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A MULTI-CRITERIA DECISION-MAKING (MCDM) MODEL IN THE SECURITY FORCES OPERATIONS BASED ON ROUGH SETS

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Abstract: *The paper points to a multi-criteria decision-making model based on the rough set theory application. The model demonstrates exceptional importance of the software application of the rough sets to decision-making in the security forces operations. Applying the rough sets represents a useful tool when the data, needed for the decision-making process, include vagueness and uncertainty. By applying the model based on the applicative use of the rough sets, specific decision-making rules are formulated. These rules guide the decision-makers through the complete process of planning the security operations.*

Key Words: *Multi-criteria Decision-making, Rough Sets, Course of Action, ROSETTA, ROSE2.*

1. Introduction

Modern international relations are very unpredictable in the political, economic and social life. In such an environment, there is a frequent need for engaging security forces due to the demand for protection of national interests or democratic order.

The security forces are engaged in various operations. In recent years, the security forces have often been involved in counterterrorism and counter-insurgency assignments in the world. However, the objective of these operations could also be to support civilians in the case of natural disasters, fight against crime or have various other combat and non-combat engagements involving military, police and other security forces (Slavkovic et al., 2012, 2013). The complexity of managing security forces operations, especially of deciding how to use the security forces, represents a major challenge. Choosing one from a set of available courses of action (COA) is a part of multi-criteria decision-making (MCDM) process which cannot be avoided. In this respect, the problem is how to choose a COA based on incomplete, inaccurate

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and inseparable data in the security forces operations with the help of various decision-making support models.

The significance of this problem is reflected in possible major losses of resources, both human and material. In that sense, every model contributing to a well-timed and better decision made by the managing authorities, will contribute to a more efficient implementation of the security forces operation. So far, the following have been considered for the needs of the security forces: a fuzzy logical system in support to the decision-making process in military organization (Pamučar et al., 2011), a hybrid model FAHP-MABAC in selecting locations for the preparation of laying-up positions (Božanić et al., 2016), as well as combined GIS and multi-criteria techniques in the selection of sites which are suitable for ammunition depots (Gigović et al., 2016). Due to secrecy and licenses, various world experiences are rather difficult to access. They are also limited to learning about general settings of functioning.

In other areas, applying the rough sets theory (RST) in decision-making focuses its use on modern business environment (Shen & Chen, 2013, Shen, et al., 2017), estimation of bridges construction (Kuburić et al., 2012), performance improvement of transportation systems (Deshpande & Bajaj, 2017) and mining for underground deep-hole mining (Jiang et al., 2009). Applying the RST is significant in the medical field in preventing diseases (Chowdhary & Acharjya, 2016) diagnostics (Stokić et al., 2010; Ji et al., 2012; Burney & Abbas, 2015), and processing medical data (Durairaj & Sathyavathi, 2013). The RST has also been used in data mining (Greco et al., 2002; Jia et al., 2007; Chen et al., 2015), with different computer models (Dobrilovic et al., 2012).

The methods dealing with support in the decision-making operations of security forces choose a COA based on different methodologies of attribute comparison and suggest a given solution to the decision-makers. The application of the model based on the rough sets uses the previously performed security forces operations. By using the software systems with reduction principle, the most important attributes for decision-making are discovered. Through decision algorithms, guidelines are given to decision-makers in the decision-making process. The advantage of this model is not only in providing support to the decision-making process in choosing a COA but also in guiding the whole decision-making process. At the same time, a great amount of time is saved.

The paper is divided into several sections, namely: Section 2 explains the problems of decision-making in a modern security environment, while Section 3 presents the basics of the RST. Section 4 refers to the existing software systems based on the RST, while Section 5 shows the use of the proposed model based on the RST. Section 6 gives a discussion of the model results. Finally, Section 7 presents the conclusions highlighting directions for further research.

2. Problems of decision-making in security operations in a modern environment

A modern security environment does not represent a precisely defined set of variables. It is an extremely complex part of the society that expresses all its interactions. The use of the security forces in operations is certainly susceptible to the impact of such an environment. Each of the possible impacts consists of a subsystem spectrum and contains different interconnections. A great number of factors, which could more or less affect the operation results, emerge from a complex and unpredictable environment. Those factors can be observed as criteria or attributes in the decision-making process. Persons who decide on the use of force are trying in various ways to make the most appropriate choice among the COAs offered. The appropriate decision is often reflected in human lives, and the proper approach is extremely important.

Such problems represent a major challenge for decision-makers. They are semi-structured and unstructured which makes it difficult to solve them. Therefore, there is space for implementing different decision-making support models that need to improve the decision-making process. They represent symbiosis of information systems, the application of a set of functional knowledge and the ongoing decision-making process (Suknović & Delibašić, 2010). For their work, they search for a database that forms the source of information, certain model solutions, and the corresponding user interface. The models should improve the knowledge of the decision-maker in order to help him make the right decision.

Supporting the choice of the COA in security forces operations is a very complex process. In addition to a large number of inseparable factors, there is a constant time constraint as well as the need for a quick response of the entire system. Time constraint is one of the biggest problems since it affects, directly or indirectly, different parts of the planning process and the organization of operations. In the process of preparing such operations, time limits the implementation of various expert methods and disables the complete analysis of the environment. The time for decision-making, usually measured in hours, is very brief and it can be even shorter. The short time can make the entire decision-making process even harder. These problems are often expanded by a large number of contradictory, unclear and inseparable pieces of information, which arise in the later stages of the decision-making process. The time frame in those situations does not allow a detailed analysis and precise classification.

Various software systems have been developed for the needs of the entire decision-making process in security forces operations. These systems provide different types of support to the decision-making process. One of such systems is TOPFAS (Tamai, 2009) developed especially for the needs of the comprehensive approach to planning the use of NATO forces. It contains support for all levels of planning. It enables a detailed and rapid system analysis, support to decision-making and assistance in monitoring the implementation of the decision.

3. The basis of the rough sets

Imperfect knowledge has always been the subject of study in various fields of science. Many approaches to the problem, such as how to understand imperfect knowledge and how to handle it, have been developed. One of the approaches to the problem is the RST.

The rough set theory is a mathematical theory presented by the Polish scientist Zdzisław Pawlak at the beginning of the 80's in the 20th century (Pawlak, 1982). This theory has found a number of interesting applications and it is essential for artificial intelligence and cognitive sciences, especially in the areas of machine learning, knowledge acquisition, decision analysis, knowledge discovery from databases, expert systems, inductive reasoning, and pattern recognition.

The rough set theory starts from the assumption that each object in the Universe (**U**) is described by some characteristic information. Different objects that are described by the same piece of information are considered to be inseparable, i.e.

similar to each other. The indiscernibility relation (**I**) created in this way represents the mathematical foundation of the RST and in certain sense describes our lack of knowledge about the universe.

Every rough set contains an appropriate boundary area with objects. These objects cannot be regarded, with any certainty, as belonging to any observed set or its complement. Accordingly, it is assumed that a rough set can be represented by a pair of classical sets, which we call its upper and lower approximation. The lower approximation contains objects which certainly belong to the set, while the upper approximation contains objects which possibly belong to the observed set. These two basic operations can be displayed in the following way:

upper approximation $\mathbf{I}^*(\mathbf{X}) = \{\mathbf{x} \in \mathbf{U}: \mathbf{I}(\mathbf{x}) \cap \mathbf{X} \neq \mathbf{0}\}$ and (1)

lower approximation $\mathbf{I}_*(\mathbf{X}) = \{\mathbf{x} \in \mathbf{U}: \mathbf{I}(\mathbf{x}) \subseteq \mathbf{X}\}$, (2)

where **x** is a subset of **U.**

The difference between the upper and lower approximation is the boundary region of the rough set (Figure 1). The specified operation can be displayed as follows:

boundary region $\mathbf{BR_I}(\mathbf{X}) = \mathbf{I}^*(\mathbf{X}) - \mathbf{I}_*(\mathbf{X})$ (3)

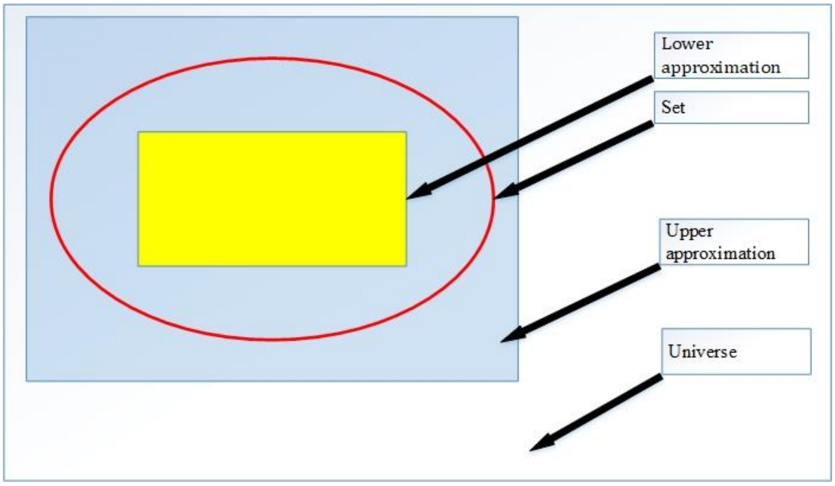


Figure 1. Graph view of the rough set with upper and lower approximation

Rough sets are defined by approximations. Approximations have the following properties:

$\mathbf{I}_*(\mathbf{X}) \subseteq \mathbf{X} \subseteq \mathbf{I}^*(\mathbf{X})$ (4)

$\mathbf{I}_*(\emptyset) = \mathbf{I}^*(\emptyset) = \emptyset,\ \mathbf{I}_*(\mathbf{U}) = \mathbf{I}^*(\mathbf{U}) = \mathbf{U}$ (5)

$\mathbf{I}_*(\mathbf{X} \cap \mathbf{Y}) = \mathbf{I}_*(\mathbf{X}) \cap \mathbf{I}_*(\mathbf{Y})$ (6)

$\mathbf{I}_*(\mathbf{X} \cup \mathbf{Y}) \supseteq \mathbf{I}_*(\mathbf{X}) \cup \mathbf{I}_*(\mathbf{Y})$ (7)

$\mathbf{I}^*(\mathbf{X} \cap \mathbf{Y}) \subseteq \mathbf{I}^*(\mathbf{X}) \cap \mathbf{I}^*(\mathbf{Y})$ (8)

$\mathbf{I}^*(\mathbf{X} \cup \mathbf{Y}) = \mathbf{I}^*(\mathbf{X}) \cup \mathbf{I}^*(\mathbf{Y})$ (9)

if $\mathrm{X} \subseteq \mathbf{Y}$, then $\mathbf{I}_*(\mathbf{X}) \subseteq \mathbf{I}_*(\mathbf{Y})$ and $\mathbf{I}^*(\mathbf{X}) \subseteq \mathbf{I}^*(\mathbf{Y})$ (10)

$$\mathbf{I}_*(-\mathbf{X}) = -\mathbf{I}^*(\mathbf{X}) \tag{11}$$

$$\mathbf{I}^*(-\mathbf{X}) = -\mathbf{I}_*(\mathbf{X}) \tag{12}$$

$$\mathbf{I}_*(\mathbf{I}_*(\mathbf{X})) = \mathbf{I}^*(\mathbf{I}_*(\mathbf{X})) = \mathbf{I}_*(\mathbf{X}) \tag{13}$$

$$\mathbf{I}^*(\mathbf{I}^*(\mathbf{X})) = \mathbf{I}_*(\mathbf{I}^*(\mathbf{X})) = \mathbf{I}^*(\mathbf{X}) \tag{14}$$

It is concluded that the upper and the lower approximation were, in a sense, created under the influence of the indiscernibility relation.

The pieces of information we have about the objects in the boundary region are often inconsistent or even unclear. When the boundary region is empty ($\mathrm{BR_I} = 0$), i.e. when the lower and upper approximations match, the case is about crisp (precise) set. The larger the boundary region, the rougher the set becomes. This can be shown by using the accuracy approximation coefficient:

$$\boldsymbol{\alpha}_{\mathbf{I}}(\mathbf{X}) = |\mathbf{I}_*(\mathbf{X})| \; / \; |\mathbf{I}^*(\mathbf{X})| \tag{15}$$

where |X| is the cardinality of X. For$\boldsymbol{\alpha}_{\mathbf{I}}(\mathbf{X})$=1 the set is precise. For all the values $\mathbf{0} \leq \boldsymbol{\alpha}_{\mathbf{I}}(\mathbf{X}) \leq \mathbf{1}$ the set is rough. Therefore, the cardinality of the border region can be used to determine the measure of vagueness, that is, the uncertainty in relation to the observed set (Čupić & Suknović, 2010).

The uncertainty is connected to the elements that belong to the set. Because of the above, rough sets can be also defined by the rough membership function. It defines the uncertainty through indiscernibility relation **I**:

$$\boldsymbol{\mu}_X^{\mathbf{I}}(\mathrm{x}) = |\mathbf{X} \cap \mathbf{I}(\mathbf{x})| \; / \; |\mathbf{I}(\mathbf{x})| \tag{16}$$

where $\mathbf{0} < \boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) < \mathbf{1}$. If $\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) < 1$, the set X is rough due to I for every x ∈ X, in the case $\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) = \mathbf{1}$, the set is precise.

Rough membership function has the following properties:

$$\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) = 1, \text{ iff } \mathrm{x} \in \mathbf{I}_*(\mathbf{X}) \tag{17}$$

$$\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) = 0, \text{ if } \mathrm{x} \in \mathbf{U} - \mathbf{I}^*(\mathbf{x}) \tag{18}$$

$$\mathbf{0} < \boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) < \mathbf{1}, \text{ iff } \mathrm{x} \in \mathbf{BR_I}(\mathbf{X}) \tag{19}$$

$$\boldsymbol{\mu}_{U-X}^{\mathbf{I}}(\mathbf{x}) = 1\text{-}, \text{ if } \mathrm{x} \in \boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}), \text{ for any } \mathrm{x} \in \mathbf{U} \tag{20}$$

$$\boldsymbol{\mu}_{U\cap X}^{\mathbf{I}}(\mathbf{x}) \leq \min\left(\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}), \boldsymbol{\mu}_Y^{\mathbf{I}}(\mathbf{x})\right), \text{ for any } \mathrm{x} \in \mathbf{U} \tag{21}$$

$$\boldsymbol{\mu}_{U\cup X}^{\mathbf{I}}(\mathbf{x}) \geq \max\left(\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}), \boldsymbol{\mu}_Y^{\mathbf{I}}(\mathbf{x})\right), \text{ for any } \mathrm{x} \in \mathbf{U} \tag{22}$$

Generally, the rough membership function represents a coefficient which expresses the uncertainty of element x, where x ∈ **X.** The rough membership function can be used to define approximations and the boundary region of a set, as follows:

$$\mathbf{I}^*(\mathbf{X}) = \left\{\mathbf{x} \in \mathbf{U} \colon \mathbf{I}\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) > \mathbf{0}\right\} \tag{23}$$

$$\mathbf{I}_*(\mathbf{X}) = \left\{\mathbf{x} \in \mathbf{U} \colon \mathbf{I}\boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) = \mathbf{1}\right\} \tag{24}$$

$$\mathbf{BR_I}(\mathbf{X}) = \left\{\mathbf{x} \in \mathbf{U} \colon \mathbf{0} < \boldsymbol{\mu}_X^{\mathbf{I}}(\mathbf{x}) < \mathbf{1}\right\} \tag{25}$$

When solving the problem by using the RST, the rules having different decisions for more elements of the same kind can be noticed. These rules are called inconsistent and, when used, they lead to an inability to make the right decision. The problem of inconsistent rules is solved by using consistency factor C. Based on the decision rule δ(x), this factor is defined as follows:

$$C(\delta(x)) = \begin{cases} 1, & \text{for } \mu_X^I(x) = 0 \text{ or } 1 \\ \mu_X^I(x), & \text{for } 0 < \mu_X^I(x) < 1 \end{cases} \quad (26)$$

The closer the value of the consistency factor gets to one, the more authentic the rule becomes. Should the factor be equal to one, the rule is consistent. In the rough set theory, there is a strict link between vagueness and uncertainty (Boričić, 2004). Vagueness relates to sets while uncertainty to objects. Due to that, approximations are necessary when speaking about vagueness of the set while the rough membership function is necessary when speaking about uncertainty of the given objects' belonging to the observed set.

Input data can be quantitative and qualitative. Output data represent decisive rules in the form of the statement "if ... then ...", which can be exact or approximate. Based on these rules, decisions relating to the observed objects are made.

4. Software systems for applying the rough set theory

In order to apply the RST to data sets, a large number of software systems, which support RST, has been developed (Abbas, 2016). This development can be attributed to the successful application of rough sets to data mining and knowledge discovery. For the purposes of this paper, two applications, namely ROSETTA and ROSE2, will be presented. These applications enable the work with the data needed to support the decision-making of the security forces.

4.1. ROSETTA

ROSETTA was developed by the joint efforts of two groups of researchers from the Norwegian University of Science and Technology and the Mathematical Institute of the University of Warsaw. The project leaders were Jan Komorovski and Andrej Skovron (Komorowski, 2002).

The application design and the graphical user interface were developed by a Norwegian group led by Alexander Ohrn. The rough set algorithms were applied in the software and further developed in the Polish group. The ROSETTA system is a software package based on the concept of rough sets. The system includes a large number of algorithms for discretization and attribute reduction and data classification. It also generates IF-THEN rules and allows data sharing for training, testing and validating of the induced rules and patterns. All these features in used version 1.4.41, are supported by the graphical user interface available for Windows systems. The system is widely used in different areas.

4.2. ROSE2

ROSE2 is a software system that implements a large number of tools for working with rough sets. The system includes pre-processing (addition of missing values and discretization), approximation of values (determination of upper and lower approximation and boundary regions), calculating the core, attribute reduction, generating decision rules, classification and validation (Predki et al., 1998). The basic version of the ROSE software system has been upgraded several times, adapted to various operating systems, and is now up-to-date as ROSE2. Graphically and visually in the Windows environment, this system in used version 2.2, does not seem to be intuitive when presenting solutions like ROSETTA, but it contains different algorithms that can be applied to the reduction and generation of decision rules.

It was developed at the Laboratory for Intelligent Support to Decision-making of the Institute of Computer Sciences in Poznan, Poland.

5. Model application based on rough sets in security forces operations

The support to the decision-making process in the security forces operations will be included in the proposed model. The phases of the model are as follows:

1) Selecting the COA and defining the attribute values,
2) Determining the attribute values of the selected COA and forming the decision table,
3) Attribute reduction, and
4) Generating decision-making rules.

The model (Figure 2) will be elaborated through the application of two software systems, and the results will be compared and analyzed.

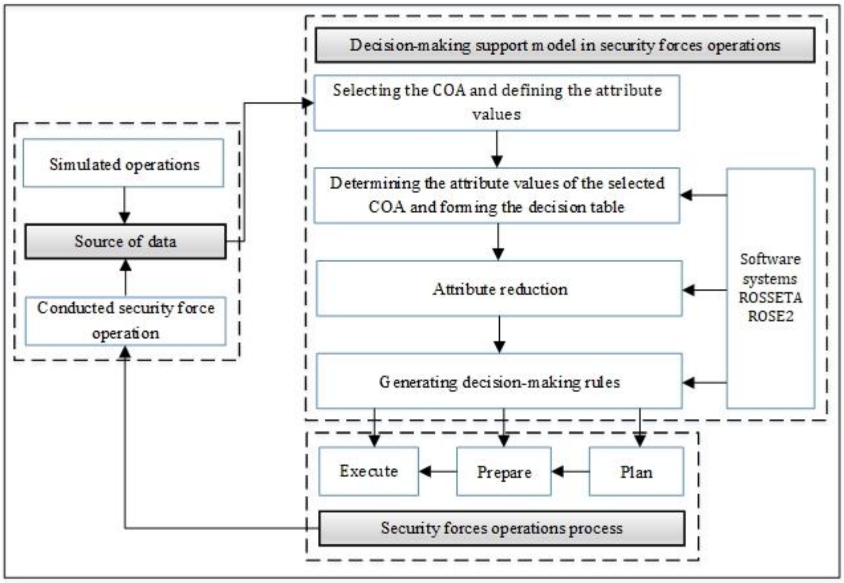


Figure 2. Decision-making support model in security forces operations

5.1. Selection of COA and defining the attribute values

In order to apply the RST and the proposed model, a source of data on security forces operations is required. The data of COA can be obtained in two ways: (1) from a previously conducted security force operation, and (2) from different simulated operations. The experiences from the conducted security forces operations are a good base for guiding the decision-making process. By analyzing the aforementioned operations, the data that will be used is found. Project number 98-98 of the University of Defence in Belgrade - Rationalization of the Military Decision-Making Process, 2011 - is especially significant for the data source. Simulations of security forces operations contribute to the checking of selected COAs and represent an experienced basis that leads to the improvement of the decision-making process. The University of Defence Simulation Center simulates the operations of the JCATs and

JANUS programs and presents the data source that will be used in this paper. The COA data is entered into the model through the criteria - attributes.

In the evaluation process, it is necessary to assign certain values to each of these attributes. Therefore, it will be necessary to specifically describe or define the values for every attribute. The application of rough sets does not exclusively require quantitative values, and the attributes in this section will be presented in a descriptive or linguistic way (Table 1). However, for the needs of a more compact display and later for easier software data processing, the values of the attributes can be replaced by the corresponding numerical or letter substitutions. One of the ways to evaluate attributes is presented in the following text.

Table 1. Overview of the attributes with values in security forces operations

Attribute	Description	Values
The strength of our forces (A1)	It represents the number of people and units through doctrinal principles for performing various security forces operations	3 – more than needed; 2 - adequate (sufficient forces according to the doctrinal principles); 1 - insufficient
The strength of enemy forces (A2)	In terms of the strength and sufficiency of the enemy, the location of the operation is examined. The number and sufficiency of the enemy are viewed through the environment in which the operation is carried out (e.g. the number of enemies in the urban environment or in the classical frontal operation is seen).	3 – very strong forces; 2 – adequate for the planned operation (sufficient forces and strength); 1 - weaker enemy forces
Operations preparing time(A3)	A time determination showing the total time available for planning the operation at all levels. In case of decrease the time for planning, harmful consequences can arise because the enemy's action will not be prevented.	3 – sufficient time; 2 - limited time, which requires greater and faster approximations; 1 – insufficient time
Combat environment (A4)	It is considered through the prism of organization complexity and the limitation of the use of our various forces in different environments.	3 - favorable - unpopulated (unlimited use of our forces); 2 - usual (poorly populated, the terrain is different); 1 - complex (most often urban)
Our forces casualties (A5)	The losses are perceived in accordance with the principles of conducting the operation.	3 – big losses; 2 –average losses; 1 – small losses
Civilian	Assessed based on the scope of the	3 – big losses;

Attribute	Description	Values
casualties (A6)	operation and the complexity of the environment in which the operation is performed.	2 –average losses; 1 – small losses
Maneuver (A7)	Skillful use of movement and fire in order to bring our own forces into a more favorable position in relation to the enemy. The success of the maneuver realization greatly contributes to the realization of the operation's goal.	3 – completely successful; 2 - partially successful; 1 - unsuccessful
Combat support (A8)	Reflected in the sufficiency of combat support resources in different environment. It represents the fire and operational support of our forces that conduct the operation.	2 - adequate or sufficient; 1 -inadequate or insufficient
Protection of our forces (A9)	Includes various activities that are planned and undertaken in order to reduce the ability of detecting our own forces and preventing or reduce the effects of the enemy's actions.	2 – sufficient; 1 -insufficient
Sustainability of our forces (A10)	For efficiency and autonomy of forces during their use, it combines various activities, measures and procedures of logistical support, personnel and financial security in operations.	2 – favorable; 1 - unfavorable
Simplicity of action (A11)	It implies the complexity of the conducted operation. Greater complexity in accordance with doctrinal principles leads to a more difficult achievement of the planned goal. It is related to the success of the maneuver.	3 – simple; 2 - partly complex; 1 – fully complex
Morale (A12)	It implies the moral-psychological state and the determination to carry out the task. It refers to our forces that participate in the operation, but also to the condition and readiness of civilian structures to accept the consequences of the operation. The extraordinary significance of the moral aspect is manifested in unforeseen situations when it can bring a dominance over the enemy.	3 – favorable; 2 - partly favorable; 1 - unfavorable
Intelligence system (A13)	Collecting, processing and using intelligence data is inseparably linked to the success of the operation. Quality work of the services will contribute to more precise data and reduce the uncertainty in the decision-making process	2 – adequate; 1 -inadequate
Command and control – C2 (A14)	It implies the expertise and experience of persons who manage the operation, their organization, operability, efficiency and elasticity in conducting the operation. It is	3 – high level; 2 – adequate; 1 - insufficient

Attribute	Description	Values
	related to the speed of information transmission and timely response to emerging situations.	
Coordination with civil structures (A15)	Cooperation with civil administration authorities in the operations zone	2 – adequate; 1 - inadequate
Decision attribute - Success of the operation (D)	The result of the operation	2 – successful with minor or greater losses 1 - unsuccessful

5.2. Assigning values to the attributes of the selected COA and forming a decision table

The decision table is a data table that distinguishes two attribute classes - condition attributes (A1, A2 ... A15) and decision (action) attributes (D).Table 2 shows the overview of the COA and attributes. In each row, one COA is described, and in each column, one attribute is described. The records in the table are the values of the attribute. Attribute values can be expressed linguistically, but due to a more compact display, they will be replaced by numerical substitutions. In this way, each row can provide a piece of information on a particular COA in the operation.

Table 2. Decision-making table

COA	A 1	A 2	A 3	A 4	A 5	A 6	A 7	A 8	A 9	A 10	A 11	A 12	A 13	A 14	A 15	D
1.	3	3	3	3	2	2	3	2	2	2	3	2	2	3	2	2
2.	3	1	2	1	2	3	2	2	2	2	2	2	1	2	1	2
3.	1	2	1	1	3	3	1	2	1	1	2	2	2	2	2	1
4.	2	2	2	2	2	2	1	2	2	2	1	1	1	1	1	1
5.	3	2	2	2	2	2	3	2	1	2	2	2	2	3	1	2
6.	3	3	2	2	1	1	3	2	2	2	2	2	2	3	2	2
7.	1	2	1	2	2	1	1	2	1	2	2	2	2	2	2	1
8.	3	1	3	1	2	3	3	2	2	2	3	2	2	3	1	2
9.	1	2	1	3	2	2	1	1	1	1	3	1	1	1	1	1
10.	3	1	3	1	2	2	2	2	2	2	2	2	2	3	2	2
11.	2	2	3	2	3	2	3	2	2	2	2	2	2	2	1	2
12.	2	1	2	1	2	2	3	1	2	1	2	2	2	3	1	2
13.	3	1	3	2	1	2	3	2	2	2	2	2	2	2	2	2
14.	2	3	1	2	1	2	2	2	2	2	2	2	2	2	2	1
15.	3	1	2	2	1	2	3	2	1	2	2	2	2	3	1	2
16.	3	2	3	1	2	3	2	2	2	2	2	2	1	1	1	2
17.	3	3	3	2	3	2	3	2	2	2	2	2	2	2	2	2
18.	2	2	1	3	1	2	1	2	2	2	3	2	2	2	2	1
19.	1	2	1	2	3	2	1	2	2	2	3	2	2	2	2	1
20.	3	1	3	3	2	2	3	2	1	2	3	2	2	1	2	2
21.	2	2	1	2	2	2	2	2	2	1	1	2	2	3	2	1
22.	2	2	1	3	2	1	1	1	2	2	2	2	2	2	1	1

COA	A 1	A 2	A 3	A 4	A 5	A 6	A 7	A 8	A 9	A 10	A 11	A 12	A 13	A 14	A 15	D
23.	2	2	3	2	2	2	3	2	2	1	1	2	2	3	2	2
24.	2	2	3	2	1	1	3	1	2	2	2	2	2	2	1	2
25.	1	1	3	2	1	1	3	1	2	2	2	2	2	2	1	2
26.	2	3	1	2	1	2	2	2	2	2	2	2	2	2	2	1
27.	3	1	2	2	1	2	3	2	1	2	2	2	2	3	1	2
28.	3	2	3	1	2	3	2	2	2	2	2	2	1	1	1	2
29.	3	3	3	2	3	2	3	2	2	2	2	2	2	2	2	2
30.	2	2	1	3	1	2	1	2	2	2	3	2	2	2	2	1
31.	1	2	1	2	3	2	1	2	2	2	3	2	2	2	2	1
32.	3	1	3	3	2	2	3	2	1	2	3	2	2	1	2	2
33.	2	2	1	2	2	2	2	2	2	1	1	2	2	3	2	1
34.	2	2	1	3	2	1	1	1	2	2	2	2	2	2	1	1
35.	2	2	3	2	2	2	3	2	2	1	1	2	2	3	2	2
36.	2	2	3	2	1	1	3	1	2	2	2	2	2	2	1	2
37.	1	1	3	2	1	1	3	1	2	2	2	2	2	2	1	1

In Figures 3 and 4 screen review decision table in software systems ROSETTA and ROSE2 can be seen. In software system ROSETTA, the names of the attributes are given linguistically, while in ROSE2 they are written in symbols.

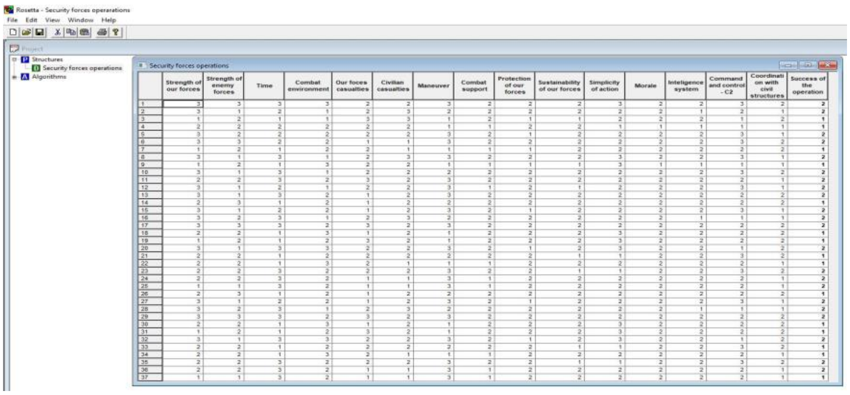


Figure 3. Decision table in software system ROSETTA

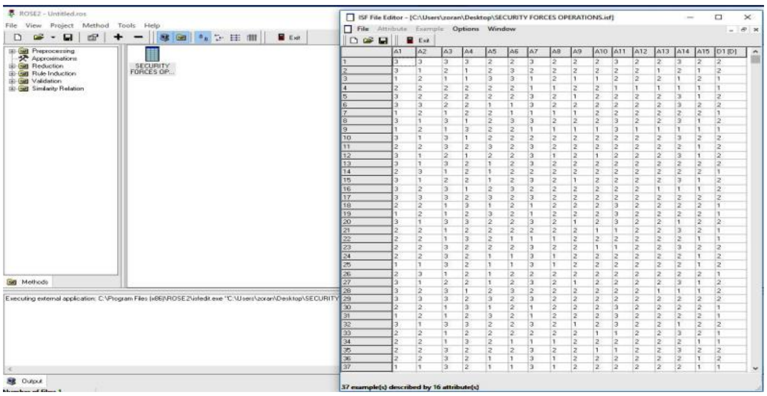


Figure 4. Decision table in software system ROSE2

The software system ROSE2 can be used for determining the upper and lower approximation of the sets ''COA that was successful (i.e. the security forces operation is successful according to the selected COA)'' and sets ''COA that was unsuccessful (i.e. security forces operation was unsuccessful according to the selected COA'' (Figure 5). The software system displays the number of objects by the decision attribute, upper and lower approximation and accuracy approximation coefficient. The software system ROSETTA does not have such possibilities.

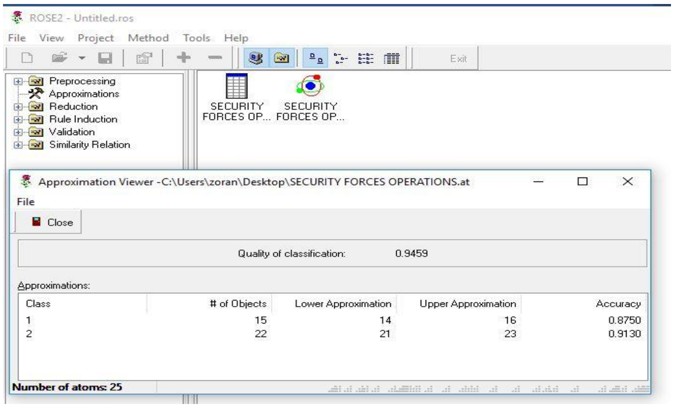


Figure 5. Determining the upper and lower approximation and the accuracy approximation coefficient in the software system ROSE2

Accuracy approximation coefficient $\alpha_I(X)$ in the software system ROSE2 is shown as Accuracy. It can be seen that α (successful) = 0,875 and α (unsuccessful)= 0,9130. Based on equations (15), in case of $\alpha_I(X) \rightarrow 1$through equations (3) $BR_I(X) \rightarrow 0$is obtained. It means that the upper and lower approximations are approaching each other. For $\alpha_I(X) = 1$ follows $BR_I(X) = 0$. The above implies that the combinations of attributes in COA are unique, i.e. there are no identical condition attributes for different decision attributes. In that case, the set is crisp. By increasing the number of COA, the given sets would increase their degree of vagueness. The set would become more "rough". Then, the coefficient of approximation accuracy would be smaller, and the available knowledge would be more difficult to classify, but this would not affect the capabilities of these software systems. The work with reduced consistency of the rules is a fundamental advantage of the RST when working with incomplete and unspecified data.

5.3. Attribute reduction

The next step is to assemble a minimal subset of independent attributes, i.e. reductions. These reductions guarantee the quality of classifications as a whole set. Output data form the attribute core. Reduction of attributes implies a decrease in volume of the core or the number of all attributes that influence the decision-making process. The aim is to identify those attributes, which according to the requirements of the decision-maker, significantly influence the decision-making process. Attribute reduction is used only in the case when it does not disturb the quality of the approximation.

Finding the reductor will be perceived through the ROSETTA and ROSE2 software systems by using the most important reduction algorithms offered.

5.3.1. Attribute reduction with software system ROSETTA

ROSETTA offers more various reductors or reduction algorithms which can be applied to data. One part of the reductors is implemented as a variant of the original form of the algorithm, and the other as customized and perfected reductors regarding existing algorithms for application in the software system. Perfected reductors for applying the RST are developed for the needs of the ROSETTA software system and they have the prefix RSES.

Johnson Reducer is a variant of the simple ''greedy'' algorithm (Johnson's algorithm) used for calculating only one shorter reduction. The algorithm tends to find the main implication of a minimum length (Johnson, 1974). It always selects the most frequent attribute in the decision-making function or a row of decision-making matrices and it continues until the reducts are obtained. This algorithm considers the attribute that most often appears as the most significant one. Even though this is not true in all cases, an optimal solution is usually found (Abbas, 2016). The result of the application on the decision-making table is shown in Figure 6.

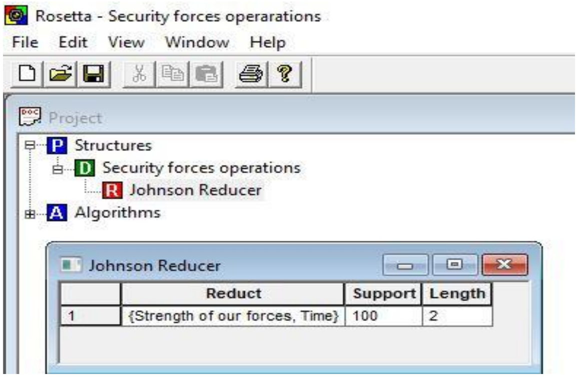


Figure 6. ROSETTA reduction - Johnson Reducer

RSES Exhaustive Reducer calculates the reductions by the principle of rough computer power without approximations, comparing all the given combinations of attributes with one another. The output gives more reductions that significantly affect the decision attribute (Dobrilovic et al., 2012; Romański, 1988). The result of the application on the decision-making table is shown in Figure 7.

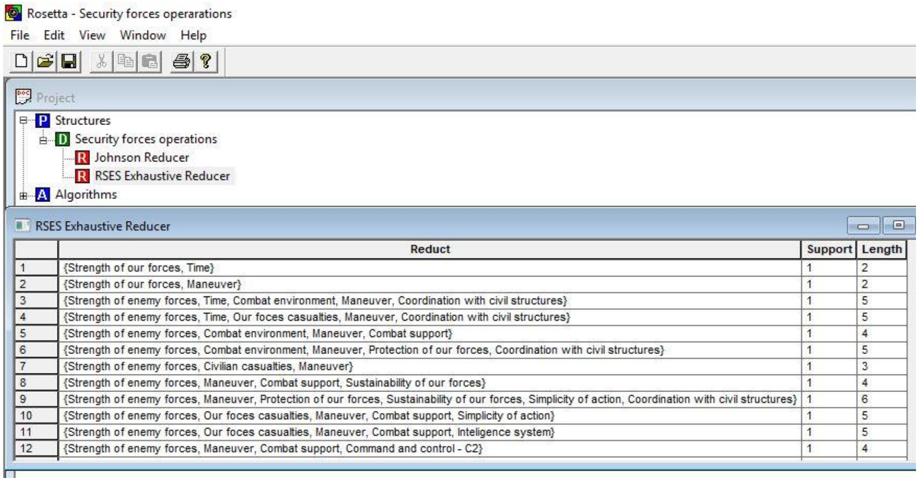


Figure 7. ROSETTA reduction - RSES Exhaustive Reducer

RSES Johnson Reducer is an advanced version of a simple Johnson algorithm adapted to the ROSETTA software system (Li, 2014). The result of the application on the decision-making table is shown in Figure 8.

Figure 8. ROSETTA reduction - RSES Johnson Reducer

RSES Genetic Reducer implements a variant of the genetic algorithm (Jaddi & Abdullah, 2013; Wroblewski, 1995) to search for reductions until the search area is exhausted, i.e. until the maximum number of reductions is noticed. As the aforementioned, the reducer is adapted to the ROSETTA software system and it provides various options for selecting the parameters depending on the search speed requirements and the coverage of the reduction. The result of the application on the decision-making table is shown in Figure 9.

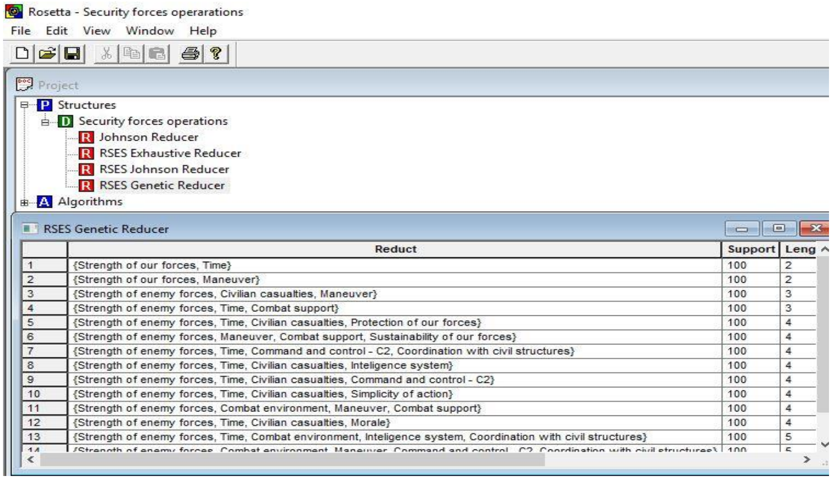


Figure 9. ROSETTA reduction - RSES Genetic Reducer

5.3.2. Attribute reduction with software system ROSE2

The ROSE2 software system also offers multiple reducers based on different algorithms.

The Lattice search reducer attempts to reduce search space by extracting a part that has no potential to include reduction of including a reduct (Grabowski, 2016; Prędki & Wilk, 1999). The result of the application on the decision-making table is shown in Figure 10.

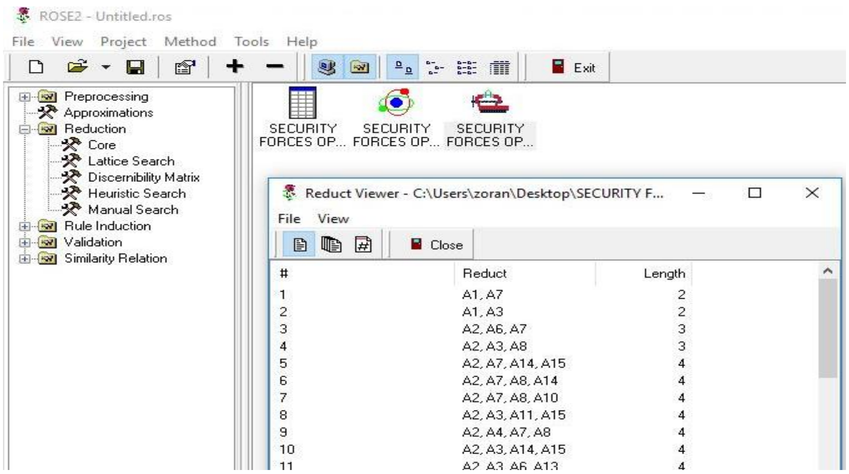


Figure 10. ROSE2reduction - Lattice search

Discernibility matrix reductor is a more computer-efficient algorithm for generating reductions based on an open matrix (Skowron & Rauszer, 1992). The result of the application on the decision-making table is shown in Figure 11.

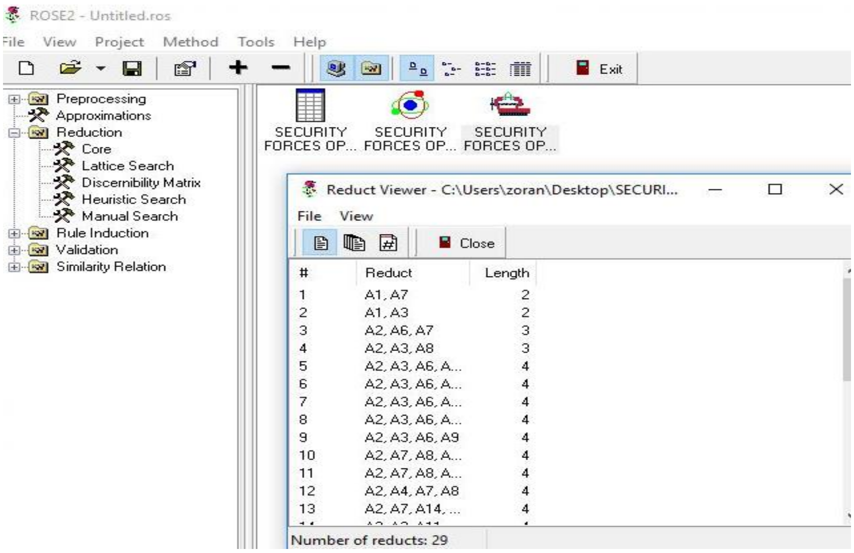


Figure 11. ROSE2reduction - Discernibility matrix

Heuristic search reducer implements a strategy based on adding attributes to the core. It determines approximately the reduction value when it is not possible to accurately determine other algorithms. Because of this characteristic, Heuristic search reducer is significant when other methods fail (Liang et al., 2014).The result of the application on the decision-making table is shown in Figure 12.

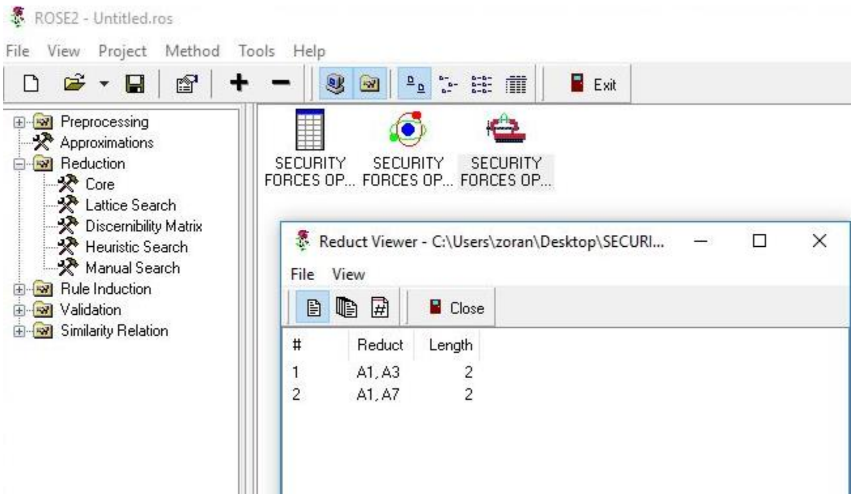


Figure 12. ROSE2reduction - Heuristic search

5.3.3. Review of reduced attributes

It is important to highlight that, due to the essence of the decision-making support process, finding a shorter coordinated core is of crucial importance. Such a need arises from the demand that the time for considering attribute conditions be shortened because analyzing every additional attribute takes additional time and that is always a limiting factor. Some reducers offer only shorter cores while others offer cores of different lengths sorted by the quality of reduction. Because of this, only the cores of the shortest length (in our case, two attributes) and the highest quality reduction will be considered.

Comparison of various components of ROSETTA and ROSE2 software systems and attributes obtained by reduction are given in Table 3.

Table 3. Results of attributes' reduction

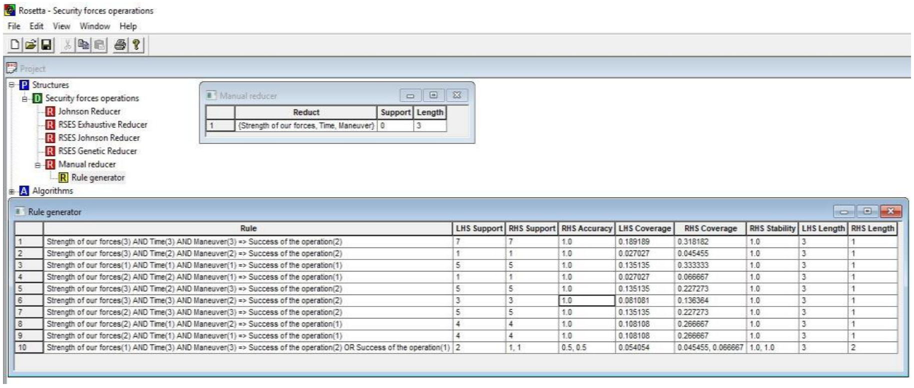
Software system	Reductor	Attributes obtained by reduction	
		1. reduction	2. reduction
ROSETTA	Johnson Reducer	A1, A3	
	RSES Exhaustive Reducer	A1, A3	A1, A7
	RSES Johnson Reducer	A3, A1	
	RSES Genetic Reducer	A1, A3	A1, A7
ROSE2	Lattice search	A1,A7	A1, A3
	Discernibility matrix	A1, A7	A1, A3
	Heruistic search	A1, A3	A1, A7

It can be seen from the previous table that different reducers give very similar results. The mild differences are the result of the applied algorithms, their way of attribute reduction and limitations in the reduction process, but also of the number of COAs being considered. With the increase in the number of COAs, it is expected that there would be equalization of different algorithm reduction results.

Looking at the results of all the obtained reductions, it can be concluded that there is no unique combination of two attributes around which the offered algorithms are completely "compatible". The most compatible attribute combination is A1 and A3 (The strength of our forces and Operations preparing time). However, it is noticeable that three attributes are repeated in the results of all reducers both on the first and the second reduction. Therefore, the final reduction cannot be performed by using the shortest combination of two attributes. Instead, three attributes will be used: A1, A3, A7 that is, The strength of our forces, Operations preparing time and Maneuver. These attributes essentially represent the core of the attributes required for decision-making. Other attributes are rejected because their values will not have a significant effect on classifying COA and generating the decision-making rules.

5.4. Generating decision-making rules

The obtained attributes are sufficient to form a reduced decision-making table. The ROSETTA software system allows the consideration of the harmonized reduced decision-making table through the Manual reducer and generating decision-making rules for the specified attributes (Figure 13). Also, each of the aforementioned reducers generates its decision-making tables. However, the above will be used due to a more comprehensive view of the selected condition attributes.



	Reduct	Support	Length
1	{Strength of our forces, Time, Maneuver}	0	3

	Rule	LHS Support	RHS Support	RHS Accuracy	LHS Coverage	RHS Coverage	RHS Stability	LHS Length	RHS Length
1	Strength of our forces(3) AND Time(3) AND Maneuver(3) => Success of the operation(2)	7	7	1.0	0.189189	0.318182	1.0	3	1
2	Strength of our forces(3) AND Time(2) AND Maneuver(2) => Success of the operation(2)	1	1	1.0	0.027027	0.045455	1.0	3	1
3	Strength of our forces(1) AND Time(1) AND Maneuver(1) => Success of the operation(1)	5	5	1.0	0.135135	0.333333	1.0	3	1
4	Strength of our forces(2) AND Time(2) AND Maneuver(1) => Success of the operation(1)	1	1	1.0	0.027027	0.066667	1.0	3	1
5	Strength of our forces(3) AND Time(2) AND Maneuver(3) => Success of the operation(2)	5	5	1.0	0.135135	0.227273	1.0	3	1
6	Strength of our forces(3) AND Time(3) AND Maneuver(2) => Success of the operation(2)	3	3	1.0	0.081081	0.136364	1.0	3	1
7	Strength of our forces(2) AND Time(3) AND Maneuver(3) => Success of the operation(2)	5	5	1.0	0.135135	0.227273	1.0	3	1
8	Strength of our forces(2) AND Time(1) AND Maneuver(2) => Success of the operation(1)	4	4	1.0	0.108108	0.266667	1.0	3	1
9	Strength of our forces(2) AND Time(1) AND Maneuver(1) => Success of the operation(1)	4	4	1.0	0.108108	0.266667	1.0	3	1
10	Strength of our forces(1) AND Time(3) AND Maneuver(3) => Success of the operation(2) OR Success of the operation(1)	2	1, 1	0.5, 0.5	0.054054	0.045455, 0.066667	1.0, 1.0	3	2

Figure 13. ROSETTA –Reduced decision-making table

It can be noticed that besides generating complete decision-making algorithms, the ROSETTA software system also generates various other data related to certain probability properties. The most important characteristics for observation and further consideration of the attributes are support, strength, certainty and coverage (Pawlak, 2002). These factors have various names in different software systems, and therefore, direct translations can be diverse, but for the purposes of this work, previously given property names will be kept.

The support factor represents the number of COA with all identical attributes. In Figure 13, it is presented as the RHS Support. The software system also offers the LHS Support feature, which represents the number of COAs with equal attribute conditions. This is less important for further consideration. By reducing the consistency of the decision-making rules, differences between the two properties indicated would be made.

The strength factor represents the participation of the COA determined by the observed attributes in the total number of the monitored COAs and the sum of all must be 100%. Basically, it represents the Support factor in percentages compared to the total number of COAs considered. It gives an important indicator of the COA towards which should be strived. It is a significant statistic prediction indicator if the values are higher. The strength factor is most often calculated from data, but it can be also obtained by estimation (Pawlak, 2002). It is obtained by estimation when an expert in a particular field estimates that the appropriate combination of attributes in COA is more significant than a simple percentage participation in the sum of all COAs. In Figure 13, it is presented in the LHS Coverage column and it is derived from the existing table data.

The certainty factor is at a high level, due to different combinations of condition attributes in a reduced decision-making table. This feature represents practically the participation of the support factor of a particular condition attribute combination in the total support of that condition attribute combination. It gives knowledge on certainty of the observed COA. The value will decrease if there are identical condition attributes with different decision attributes. Because of its importance, this property of probability leads us to consider the COAs that have a higher value of certainty, i.e. closer to the number 1.00. In this sense, the certainty factor can be identified with the previously defined consistency factor C (δ (h)) and it should be the first property and the most important factor to be considered in the analysis of the further offered algorithms. The COA with a smaller consistency factor will further focus consideration of the generated rules. This property is shown in Figure 13 in the RHS Accuracy column.

The coverage factor provides significant information about the participation of a particular value of the decision attribute. It implies percentage of one attribute combination in the given decision attribute. The sum of all factor values must be 100% by one value of the decision attribute. It is particularly emphasized in considering a single decision attribute in a large number of COAs. This is shown in Figure 13 in RHS Coverage column.

Further reduced decision-making table can be presented by the following decision-making algorithms and prominent probability properties (Table 4). The generated decision rules for C(δ(x))=1 were taken into account.

Table 4. ROSETTA -Decision-making algorithms for C(δ(x))=1

IF			THEN	Strength factor (%)	Coverage factor (%)
Condition attributes			Decision attribute		
Strength of our forces	Operations preparing time	Maneuver	Success of the operation		
more than needed	sufficient	completely successful	successful	18,9	31,8
more than needed	limited	partially successful	successful	2,7	4,5
insufficient	insufficient	unsuccessful	unsuccessful	13,5	33,3
adequate	limited	unsuccessful	unsuccessful	2,7	6,6
more than needed	limited	completely successful	successful	13,5	22,7
more than needed	sufficient	partially successful	successful	8,1	13,6
adequate	sufficient	completely successful	successful	13,5	22,7
adequate	insufficient	partially successful	unsuccessful	10,8	26,6
adequate	insufficient	unsuccessful	unsuccessful	10,8	26,6

The mentioned prominent properties of probability in the decision-making algorithm are directed to the specific IF-THEN rules, which, due to the above properties, further emphasize their significance.

The ROSE2 software system offers a different approach to generating decision rules. It uses a modified LEM2 (ModLEM) algorithm that recognizes extreme differences in rules and separates the most positive and most negative attributes from the impact on decision attributes. All the offered variants of this algorithm have a "greedy" approach and give short decision-making rules. For the purposes of this paper, the rule generator will be considered with the Extended minimum coverage as can be seen in Figure 14.

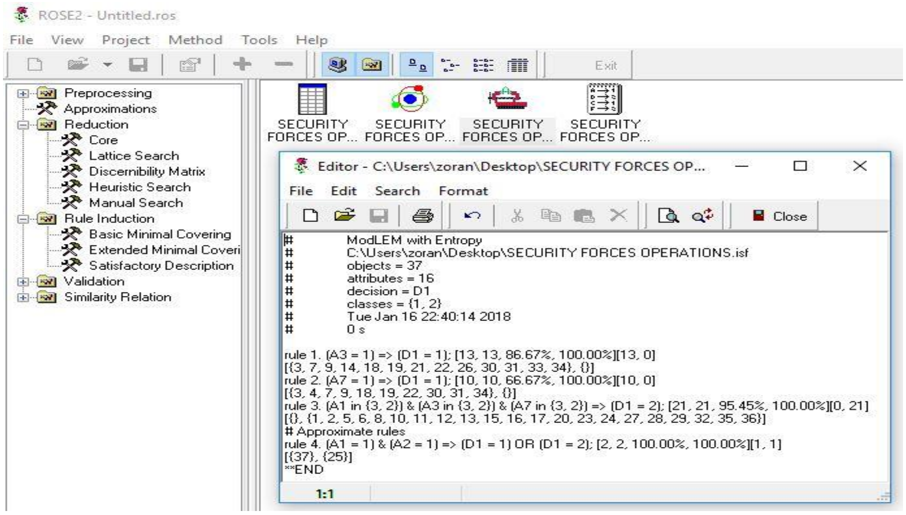


Figure 14. ROSE2–Decision rules

The obtained data can be used. However, due to the lack of a certain number of probabilities and the combination of condition attributes, they are less important in the further decision-making process than the results of the ROSETTA program. They represent a shortened lead with the described coverage factor, which should be sought in the further decision-making process.

The software system also directs to the decision rules with consistency factor C (δ (h)) = 1. In accordance with the possibilities of the RST, it shows the rules for which C (δ (h)) <1, but do not give a precise value. Those rules are called Approximate rules. The decision-making algorithms, derived from the software system ROSE2 for C(δ(x)) = 1, are presented in Table 5.

Table 5. ROSE2 -Decision-making algorithms for C(δ(x))=1

IF			THEN	Coverage factor (%)
Condition attributes			Decision attribute	
Strength of our forces	Operations preparing time	Maneuver	Success of the operation	
	insufficient		unsuccessful	86,6
		unsuccessful	unsuccessful	66,6
more than needed or adequate	sufficient or limited	completely or partially successful	successful	95

ROSE2 directs with the coverage factor. In this way, the shorter coverage of the rules in percentages as the only property of the probability of the given rule, as given by the ROSE2 software system, is not sufficiently strong to lead to the desired decision attribute. However, even this coverage of the rule can be significant in the decision-making process where it gives certain knowledge about processes that are shaped and at least partially directs the decision-makers.

6. Discussion of results

The obtained attribute core is essential for the success of the operation, but also for other condition attributes. The influence of the attribute core on the success of the operation can be considered through other condition attributes (US Army, 2015). For example, Operations preparing time (core attribute A3) affects the quality of planning all elements of the operation. It also affects Combat support (A8), Protection of our forces (A9) and Sustainability of our forces (A10). Time also has an effect on all activities that completely or partially precede performing of the operation. Some of those activities are Intelligence system (A13) and Coordination with civil structures (A15). Within the sufficient time frame, shortcomings in Command and Control - C2 (A14) can be compensated. Additionally, Our forces casualties (A5) can be reduced through greater preparation of the Protection of our forces (A9). Similarly, other core attributes dominantly affect other condition attributes. The strength of our forces (core attribute A1) can compensate for different negativities in other attributes.

On the other hand, there is a certain feedback between all attributes. Moreover, there is a mutual influence which is impossible to fully comprehend due to the stated complexity of the environment. Such feedback is also present between the core attributes, but less significant than with other attributes. An example for that is the influence of Operations preparing time (core attribute A3) on Maneuver (core attribute A7). In practice it can have a positive influence, but not necessarily. By using this decision-making support model, the complexity of the mutual influence of all condition attributes can be partially overcome. This is one of its biggest advantages.

The obtained decision algorithm, especially the one from the ROSETTA software system, directs and manages the authorities that plan the COA of the security forces operations to the rules that bring success in operations in a complex environment (Gordic et al., 2013). They also provide information on combinations of attributes that will lead to unsuccessful operation. Guided by these rules in different situations, time spent on certain options in entire planning and decision-making process is reduced. It is a necessary time-saving. The application of the decision-making support system based on the RST enables an additional source of information to the decision-maker and the persons who take part in the entire decision-making process. Thus, the purpose of such a system is fulfilled.

7. Conclusion

The RST in the decision-making support model uses entirely internal knowledge, unlike other methods whose application requires additional assumption models or some form of preprocessing. The internal knowledge represents the existing operational data, and there is no need to rely on modeling assumptions.

The advantage of the decision-making model based on the RST in the decision-making process is the ability to use qualitative-quantitative data, as well as the IF-THEN decision-making algorithms. These algorithms can be applied to the whole decision-making process by directing the decision-maker in every moment of the process, and not just at the moment of selecting a COA.

Using the proposed decision-making support model makes it possible to reach extremely valuable indicators in a rather simple way, which can help in the decision-making process. The paper presents one method of use; however, due to the complexity of the environment in which security forces operations are planned and implemented, it is possible to apply the rough set concept to lower levels - the sublevels of these attributes. Simultaneous application of the rough set concept to lower and higher levels of attributes in security forces operations, complemented by classifying and/or clustering at lower levels, can be a challenge for future work. In this way, the support for decision-making in security forces operations in the modern security environment would be raised to a higher level.

Acknowledgements

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