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MANAGING UNCERTAINTY IN THE CONSTRUCTION INDUSTRY THROUGH THE ROUGH SET THEORY

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Abstract: Application of the rough sets theory in the construction industry is shown. Rough sets are introduced owing to the imprecision and vagueness which are present in construction production systems. It is demonstrated that the rough set theory is a very effective methodology for data analysis in the attribute-value based domain. The presentation is supported by examples.

Keywords: Rough set, construction industry, uncertainty, artificial intelligence, decision rules.

> "The idea of rough set has been proposed as a mathematical tool to deal with vague concepts, and seems to be of some importance to artificial intelligence and cognitive science, in particular expert systems, decision support systems, machine learning, machine discovery, pattern recognition and decision tables."
>
> Zdzislaw Pawlak - "Rough Sets: A New Approach to Vagueness"

1. INTRODUCTION

Rough set theory, introduced by Zdzislaw Pawlak in 1982 [13], is a new mathematical tool managing uncertainty and vagueness in data sets. This emerging new technology concerns the classificatory analysis of imprecise, uncertain or incomplete information. The theory was originated as a result of a long-term program of fundamental research on the logical properties of information systems, carried out by Pawlak and a group of logicians from the Polish Academy of Sciences and the University of Warsaw, Poland. The methodology is concerned with the classificatory analysis of imprecise, uncertain or incomplete information or knowledge expressed in terms of data acquired from experience. The main concept of the rough set theory is an indiscernibility relation, normally associated with a set of attributes. Sets that are indiscernible are called elementary sets. Any finite union of elementary sets is called a definable set. Two notions are fundamental: lower and upper approximations of a set. The lower approximation of a set is the set being the union of all elementary sets contained in the given set. The upper larger approximation of a set is the smallest set being the union of all elementary sets containing the given set.

The rough set theory provides a methodology for simplifying and reducing the extraneous information in a database, thus exposing any underlying patterns. Typical issues are the discovery of data dependencies, the discovery of predictive rules, representation of data, etc. Knowledge can be understood as the ability to classify objects from available information. The rough set theory was one of the first nonstatistical methodologies for data analysis, as it was referred by G. Paterson [12]. It extends classical set theory by incorporating into the set model the notion of classification as an indiscernibility relation.

Starting in 1982 a large number of papers have been published that further develop the rough set theory - Z. Pawlak [14], mathematical rules and liaison with other theories - Z. Pawlak and A. Skowron [16], decision patterns - R. Slowinski and J. Stefanowski [21], and application of the theory to decision analysis - Z. Pawlak [15] and Z. Pawlak and R. Slowinski [17], [18]. The rough set theory is a convenient tool for decision support systems particularly when a decision-making process involves imprecise notions and uncertain data. The main assumptions of the rough set theory are: 1) that the objects in the universum are linked with some kind of information (knowledge) and 2) that the objects that are characterized by identical information do not differ with respect to the available information. Vague notions, contrary to precise notions, cannot be characterized in the sense of information about their elements. This indiscernibility relation is the mathematical base of the rough set theory, as noted by Z. Pawlak and A. Skowron [16]. According to this, an elementary set is any set of objects that do not differ, a sharp (precise) set is any union of certain elementary sets, while in the opposite case a set is rough (imprecise, vague).

Each rough set has its own boundary examples (on the boundary line). Those are objects that cannot be with certainty classified as members of a set or as its complement. Sharp sets do not possess boundary elements. Each vague notion is characterized by a pair of exact notions - lower and upper approximations of a vague notion. The lower approximation consists of all the objects which certainly belong to an object. The upper approximation contains all the objects that may belong to an object. The difference between the lower and upper approximations represents the boundary zone of a vague notion. Approximations are two main operations in the rough set theory, according to Z. Pawlak and A. Skowron [16].

The paper is organized in the following way:

Section 2: Similarities, differences and analogies between rough and fuzzy sets.
Section 3: The mathematical base of rough sets.
Section 4: Application of rough set theory in the construction industry, with some practical examples, discussion of results, and recommendations for future directions in this field.

2. THE MUTUAL RELATIONS BETWEEN ROUGH SETS AND FUZZY SETS

It must be emphasized that the concept of rough set should not be confused with the idea of fuzzy set as they are fundamentally different notions, although in some sense complementary. The fuzzy set theory was introduced by Lofti Zadeh in 1965 and 1978 [23], [24]. The fuzzy set theory contains an algebra and a set of linguistics that facilitate descriptions of complex and ill-defined systems. The fuzzy model combines elements of the rule-based and probabilistic approaches and sets of symbols.

Rough sets and fuzzy sets are complementary generalizations of classical sets. Fuzzy sets allow partial set membership to handle vagueness, while rough sets allow multiple set membership to deal with indiscernibility. These two approaches to generalized sets form the beginning of the "soft mathematics" and provide the basis for "soft computing", which includes, along with rough sets, at least fuzzy logic, neural networks, probabilistic reasoning, belief networks, learning, connectionist computing, genetic algorithms, and chaos theory.

The rough set method is a symbolic method of data analysis. It is the first (and sometimes sufficient) step in analyzing incomplete or uncertain information. Rough set analysis uses only internal information and does not rely on additional model assumptions as the fuzzy set method or probabilistic models do.

As mentioned above in the rough set theory, vagueness refers to sets, and uncertainty refers to the elements of sets. To this end, approximations are used for vague notions and rough membership for uncertain data. As mentioned, the rough set theory can be compared with the fuzzy set theory and similarities and dissimilarities noticed. In the fuzzy set theory, imprecision is expressed as a membership function and in the rough set theory imprecision is based on indiscernibility and approximation. The fuzziness in fuzzy sets may be taken to correspond to a set boundary zone in the rough set theory.

Decision logic for imprecise reasoning in the rough set theory is analogous to the logic of fuzzy sets. The analytical property of decision rules in the rough set theory is analogous to the analytical property of rules in approximative reasoning in fuzzy sets. The mathematical tool in rough sets is analogous to the mathematical tool in fuzzy sets, as suggested by A. Kaufman and M. Gupta [11].

An advantage of the rough set theory lies in the fact that it does not require any preceding or supplemental information about data, such as the degree of membership to a possibility in the theory of fuzzy sets or the probability of events in statistics, as quoted by Z. Pawlak [15]. A disadvantage of the fuzzy set theory lies in the difficulty of formulating membership functions of possibility and in the rough set theory in the impossibility of obtaining all deterministic rules in each individual case when they are applied to decision analysis.

Recently there have been studies on fuzzy set roughness or rough set fuzziness analogous to the probability of possibility, particularly in the works of D. Dubois and H. Prade [9], [10] and of W. Ziarko [25].

3. THE MATHEMATICAL PRELIMINARIES

Following are the mathematical expressions for indiscernibility and approximation in rough sets. Let U be a finite set of objects - universum and let X be such that $X \subseteq U$, when $x \in X$ (Fig. 1). A binary relation I in terms of U is introduced and is called an indiscernibility relation. For the purpose of simplicity let us assume that the binary relation I is an equivalence relation. $I(x)$ is introduced and is called an indiscernibility relation.

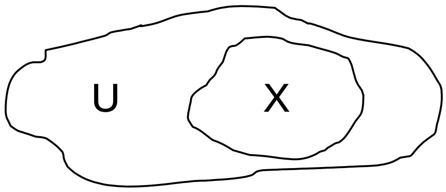

Figure 1: Universum and the rough set

I – the lower approximation of X is defined as follows:

$$I_*(X) = \{x \in U : I(x) \subseteq X\} \tag{1}$$

and I the upper approximation of X:

$$I^*(X) = \{x \in U : I(x) \cap X \neq 0\} \tag{2}$$

The boundary zone X is the set:

$$BN_I(X) = I^*(X) - I_*(X) \tag{3}$$

If the boundary zone X is an empty set:

$$BN_I(X) = 0 \tag{4}$$

the set X is sharp (clear) in relation to I and in the opposite case:

$$BN_I(X) \neq 0 \tag{5}$$

the set X is rough in relation to I.

Roughness (vagueness) is expressed by the coefficient of:

$$\alpha_I(X) = |\, I_*(X)\,| \,/\, |\, I^*(X)\,|, \text{ where } 0 \leq \alpha_I(X) \leq 10 \tag{6}$$

where $|X|$ is the X set cardinalship. The coefficient $\alpha_I(X)$ is the accuracy of the approximation of X notion. If:

$$\alpha_I(X) = 1 \tag{7}$$

the X set is sharp in relation to I and if:

$$\alpha_I(X) < 1 \tag{8}$$

the X set is rough in relation to I.

The function of rough membership means the membership in relation to the rough set notion, and is defined by using the binary relation of indiscernibility I:

$$\mu_X^I(x) = |X \cap I(x)| / |I(x)|, \text{ where } 0 \le \mu_X^I(x) \le 1 \tag{9}$$

The lower and upper approximations and the boundary zone of a set can be formulated by a rough membership function in the following way:

$$I_*(X) = \{x \in U : \mu_X^I(x) = 1\} \tag{10}$$

$$I^*(X) = \{x \in U : \mu_X^I(x) > 0\} \tag{11}$$

$$BN_I(X) = \{x \in U : 0 < \mu_X^I < 1\} \tag{12}$$

Here below are defined the reductors of a binary relation I, according to Z. Pawlak [14]. They are introduced in order to eliminate certain properties of a classification model that formulate the rules of a problem resolved by means of rough sets and to avoid changing the elementary sets' family, thus safeguarding indiscernibility. If a family of indiscernibility relations is formulated:

$$I = \{I_1, I_2, ...I_n\} \tag{13}$$

then the set of intersections of individual equivalence relations I_i that belong to the family is also an equivalence relation:

$$\bigcap I = \bigcap_{i=1}^{n} I_1 \tag{14}$$

The I reductor is a minimum subset I' of I, where $\bigcap I = \bigcap I'$. In principle, I may have several reductors.

The starting points in rough set philosophy regarding computation are data tables or attribute-values or decision tables in which attributes of conditions and attributes of decision are presented (Table 1). Table 1 shows data on n number of the considered cases. The rows stand for objects. They are represented by decision rules $\delta(x)$ shown in n rows. The columns are attributes, namely Au_j $(j = 1,...,m)$ for attributes of conditions, and Ao for decision attributes. The values in the table are attribute values namely au_{ij} $(i = 1,...,n;\ j = 1,...,m)$ for attributes of condition and ao_i $(i = 1,...,n)$ for the decision attributes. In this way, each row can be considered to contain information about an individual case. So, a decision table represents a sum of decision rules, namely a decision algorithm consisting of decision rules in the form "IF.... THEN..." according to Z. Pawlak [15] and R. Slowinski and J. Stefanowski [21]. For example, the i-th row can be presented, using the decision algorithm, in the following way, namely the i-th object in the table is characterized by the following set of attribute-values:

$$\text{IF } (Au_i, au_{ui})\ \&...\&\ (Au_j, au_{ij})\ \&...\&\ (Au_m, au_{im}) \Rightarrow \text{THEN } (Ao, ao_i)$$

Table 1: Table of attribute-values

$\delta(x)$	Au_1	...	Au_j	...	...	Au_m	Ao_i
$\delta(1)$	au_{11}	...	au_{1j}	...	...	au_{1m}	ao_1
...	...	...	...	...	...	...	...
$\delta(i)$	au_{i1}	...	au_{ij}	...	...	au_{im}	ao_i
...	...	...	...	...	...	...	...
$\delta(n)$	au_{n1}	...	au_{nj}	...	....	au_{nm}	ao_n

The reliability factor is a coefficient by which the reliability of any possible decision is appraised in the decision rules. Let $\delta(x)$ be a decision rule related to object x. The reliability factor for this rule is:

$$C(\delta(x)) = 1, \quad \text{if} \quad \mu_X^I(x) = 1 \text{ or } 0 \qquad (15)$$

$$C(\delta(x)) = \mu_X^I(x), \quad \text{if} \quad 0 < \mu_X^I(x) < 1 \qquad (16)$$

The closer the reliability factor is to 1, the greater the reliability of the rule. Rules that have the same conditions but different decisions are called inconsistent or indeterministic. Other rules are consistent or deterministic.

Partial dependence is the ratio of the number of deterministic rules to the number of all rules in the decision table. If the dependence coefficient is 1, the dependence is full (total).

4. APPLICATION IN THE CONSTRUCTION INDUSTRY

Application of the rough set theory is developing along two paths. The first path represents the application of rough sets in artificial intelligence, which means machine learning, machine discovery from data bases, expert systems, inductive reasoning, recognition of models and heuristic forecasts. The second path is decision support system development and decision analysis according to the works of Z. Pawlak and R. Slowinski [17]. The objective of a decision analysis is to explain a decision within the framework of circumstances under which it was made, particularly when such a decision was made under specific circumstances. According to Z. Pawlak [15] the main problems that can be resolved by a rough set approach are: 1) the description of objects by means of attribute values, 2) the description of total or partial dependence among the attributes, 3) attribute reduction, 4) attribute meaning, and 5) decision rules generation.

Though numerous software systems based on the rough set theory are commercially available, and successfully applied in many fields, it can be noted that the application rough sets has not gained ground in the construction industry yet. This paper is a contribution to the application of this theory in the field of analytical studies of technology solutions - building by means of a conveyable formwork according to the studies of G.]irovi} [5], [6] and organization patterns - the choice of a convenient pattern of organization.

4.1. Selection of the optimum formwork pattern in a semi-prefabricated system of construction

Without any in-depth technological elaboration of the construction process using a conveyable formwork, a model of the rough set application will be here in explained. Having first studied well the contribution of formwork properties to satisfactory construction with respect to time and economy, there was a time when the knowledge of a conveyable formwork technology for the construction of reinforced concrete walls for housing units, built by a semi-prefabricated system of construction, enabled rapid evaluation of optimum formwork layout by means of expert systems, proposed by G.]irovi} and Z. \or|evi} [7]. In this practical example, rough sets are used to describe the building bases built with conveyable prefabricated formwork, the dependence and reduction of the attributes and to generate decision rules whether to start construction production with the said conveyable formwork, namely whether a certain base is usable or not. The following criteria are formulated to assess the quality of the solution: a) rate of execution, b) low quantity of formwork, c) possibility to prefabricate ceilings. These criteria are in fact the attributes of condition, and a decision on a usable (or non-usable) base is an attribute of decision with definite attribute values for parameters that affect the quality of the solution (formwork lengths, number of panels, number of tacts, number of prefabricated ceilings per one tact and floor in a building, quantity of concrete to be placed per one tact). The attribute values are expressed in a linguistic way. A total of six different bases was considered for typical floors in buildings constructed using conveyable formwork.

4.1.1. Results

Table 2 shows data from the six bases considered. It is an attribute-value table or a decision table. The columns are designated by attributes (formwork properties) and the rows by the objects (bases of a construction project to be executed) while the values in the Table are attribute values. In that way, each row can be taken to contain information related to a specific base. For example, base 2 in the Table is characterized by the following attribute-value set:

(Fast Execution, yes), (Low Quantity of Formwork, no) (Prefabrication of Ceilings, good), (Usable Base, yes)

and they together give full information about the base.

Table 2.

BASE	FAST EXECUTION	LOW QUANTITY OF FORMWORK	PREFABRICATED CEILINGS	USABLE BASE
1	no	yes	good	yes
2	yes	no	good	yes
3	yes	yes	excellent	yes
4	no	yes	medium	no
5	yes	no	good	no
6	no	yes	excellent	yes

Bases 2, 3 and 5 in this Table do not differ with regard to the Fast Execution attribute, Bases 3 and 6 do not differ with regard to the attributes: Low Quantity of Formwork and Usable Base, while Bases 2 and 5 do not differ with regard to the attributes: Fast Execution, Low Quantity of Formwork and Prefabricated Ceilings. Thus, for example, the Fast Execution attribute generates two elementary sets {2, 3, 5} and {1, 4, 6} while the attributes Fast Execution and Low Quantity of Formwork generate the following elementary sets {1, 4, 6}, {2, 5} and {3}. An elementary set generated by each of the attribute subsets can be defined in a similar way.

As Base 2 is a Usable Base, namely suitable to make a decision to prepare prefabricated formwork for it, and Base 5 is not, and they do not differ with respect to the attributes: Fast Execution, Low Quantity of Formwork and Prefabricated Ceilings, base usability cannot be characterized with respect to conveyable prefabricated formwork in the attributes: Fast Execution, Low Quantity of Formwork, and Prefabricated Ceilings. For this reason, Bases 2 and 5 are boundary cases (on the boundary line) that cannot be duly classified with the available cognitive means. The remaining Bases 1, 3 and 6 show properties that enable us to classify them being certain of their usability, while with regard to Bases 2 and 5 it cannot be excluded that the base is not usable and with regard to Base 4 the formwork is surely not made with the selected prefabricated properties, namely the base is not usable. So, the lower approximation of the Usable Base set (for which the formwork will be fabricated) is the set {1, 3, 6} while the upper approximation of this set is the set {1, 2, 3, 5, 6} where the boundary cases are Bases 2 and 5. Similarly, Base 4 is not usable, namely it is decided not to fabricate the formwork while for Bases 2 and 5 it cannot be excluded that the base is not usable, i.e. that no formwork will be made, and the lower approximation of the notion of an Unusable Base is the set {4} while the upper approximation is the set {2, 4, 5} and the boundary zone of the notion "Unusable Base" is the set {2, 5}, the same as in the preceding case.

The coefficient of precision (roughness) of the "Usable Base" notion according to (6) is:

$$\alpha_I \text{ (Usable Base)} = |\{1,3,6\}| / |\{1,2,3,5,6\}| = 3/5$$

The coefficient of precision (roughness) of the "Unusable Base" notion is:

$$\alpha_I \text{ (Unusable Base)} = |\{4\}| / |\{2,4,5\}| = 1/3$$

The rough membership function values for individual bases for the notion Usable base according to (9) are:

$$\mu^I_{\text{Usable Base}}(1) = |\{1,2,3,6\} \cap \{1\}| / |\{1\}| = 1$$

$$\mu^I_{\text{Usable Base}}(2) = |\{1,2,3,6\} \cap \{2,4\}| / \{2,4\} = 1/2$$

$$\mu^I_{\text{Usable Base}}(3) = |\{1,2,3,6\} \cap \{3\}| / |\{3\}| = 1$$

$$\mu^I_{\text{Usable Base}}(4) = |\{1,2,3,6\} \cap \{4\}| / |\{4\}| = 0$$

$$\mu^I_{\text{Usable Base}}(5) = |\{1,2,3,6\} \cap \{2,5\}| / |\{2,5\}| = 1/2$$

$$\mu^I_{\text{Usable Base}}(6) = |\{1,2,3,6\} \cap \{6\}| / |\{6\}| = 1$$

Superfluous attributes can be eliminated from the cited case through reductors (Fast Execution, Prefabricated Ceiling) and (Low Quantity of Formwork, Prefabricated Ceiling). One of the attributes Fast Execution and Low Quantity of Formwork could be eliminated from Table 2 without changing any elementary sets. Thus this table can be replaced by Table 3 and Table 4 respectively in the decision analysis without any risk of information loss.

Table 3.

BASE	FAST EXECUTION	PREFABRICATED CEILINGS	USABLE BASE
1	no	good	yes
2	yes	good	yes
3	yes	excellent	yes
4	no	medium	no
5	yes	good	no
6	no	excellent	yes

Table 4.

BASE	LOW QUANTITY OF FORMWORK	PREFABRICATED CEILINGS	USABLE BASE
1	yes	good	yes
2	no	good	yes
3	yes	excellent	yes
4	yes	medium	no
5	no	good	no
6	yes	excellent	yes

Table 3 can be represented in the following way using the decision algorithm that consists of decision rules in the form "IF... THEN...":

IF (Fast Execution, no) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, yes)

IF (Fast Execution, yes) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, yes)

IF (Fast Execution, yes) & (Prefabricated Ceiling, excellent) ⇒ THEN (Usable Base, yes)

IF (Fast Execution, no) & (Prefabricated Ceiling, medium) ⇒ THEN (Usable Base, no)

IF (Fast Execution, yes) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, no)

IF (Fast Execution, no) & (Prefabricated Ceilings, excellent) ⇒ THEN (Usable Base, yes)

According to Z. Pawlak [13] the decision algorithm reached by discovering the dependence between the rules and eliminating superfluous rules can be simplified to:

IF (Fast Execution, no) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, yes)

IF (Fast Execution, yes) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, yes)

IF (Prefabricated Ceiling, excellent) ⇒ THEN (Usable Base, yes)

IF (Prefabricated Ceiling, medium) ⇒ THEN (Usable Base, no)

IF (Fast Execution, yes) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, no)

In this way decision rules are practically optimized, namely an optimum set of rules is generated.

4.1.2. Discussion of the results

The rules:

IF (Fast Execution, yes) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, yes)

IF (Fast Execution, yes) & (Prefabricated Ceiling, good) ⇒ THEN (Usable Base, no)

have identical conditions but different decisions; they are inconsistent, namely indeterministic. Other rules are consistent; namely deterministic. In a concrete case, the inconsistent rules do not lead to a definitive answer so that a proper decision cannot be made using these rules. These rules define a set of possible decisions on the basis of the given conditions.

The factor of reliability for the specified inconsistent rules according to Z. Pawlak and A. Skowron [16] is 0.5.

There is partial dependence in 4/6 and 2/3 respectively.

4.2. Selection of a suitable organization pattern

It is possible to select a suitable pattern of organization with respect to units or tasks. Various organization patterns are known to have various impacts upon project implementation according to G.] irovi} [2] and G.] irovi} and @. Pra{~evi} [8]. This impact gains in importance when changes and their influence upon the efficiency of an investment undertaking are considered. This impact has been studied by G.] irovi} [3] particularly where such changes are not planned. This matter was also covered in G.] irovi} [4].

An analytical study and appraisal of a suitable pattern of organization can also be made for the preceding case. Tables of attribute values can be formed with the organization patterns for objects, the attributes of conditions can contain technology tasks, types of buildings to be erected, the size of sites and other internal or exogenous organization factors and decision attributes will be the organization pattern used to meet a certain target. This case could also be represented by a decision algorithm, the rough membership function for some projects can be computed, and the reliability of individual decision rules and partial dependence determined.

A simple example of ranking a suitable organization pattern, i.e. a pattern with good prospects for successful execution for which specific experience is required, is described here in accordance with the model proposed by W. Ziarko [26] - Table 5.

Table 5: Ranking a suitable organization pattern

No.	Experience	Decision (Good Prospects)
1	Customary	No
2	Customary	Yes
3	Elementary	No
4	Specific	Yes
5	Specific	Yes

So, the set of positive examples of organizational structure with good prospects is:

$$O = OBJ = \{2,4,5\}$$

The set of attributes:

```
A = AT = {Experience}
```

The equivalence classes:

```
R(A)* = {{1,2}, {3}, {4}, {5}}
```

The lower approximation and positive region:

```
POS(O) = LOWER(O) = {4,5}
```

The negative region:

```
NEG(O) = OBJ - POS(O) = {3}
```

The boundary region:

```
BND(O) = UPPER(O) - LOWER (O) = {1,2}
```

The upper approximation:

```
UPPER(O) = POS(O) + BND(O) = {4,5,1,2}
```

The rough set theory can be used in this case for inductive learning systems, generating rules of the form:

```
description (POS(O)) --> positive decision class
description (NEG(O)) --> negative decision class
description (BND(O)) ~~> (probabilistically) positive
                                               decision class
```

Decision rules we can derive in this case:

```
des (POS(O)) -->  Yes
des (NEG(O)) -->  No
des (BND(O)) ~~>  Yes
```

That is:

```
(Experience,Specific)or(Experience,Very specific)-->
                                        Good prospects
(Experience,Elementary) --> No good prospects
(Experience,Customary) ~~> Good prospects (i.e.
                                             possibly)
```

4.3. Rough heuristic application

The heuristics can be formulated here as a set of rules and a rough inference which will be able to determine the control. An optimal algorithm guarantees the optimal solution will be found. The heuristic algorithm has no such guarantee - a solution is found, but this solution is not guaranteed to be optimal or even close to optimal, and it may not even (in extreme cases) be feasible as noted by J. Beasley [1]. This is because the size of the problem is beyond the effective computational limit of known methods, or because the problem can be solved optimally but this is not worth the effort (time) spent in finding the optimal solution. The principal advantages of heuristic algorithms are that such algorithms are often conceptually simpler. This includes the intuition, knowledge, creativeness and experience referred to by @. Pra{~evi} [19]. A heuristic evaluation includes usability criteria such as that the behavior of the system is predictable and consistent, and that feedback is provided. The first criteria means that one can guess what happens next, and the second criteria means that what happens in one situation happens much the same for similar situations. That is exactly what happens in the construction industry - advanced experience has already been developed, as well decisions close to optimum ones. This implies that many acts in the course of construction production are results of what is known. Since it has been concluded that at the core of some resolutions in the construction industry there is a whole lumen of experience, the use of heuristic approach in improving these resolutions is used. In the paper by J. Stefanowski [22] it has been assigned the use of experience in the domain of rough sets. Having made a general heuristic evaluation close to rough sets in the case mentioned above, a few of the possible usability criteria can be used:

1. If the formwork is placed rapidly and the placing of ceilings is good, continue the execution.
2. If the formwork is placed rapidly, but the placing of ceilings is medium, stop the execution.
3. If the formwork is not placed rapidly, but the placing of ceilings is excellent, continue the execution.

In the above rules there are elements of fuzziness in rough sets. These heuristic rules are about the same as for the conventional control. They soften the constraints.

4.4. Further investigations in two directions

In the application of the rough set theory to resolve practical and theoretical problems in construction production, the primary path of investigations shall be directed towards expert systems development and the recognition of certain models for decision analysis, as well as to learning from data bases. Naturally, it will be necessary to check whether there are possibilities for the broad development of decision support systems with a view to the suitability of the properties and mathematical tools of rough sets for such an application.

The second path of development could be an analysis of links with the fuzzy set theory since that theory has been already largely applied to resolve certain problems in construction production, and rough sets somewhat overlap it. It is hereby suggested to consider the use of the rough set theory for the phased solving of problems that have traits of uncertainty. For example, in the work of @. Pra{~evi} and G.]irovi}

[20] the optimal variant for the choice of technology was obtained by a multi-phase fuzzy decision process, precisely, by a fuzzy ranking operation that was close to fuzzy scheduling. Since each decision phase needs to carry out a comprehensive decision analysis with respect to its success or failure, being attributes of conditions, it is evident that this problem area lends itself to being solved by the non-conventional treatment of uncertainty.

5. CONCLUSION

The paper shows that some cases in construction production can be demonstrated, measured and studied by the rough set theory as one of the mathematical tools to treat imprecision, vagueness and uncertainty.

An advantage of the rough set theory-based decision logic based on decision rules is that no preliminary or supplemental information on data is requested, but its defect is that no finite answer can be obtained in the case of inconsistent rules.

The rough set approach to knowledge-based decision support is assigned with emphasis on the importance of the rough set theory for data analysis in the attribute-value based domain.

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