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FUZZY DELPHI APPROACH TO DEFINING A CYCLE FOR ASSESSING THE PERFORMANCE OF MILITARY DRIVERS

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Abstract: *This paper presents the Fuzzy Delphi approach to defining a cycle for assessing the performance of military drivers. This approach is based on the Delphi decision-making process under uncertainty. These uncertainties are described by linguistic terms modeled with triangular fuzzy numbers. The approach is modeled to take into the account the importance - weight of each decision-maker and the homogeneity of their individual fuzzy preferences. The vertex method calculates the distance between the aggregated Fuzzy estimation and the triangular fuzzy numbers in which the linguistic terms which experts had chosen are modeled. Defuzzification of the fuzzy preference of the experts was carried out by a Graded Mean Integration Representation.*

Key Words: *Fuzzy Delphi Approach, Cycle, Evaluating Performance, Military Drivers.*

1. Introduction

Depending on the work industry, job characteristics and used techniques, estimation can be done on daily, weekly, monthly, quarterly, half yearly or yearly basis (Noe et al., 2006; Grout, 2008; Jovanović et al., 2004; Vujić 2008; Bogićević–Milikić, 2008).

Common practice for performance rating in most organizations is on the yearly level. This choice has its advantages and disadvantages. The organization financial reporting dynamics is similar to the performance estimation cycle on the yearly basis; this is one of the advantages for such decision. However, some authors assert that such dynamics does not have to match the time cycle of a certain job, which is why many of the dimensions that are being evaluated stay blurred: in some executive jobs, which are low in the organizational hierarchy, the time cycle can be very short (e.g. seasonal jobs), which leads to a very short period for evaluating the performance of top managers. It is wrong to start with performance evaluation

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before it can be measured. In situations when individuals do not work long enough on particular workplace, a premature performance evaluation leads to stimulation of short goals only. On the other side, if you are waiting too long for formal evaluation, estimates can be wrong, whereby a significant loss of the motivation potential is considered. Also, it can be considered as a loss of the development potential during evaluation since the employees find out too late what they should improve in their work (Bogićević–Milikić, 2008).

However, same authors suggest that for some organizations it is completely impossible or either problematic, for practical reasons, to adopt evaluating system in which assessment is carried out in different time periods for different jobs. One of the possible compromises between demands for performance evaluation of all employees on the yearly basis, on one side, and demands for performance evaluation corresponding to the time cycle of a particular job, lies in performance evaluation of employees on the annual basis, except for executives and new employees. For them, the performance evaluation should be done more often.

A decision that specifies the start and the end of a single assessment cycle is an important component of the employees' performance evaluation system. In terms of defining the start and the end of the evaluation period, in literature and practice, there are two basic models (Bogićević–Milikić, 2008):

1. Model I (anniversary date appraisals) – An appraisal system in which all of an organization's employees are reviewed on the anniversaries of their individual hire dates;
2. Model II (focal point reviews) – also called common date or scheduled reviews, have organizations evaluate all of their employees at one set time, usually at the end of the calendar year.

Model I has many disadvantages: they are difficult to manage as an employee's role changes from one manager or department to another; the manager is constantly evaluating individual performance rather than that of the department as a whole; it is difficult to complete the process on time.

Focal performance appraisal strategy can be very helpful if the company is facing changes and must quickly alter its strategy. This model also enables managers to compare the performance of different employees simultaneously, which can result in appraisals that are more accurate and fair.

The aim of this paper is to define the cycle for assessing the performance of military drivers. The basic assumption is based on the view that the Extended Fuzzy Delphi Model is a convenient tool for achieving this goal. This paper is organized as follows: section 2 describes the basic assumptions of the Delphi method; section 3 describes the basic concepts of the Fuzzy logic theory; section 4 describes the Fuzzy Delphi approach to defining a cycle for assessing the performance and results obtained by applying the proposed algorithm; and section 5 provides concluding remarks.

2. Delphi method

The Delphi method is a widely used and accepted method for gathering data from respondents within their domain of expertise. The method is designed as a group communication process which aims at achieving a convergence of opinions on a specific real-world issue. The Delphi method is well suited as a means and method for consensus-building by using a series of questionnaires to collect data from a panel of selected subjects (Young & Jamieson, 2001). The method was implemented with a selected set of experts who were anonymous to each other, in as many rounds as necessary for the deviation in the mean limit values of the observed variables to be negligible.

After receiving the response from all the participants from the first round, the statistical processing is made, which involves calculating mean values, variance and standard deviation. Information about answers given by all experts is put in materials for the second round so that the experts have a chance to change their prognosis. The answers are being collected again and processed in the same way as in the first round. This procedure is repeated until the value of the coefficient of variation is not satisfactory. When an acceptable degree of consensus is obtained the process ends. Delphi method is shown in Fig. 1.

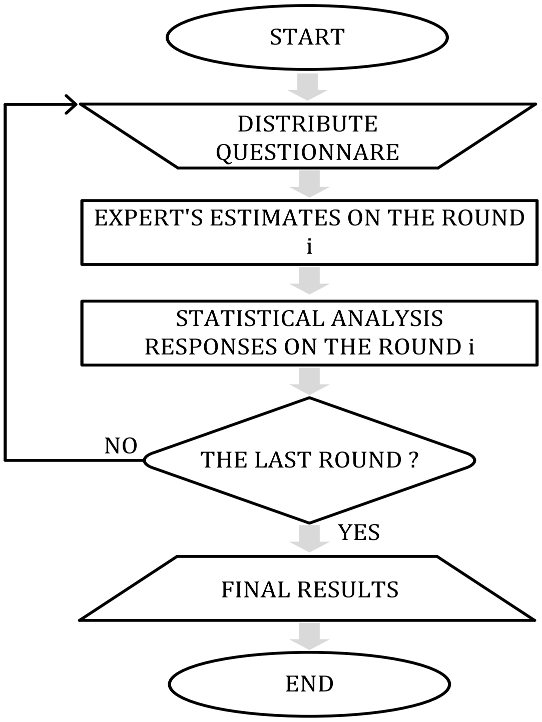

Figure 1. Implementation of the Delphi method (Lukovac, 2016)

Fuzzy logic is a very convenient tool for exploiting uncertainties and subjectivity that characterize the Delphi method.

3. Fuzzy logic theory

Fuzzy logic theory was introduced by Zadeh in 1965 as an extension of the classical notion of set. The fuzzy logic theory is based on fuzzy sets which are a natural extension of the classical set theory. A fuzzy set is determined by a membership function which accepts all intermediate values between 0 and 1. The values of a membership function precisely specify to what extent an element belongs to a fuzzy set, i.e. to the concept it represents. In the fuzzy sets, the decision-maker should determine the form of the membership function. In the literature, the most common fuzzy numbers are triangular, trapezoidal and bell shape numbers. The use of these fuzzy numbers does not require complex mathematical calculations, and the accuracy of the results obtained is quite satisfactory. According to some authors, the use of higher order fuzzy sets (parabolic shape, logarithmic curve, and itc) has no meaningful application in the uncertainty modeling that exists in real problems (Klir & Yuan, 1995).

In this paper, triangular fuzzy numbers (TFN) were used to model the uncertainty. Fig. 2 shows a typical example of a TFN A symbolized by $A=(l,m,r)$, with peak (or center) *m*, left width *l* > 0 and right width *r* > 0.

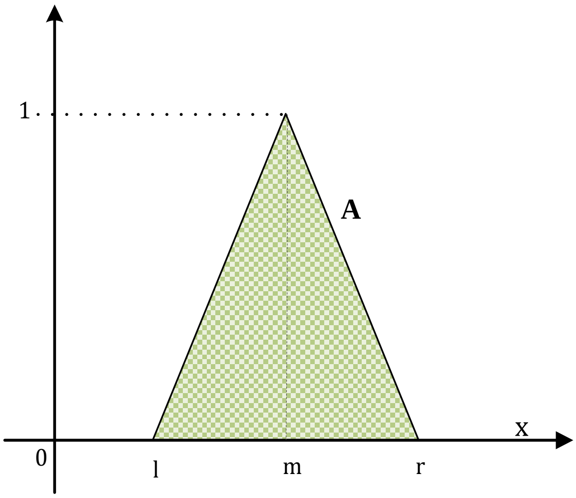

Figure 2. Fuzzy number A

Basic operations over TFN are defined in (Dubois & Prade, 1980). If we consider two TFN $A=(l_1,m_1,r_1)$ and $B=(l_2,m_2,r_2)$, the algebraic rules that apply to these two TFN are:

$$A+B=(l_1+l_2,m_1+m_2,r_1+r_2) \tag{1}$$

$$A-B=(l_1-r_2,m_1-m_2,r_1-l_2) \tag{2}$$

$$A*B=(l_1*l_2,m_1*m_2,r_1*r_2) \tag{3}$$

$$A:B=(l_1:r_2,m_1:m_2,r_1:l_2) \tag{4}$$

$$k*A=(k*l_1,k*m_1,k*r_1),k=const \tag{5}$$

$$A^{-1}=(l_1,m_1,r_1)^{-1}=\left(\frac{1}{r_1},\frac{1}{m_1},\frac{1}{l_1}\right) \tag{6}$$

Defuzzification is the process of producing a quantifiable result in fuzzy logic, given fuzzy sets and corresponding membership degrees. There are many different methods of defuzzification available, and which will be used depends on the decision-maker.

4. Fuzzy Delphi approach to defining a cycle for assessing the performance

The need to improve the Delphi method by introducing uncertain data was explained in papers (Ishikawa et al., 1993; Wu, 2011). Fuzzy Delphi methods (FDM) have been investigated by different researchers. In (Chang et al., 2011) author deals with the problem of controlling the quality of services in rail traffic with the FDM. In (Tadić et al., 2013) the authors considered the problem of selecting appropriate technologies by following 14 criteria. FDM determines the aggregation of the relative importance of the criteria.

In (Cheng & Lin, 2002), the FDM was developed to determine relative importance of business goals. According to this model, each decision-maker carries out a direct assessment of the importance of business goals on each hierarchical model. Then the group's opinion mean value is calculated, which is also described by the TFN based on the algebra. Also, the fuzzy distance between the mean value of a group and fuzzy numbers is calculated, which describes predefined linguistic terms. Based on this information, the decision-makers in the first iteration correct their estimations. The consensus is considered to be achieved in the second iteration of the FDM.

In the majority of papers, the authors consider that the number of iterations is a criterion according to which the stability of FDM is achieved. In (Lukovac, 2016), the authors expose consideration that the difference between the Fuzzy numbers of two consecutive iterations for the referred item should not be greater than 0.2.

In this paper, the extended FDM (EFDM - Extended Fuzzy Delphi Model) developed in (Kashdan, 2004), which takes into account the importance (weights) of decision-makers and the homogeneity of their expressed Fuzzy preferences, was used to define the start/end of the military performance assessment cycle. The EFDM algorithm consists of six steps:

Step 1: Decision-makers express their opinion by choosing one of the six offered responses described by linguistic terms (analogous to Saaty, 1980) via TFN. The domains of these TFN's are defined in the Saaty's scale of measurement (Chen & Tzeng, 2004). Value 1 or value 9, indicates the lowest or highest value of the variables. Table 1 shows the domains of these TFN's.

Table 1. Linguistic terms of EFDM (Lukovac, 2016 ; Lukovac & Popović, 2017)

Linguistic terms	TFN
Disagree strongly (DST)	(1,1,2.5)
Disagree moderately (DMO)	(1.5,3,4.5)
Disagree a little (DLI)	(3,4.5,6)
Agree a little (ALI)	(4,5.5,7)
Agree moderately (AMO)	(5.5,7,8.5)
Agree strongly (AST)	(7.5,9,9)

The graphical representation of EFDM's linguistic terms from Table 1 is shown in Figure 3.

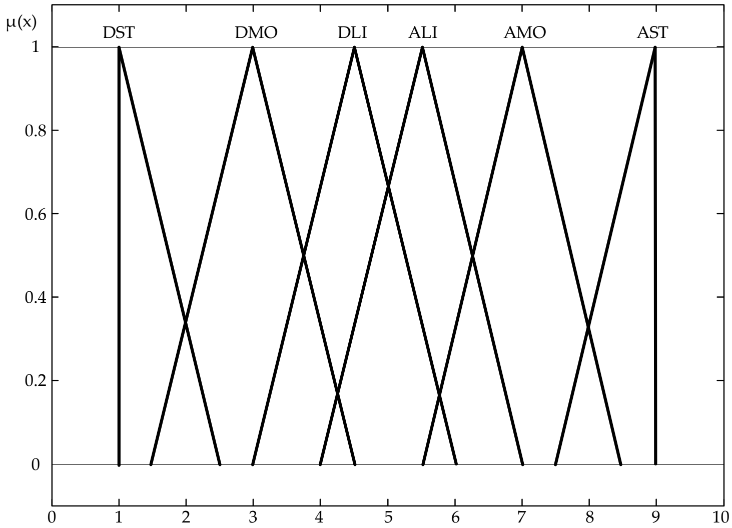

Figure 3. The graphical representation of EFDM's linguistic terms (Lukovac & Popović, 2017)

Step 2: The aggregation of the decision-makers fuzzy estimations is accessed according to the expression:

$$A=\left(l_a, m_a, r_a\right)=\left\{\begin{array}{l} l_a=\sum_{i=1}^{n} l_i \alpha_{Ei} \\ m_a=\sum_{i=1}^{n} m_i \alpha_{Ei} \\ r_a=\sum_{i=1}^{n} r_i \alpha_{Ei} \end{array}\right\}, i=(1,\ldots,n) \tag{7}$$

where are:

A – aggregating experts' fuzzy estimate;

l_a – the left margin of aggregated Fuzzy assessment;

m_a – the value in which the function of the aggregated Fuzzy assessment has the highest value i.e., $m_a = 1$;

r_a – the right margin of aggregated Fuzzy assessment;

n –number of experts;

α_{Ei} – the normalized weight of *i* expert.

Step 3: The vertex method calculates the distance (d^+) between the aggregated Fuzzy estimation and the triangular fuzzy numbers in which the linguistic statements, according to the expression (Gigović et al., 2016; Pamučar et al., 2011):

$$d_i^+ = \sqrt{\frac{1}{3} * \left[\left(l_a - l_i\right)^2 + \left(m_a - m_i\right)^2 + \left(r_a - r_i\right)^2 \right]} \tag{8}$$

where is:

i –index of linguistic term in Table 1, i=(1,...,6);

The decision-makers' aggregated opinion can be described by linguistic terms that the least distance value is associated with.

Step 4: The approach is towards the second iteration of FDM, with the prior knowledge of decision-makers with the results of the first FDM iteration.

Step 5: The distance between aggregated Fuzzy estimations is calculated in two consecutive iterations:

$$d^{+} = \left(\left(l_{a+1}, m_{a+1}, r_{a+1}\right), \left(l_a, m_a, r_a\right)\right) \tag{9}$$

If the value of the distance between the aggregated stages of the estimation in two consecutive iterations is less than 0.2 (analogously [9]), the decision-makers' consensus has been reached.

Step 6: The defuzzification of individual Fuzzy estimations from the second iteration of the EFDM is carried out, and its homogeneity on the Saaty's scale, by the mean value, the standard deviation and the coefficient of variation, is investigated:

$$Std.Deviation < \frac{Mean}{3}; C.Variance < 30\% \tag{10}$$

If the condition of homogeneity of the individual fuzzy estimation of the decision-makers is satisfied, it is established that a complete consensus has been reached and the process is therefore completed. Otherwise, the process is repeated.

In line with the presented EFDM algorithm, the definition of the cycle for assessing the performance of military drivers has begun. The expert group was made of 20 decision-makers who conducted the research on the development of a model for the elimination of errors in the system for assessing the performance of drivers of military motor vehicles (Lukovac, 2016). Experts expressed their preferences about alternatives for the cycle length, as well as its start/end, by choosing one of the linguistic terms in Table 1.

4.1. Determining the cycle length of assessment

Experts used linguistic terms from the Table 1 to determine the cycle length of assessment. They evaluated the offered alternatives for the time period that the performance of military drivers should be assessed for (3, 6 and 12 months) and their preferences in the second iteration are shown in Table 2. Based on the distance value between aggregating experts' fuzzy estimate in two consecutive EFDM iterations, the first condition for accepting a decision is satisfied in the second iteration.

Expert weights (α_E) were obtained by normalizing their coefficients of competence, calculated according to the approach shown in [11]. Distances between aggregated fuzzy numbers (Table 2) and triangular fuzzy numbers in which the linguistic terms which experts had chosen are modeled, are shown in Table 3.

Table 2. Fuzzy preferences of the experts regarding the time period of the assessment (Lukovac, 2016)

Experts	3 Months	6 Months	12 Months	α_E
1.	(1,1,2.5)	(1,1,2.5)	(7.5,9,9)	0.0540
2.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0456
3.	(1.5,3,4.5)	(1,1,2.5)	(7.5,9,9)	0.0461
4.	(7.5,9,9)	(1.5,3,4.5)	(1,1,2.5)	0.0476
5.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0456
6.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0455
7.	(1,1,2.5)	(7.5,9,9)	(3,4.5,6)	0.0457
8.	(1,1,2.5)	(1,1,2.5)	(7.5,9,9)	0.0561
9.	(1,1,2.5)	(1,1,2.5)	(7.5,9,9)	0.0582
10.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0463
11.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0498
12.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0508
13.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0557
14.	(5.5,7,8.5)	(1.5,3,4.5)	(1,1,2.5)	0.0547
15.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0511
16.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0485
17.	(7.5,9,9)	(3,4.5,6)	(1,1,2.5)	0.0543
18.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0476
19.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0505
20.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0463
Aggregation	(1.93,2.24,3.58)	(1.75,2.93,4.36)	(6.28,7.54,7.85)	1

Table 3. Distance values for the assessment cycle length (Lukovac, 2016)

Linguistic terms	3 Months	6 Months	12 Months
Disagree strongly	1.090	1.605	5.750
Disagree moderately	0.733	0.170	4.267
Disagree a little	2.009	1.498	2.792
Agree a little	2.978	2.495	1.832
Agree moderately	4.458	3.992	0.665
Agree strongly	5.947	5.523	1.286

Analyzing the results shown in Table 3, it can be observed that, for the considered alternatives of 3 and 6 months, the distance value is the smallest for linguistic term "Disagree moderately" (0.733 i.e. 0.170); after that term the closest term is "Disagree strongly". For alternative of 12 months its closest linguistic term is "Agree moderately" (0.665), and then term "Agree strongly". Distance values between aggregated fuzzy decisions for the assessment cycle length in the first and the second EFDM iterations are shown in Table 4.

Table 4. Distance value between aggregated fuzzy decisions for the assessment cycle length (Lukovac, 2016)

Aggregation	3 Months	6 Months	12 Months
Iteration I	(2.04,2.34,3.61)	(1.95,3.01,4.45)	(6.18,7.45,7.82)
Iteration II	(1.93,2.24,3.58)	(1.95,2.93,4.36)	(6.28,7.54,7.85)
Distance	0.090	0.136	0.076

Since the distance between the aggregated fuzzy estimates of the experts in the first and second iteration of the EFDM for selecting the cycle length is less than 0.2, the first condition for accepting a decision is satisfied (according to the proposed EFDM algorithm).

Defuzzification of the fuzzy preference of the experts was carried out by a Graded Mean Integration. Representation according to the expression:

$$defuzzy\,A = \left(l_1 + 4m_1 + r_1\right)/6 \tag{11}$$

Defuzzification of the fuzzy preference of the experts from Table 4 carried out by an IBM SPSS Statistics 22.0, is shown in Table 5.

Table 5. Indicators of homogeneity of the EFDM decision for the assessment cycle length (Lukovac, 2016)

Statistical indicators	3 Months	6 Months	12 Months
Mean	0.1205	0.1485	0.3691
Standard deviation	0.1332	0.0727	0.1444
Variance	108%	48%	38%

Statistical analysis in Table 5 indicated the inhomogeneity of the fuzzy preference of the experts, so the EFDM process had to be continued with a new (third) iteration. In the third iteration there was no deviation from the fuzzy preference of the experts from the second iteration; therefore, it began to determine the cause of inhomogeneity. In order to determine the cause of inhomogeneity it calculated the distance between the linguistic terms chosen by the experts and a linguistic term that is equivalent to aggregating fuzzy decisions. These results are shown in Table 6.

Table 6 shows that the individual fuzzy preferences of the expert 4, 7, 14 and 17 are far away from the linguistic terms that are equivalent to aggregated fuzzy decisions. In other words, the preferences of these experts are in contrast to the group's preference, which is the cause of inhomogeneity. By eliminating the preference of these four experts, separated aggregated fuzzy decisions were obtained (Table 7).

Table 6. Values of individual distance by experts for the assessment cycle length (Lukovac, 2016)

Experts	DISTANCES VALUES		
	3 Months (1.5,3,4.5)	6 Months (1.5,3,4.5)	12 Months (5.5,7,8.5)
1.	1.658	1.658	1.658
2.	1.658	0.000	1.658
3.	0.000	1.658	1.658
4.	5.545	0.000	5.545
5.	1.658	0.000	1.658
6.	1.658	0.000	1.658
7.	1.658	5.545	2.500
8.	1.658	1.658	1.658
9.	1.658	1.658	1.658
10.	1.658	0.000	1.658
11.	1.658	0.000	1.658
12.	1.658	0.000	1.658
13.	1.658	0.000	1.658
14.	4.000	0.000	5.545
15.	1.658	0.000	1.658
16.	1.658	0.000	1.658
17.	5.545	1.500	5.545
18.	1.658	0.000	1.658
19.	1.658	0.000	1.658
20.	1.658	0.000	1.658

Table 7. Separated aggregated fuzzy decisions (Lukovac, 2016)

Experts	3 Months	6 Months	12 Months	α_E
1.	(1,1,2.5)	(1,1,2.5)	(7.5,9,9)	0.0677
2.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0571
3.	(1.5,3,4.5)	(1,1,2.5)	(7.5,9,9)	0.0577
5.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0571
6.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0570
8.	(1,1,2.5)	(1,1,2.5)	(7.5,9,9)	0.0704
9.	(1,1,2.5)	(1,1,2.5)	(7.5,9,9)	0.0730
10.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0580
11.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0625
12.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0637
13.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0699
15.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0640
16.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0607
18.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0597
19.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0634
20.	(1,1,2.5)	(1.5,3,4.5)	(7.5,9,9)	0.0580
Aggregation	(1.03,1.12,2.62)	(1.37,2.46,3.96)	(7.5,9,9)	1

Distances between aggregated fuzzy numbers (Table 7) and triangular fuzzy numbers in which the linguistic terms which experts had chosen are modeled, are shown in Table 8.

Table 8. Distances values of separated aggregated fuzzy decisions (Lukovac, 2016)

Linguistic terms	3 Months	6 Months	12 Months
Disagree strongly	0.096	1.213	7.036
Disagree moderately	1.563	0.446	5.545
Disagree a little	2.989	1.913	4.062
Agree a little	3.970	2.909	3.082
Agree moderately	5.454	4.407	1.658
Agree strongly	6.948	5.937	0.000

Based on the results of values of distances (Table 8), alternative with cycle length of 3 months is equivalent to linguistic term "Disagree strongly" (0.096). Alternative with cycle length of 6 months is equivalent to linguistic term "Disagree moderately" (0.446). Linguistic term "Agree strongly" (0.000) is equivalent to an alternative with cycle length of 12 months. Distances values of separated aggregated fuzzy decisions in the last two iterations of EFDM is 0 (zero) because the experts, in the last (third) iteration of EFDM, did not change their fuzzy orientations with respect to the previous ones, and the first condition for accepting a decision is satisfied. The results of statistical analysis of separated defuzzification of fuzzy expert's estimation from Table 8, using IBM SPSS Statistics 22.0, are shown in Table 9.

Based on the results (Table 11.), alternative A1 has the smallest distance value for linguistic term "Disagree strongly" (0.000). Alternatives A2 is equivalent to linguistic term "Agree strongly", based on the least distance value (0.568). Values of distances between aggregated fuzzy numbers Iteration I and Iteration II to the time at the start and the end of a cycle for assessing are shown in Table 12.

Table 9. Statistical analysis of the homogeneity of the fuzzy preference for the assessment cycle length (Lukovac, 2016)

Statistical Indicators	3 Months	6 Months	12 Months
Mean	0.0844	0.1581	0.5469
Standard deviation	0.0245	0.0455	0.0463
Variance	28%	28%	8%

Statistical analysis in Table 9 indicates the homogeneity of the fuzzy preference of the experts, which complies with the second condition of the stability of the EFDM decision and it can be concluded that the performance of a military driver should be evaluated at 12 months.

4.2. Defining to the start/end of the cycle for assessing

The EFDM algorithm was used to define the start/end of the military performance assessment cycle. An alternative A1 represented an estimation model in which the start and the end of the assessment period relate to the start of employment, while the model of assessment by which all employees are assessed at the same time, i.e., at the end of the calendar year, was an alternative A2. An acceptable consensus was reached in the second iteration of EFDM, Table 10.

Table 10. Experts' fuzzy preference to the start/end of the assessment cycle (Lukovac, 2016; Lukovac & Popović, 2017)

Experts	A1	A2	α_E
1.	(1,1,2.5)	(7.5,9,9)	0.0540
2.	(1,1,2.5)	(7.5,9,9)	0.0456
3.	(1,1,2.5)	(7.5,9,9)	0.0461
4.	(1,1,2.5)	(7.5,9,9)	0.0476
5.	(1,1,2.5)	(5.5,7,8.5)	0.0456
6.	(1,1,2.5)	(7.5,9,9)	0.0455
7.	(1,1,2.5)	(7.5,9,9)	0.0457
8.	(1,1,2.5)	(5.5,7,8.5)	0.0561
9.	(1,1,2.5)	(7.5,9,9)	0.0582
10.	(1,1,2.5)	(5.5,7,8.5)	0.0463
11.	(1,1,2.5)	(5.5,7,8.5)	0.0498
12.	(1,1,2.5)	(5.5,7,8.5)	0.0508
13.	(1,1,2.5)	(7.5,9,9)	0.0557
14.	(1,1,2.5)	(7.5,9,9)	0.0547
15.	(1,1,2.5)	(7.5,9,9)	0.0511
16.	(1,1,2.5)	(7.5,9,9)	0.0485
17.	(1,1,2.5)	(7.5,9,9)	0.0543
18.	(1,1,2.5)	(5.5,7,8.5)	0.0476
19.	(1,1,2.5)	(7.5,9,9)	0.0505
20.	(1,1,2.5)	(5.5,7,8.5)	0.0463
Aggregation	(1,1,2.5)	(6.8,8.3,8.8)	1

The distance values between aggregated fuzzy numbers (Table 10) and linguistic terms are shown in Table 11.

Table 11. Values of distances to the start/end of the assessment cycle (Lukovac, 2010; Lukovac & Popović, 2017)

Linguistic terms	A1	A2
Disagree strongly	0.000	6.516
Disagree moderately	1.658	5.008
Disagree a little	3.082	3.517
Agree a little	4.062	2.529
Agree moderately	5.545	1.090
Agree strongly	7.036	0.568

Based on the results (Table 11), alternative A1 has the smallest distance value for linguistic term "Disagree strongly" (0.000). Alternative A2 is equivalent to linguistic term "Agree strongly", based on the least distance value (0.568). Values of distances between aggregated fuzzy numbers Iteration I and Iteration II to the time at the start and the end of the assessment cycle are shown in Table 12.

Table 12. Values of distances between aggregated fuzzy numbers to the start/end of the assessment cycle (Lukovac, 2016; Lukovac & Popović, 2017)

Aggregation	A1	A2
Iteration I	(1.1,1.2,2.7)	(6.7,8.2,8.8)
Iteration II	(1,1,2.5)	(6.8,8.3,8.8)
Distance	0.166	0.080

Since the distance values are less than 0.2, the first condition for accepting a decision is satisfied.

The mean standard deviation and the variance were performed using statistical software IBM SPSS 22.0 and are shown in Table 13.

Table 13. The EFDM statistical indicators for defining the start/end of the cycle (Lukovac, 2016; Lukovac & Popović, 2017)

Statistical indicators	A1	A2
MEAN	0.0625	0.4075
Standard deviation	0.0052	0.0596
Variance	8%	14%

Statistical analysis in Table 13 indicates the homogeneity of the fuzzy preference of the decision-makers, which complies with the second condition of the stability of the EFDM decision.

5. Conclusion

An important component of the performance assessment system for military drivers, which can cause errors in the system for assessing their performance, is a decision concerning the defining the period of their assessment: the duration of one cycle and the determination of the start and the end of one assessment cycle (Lukovac, 2010; Lukovac et al., 2012, Lukovac et al., 2014). The results of the conducted EFDM have confirmed that this technique is a suitable tool for correctly defining the cycle for assessing the performance of military drivers and it can be concluded that the performance of a military driver should be evaluated at the same time - at the end of a calendar year.

The presented EFDM enables faster, more complete, more flexible and more realistic modeling of the decision-making process compared to the classic Delphi model. Developed EFDM contributes to the greater stability of the final decision, taking into account the importance of the decision-makers and the homogeneity of their individual Fuzzy preferences. Also, the proposed EFDM is of a general character, and as such, it is applicable to solving similar problems in different areas. In order to upgrade the presented EFDM, the direction of further research should focus on linking this technique with one of the multi-criteria decision-making methods under uncertainty conditions, the results of which would be the starting point for the implementation of the presented EFDM.

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