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SELECTION OF A COURSE OF ACTION BY OBSTACLE EMPLOYMENT GROUP BASED ON A FUZZY LOGIC SYSTEM

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Abstract: The paper has focused on the point at which a decision is to be made to activate the Obstacle Employment Group (OEG), which is a defining moment for the overall engagement of the group. The course of action is selected based on a Fuzzy Logic System (FLS), created by translating the experience of decision-makers into a single knowledge base. The FLS mainstays are four input criteria and one output, interconnected by a rule base.

Keywords: Decision-making, fuzzy logic, Fuzzy Logic System (FLS), Obstacle Employment Group (OEG).

MSC: 03B52, 03E72, 93C42, 68U35.

1. INTRODUCTION

The Army of Serbia performs combat and non-combat operations. The combat operations involve offensive and defensive missions. The defensive operations relevant to this paper are those taking place when the enemy takes initiative in a bid to seize a territory or break out into a defended area [3]. The objective of defensive operations in general is to defeat the will and intentions of the enemy and neutralize the forces the enemy's offensive powers rest on [3].

Engineering units prepare defensive terrain by performing a broad range of engineering tasks. These are designed to inflict losses on the enemy, and to halt, inhibit and control the movement and maneuver of the enemy; barriers and obstacles are employed to block access to facilities, areas and routes [3]. The term "obstacle employment" means to make and deploy different types of explosive and non-explosive artificial obstacles and/or to reinforce natural obstacles. The purpose of these operations is to slow down the pace of an enemy assault, to inhibit and keep in check the combat operations, chiefly by armored and mechanized units, to hamper airborne assault landings, obstruct transportation and supply lines, inflict losses and create favorable conditions for the offensive by our forces [13].

The obstacle employment is a duty shared by all units of the Army of Serbia, but the center of gravity involves combat engineers, i.e. pioneers. The obstacle employment in a defensive operation preferably takes place while the operational environment is prepared. Limited time, insufficient human and material resources, however, can make it very difficult, and the process usually stretches into the operation; pioneers are grouped into provisional units, and it is usually the Obstacle Employment Group (OEG). The chief task of the OEG is to make additional explosive obstacles to counter an enemy breakthrough, especially if it involves armored and mechanized unites. In principle, those in charge of defining the task, allocate to the OEG one or two courses of action, and two to three routes for each, to build explosive obstacles along [7]. The OEG mission is to respond to an enemy breakthrough by deploying anti-tank landmines along the pre-assigned routes to slow down or stop the enemy maneuver [6]. The group might also demolish smaller structures (minor bridges, small buildings, etc.), but not very often.

For the OEG to be used properly and most effectively, the decision-maker must select the course of action allowing the group to perform the best result. There's always more than one course of action available, and it is up to the decision-maker to choose one or two.

2. FUZZY LOGIC AND FUZZY SETS

Fuzzy sets are used to represent and model a linguistic uncertainty in a mathematically formalized manner. The sets defined this way might be interpreted as an attempt to generalize the classic set theory. The idea behind the fuzzy sets is quite simple. In classic (non-fuzzy) sets, a certain element (a member of the universal set) either belongs to a defined set, or it does not. In that sense, the fuzzy set does simplify the classic set, because the membership of an element in the set is valued in the interval [0, 1]. In other words, the membership function of a fuzzy set mirrors each element of the universal set in the real unit interval. A major difference between classic and fuzzy sets is that the classic sets always have unique membership functions, whereas there is an infinite number of membership functions to describe a fuzzy set. This fact allows the fuzzy systems to adjust properly to the situations they apply to. *Lotfi Zadeh* [14] placed emphasis on this fact while defining the fuzzy set, and noted that any area can be fuzzified and the conventional approach to the set theory generalized accordingly.

While calculating the time necessary to perform a task by a Serbian army unit, a very frequent estimate is "approximately a few minutes." The "approximately three minutes" is the nearest whole number to express the approximate time necessary to complete the task.

The argument that the time required for the completion of the task is three minutes will be interpreted in the same manner in any situation. However, when we say that it might take nearly three minutes to complete the task, we might also want to quantify "nearly" and to have a "maximum error" estimate, and sometimes it is all we need to know. If we say that the time needed for an activity to be completed is "approximately three minutes", it might be sufficient information for us, while on the other hand, it can only expand uncertainty.

Similar descriptions are used successfully in any decision-making process, and fuzzy logic makes it possible for us to use seemingly vague information in different areas of science. Figure 1 illustrates the idea of replacing the precise, rigorous descriptions of complex occurrences with quite the opposite concept, allowing for indistinctness [9].

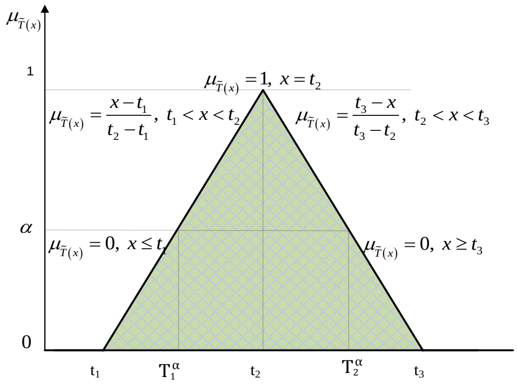

Figure 1: Fuzzy number

Typically, a discrete set is a set of elements with the same characteristics. Each element belongs to the discrete set one hundred percent, or, on the scale from 0 to 1, the degree of membership for each is 1. Of course, a discrete element can be completely outside the set, and the membership degree is 0.

The fuzzy set expands and generalizes the classic discrete set [4]. It is a set of elements with similar characteristics. The degree of membership in a fuzzy set can be any real number from the interval [0, 1].

The fuzzy set $\tilde{A}$ in a nonempty set is the ordered pair $(\mu_A(x), x)$, where $\mu_A(x)$ is a degree of membership of the element $x \in U$ in the fuzzy set $\tilde{A}$ [12]. The membership degree is a number from the interval [0,1]. The higher the membership degree, the more corresponding the element of the universal set U is to the characteristics of the fuzzy set.

Formally, the fuzzy set A is defined as a set of ordered pairs

$$A = \{(x, \mu_A(x)) | x \in X, 0 \le \mu_A(x) \le 1\} \tag{1}$$

If we define the reference set V={*o, p, r, s, t*}, a fuzzy set might look like this: B ={(0.3, *o*), (0.1, *p*), (0, *r*), (0, *s*), 0.9, *t*) }. This means that the element *o* belongs to the set B with a membership degree of 0.3, *p* with a membership degree of 0.1, *t* with a membership degree of 0.9, while *r* and *s* do not belong to the set B [9].

The membership function defines the fuzzy set. If the reference set is discrete, the membership function is a set of discrete values from the interval [0, 1], the same as above. If the reference set is continuous, we can formulate it analytically based on a membership function.

The following are the most frequently used membership functions [10]:

- Triangular membership function, Figure 2c
- Trapezoidal membership function, Figure 2a
- The Gaussian Curve, Figures 2d and 2b.

In Figure 2, the ordinate refers to a degree of membership, and the abscissa to the fuzzy variable *x*.

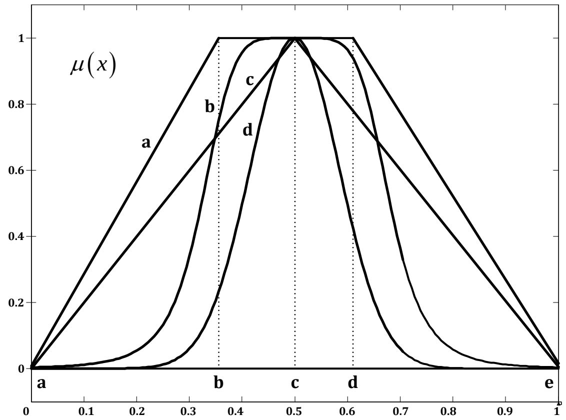

Figure 2: The most commonly used forms of membership functions

The following are mathematical formulas describing the membership functions displayed in Figure 2:

$$\mu_c(x) = \begin{cases} 0, & 0 < x < a \\ (x-a)/(c-a), & a \le x \le c \\ (e-x)/(e-c), & c \le x \le e \\ 0, & x > e \end{cases} \quad (2)$$

$$\mu_a(x) = \begin{cases} 0, & 0 < x < a \\ (x-a)/(b-a), & a \le x \le b \\ 1, & b \le x \le d \\ (e-x)/(e-c), & d \le x \le e \\ 0, & x > e \end{cases} \quad (3)$$

$$\mu_d(x) = e^{-\frac{1}{2}(\frac{x-c}{e})^2} \quad (4)$$

$$\mu_b(x) = \frac{1}{1+(x-c)^2} \quad (5)$$

Most of the fuzzy system design tools make it possible for the user to define different arbitrary membership functions [9].

The elements of fuzzy sets are taken from the universe of discourse, which contains all the elements to be considered. In other words, the fuzzy variable can assume values over the universe of discourse only.

The term "universe of discourse" will be clarified based on the variable *the time required for the completion of a task*. The time required for the completion of a task implies a high level of uncertainty, but it is certain that the time will not exceed t_3 or be under t_1. In other words, it is certain that the time belongs to the closed interval $[t_1, t_3]$. This closed interval is called the universe of discourse, symbolically described as $T = [t_1, t_3]$, Figure 1.

To define the universe of discourse for each fuzzy variable is the responsibility of the fuzzy system designer, and the most natural solution is to adopt a universe of discourse corresponding with the physical boundaries of the variable. If the variable is not of physical nature, a standard universe of discourse will be adopted, or an abstract one defined [1], [11].

Apart from the universe of discourse, a triangular fuzzy number – fuzzy time in this particular case – is characterized by an interval of confidence, too. The concept allowing for a fuzzy number to be expressed based on a universe of discourse and a corresponding interval of confidence was devised by Kaufmann and Gupta [5]. Figure 1 shows the fuzzy number $\tilde{T}$. The universe of discourse that corresponds to the interval of confidence α is denoted as $\left[T_1^\alpha, T_2^\alpha\right]$.

3. FUZZY LOGIC SYSTEM DESIGN

Fuzzy logic is most commonly used to model the complex systems in which other methods failed to establish the interdependence between individual variables [11].

The models based on fuzzy logic are composed of "IF-THEN" rules. Each rule establishes a relation between the linguistic values through an "IF-THEN" statement:

$$IF\ x_1\ is\ A_{j1}\ AND \ldots AND\ x_i\ is\ A_{ji}\ AND \ldots AND\ x_n\ is\ A_{jn}\ THEN\ y\ is\ B_j$$

Where $x_i, i = 1,...,n$ are the input variables, y is the output variable A_j and B_j are linguistic values labeling fuzzy sets. The degree with which the output variable y matches the corresponding fuzzy set B_j, depends on the degree to which the input variables $x_i, i = 1,...,n$ match their fuzzy sets, A_j, and on the logic format (AND, OR) of the antecedent part of the rule, Figure 3.

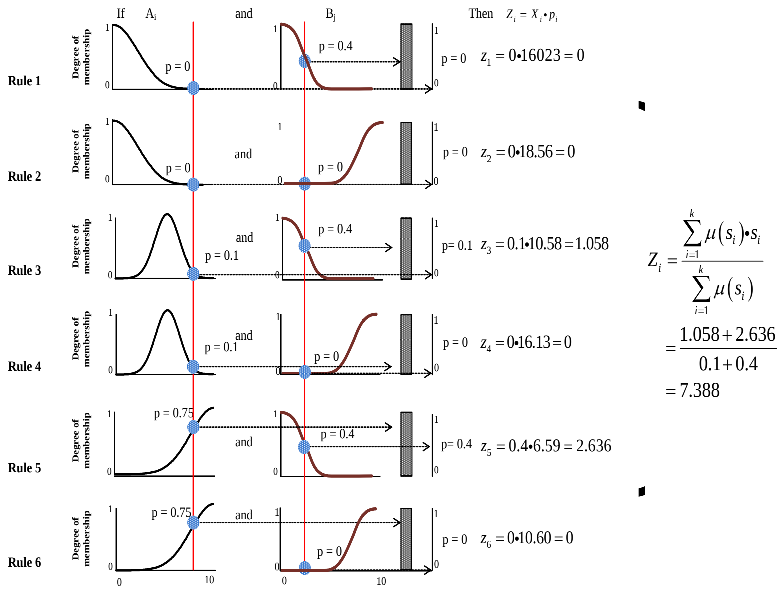

Figure 3: Applying rules in Sugeno fuzzy systems [10]

If *n* paralel rules are interpreted by the conjuction “or“, they can be formulated based on the fuzzy relation below:

$$\tilde{R} = \bigcup_{k=1}^{n} \tilde{R}_k \tag{6}$$

The membership function of this relation is as follows:

$$\mu_{\tilde{R}}(x, y) = \tilde{\vee}_{k}\, \mu_{\tilde{R}}(x, y) = \max_{k} \mu_{\tilde{R}}(x, y) = \max_{k}(\min \mu_{\tilde{R}}(x), \mu_{\tilde{R}}(y)) \tag{7}$$

Each rule gives as a result a fuzzy set, with a membership function cut in the higher zone. Applying all the rules gives a set of fuzzy sets with differently cut membership functions, whose deterministic values all have a share in the inferential result. A single value is needed in order to have a useful result figure 4.

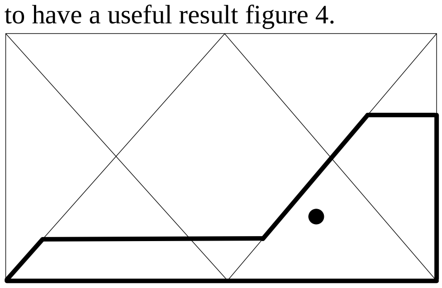

Figure 4: Defuzzification

A fairly large set of rules, where a solution to a problem is described in words, constitutes a rule base, or expert rules. For easier understanding, the rules are written in an appropriate sequence, but the sequence is not essential in the process. The rules are tied together with the conjunction “or”, which is often omitted. Each rule is composed of antecedents most commonly linked with the conjunction “and”. The antecedents create the criteria based on which a selection is made from suggested alternatives. The text below describes the criteria (antecedents) to be used in a fuzzy logic system for the selection of a course of action for the OEG.

The decision-maker sometimes have only one location to consider, when making a decision boils down to accepting or rejecting the location. More often, however, the decision-maker needs to rank several locations and chose one over the others. Ranking the locations means attaching a value to each location, the overall goal being to choose the best from the set of available solutions, based on the importance of selected criteria. If there is a possibility of change, the number of variables grows, and the optimization of the choice is getting more complex [10], [11].

Reconnaissance is a date collection effort to facilitate the choice of a proper course of action for the OEG. The first step in the decision-making process is to formulate all the options, and then discard the solutions that do not satisfy the pre-defined criteria. Ultimately, the alternatives are valued and ranked.

Alternative Ranking Criteria [2]:

– *Estimates related to a possible breakthrough by enemy along a specific route* (C_1). This criterion allows for an estimate of the probability of enemy breakthrough along a route. The estimate hinges on the assessment of enemy intent and how successful the enemy’s plans might turn out, depending directly on the deployment of our units (the number of units to defend the route, the level of anti-tank defense, the interspace, exposed flanks, an area favoring an air assault, etc.).
– *The impact of closing a specific route* (C_2). This criterion unifies the degree to which it is possible to slow down the pace of enemy attack, and possible losses in personnel and equipment inflicted on the enemy by activating the OEG.
– *The estimate of negative effects of a minefield on subsequent actions by our units* (C_3). Within this criterion an estimate is made regarding possible extent of (negative) impact, if any, which deploying mines along a route might have on future operations by our units.
– *Characteristics of a route* (C_4). This criterion is based on the influence of terrain features on the structure of a minefield, the time needed to prepare the lines for explosive obstacles along the given route, and the time needed to reach the route and deploy the mines.

In the fuzzy system to value the available alternatives, the values of input criteria are either numbers or linguistic terms. The fuzzy system consists of four input variables and one output. The characteristics of the input variables are displayed in Table 1.

Table 1: Criteria for the selection of courses of action OEG

Criterion mark	Criterion	Numerical	Linguistic	Min	Max
C_1	Estimates related to a possible breakthrough by enemy along a specific route	x			x
C_2	The impact of closing a specific route		x		x
C_3	The estimate of negative effects of a minefield on subsequent actions by our units		x	x	
C_4	Characteristics of a route		x		x

The interval of confidence for the input and output variables is within the range [0, 1].

A set of criteria C_i (i=1,...,4) consists of two subsets:

- C^+ - a subset of benefit type criteria, meaning the higher the value, the more preferable the alternative (the criteria C_1, C_2, C_4), and
- C^- - a subset belonging to the cost category, meaning the lower the value, the more preferable the alternative (criterion C_3).

The C_1 criterion is attached numerical values, and linguistic descriptors are used for the criteria C_2, C_3 and C_4.

The values of the input variables C_2, C_3 and C_4 are described by a set of linguistic descriptors $S=\{l_1, l_2,...,l_i\}$, $i \in H\{0,...,T\}$, where T is a total number of linguistic descriptors. The linguistic variables are represented by a triangular fuzzy number defined as (a_i, α_i, β_i), where α_i is a point at which the membership function of the fuzzy number has the maximum value 1.0. The values α_i and β_i are the left and right distribution of the membership function, from the value where the membership function has reached the maximum value.

The number of linguistic descriptors is T=9: unessential – U; very low – VL; fairly low – FL; low – L; medium – M; high – H; medium high – MH; very high – VH, and perfect – P, (Figure 5).

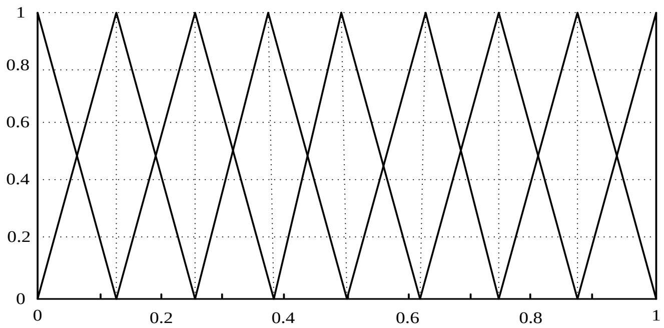

Figure 5: Graphic display of linguistic descriptors

The membership functions of the fuzzy linguistic descriptors are defined by the formula:

$$\mu_{l_U} = \begin{Bmatrix} 0, & 0 < x \\ (0.125 - x) / 0.125 & 0 \le x \le 0.125 \end{Bmatrix} \tag{8}$$

$$\mu_{l_{VL}} = \begin{Bmatrix} x / 0.125, & 0 \le x \le 0.125 \\ (0.250 - x) / 0.125, & 0.125 \le x \le 0.25 \end{Bmatrix} \tag{9}$$

$$\mu_{l_{FL}} = \begin{Bmatrix} (x - 0.125) / 0.125, & 0.125 \le x \le 0.250 \\ (0.375 - x) / 0.125 & 0.250 \le x \le 0.375 \end{Bmatrix} \tag{10}$$

$$\mu_{l_L} = \begin{Bmatrix} (x - 0.25) / 0.125, & 0.25 \le x \le 0.375 \\ (0.50 - x) / 0.125 & 0.375 \le x \le 0.50 \end{Bmatrix} \tag{11}$$

$$\mu_{l_M} = \begin{Bmatrix} (x - 0.375) / 0.125, & 0.375 \le x \le 0.50 \\ (0.625 - x) / 0.125 & 0.50 \le x \le 0.625 \end{Bmatrix} \tag{12}$$

$$\mu_{l_H} = \begin{Bmatrix} (x - 0.50) / 0.125, & 0.50 \le x \le 0.625 \\ (0.75 - x) / 0.125 & 0.625 \le x \le 0.75 \end{Bmatrix} \tag{13}$$

$$\mu_{l_{MH}} = \begin{Bmatrix} (x - 0.625) / 0.125, & 0.625 \le x \le 0.75 \\ (0.875 - x) / 0.125 & 0.75 \le x \le 0.875 \end{Bmatrix} \tag{14}$$

$$\mu_{l_{VH}} = \begin{Bmatrix} (x - 0.75) / 0.125, & 0.75 \le x \le 0.875 \\ (1 - x) / 0.125 & 0.875 \le x \le 1 \end{Bmatrix} \tag{15}$$

$$\mu_{l_P} = \begin{Bmatrix} (x - 0.875) / 0.125, & 0.875 \le x < 1 \\ 1, & x \ge 1 \end{Bmatrix} \tag{16}$$

All input variables of the fuzzy logic model are described with three membership functions each. The output variable is described with five membership functions. Figure 6 shows a general model of the fuzzy logic system.

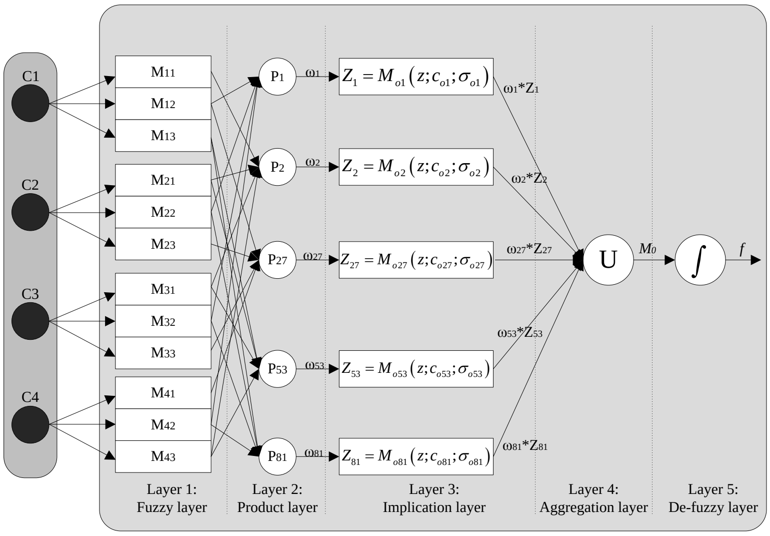

Figure 6: General model of FLS

The choice of membership functions and their range in the universe of discourse is a critical point in creating the model. Gauss curves were chosen for this particular fuzzy system, being easy to manipulate while adjusting the output.

Once the FLS is finished, the results need to be verified. An arbitrary set of input values are passed through to produce a set of solutions (outputs). When the FLS is used to compare the output values with the expected set of solutions, the result might be unsatisfactory. More precisely, there might be a considerable discrepancy between the results produced by the FLS and the expected set of solutions, which is unacceptable. Significant deviations would place the difference outside a margin of error, which is why the FLS requires adjustment. The system is adjusted by correcting the membership functions, and passing a set of values through the FLS periodically, in order to compare the results with the expected set of solutions. Table 2 offers a comparative overview of the expected results and the results obtained at different stages of adjustment.

Table 2: Test results for the fitting capability of the FLS

No.	Relative error (0.204)		Relative error (0.145)		Relative error (0.086)		Relative error (0.030)	
	Measure d value	Predicted value	Measure d value	Predicted value	Measure d value	Predicted value	Measure d value	Predicted value
1.	0.637	0.313	0.637	0.501	0.637	0.558	0.637	0.623
2.	0.613	0.363	0.613	0.467	0.613	0.527	0.613	0.587
3.	0.532	0.282	0.532	0.382	0.532	0.473	0.532	0.490
4.	0.387	0.137	0.387	0.241	0.387	0.310	0.387	0.358
5.	0.705	0.455	0.705	0.559	0.705	0.610	0.705	0.673
6.	0.332	0.082	0.332	0.196	0.332	0.253	0.332	0.290

No.	Relative error (0.204)		Relative error (0.145)		Relative error (0.086)		Relative error (0.030)	
	Measure d value	Predicted value	Measure d value	Predicted value	Measure d value	Predicted value	Measure d value	Predicted value
7.	0.569	0.319	0.569	0.453	0.569	0.485	0.569	0.519
8.	0.884	0.434	0.884	0.748	0.884	0.780	0.884	0.857
9.	0.458	0.208	0.458	0.324	0.458	0.371	0.458	0.433
10.	0.395	0.145	0.395	0.249	0.395	0.306	0.395	0.365
11.	0.732	0.482	0.732	0.596	0.732	0.645	0.732	0.699
12.	0.250	0.100	0.250	0.134	0.250	0.162	0.250	0.215
13.	0.549	0.299	0.549	0.400	0.549	0.465	0.549	0.519
14.	0.334	0.084	0.334	0.198	0.334	0.256	0.334	0.313
15.	0.588	0.338	0.588	0.442	0.588	0.502	0.588	0.552
16.	0.590	0.340	0.590	0.470	0.590	0.534	0.590	0.554
17.	0.574	0.224	0.574	0.428	0.574	0.456	0.574	0.538
18.	0.493	0.243	0.493	0.365	0.493	0.432	0.493	0.477
19.	0.463	0.213	0.463	0.317	0.463	0.368	0.463	0.436
20.	0.670	0.420	0.670	0.513	0.670	0.590	0.670	0.640
21.	0.710	0.460	0.710	0.544	0.710	0.620	0.710	0.687
22.	0.622	0.372	0.622	0.476	0.622	0.534	0.622	0.589
23.	0.418	0.168	0.418	0.252	0.418	0.337	0.418	0.386
24.	0.643	0.393	0.643	0.476	0.643	0.552	0.643	0.627
25.	0.528	0.278	0.528	0.324	0.528	0.412	0.528	0.489

The FLS adjustment was performed in three steps. The initial FLS error was 0.204 (Figure 7a). Phase I reduced the error to 0.145 (Figure 7b). In Phase II, the error dropped by 40.68% to 0.086 (Figure 7c). Phase III cut it by 65.11% to 0.030 (Figure 7d). Having compared the values after Phase 3, the authors decided the errors were minimized and negligible compared to the expected set of solutions. This leads to the conclusion that the FLS can successfully generalize new data it was not trained for.

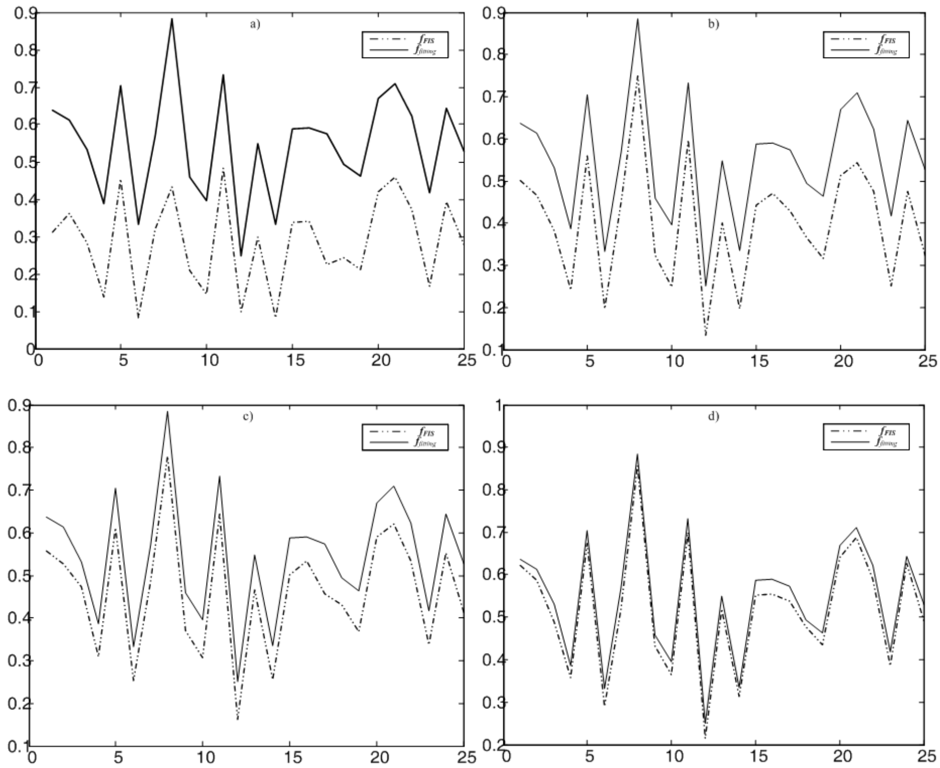

Figure 7: Fitting data - FLS output

The membership functions of input variables after the adjustment are presented in Figure 8. Table 3 shows the parameters of the membership functions.

Table 3: The parameters of FLS membership functions

Criterion mark	MF 1	MF 2	MF 3
C1	(0.233, 0.111)	(0.181, 0.50)	(0.262, 0.966)
C2	(0.221, 0.0079)	(0.2236, 0.5)	(0.2123, 1)
C3	(0.2663, 0.00265)	(0.247, 0.506)	(0.251, 0.997)
C4	(0.246 0,0003)	(0.197, 0.503)	(0.2348, 1)

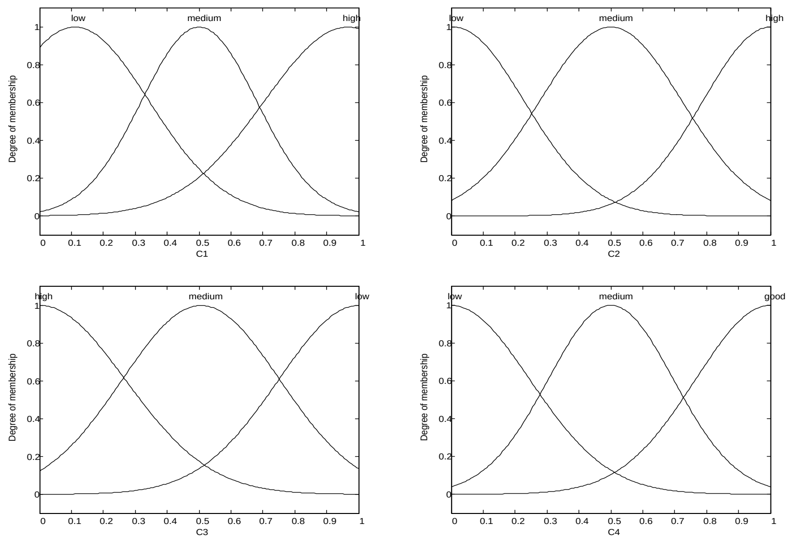

Figure 8: Membership functions of FLS input variables

Linguistic rules were the link between the input and the output of the fuzzy system. An expert's knowledge of the process can be expressed by a number of linguistic rules, using the words of a spoken or artificial language [10].

The domain expert introduces his knowledge through production rules. It is very important that for each combination of linguistic variable inputs, the domain expert suggests corresponding output values. As said before, there are four input linguistic variables (n=4) with three linguistic values each (M=3), and they can be combined in a base totaling $M^n=3^4= 81$.

The most frequently used deduction methods are MIN-MAX and PROD-SUM. In this paper the PROD-SUM method of direct deduction has been used, as one of the chief requirements was to reach the satisfactory sensitivity of the system. In other words, a slight change to the input is expected to produce a slight change to the output, which other methods failed to achieve [8]. Selecting the PROD-SUM method and adjusting the membership functions produced an appropriate form of solutions, which were ultimately accepted (Figure 9).

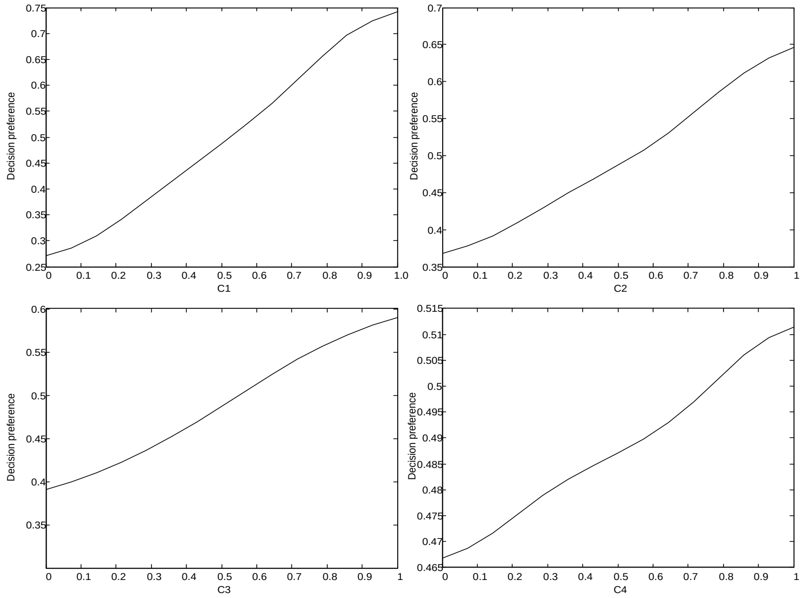

Figure 9: The set of the possible solutions of input variables

The center of gravity method was the defuzzification method of choice, being universal, most fitting option for the creation of the fuzzy system, ensuring both continuity and the gradience of output.

4. TESTING THE FUZZY LOGIC SYSTEM

The testing process employed the illustrative data describing ten alternatives, which were possible courses of action for the OEG. Their characteristics are listed in Table 4.

The results following the application of the model are displayed in Table 5. The course of action No. 10 has been selected as the best alternative, with the highest value compared to the other observed preferences.

Table 4: Characteristics of the chosen courses of action

Alternatives	C_1	C_2	C_3	C_4
Course of action No. 1	0.2 (20%)	P	VL	M
Course of action No. 2	0.8 (80%)	U	M	VH
Course of action No. 3	0.6 (60%)	VL	MH	FL
Course of action No. 4	0.3 (30%)	MH	FL	MH
Course of action No. 5	0.5 (50%)	H	U	VH
Course of action No. 6	0.9 (90%)	H	VH	VL
Course of action No. 7	1 (10%)	M	H	M
Course of action No. 8	0.7 (70%)	L	U	H
Course of action No. 9	0.4 (40%)	FL	L	U
Course of action No. 10	0.65 (65%)	VH	M	P

Table 5: Decision Preference

Alternatives	Decision preference	Rank
Course of action No. 1	0.548	4.
Course of action No. 2	0.589	3.
Course of action No. 3	0.358	9.
Course of action No. 4	0.544	5.
Course of action No. 5	0.505	7.
Course of action No. 6	0.695	2.
Course of action No. 7	0.275	10.
Course of action No. 8	0.506	6.
Course of action No. 9	0.372	8.
Course of action No. 10	0.711	1.

Having compared the results following the FLS application with the preferences of decision-makers (experts), the conclusion was that the values of FLS criteria functions were close to the preferences of the decision-maker, $F_{FLS} \approx F_{experts}$ (Figure 10).

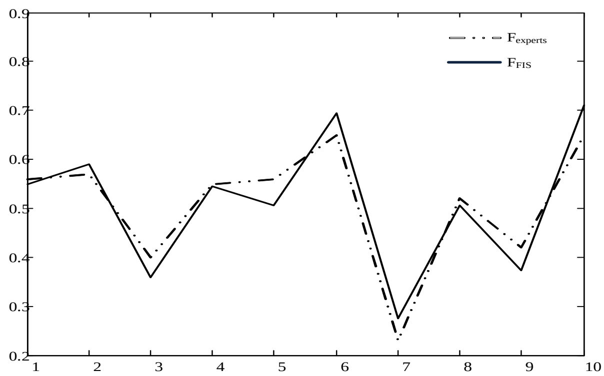

Figure 10: Comparative review of the fuzzy system output and decision preferences by the experts

5. CONCLUSION

Having studied the results, the authors have decided that the FLS system can successfully value pre-defined courses of action for the OEG, formulating a decision-making strategy in the selection process. The significance of the research lies in the amalgamated experience of several experts incorporated in the model. This is very important insofar as the decision-maker is no longer limited to his own knowledge. In addition, the model ranks the alternatives successfully even if data are fairly unknown, which is rather typical of the criterion $C_{1.}$

The development of the fuzzy logic model allows for a strategy to select a course of action for the OEG to translate into an automatic control strategy. The performance of the system depends on the number of experienced officers – decision-makers, who participated in the FLS research and development, and on the ability of the system analyst to formulate a decision-making strategy based on extensive communication with them.

The model can save time in the decision-making process and make the decision to be a better one. The performance of the sophisticated fuzzy system can be improved by translating it into an adaptive neural network, which can be trained to replicate decision-making by experts. The development of the ANFIS system will be the subject of future research in the field.

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