & Kaya, 2009) or COPRAS (Zavadskas et al., 2008) are examples of modern methods available that could also be used for comparative test. Nevertheless, we have compared our results with fuzzy TOPSIS for three middle managers to assure top managers that the proposed model not only matches with a similar method but also can enhance the process. As a result, this F.D.S.S. is implemented in IKCO as a replacement for the traditional method to solve the issues observed in evaluation of managers.

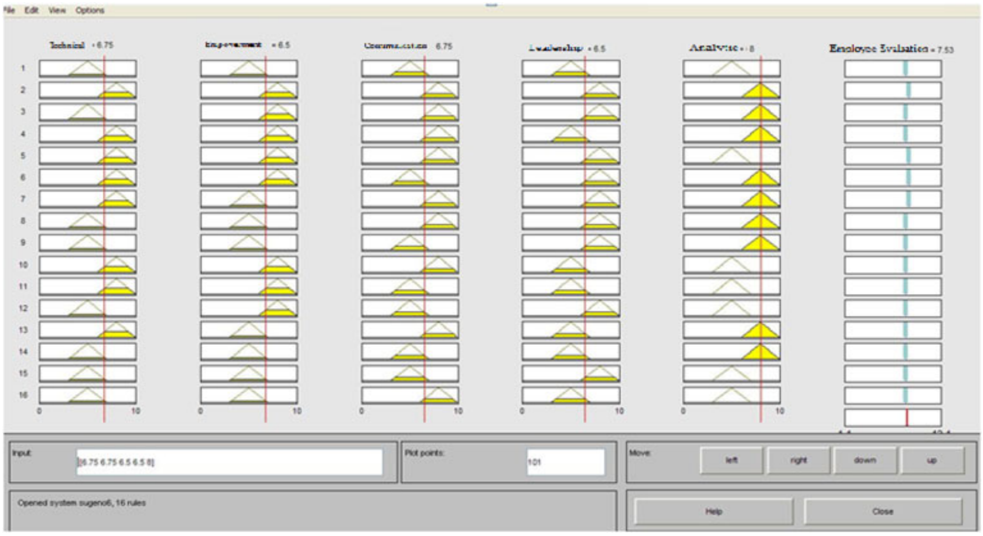

Figure 3. The status of candidate C. Source: authors.

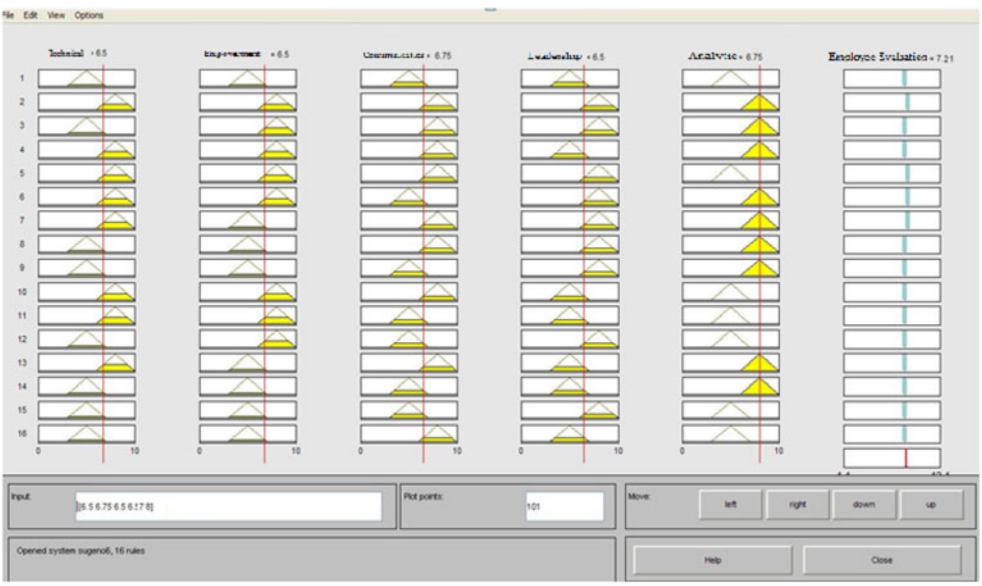

Figure 4. The status of candidate B. Source: authors.

The main reason that F.D.S.S. is suggested in IKCO roots in the simplicity and the advantages of this method to other similar methods. Although other methods such as fuzzy A.H.P., fuzzy TOPSIS or fuzzy VIKOR are also possible, there is no reliable source to prove the advantage of one model over another in all conditions, which is the basic reason that many papers are published in order to compare different models in different problems. Given that the main aim of this paper is to develop an initial model, this study just shows the first step of the change plan implemented in IKCO by proving that F.D.S.S. is a valid and advanced tool in comparison with the traditional methods of employee evaluation.

References

Barua, A., Mudunuri, L. S., & Kosheleva, O. (2014). Why trapezoidal and triangular membership functions work so well: Towards a theoretical explanation. *Journal of Uncertain Systems*, *8*(3), 164–168.

Billsberry, J. (2007). *Experiencing evaluation and selection*. Hoboken, NJ: Wiley & Sons.

Bouchon-Meunier, B., Dotoli, M., & Maione, B. (1996). On the choice of membership functions in a Mamdani-type fuzzy controller. In Proc. Online Workshops. Soft Computation, Nagoya, Japan, 1996, pp. 1–6.

Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems*, *17*(3), 233–247.

Cevikcan, E., Cebi, S., & Kaya, I. (2009). Fuzzy VIKOR and fuzzy axiomatic design versus to fuzzy TOPSIS: An application of candidate assessment. *Multiple-Valued Logic and Soft Computing*, *15*(2–3), 181–208.

Hennman, H. G., & Schwab, D. P. (1985). Pay satisfaction: Its multidimensional nature and measurement. *International Journal of Psychology*, *20*, 129–141.

Jang, J. S. R., Sun, C.-T., & Mizutani, E. (1997). *Neuro-fuzzy and soft computing: A computational approach to learning and machine intelligence*. Upper Saddle River, NJ: Prentice Hall, Inc.

Kaufmann, A., & Gupta, M. M. (1991). *Introduction to fuzzy arithmetic: Theory and applications*, New York: Van Nostrand Reinhold.

Karabasevic, D., Zavadskas, E. K., Turskis, Z., & Stanujkic, D. (2016). The framework for the selection of personnel based on the SWARA and ARAS methods under uncertainties. *Informatica*, *27*(1), 49–65.

Keršulienė, V., & Turskis, Z. (2012). Integrated fuzzy multiple criteria decision-making model for architect selection. *Technological and Economic Development of Economy*, *17*(4), 645–666.

Keršulienė, V., & Turskis, Z. (2014). A hybrid linguistic fuzzy multiple criteria group selection of a chief accounting officer. *Journal of Business Economics and Management*, *15*(2), 232–252.

Keršuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new stepwise weight assessment ratio analysis (SWARA). *Journal of Business Economics and Management*, *11*(2), 243–258.

Klir, G. J., & Yuan, B. (1995). *Fuzzy sets and fuzzy logic: Theory and applications*. Upper Saddle River, NJ: Prentice-Hall Inc.

Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, *7*(1), 1–13.

Negi, D. S. (1989). *Fuzzy analysis and optimization* (Unpublished doctoral dissertation). Kansas State University. Manhattan, KS.

Neluheni, G. N., Pretorius, W., & Ukpere, W. I. (2014). The role of quality the role of quality strategic planning on organisational success. *Mediterranean Journal of Social Science*, *15*(1), 697–708.

Šaparauskas, J., Kazimieras Zavadskas, E., & Turskis, Z. (2011). Selection of facade's alternatives of commercial and public buildings based on multiple criteria. *International Journal of Strategic Property Management*, *15*(2), 189–203.

Sivilevičius, H., Zavadskas, E. K., & Turskis, Z. (2008). Quality attributes and complex assessment methodology of the asphalt mixing plant. *Baltic Journal of Road & Bridge Engineering*, *3*(3), 161–166.

Stanujkic, D., Zavadskas, E. K., Ghorabaee, M. K., & Turskis, Z. (2017). An extension of the EDAS method based on the use of interval grey numbers. *Studies in Informatics and Control*, *26*(1), 5–12.

Štreimikienė, D., Šliogerienė, J., & Turskis, Z. (2016). Multi-criteria analysis of electricity generation technologies in Lithuania. *Renewable Energy*, *85*, 148–156.

Sugeno, M. (1985). An introductory survey of fuzzy control. *Information sciences*, *36*(1-2), 59–83.

Turskis, Z., & Juodagalvienė, B. (2016). A novel hybrid multi-criteria decision-making model to assess a stairs shape for dwelling houses. *Journal of Civil Engineering and Management*, *22*(8), 1078–1087.
Turskis, Z., Zavadskas, E. K., Antucheviciene, J., & Kosareva, N. (2015). A hybrid model based on fuzzy AHP and fuzzy WASPAS for construction site selection. *International Journal of Computers Communications & Control*, *10*(6), 113–128.
Yousefi, V., Haji Yakhchali, S., Šaparauskas, J., & Kiani, S. (2018). The impact made on project portfolio optimisation by the selection of various risk measures. *Engineering Economics*, *29*(2), 168–175.
Zadeh, L. A. (1973). Outline of a new approach to the analysis of complex systems and decision processes. Systems. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-3*(1), 28–44.
Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning. *Information Sciences*, *8*(3), 199–249.
Zavadskas, E. K., Turskis, Z., Tamosaitiene, J., & Marina, V. (2008). Selection of construction project managers by applying COPRAS-G method. *Computer Modelling and New Technologies*, *12*(3), 22–28.
Zavadskas, E. K., Govindan, K., Antucheviciene, J., & Turskis, Z. (2016). Hybrid multiple criteria decision-making methods: A review of applications for sustainability issues. *Ekonomska Istraživanja*, *29*(1), 857–887.
Zavadskas, E. K., Turskis, Z.,& Kildienė, S. (2014). State of art surveys of overviews on MCDM/MADM methods. *Technological and economic development of economy*, *20*(1), 165–179.
Zavadskas, E. K., Turskis, Z., Volvačiovas, R., & Kildienė, S. (2013). Multi-criteria assessment model of technologies. *Studies in Informatics and Control*, *22*(4), 249–258.