Fuzzy Data Mining and Multi-Criteria Forecastingin the Process of Targeting

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Abstract—The object of the research is the process of targeting where we are able to successfully manage the decision-making process by applying a combination of data mining and multi-criteria analysis. These methods are useful in military decision-making processes, where they are already used in the technique of managing different military systems, the acquisition of specialized military assets and the rating of performance. One of the unexplored military topics remains forecasting in the process of targeting. Data processing is based on flexible and uncertain data of different sensors. The task is to classify these data with respect to tactics. Predicting on the basis of classified data is a particular challenge, especially in terms of group decision-making. The objective of the paper is the realization of a model for an easier, faster and more successful prediction of the process, based on data mining and multi-criteria decision-making (MCDM) methods. The model represents an interdisciplinary solution that can be applied in many areas, such as industry, economy, logistics and various management processes.

IndexTerms—Multi-criteria decision-making model, data mining, targeting process, fuzzy logic.

1 Introduction

Military commanders are constantly faced with the problem of forecasting and decision-making amidst changes on the battlefield. There is a constant need for the study of the military decision-making process, where research is based on the processes of forecasting, decision-making and solving complex problems[1].

A typical forecasting process that occurs at all levels of command is the process of targeting. Targeting is a part of a common operational picture (COP) which includes earlier expressed demands to develop systems for the decision-making process[2], which were confirmed lately[3, 4].

This paper presents a new model for the prioritization of targets, based on the data obtained from various sensors. A mentally unmanageable large number of data is treated with the fuzzy data mining method and edited according to a relevant key. The classified values of fuzzy numbers are the basis for the expression of preferences of the decision-makers. The basis for this is the fuzzy MCDM model (FMCDM). Further the process of using linguistic variables is presented, where, by applying FMCDM together with the fuzzy group technique for order of preference by similarity to ideal solution (FGTOPSIS)[5], the most profitable target is selected.

For the operationalization of the model described above, a new computer program for predictions is developed, summarizing the described characteristics. The support model for the targeting process – the fuzzy logic data targeting system (FLDTS) – is developed with the aim of improving the tactical level on the basis of intuitive decision-making rules, which are the fundament of the analytical model. The results show the effectiveness of our proposed method.

The paper is organized as follows. Section2 gives a general overview of the topic.Section 3 addresses some basic theories used in this model.In Section 4 the steps of this method are presented, including the assessment of the classification and profitability of individual targets. Sections 5 and 6conclude with a summary and further research options.

2 General Overview

2.1 Data mining

Data mining is a tool that helps obtain knowledge that is hidden in the data[6]. It is used mainly for analyzing collected observations[7].

Revels[8] describes the functionality of data mining as a characterization based on the analysis of sequences, classifications, integrations, forecasts, variances, and assessments. There are also other techniques of data mining, including the extended models of reasoning, genetic algorithms and fuzzy logic.

For the proper method of data classification we chose fuzzy logic, as it effectively addresses vague, inaccurate, stochastic and dynamic input parameters[9].

Bhuvaneswari[10]introduced the use of fuzzy logic in data mining with the aim of analyzing advanced technologies of fuzzy logic in data mining and achieving more understandable and useful results.

2.2 Two approaches for the process of forecasting and decision-making

Researchers in the tradition of analytical models emphasize explicitly computable procedures for obtaining information[11]. The core of the assumptions of the analytical theories is that the purpose of decision-making is to achieve optimal decisions, based on estimated average values[12]. Studies have shown that decision-makers professionally create only a few possible solutions for solving complex

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problems[13]. Furthermore, it is often not possible to build a complete representation of the problem space, including an evaluation of the objectives and values of the possible outcomes. This is especially true for complex military problems[14].

Intuitive theories of decision-making are based on the descriptive rather than the normative method. Model strategies are run by experienced decision-makers, by confronting real problems[15].

Debanneand Laffaye[16], for example, emphasize the basics of the assessment of the quality of behavioral decisions expressed by experts rather than a formal model.

The main research problem in the case of the intuitive approach to decision-making is the generally unclear level of the model design.McGuinness[17]actually argued that decision-making processes, applied in real environments, cannot be transferred into formal models.

2.3. Synthesis of decision-making approaches in the military field

Both theories are acknowledged as support tools for forecasting and decision-making in various military processes[18]. Analytical models generally poorly describe how decisions are actually made by people, but they are very easy to understand and regulate. The advantage of the intuitive theory is closely related to the processes that have actually been used by decision-makers in the real world, applied in dynamic, uncertain and highly risky environments[19].

A key factor in the choice between the analytical and the intuitive strategy is whether it is only possibly to get a feasible solution or whether we can ask for an optimal solution[20].

At the same time, it seems fruitful to rethink the analytical and intuitive decision-making approaches as a coordination of styles, with the goal of increasing the effect of decision-making[21].

2.4. The process of targeting

The selection and operation of the target can be defined as the process of the prioritization of objectives that takes into account the environment, capacity and coordination of the appropriate effect[22]. For the selection and operation process the commander will establish a target-oriented group, focused on the synchronization and integration of the joint operation[23].

2.5. Group decision-making

Johnsonand Johnson[24]define a group as two or more individuals in a mutual interaction, being aware of their membership in the group. The group is used as a much broader concept than the team is. It is alleged that the team is more structured, that each member has a role and act interdependently towards a common goal[25].

2.6. Multi-criteria decision model of targeting

The approach to forecasting and decision-making can be very different. The choice depends on the nature of the problem, the time, the economic resources, and the abilities of decision-makers[26]. An effective decision-making process should be simple, reliable, user-friendly, and flexible. It must take into account the subjective and objective factors and the synergy of analytical and intuitive thinking[27]. Decision-making in a complex environment requires an orderly and organized thinking process which leads to a correct decision by a method that allows us to solve complex problems in a simple way[28]. When solving holistic problems, where only intuitive decision-making is not sufficient, we use the MCDM model. MCDM is a collection of methods in decision-making, using many different criteria. The viability assessment of a target is one of the most important processes of military command and control, as its result supports the decision-making of the commander and his selection of suitable alternatives. Many researchers have studied the definition of targets[29, 30] and threats[31], but the threat assessment is still an open question.

For an accurate assessment of the targets a combination of large amounts of data from various sensors is required, as well as a definition of the various characteristics and levels of risk. The information provided by these sensors are often incomplete, uncertain and unclear[32]. In this way we process incomplete data, which was proven by numerous studies, that helped to solve many problems[33].

2.7.Models of multi-criteria decision analysis

MCDM models are useful in a wide decision-making environment encompassing technology, economics, management, military, logistics, etc. Different approaches and techniques are primarily dependent on the complexity of the problem and the final goal. The Analytic Hierarchy Process (AHP), the Elimination and Choice Translating Reality (ELEKTRE), the Technique for Order of Preference by Similarity of the Ideal Solution (TOPSIS), the Preference Ranking Organization Method (PROMETHE), and their derivatives constitute the basic versions[34, 35, 36]. All recent versions already follow the fuzzy logic approach[37, 38, 39, 40, 41]. We also know a couple of derivations of group decision-making: Group AHP (GAHP) and Group TOPSIS (GTOPSIS)[1, 2].

The selection of the appropriate method of MCDM based on several criteria is a problem by itself. However, the choice of the appropriate method of MCDM is slightly different. Instead of measuring the strength of the different methods under certain criteria, methods either have certain characteristics or not. For example, the method either includes multi-dimensional data or it does not. According to Sillarset al.[44], it is clear that we are faced with complex decisions and that the TOPSIS method is the appropriate and in our case also the chosen method.

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The TOPSIS algorithm is used to evaluate the results in a similar environment. The data used in the algorithm are numerical, so the output is also quantitative data[45]. For the evaluation of individual criteria and alternatives triangular numbers are used that define the fuzzy values – Fuzzy TOPSIS (FTOPSIS)[46]. Some of the techniques of determining preferences based on conceptual TOPSIS solutions in the case of group decision-making – GTOPSIS – are already described too. In that manner all of the experts are adequately addressed[47].Hence, the FGTOPSIS method is recommended for the newly suggested model of target processing.

2.8. Linking MCDM and data mining

From the previous section it is apparent that both methods are important in practice. The use of them depends on the problem that has to be solved.

Roy[48] states that the objective of multi-criteria approaches is to provide assistance for "better" decisions. He mentions that the purpose of adopting help is to improve decisions in the presence of ambiguity, uncertainty, and numerously diverse data. This clearly separates MCDM from data-mining. The decision-making process as well as data mining are practically oriented. Some authors even argue that data mining is a natural extension of the decision-making process[49].

3 Basic Theory

3.1 Data mining

In this article a method of data mining, which is based on fuzzy logic, is recommended. The method is used for the classification of data, obtained from various sensors. These data are raw in terms of tactical ideas obtained from the process of fighting. Since the information is presented as a fuzzy set, every point in the information belongs to a group with a certain degree of senior level. Thus, the event can be accurately predicted.

3.2 Fuzzy logic basics

Fuzzy logic is based on the concept of fuzzy sets. A fuzzy set eliminates the deficiencies of crisp sets, since the set has no clear and crisp boundaries, its boundaries are vague and undefined[50]. The fuzzy set differs from a normal or crisp set in the fact that its elements can have a grade of affiliation in an interval from 0 to 1, and that the transition from elements standing outside the set to elements being a part of the set is gradual and determined by the membership function (Figure 1)[51].

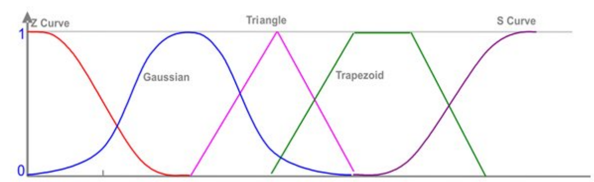


Fig. 1. Functions of belonging

3.3 Linguistic variable

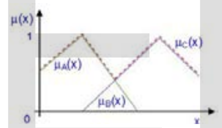
The linguistic modeling system increases the transparency and the optimization possibilities. Basic operations are simple and include a small number of parameters[52]. The value of linguistic variables is given by words of the natural language (large, small, slow, heavy, ...). It is determined by three data:

(X, A (X), Rule),

where X is the name of the variable, A (X) is the set of possible values, and the rules cover the relationship between linguistic expressions and their physical meaning.

3.4 Basic Operations

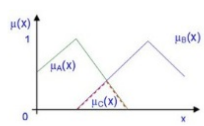
The union A ∪ B of two fuzzy sets A and B is defined by the maximum of the membership functions μA (x) and μB (x):



C = A and B ∪ c (x) : = max (μA (x) , μB (X)) , for all x ∈ X

This operation is also known as operation OR.

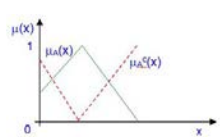
The intersection A ∩ B of two fuzzy sets A and B is defined by the minimum of the membership functions μA (x) and μB (x):



C = A and B ∩ c (x) : = min (μA (x) , μB (X)), for all x ∈ X

Operation AND is defined by using the tool mine.

The complement AC of fuzzy sets is defined by the negation of its function of membership:



μAc (x) = 1 - μA (x)

3.5 Fuzzy conclusion

The process of fuzzy conclusions is used in systems where several expanded rules of the form "if … then …" are used in building the model.

Relationships between variables are absorbed by rules. If there are many of these relationships, we need a more comprehensive conditional or final part of rules, or also a larger number of rules. Each individual rule Ri is a fuzzy argument with a basic form that has one condition (input) and one result (output):

R: if (X is Ai), then (Y is Bi)

In practice, we design several basic or combined rules.

The implication enables a conclusion respectively a transition from the "if" to the "then" part of the fuzzy rule.

Aggregation is necessary if we have more than one set in the conditional part of the rule. The aggregation allows us to compose multiple conditions in one composite condition, thus moving from individual spaces with fuzzy sets to a common space, hence into the Cartesian product[53].

Accumulation takes care of the correct inclusion of the partial results into the total fuzzy set. The result of the fuzzy deduction process on the basis of "if … then …" rules is a fuzzy output variable. Depending on the form of the fuzzy output variable in the rule, we distinguish between three basic types of fuzzy rules: Mamdani, Takagi-Sugeno and Singleton rules[54].

3.6Fuzzificationof the crisp values

It rarely happens that the input values in the fuzzy system are fuzzy already in the beginning, as they are usually numerical data from sensors. What is needed is therefore a transition from crisp to fuzzy values. For numeric data usually the singleton fuzzification is used, viz. the grade of the affiliation of the fuzzy set is adapted to the crisp input value[55].

3.7Defuzzification of the fuzzy values

The result of the fuzzy concluding process is a fuzzy set with an adequate affiliation function. These fuzzy values must be converted into crisp values.

There are various methods of defuzzification[56]. Basically they are applied in two steps. Firstly, for each linguistic variable the most characteristic value is defined. Secondly, these values are aligned. Considering this calculation we distinguish several methods of defuzzification.

3.8Fuzzy system

Since all the above mentioned concepts do not have any practical value standing by themselves, we have to bind them into a system. Such a system is called the fuzzy system (Figure 2).

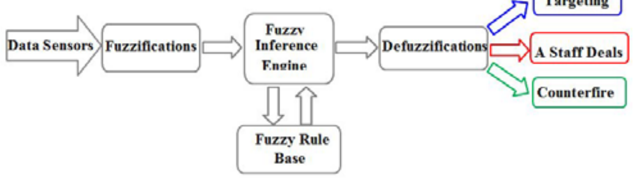


Fig. 2. Fuzzy system

3.9The process of targeting with the MCGDM FGTOPSIS method

The group multi-criteria decision model (MCGDM) is accompanied by the following steps:

(1) It is necessary to determine the number of alternatives and the criteria.

The decision-makers determine the number of alternatives and the corresponding relevant criteria. For example, C = {C1, C2, ..., Cm} is a list of alternatives, K = {K1, K2, ..., KN} is the list of criteria, and A = {a_{ij} | i = 1,2, ..., m , j = 1,2, ..., n} is a decision matrix, wherea_{ij} is the numeric value of the alternative i for the criterion j.

(2) Expressing the preferences of decision-makers:

(a) Selection of a set of values for the definition of the weight of individual criteria.

(b) Definition of the degree of suitability of each alternative by these criteria.

The FGTOPSIS method is accompanied by these steps:

(1) Normalization of the fuzzy decision matrix:

In the GTOPSIS method we have to evaluate each alternative by Equation 1.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$; as x = decision matrix ; i = 1,2, ... m and j = 1,2, ... n. (1)

(2) The weighted normalized fuzzy decision matrix:

The positively ideal solution A^+ and the negatively ideal solution A^- can be determined on the basis of the weighted normalized rating (y_{ij}) as:

$y_{ij} = w_i r_{ij}$; as i = 1,2, ... , m and j=1,2, ..., n. (2)

(3) Determination of the positive and the negative ideal solution:

The positively ideal solution of the matrix is calculated by Equation 3, while the negatively ideal solution can be calculated by Equation 4.

$$A^+ = (y_1^+, y_2^+, \ldots\ldots, y_n^+); \quad (3)$$

$$A^- = (y_1^-, y_2^-, \ldots\ldots, y_n^-); \quad (4)$$

(4) The distance of each alternative to the positive and negative ideal solution:

The distance between the alternative A_i and the positively ideal solution is calculated by Equation 5, the distance between alternative A_i and the negatively ideal solution is given by Equation 6:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (y_i^+ - y_{ij})^2}$$; i = 1,2, ..., m. (5)

$$d_i^- = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_i^-)^2}$$

; i = 1,2, ..., m. (6)

(5) Determination of the value of preferences for each alternative:

The value of the preferences for each alternative (Ti) is given as:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \quad ; i = 1,2, ..., m. \quad (7)$$

4 Proposed Method

For the new proposed model of the decision-making process we have developed a computerized program that enables users to apply a simple and understandable execution of the entire process. The basis is data classification by means of data mining, which continues into a multi-criteria decision-making analysis, with which a group of experts adequately evaluates the obtained alternatives. The forecasting process is shown in Figure 3.

4.1 Fuzzy logic data mining method in the process of targeting

A dynamic process of targeting has a constant input of numerous data. The question is how to adequately treat this information. The system includes both quantitative and qualitative information.

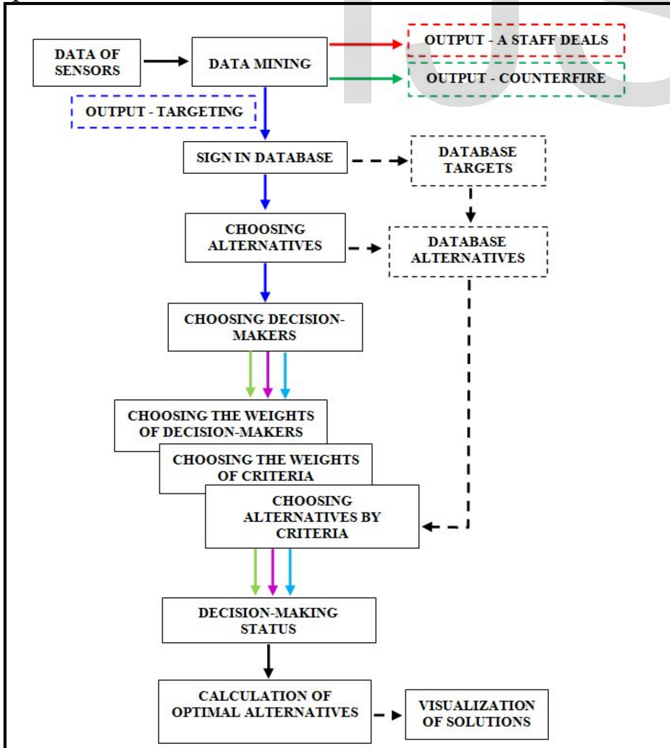


Figure 3: Forecasting process

With data mining we achieve an optimal input of the information into the system and allow the inappropriate data to continue their journey to the appropriate places. The data is shown in Figure 4.


Database Targets

	Targets	UTM koord		Tipe	Width	Time	Neutral.	Az.	Land
1	Target 22	12331	1456	Perso	100	45	25	1200	forest
2	Target 23	1542	2148	Armo	400	3	90	1600	bush
3	Target 24	1622	1487	Artill	100	30	5	2500	forest
4	Target 25	1578	1344	Armo	300	30	55	1700	open
5	Target 26	1425	1522	Mort	300	15	60	1300	forest

Figure 4: Transmitted data sensors

First, we determined the fuzzy values of individual criteria. In the input we placed four criteria to which we set three values. These values were taken to the fuzzy system, as shown in Figure 5.

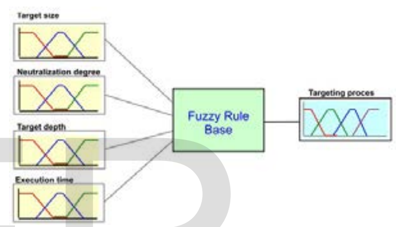


Figure 5: Fuzzy classification system of information

For the size of the target we set values: punctuated target, battery target and battalion target. Figure 6 is showing the affiliation functions:

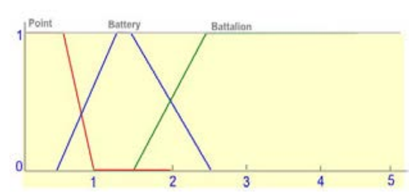


Figure 6: Fuzzy input values for the size of the target

For the criterion of the degree of neutralization we also defined three affiliation functions, namely for disturbance, neutralization, and destruction. The same was applied to the distance from the target and to the time necessary for the execution. When we chose the affiliations to the fuzzy sets in the system, we had to produce also the correct logical table (Table 1).

TABLE 1

GRAPHICAL USER INTERFACE FOR ENTERING THE "IF … THEN …" RULES

if	then
1 *if* (in1is cluster1) and (in2 is cluster1) and (in3 is cluster1) and (in4 is cluster1)	*then* (out is out cluster1)
2 *if* (in1is cluster2) and (in2 is cluster2) and (in3 is cluster2) and (in4 is cluster2)	*then* (out is out cluster2)
3 *if* (in1is cluster3) and (in2 is cluster3) and (in3 is cluster3) and (in4 is cluster3)	*then* (out is out cluster3)
4 *if* (in1is cluster4) and (in2 is cluster4) and (in3 is cluster4) and (in4 is cluster4)	*then* (out is out cluster4)

For the output values we used four output levels: individual, platoon, battery, and battalion. The linguistic variables are in this case also already suggesting the resources used. They are shown in Figure 7:

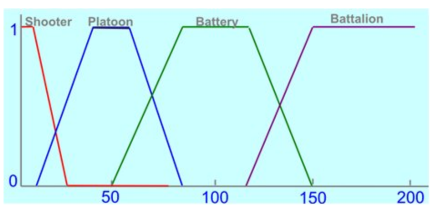


Figure 7: Output value

In order to defuzzificate the output values, the MOM method was used, because it is the most suitable for the classification of information. We intentionally chose quantitative criteria for classifiers, because we wanted to perform only the technical direction of the flow of information. According to the data from Figure 4 we descended Target 22, Target 24 and Target 26 into the system, the other two are directed to another process.

4.2 Forecasting with the FGTOPSIS method in the process of targeting

The proposed approach to a solution can be summarized in a few points.

4.2.1 Determining the number of alternatives and criteria

From the table of targets (the basis) we select five targets for the process of selecting and operating on the target.

These targets are chosen as the best alternatives and are described as T_1, T_2, T_3, T_4, and T_5.Four criteria have been defined for the selection of targets. The criteria are selected from the process of targeting as: C_1=type of target, C_2 = size, C_3 = resistance, C_4 = the degree of neutralization.

4.2.2 Defining the preferences (weight) of decision-makers

Decision-makers are defined as a group of experts. They are marked with E_1, E_2 and E_3. The commander alone is responsible for the selection of the preferences of decision-makers. The method of the eigenvector is used for the calculation of the weight of decision-makers.

4.2.3 Defining the linguistic criteria variables, alternatives and the evaluation of fuzzification

First we determine the linguistic values of the criteria ranking and assign fuzzy values to them (Table 2).

TABLE 2

LINGUISTIC EVALUATION CRITERIA AND VALUE

Acronym	Assessment	Value
L	low	0, 0, 0.2
ML	medium low	0, 0.2, 0.4
M	medium	0.2, 0.5, 0.7
MH	medium high	0.5, 0.7, 0.9
H	high	0.8, 0.9, 1
VH	very high	0.9, 1, 1

We then collect a set of linguistic assessments of the criteria ranking for every decision-maker. The selected criteria are shown in Table 3.

TABLE 3

LINGUISTIC ASSESSMENT OF THE IMPORTANCE OF THE CRITERIA BY DECISION-MAKERS

Criterion	E1	E2	E3
C1	MH	H	H
C2	MH	H	VH
C3	L	V	VH
C4	H	H	VH

Similarly we determine the linguistic assessments of alternative ranking and assign fuzzy values to them (Table 4).

TABLE 4

LINGUISTIC ASSESSMENT OF ALTERNATIVES AND VALUE

Acronym	Assessment	Value
B	bad	0, 0, 3
MB	medium bad	2, 3, 5
F	medium	4, 5, 6
MG	medium good	6, 7, 8
G	good	8, 9, 10
VG	very good	9, 10, 10

Finally, we collect a set of linguistic assessments of decision-makers about the suitability of each alternative with respect to the merits of the criteria. The decision for each alternative is shown in Table 5.

TABLE 5
PART OF THE LINGUISTIC ASSESSMENT OF DECISION-MAKERS REGARDING THE SUITABILITY OF ALTERNATIVES

Criterion	Alter.	E1	E2	E3
	T1	F	F	MB
	T2	MB	MB	G
C1	T3	F	MG	F
	T4	F	VG	F
	T5	MB	G	MB
	T1	MG	F	MB
	T2	G	MB	.
C2	T3	G	.	.
	T4	.	.	.
	.	.		

4.3 The results of the FGTOPSIS method

First we determine the weights of decision-makers according to the method of eigenvectors. After a normalization by Equation 1 we get the values $E_1 = n_1$, $E_2 = n_2$ and $E_3 = n_3$.

Then we weight the fuzzy values of the criteria with the values of the individual decision-makers, based on Equation 2. We repeat the procedure also for the fuzzy values of alternatives.

Further we determine the combined weighted value of the criteria $\hat{W}$, as $\hat{W}_j = (W_{j1}, W_{j2}, W_{j3})$ where $W_{j1} = \text{Min}\ \{W_{jk1}\}$, $W_{j2} = 1 / k\ \Sigma\ W_{jk2}$ and $W_{j3} = \text{Max}\ \{W_{jk3}\}$.

Similarly we determine also the combined weighted value of the alternatives $\check{R} = (a, b, c)$.

The values are used to obtain a common fuzzy normalized decision-making matrix.

The positively ideal solution (A^+) is calculated with Equation 3, while the negatively ideal solution (A^-) applies Equation 4. The results are shown in Table 6.

Table 6
Positive (A^+) and negative ideal solution (A^-)

	y1	y2	y3	y4
(A^+)	3.2845	5.4743	5.4743	5.4743
(A^-)	0.1170	0	0	0.1640

To calculate the distance between the alternative d_i and their ideal positive and ideal negative solution,Equations 5 and 6 are applied. The closeness coefficient value for each alternative (CCi) is calculated using Equation 7. A higher value of an alternative means a higher prioritization of the alternative T_i. The resultsare shown in Table 7.

TABLE 7
THE RESULT OF THE METHOD FOR EVALUATING ALTERNATIVES

Alt.	d_i^+	d_i^-	CC_i	place
T1	1.40201	1.09186	0.4378	1
T2	1.45416	0.96043	0.3977	3
T3	1.44007	0.87505	0.3779	5
T4	1.36847	1.04335	0.4325	2
T5	1.43422	0.93647	0.3950	4

The objective with the highest value and therefore the best alternative is T1, which with a value of CC_i=0.438[57] achieves an acceptable result inside the classification of the coefficients of proximity.

5 CONCLUSION

Despite the conceptual and model differences of the two approaches, there are clear links between data mining and multi-criteria analysis.

Data mining has been focused on the development of general forecasting models from the statistical point of view, aiming at the development of adaptive algorithms for the accurate modeling of large data sets. On the other hand, MCDA is mainly focused on the development of comprehensible decision-making models with a smaller data set, aiming primarily at the support and direction of decisions.

Although the topic of this paper already encompasses the intersection of MCDA with data mining, we believe that the current work is just the beginning of similar research in the future. The enhancing of processing methods for large data sets and applications of new models in innovative areas are just some of the raw themes, where we can expect specialized research in the future. At the same time multidisciplinary tools that take advantage of different areas will be capable to suggest new solutions for the management of this data, in particular for the support in the decision-making process.

Similarly, when considering MCDA, the analytical and the intuitive approach differ in many aspects. They have different strengths and weaknesses. It seems unlikely that any of them could be a useful example for all aspects of military decision-making. Efforts should be directed to the use of the positive trends of each approach, or toward the search of a common ground. With this approach we can better technologically support and realize effective decision-making processes in an uncertain military environment, especially after clearly expressed demands for new systems of decision-making on the latest international artillery symposium[58].

With the introduction of the new FLDTS model, an effective, robust and user-friendly system for multi-criteria analysis of the targeting process is implemented into the forecasting process for decision-makers.

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Nowadays decision-making support systems are accepted to ensure a synergy between human strengths and the advantages of the systems. These include the human capacity for creativity, flexibility, the integration of experiences with analogue conclusions and intuition. The goal of the systems is to always take advantage of the human strengths, together with the advantages provided by the decision-making support system.

6 Looking Ahead

A well-built fundament for data mining based on fuzzy logic may also enable possible extensions of the requirements and integration into the process of forecasting itself.

Given the multitude of different methods of multi-criteria decision-making, it should also be useful to develop comparative methods on the same basis. Optimistic and pessimistic fuzzy logic methods should be considered. When we go from the process of selecting and operating on a target to an instant intuitive decision-making, it is necessary to consider decision-making based on classical fuzzy logic, where intuitive processes seem suitable for input-output values of fuzzy logic. One should also consider new functions for the FLDTS program, like the execution of the program with more integrated decision-making methods and the expansion of the spectrum of decisions, trends that are increasingly present in the military field or anyother complexdecision process.

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