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APPLICATION OF THE ROUGH SET DATA ANALYSIS FOR THE DEVELOPMENT OF THE CONTROL STRUCTURE OF AN FCC UNIT

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Abstract

The rough set data analysis (RSDA) is widely used for the determination of non-linear relationships in many different areas. In this paper it is applied to investigate the dependencies among the variables in fluid catalytic cracking unit (FCC) consisting of reactor and regenerator parts. The analysis has been performed to understand FFC behaviour and to develop its control structure. About 140 operating points of an industrial FCC unit are considered and analysed using the rough set methodology. The ROSETTA toolkit is applied to discover the dependencies among the controlled and the manipulated variables. It is determined that the temperature of the regenerated catalyst has a significant influence on the product quality (motor octane number) and it should be controlled. A new control loop is designed and its controlled variable is the temperature in the regenerator unit. To avoid afterburning in the regenerator part of the FCC unit, several temperature measurements are recommended with the use of a special control unit, a high selector (HS). The manipulated variable of the new control loop is the feed flow of the bottom product of the main distillation column (BMC) in the reactor part of the FCC unit.

Keywords: rough set, FCC unit, control structure development.

1. Introduction

The Fluid Catalytic Cracking (FCC) unit is one of the major conversion unit within a refinery. The FCC receives lower-valued feedstocks from the crude, vacuum, and Coker units and vaporizes these feedstocks. Catalysts induce chemical reactions that break down longer molecules from the heavy feedstock into lighter molecules which form products that are blended into higher-valued gasoline and diesel fuel.

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The catalyst is separated from the products at the end of the process, cleaned, and reintroduced into the process. The vapours are passed on and condensed in a process.

Over 400 FCC are in operation at oil refineries around the world today. An FCC unit consists of two key elements: a reactor and a regenerator (*Fig. 1*). Six main steps determine the FCC reactor-regenerator part.



Fig. 1. The schematic picture of the FCC unit investigated

- 1. Preheated feedstock is fed into the bottom of the riser (reactor), where it is met by the very hot regenerated catalyst. This causes the feedstock to vaporize and propels the catalyst and the hydrocarbon mix up the riser. The feedstock is cracked as it passes up the riser. The mixture is only app. 2 seconds to flow from the bottom to the top of the riser. The cracking reactions are endothermic.
- 2. Depending on temperature and residence time some non-selective thermal cracking reactions can occur. At the top of the riser the mixture enters a riser termination device where separation of catalyst and product occurs. The catalyst falls to the bottom of the reactor and is then steam-stripped. 10-20 kg of steam per ton of catalyst is used to force additional product out of the pores before regeneration. The products leave the top of the reactor to the fractionators. It converts the feed of heavy petroleum fractions into lighter hydrocarbons separated in the subsequent distillation columns. The first column in the separation part is the so-called main column. The lighter products obtained are: C_1 - C_4 and lighter gases, gasoline, light fuel oil (LFO), heavy fuel oil (HFO), and the bottom product of the main distillation column (BMC) that contains heavy hydrocarbons of high boiling points.
- 3. One of the products from cat cracking reactions is a coke that forms on the catalyst surface. This poisons the acid sites on the catalyst so that it eventually becomes inactive. To reactivate the catalyst, it needs to be regenerated to remove this "coke". The regeneration reaction is exothermic.

- 4. The used catalyst is entered to the combustion part where it is mixed with preheated air. Energy released from the burning coke heats up the catalyst and this heat is transferred back to the bottom of the riser for cracking reaction.
- 5. At the top of the regenerator the cyclones separate any remaining catalyst from the flue gases. Carbon dioxide, carbon monoxide, water, and excess air are released from the regenerator as flue gas.
- 6. The regenerated catalyst is fluidized with steam and then flows back to the riser where it passes energy to the incoming feedstock so that cracking can occur without additional heating. Depending on the size of a unit anywhere from 20 to 100 tons/minute of catalyst are re-circulating in the system.

The control of the FCC unit is of a paramount importance. There have been several works to improve its control e.g. POHLENZ [1], LEE et al. [2], KURIHARA [3], Worldwide Refining Survey [4], and Advanced Control and Information Systems [5]. For the multivariable control structure, *Table 1* shows the controlled and the manipulated variables in these control structures. In every control structure, the reactor and the regenerator are operated integrally. For the first three cases of *Table 1*, the controlled variables are the different temperatures of the FCC unit.

Name of the structures	Controlled variables	Manipulated variables
T	Temperature of the reactor	Regenerated catalyst flow
Iraditional	Temperature difference be- tween the flue gas and re- generator	Air flow into the regenerator
Lee and Weekman's	Temperature of reactor- regenerator (cascade)	Air flow into the regenerator
2 ···	Temperature of flue gas	Regenerated catalyst flow
Kurihara's	Temperature difference be- tween the flue gas and re- generator	Regenerated catalyst flow
	Temperature of the regener- ator	Air flow into the regenerator
	Temperature of the reactor	Air flow into the regenerator
-	Level of catalyst in the re- actor	The spent catalyst flow
Multivariable control system	Multivariable model of reactor-regenerator	Air flow into the regenerator Temperature of the reactor Temperature of feed Pressure difference be- tween the reactor and the regenerator

Table 1. Controlled and manipulated variables of the control structures



Fig. 2. Traditional control structure



Fig. 3. The Lee and Weekman configuration

In the *traditional structure* (*Fig.* 2) there are two control loops. One of them controls the temperature of the reactor with the regenerated catalyst flow. The other controls the temperature difference between flue gas and the air stream, which is fed into the regenerator.

In the Lee and Weekman's configuration (*Fig. 3*) there are one control loop and one cascade control loop. The controlled variables are the temperatures. The temperature of the flue gas is controlled by the regenerated catalyst flow. The temperature of the reactor and the temperature of the regenerator are in the cascaded loop and the manipulated variable is the airflow.



Fig. 4. Kurihara's control structure

In the Kurihara's control structure (*Fig. 4*) there are control loops only around the regenerator. The temperature difference between the regenerator and flue gas is controlled by the flow of the regenerated catalyst. The temperature of the regenerator is controlled by air flow.

In the older control structures, the oxygen content in the flue gas was not controlled. This was due to the fact that at that time, the environmental protection was not treated as an essential design issue. The modern control structures e.g. the multivariable control (*Fig. 5*), however, deals with this problem and in this case the flue gas of the regenerator does not content carbon monoxide.



Fig. 5. The multivariable control structure of an FCC plant

In the advanced *multivariable control structure* beside the temperature control loops the spent catalyst is also controlled by the level of the catalyst in the reactor and the flow of the regenerated catalyst is controlled by the temperature of the reactor. In this case the basis of the multivariable mathematical model is a neural network. The inputs in this model are the technological parameters like the temperature of the reactor, and temperature of the feeds; and the economical parameters like quality and quantity of the product.

The performance of any control or monitoring system also depends on the quality of the measurements since without correct measurements and optimal sensors location no proper control can be realized. BAGAJEWICZ [6] has studied this problem with the formulation of a minimum capital cost optimisation problem subject to reconciliation precision bounds. Bagajewicz's work is based on mixedinteger non-linear programming (MINLP). CHMIELEWSKI et al. [7] have proved that the optimal sensor placement and sensor networks can be solved, instead of using MINLP, globally and efficiently using standard interior-point and branchand-bound search algorithms. Using this algorithm it becomes possible to bring the designer of the control and monitoring structure a step closer to the establishment of rigorous cost-to-performance trade-off curves. However, if the control structures designed for the FCC unit are considered, it can be also realized that no attempt has been made to apply a mathematical methodology which explores the connections between the physical- and chemical parameters of the system and the product quality. In this paper the rough set methodology is used to investigate the dependencies between the data and the variables of an FCC unit aiming at improvement of its control structure.

Unit of the FCC plant	Controlled variables	Manipulated variables
reactor	Temperature of the hydrocar- bon vapour stream	Regenerated catalyst flow into the reactor
	Level of catalyst	Spent catalyst flow into the re- generator
	Flue gas oxygen	Air flow rate
regenerator	Bed temperature	Internal catalyst flow in the re- generator

2. Rough Set Theory

Rough set theory is a method of information analysis and especially reduction of data sets, discovery of data patterns, classification of the objects into sets and generation of decision rules, PAWLAK et al. [8], PAWLAK [9]-[11]. Rough set theory does

not need any preliminary information about data like probability distribution (as in probabilistic analysis), basic probability assignment (as in Dempster-Shafer theory) or membership function (as in fuzzy set theory). It performs an analysis of properties of the data, allowing the identification of the redundant or irrelevant attributes. In consequence, it enables obtaining the simple rules from the database by reducing the redundant attributes while keeping the original degree of consistency.

The rough set theory is based on the concept of information system and indiscernibility relation. The information system contains data about the objects under consideration. The data are represented as the set of attributes and decisions. The information system has a form of a table. Every row corresponds to a single object. Every column represents an attribute or a decision. The example of the system is presented in *Table 6*.

The objects having the same value of attributes are indiscernible. The indiscernible objects build so called granules of knowledge. The granules are labelled elementary sets. The elementary sets are the smallest elements-atoms of our knowlq-edge about the objects under consideration.

Elementary concepts can be combined into compound concepts. The union of elementary sets is called a crisp set, and any other set is referred to as a rough one. The identification of the indiscernible elements has two objectives. First, one element is needed to represent the whole class of the indiscernible element. The second reason is that it allows rejecting of the redundant attributes. The rejected attributes do not influence the quality of the elements classification. Very often there are several such subsets of attributes. The subsets with the minimal number of the attributes are called reducts. Computing equivalence classes is relatively easy. However, finding a minimal reduct (i.e. a reduct with a minimal cardinality of attributes among all reducts) is NP-hard. The basic concepts of rough sets theory have been recently presented by KOMOROWSK1 et al. [12].

The most important notions needed to investigate and improve the control structure of fluid catalytic cracking unit are similar to the rough set problems and presented below.

Information System (S)

$$S = (U, A) \tag{1}$$

where

U – a non-empty, finite set called the universe of objects (cases, states, observations, etc.)

A - a non-empty set of attributes (variables, characteristics, etc.)

For the rough set analysis both kinds of sets are needed [9]. Every attribute $a \in A$ has a value from the domain V_a .

Equivalence Relation

$$R \subseteq X \times X \tag{2}$$

where

- R binary relation which is reflexive (i.e. an object is in relation with itself xRx), symmetric (if xRy then yRx) and transitive (if xRy and yRz then xRz)).
- $X \subseteq U$ class of the objects under considerations

 $x \in X$ – element

The equivalence class of an element $x \in X$ consists of all elements $y \in X$ such that xRy.

Indiscernibility Relation

$$IND_{A}(B) = ((x, x')cU^{2} | \forall a \in Ba(x) = a(x'))$$
(3)

 $IND_A(B)$ is the B-indiscernibility relation.

If $(x,x') \in IND_A(B)$ then objects x and x' are indiscernible from each other by attributes from B. The equivalence classes of the B-indiscernibility relation are denoted $[x]_B$.

Lower and Upper Approximations of Sets. Rough Set

$$B_*X = (x \mid x \mid_B \subseteq X) \tag{4}$$

$$B^*X = (x \mid x \mid B \cap X \neq 0) \tag{5}$$

 B_*X and B^*X are respectively called B-lower and B-upper approximation of X, where

$$A = (U, A), B \subseteq A \text{ and } X \subseteq U$$
(6)

The elements in B^*X can be with certainty classified as members of X on the basis of the attribute in B.

The elements B^*X can be classified as possible members of X on the basis of attribute in B.

$$BN_B(X) = B^* X - B_* X \tag{7}$$

is called the B-boundary region of X.

 $BN_B(X)$ consists of those elements that cannot be for sure classified into X on the basis of attribute in B. The set

$$O = U - B^* X \tag{8}$$

is called the B-outside region of X. O consists of the elements which can be classified with certainty as do not belonging to X (on the basis of attribute in B).

A set is said to be crisp if the boundary region is empty.

A set is said to be rough if the boundary region is non-empty. The graphical illustration is presented in *Fig. 6a,b*. The figures show two hypothetical situations: if the boundary region of A set is empty (crisp case), there is no information in that region, and if the boundary region is non-empty, there is information in the region (rough case).

Rough set B can be characterized numerically by the accuracy of approximation $\alpha_B(X)$

$$\alpha_B(X) = |B^*X| / |B_*X| \tag{9}$$

where $|^*|$ denotes the cardinality of $X \neq 0$.

If $\alpha_B(X) = 1$ then X is crisp with respect to B (X is precise with respect to B).

If $0 < \alpha_B(X) < 1$ then X is rough with respect to B (X is vague with respect to B).

Reducts

A reduct of A is a minimal set of attributes $B \subseteq A$ such that $IND_A(B) = IND_A(A)$.

A reduct is a minimal set of attributes from A that ensures the partitioning of the universe U and hence the possibility to carry out classifications as the whole attribute set A does.

Rules Extraction

Usually, the information system contains some attributes that are irrelevant for the given classification task. In many applications it is often difficult to know which features are relevant. The aim of data reduction is to find a minimal subset of relevant attributes that are essential for the effective classification. As a result, the minimal subset of the attributes can be used instead of the entire attributes set for the discovery of the effective classification rules. The reducts are used to build so-called minimal decision rules. The rules are constructed by overlaying the reducts over the original information system.

The ordered decision *Table 7* is used to construct the discernibility matrix, *Table 8*. The discernibility matrix shows us that the observation x_i discerns from x_j by the values of the attributes placed in the cell c_{ij} . For example, observation x_1 discerns from x_2 by the values of the temperatures T2 and T3. The diagonal elements of discernibility matrix are $c_{ii} = 0$ and $c_{ij} = c_{ji}$. The discernibility matrix is used to generate the rules.

From the definition of the discernibility matrix results that selecting the column corresponding to the observation x1 and simplifying it gives a minimal function that discerns x1 from objects belonging to the corresponding decision class, quality=good, from objects belonging to other decision class, quality=bad.

Given the reduct $T2\Lambda T4$, the rule for the first observation x_1 is

If T2 = (123 - 126) and T4 = (85 - 88) then quality = good

There is a more and more popular use of rough sets in quality control LEE and VACHTSEVANOS [13]. Rough sets have been also applied to new materials design and analysis of their properties (JACKSON et al. [14]). Process control is a vast field of rough sets applications e.g. cement kiln and blast furnace control (MROZEK), [15]. The fault diagnosis starts to be a field for rough sets application as well, (SHEN et al.) [16].

In this paper the key point is the use of the rough set methodology to investigate and improve the control structure of fluid catalytic cracking unit.

3. Description of the Control Structure of the Investigated FCC Unit

The major control loops are shown in *Fig. 1* and their controlled and manipulated variables are listed in *Table 2*. They have been analysed using optimization method described by MADRON [17], STANLEY and MAH [18]. In the case of the changing catalyst flow, slide valves are applied as final control elements. The slide valves are used to prevent the backwards flow of the catalyst.

In the reactor, the temperature of the product leaving the reactor and the level of the catalyst are controlled. If the temperature of the product, hydrocarbon vapour stream, is too low then the first slide valve opens and more regenerated catalyst flows into the reactor. In consequence, the heat input will be higher but the cracking will also be more effective. If the level of the catalyst in the reactor is high then the spent catalyst flow in the regenerator will be increased.

The regenerator has two important control loops, concentration and temperature ones. If the concentration of the oxygen in the flue gas is less than 3-5 % then the respective valve on the air input-pipe will be opened. The 3-5% oxygen concentration is important because it guarantees that after the regeneration no carbon monoxide leaves the system. This loop is essential for environmental protection purposes. The dense bed temperature control influences the internal catalyst recirculation in the regenerator. The proper recirculation is an important factor helping to avoid temperature peak in the regenerator. The peak is undesired for stable steady state operation and also detrimental for the construction material of the system. The high initial temperature, oxygen, and promoter (e.g. Ni or Fe) are necessary for the perfect coke combustion in the regenerator

4. Application of Rough Sets

There are several mathematical methods for the determination of non-linear relationships among data. The rough set data analysis (RSDA) is one of them. The

determination of non-linear dependencies is a typical problem of the control structure design. In the course of the control structure design we first determine the control objectives and the possible controlled variables that satisfy the selected objectives. The second step is the selection of those variables (manipulated variables) that have proper influence on the controlled variables. In the next step, the paring of the controlled and the manipulated variables takes place. In the course of the control structure design we are looking for the relationships among the variables, respectively, the data of the process to be controlled. These functions are usually non-linear ones due to the complex nature of the processes.

The rough set data analysis is realized by ROSETTA software, a toolkit for analysing tabular data within the framework of rough set theory. ROSETTA (ØHRN and KOMOROWSKI [19]) is designed to support the overall data mining and knowledge discovery process.

For the rough set data analysis by the ROSETTA, about 140 measured operating points of the FCC industrial unit are collected and analysed. The product quality (motor octane number, MON) depends on properties of feed, steam, catalyst, and air flows. *Table 3* contains the values of the measured variables. They are selected as attributes (input data) influencing the decision (output data) – product quality.

Technolog meters	gical para-	Location	Variables	Values
Feed oil		Reactor	Mass flow (t/h) Pressure (bar) Temperature (°C) Sulphur containing	100.0 - 203.04 4.39 - 8.33 60.56 - 131.39 0.01 - 0.12
Steam	Stripper Dispersion Fluffing Emergency	Reactor	Mass flow (t/h) Mass flow (t/h) Mass flow (t/h) Mass flow (t/h)	1.5 - 3.6 2.17 - 3.80 0.15 - 0.60 0.18 - 1.21
Catalyst		Reactor	Temperature (°C) Ratio of catalyst and feed oil	657.07 - 684.05 6.24 - 10.34
		Regenerator	Coke content (%)	1.5-3.5
Air		Regenerator	Flow (kNm ³ /h) Temperature (°C)	66.01 - 90.51 160.02 - 208.18

Table 3. Measured points of the FCC unit

It can be seen that the values of the input data cover a wide range. The value of the output data, motor octane number (MON), is between 80.4 - 83.6. A statistical model using measured values is made to describe the FCC unit. Results which are obtained using RSDA are evaluated by this statistical model.

4.1. Determination of Intervals

The first problem, when applying rough set theory, is to determine the number of the data intervals. If the number of the intervals is too high, then too many rules (if – then connections between the input and output variables) will be obtained. On the other hand, if the number of interval is too low then the set of rules will be too small and in an extreme case it becomes empty. Therefore the optimal number of intervals is a crucial point in the use of rough sets.

The ROSETTA solver is used for the manual discretization - intervals generation. For the investigated FCC unit, the interpretation of the value of each attribute, e.g. low, high, very high, and the value of decision, product quality, is reviewed by an industrial expert.

An example of the intervals determination is presented for the temperature of feed stream

under $110^{\circ}C$ = very-very low, between $110^{\circ}C - 120^{\circ}C$ = very low, between $120^{\circ}C - 135^{\circ}C$ = low, between $135^{\circ}C - 180^{\circ}C$ = normal, above $180^{\circ}C$ = too high.

In this case, the temperature of the feed stream depends on the bottom temperature of the main column because the feed is preheated by BMC (bottom product of the main distillation column, the column right after the FCC unit). If the stream of BMC is high, the temperature of the feed stream will also be high. The high BMC flow, however, indicates that the cracking is not too 'deep'. It is due to the presence of the high amount of heavy products in the output stream of the FCC reactor. If the temperature of the feed flow, after the heat recovery, is between 135-180°C then the FCC unit operates in the normal mode.

Table 4 shows the intervals determined for the investigated FCC unit. The input variables are the so-called attributes and the output variable (MON) is the so-called decision.

4.2. Generation of Rules

After determining the intervals of the variables, the ROSETTA toolkit determines the rules, in the form of if – then connections between the variables. In the case of the investigated FCC unit, the rules are checked by the statistical model of the FCC unit. Based on the statistical model 8 rules are correct out of 150 rules. The reason for this is that the statistical model is fitted to measured and not experimental data. Therefore to create a correct statistical model is not possible. If the number of the intervals is increased the system is not reduced further. In this case the optimal number of the intervals of the variables range between 6-8. A similar result has been obtained in a previous study about a pre-flash distillation column (RÁCZ [20]).

Location	Input and output var.	Intervals
	Feed flow (t/h)	<100, 100-120, 120-145, 145-160, 160-180, 180-200, 200<
Reactor	Feed pressure (bar)	<4, 4-5, 5-6, 6-7, 7-8, 8<
	Feed tempr. (°C)	<110, 110-120, 120-135, 135-180, 180<
	Feed sulphur content	<0.01, 0.01-0.035, 0.035-0.05, 0.05-0.08, 0.08-0.1, 0.1<
	Stripper steam flow (t/h)	<1.5, 1.5-2.0, 2.0-2.5, 2.5-2.9, 2.9-3.2, 3.2-3.6, 3.6<
	Disperg. steam flow (t/h)	<2.17, 2.17-2.5, 2.5-2.9, 2.9-3.3, 3.3-3.6, 3.6-3.8, 3.8<
Reactor	Fluffing steam flow (t/h)	<0.15, 0.15-0.25, 0.25-0.35, 0.35-0.45, 0.45-0.60, 0.60<
	Emergency steam (t/h)	<0.18, 0.18-0.4, 0.4-0.6, 0.6-0.8, 0.8-1.0, 1.0-1.2, 1.2<
Reactor	Temp.of the catalyst (°C)	<657, 657-660, 660-668, 668-674, 674-680, 680-684, 684<
	Ratio of cat. and feed oil	<6.2, 6.2-6.7, 6.7-7.1, 7.1-7.5, 7.5-9.5, 9.5-10.3, 10.3<
Regenerator	Coke content of the cat.	<1.5, 1.5-1.8, 1.8-2.2, 2.2-2.4, 2.4-2.8, 2.8-3.2, 3.2-3.5, 3.5<
Regenerator	Air flow (kNm ³ /h)	<66.0, 66.0-70.0, 70.0-75.0, 75.0-80.0, 80.0-85.0, 85.0- 90.0, 90.0<
	Air temperature (°C)	<160, 160-170, 170-180, 180-190, 190-200, 200<
Output	Motor octane number	<80.5, 80.5-81.5, 81.5-82.5, 82.5-83.0, 83.0-83.5, 83.5<

Table 4. The variables and their intervals

5. Results

The results are obtained with ROSETTA, and are shown in *Table 5*. These results show that finally, the initial 13 attributes of the FCC unit are reduced to 8. These attributes, input variables, are the feed flow of the reactor, catalyst temperature, air temperature, stripper steam flow, dispergating steam flow, air flow, coke content of the catalyst to be regenerated, and the feed sulphur content. The reduced set of the attributes determines the variables that are important for the operation of the FCC unit. The important variables should be included in the control structure and the right manipulated variables have to be determined if there are enough degrees of freedom of the system. The system can be controlled if the rules, connecting the attributes and decision, are known. This kind of control is similar to the fuzzy control, but 'rough set control' is not so subjective and complicated as fuzzy control. The different rules can be compared to check if they influence the same decision. Finally, the right rule can be selected for control purposes considering the simplicity of the control structure, its cost and time of the operation (settling time).

				Table 2	5. Results with th	e ROSETTA				
					AND conne	ction				Decision
_:	T _{oil} (120-135 °C)			F _{stripper} (3.2-3.6 t/h)					20	ION 81.5-82.5)
ci.	T _{oil} (110-120 °C)	T _{catalist} (660-668 °C)			Ratio of stream and oil (2.2-2.3)				20	ION 82.5-83.0)
ŝ	T _{oil} (120-135 °C)	T _{catalist} (668-674 °C)			Ratio of stream and oil (2.0-2.2)				20	ION 33.0-83.5)
4	T _{oil} (110-120 °C)			Fstripper (2.5-2.9 t/h)			Containing coke (2.2-2.4)	of	20	ION 280.5)
5.		Tcatalist (668-674 °C)	T _{air} (190-200 °C)					Containing Sulphur (0.05-0.08)	of N (3	ION 33.0-83.5)
6.	T _{oil} (135-180 °C) T _{oil} (<110 °C)		T _{air} (190-200 °C)	Fdispersion (3.6-3.8 t/h)		Ratio of catalist and oil (7.5-9.5) Ratio of catalyst and oil (<6.2)		Containing Sulphur (0.1<)	of N	ION 83.0-83.5) ION 281.5)
.		T _{catalist} (660-668 °C)		F _{air} (75.0-80.0 Nm ³ /h)	Ratio of stream and oil (2.0-2.2)				Z © .	10N 81.5-82.5)

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In the case of the studied FCC unit, it can be seen from the results shown in *Table 5* that the temperature of the catalyst is an important attribute. If it increases in the range of possible operation, the MON also increases. The statistical model of the FCC unit also confirms this result. The temperature of the catalyst depends on the operation of the regenerator that is determined basically by the quantity of coke on the spent catalyst, air flow, initial temperature at the bottom of the regenerator, and the promotor in the catalyst.

In the regenerator, the combustion of coke takes place according to the following reactions: main reaction

composed of

$2C + O_2$	$\rightarrow 2CO$	$\Delta H = -110.6 \text{ kJ/mole}$
$2CO + O_2$	$\rightarrow 2CO_2$	$\Delta H = -282.5 \text{ kJ/mole}$

 $C + O_2 \rightarrow CO_2$ $\Delta H = -393.1 \text{ kJ/mole}$

It can be seen that the reaction of CO combustion counts for 72% of the total heat of combustion of the coke. For this reason it is important that the combustion takes place in the dense phase of the catalyst, at the bottom of the regenerator. In this case the catalyst will absorb the heat of combustion (393.1 kJ/mole). If the combustion is not perfect in the dense phase than the so called 'afterburning' happens, that is the CO burns in the upper part of the regenerator where there is no catalyst and undesirable and detrimental temperature increase can take place. The "afterburning" is a harmful phenomenon and should be avoided. There is an added small amount of promotor, usually Ni or Fe, to the catalyst in order to initialize the combustion of CO to CO_2 and to limit the 'afterburning'



Fig. 6. a. The lower approximation of rough set



Fig. 6. b. The upper approximation of rough set



Fig. 7. The new control structure of an FCC plant

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The quantity of the coke formed in the reactor plays an important role in the operation of the whole FCC unit because it supplies the necessary heat for the endothermic operation of the reactor. However, the temperature of the catalyst is not controlled in the investigated FCC unit, so a control loop is to be designed to improve the operation of the control structure (*Fig. 1*). In the first step the analysis of degrees of freedom is realized and a possible manipulated variable is found. It is determined that the coke formation can be controlled by the feed flow of the bottom product of the main distillation column (BMC) which contains heavy hydrocarbons. This flow is free for this control and it is selected as manipulated variable. The recommended new control structure is presented in *Fig. 7*.

For the modification of the control structure, after defining the control purpose, it is also important to select the right measured variable. If the temperature of the regenerated catalyst is controlled it is often difficult to select the right location of the temperature measurement because of the possible afterburning. However, if we measure the temperature at several locations in the regenerator, also in the upper part where afterburning would happen, with the use of a high selector unit, which selects the highest value from several input data, the highest temperature in the regenerator can be selected. With this solution it is also possible to control the temperature of the regenerated catalyst and to avoid the detrimental afterburning.

Tal	ble	6.	The	decision	table

	T1	T2	T3	T4	Quality
x1	(50-56)	(123-126)	(145-147)	(85-88)	good
x2	(50-56)	(127 - 129)	(148-150)	(85-88)	bad
x3	(50-56)	(127 - 129)	(151-155)	(89-94)	bad
x4	(50-56)	(130-134)	(148-150)	(95-99)	good
x5	(50-56)	(123-126)	(148-150)	(95-99)	bad
x6	(50-56)	(130-134)	(145-147)	(95-99)	good
x7	(57-62)	(130-134)	(151-155)	(85-88)	good
x8	(57-62)	(127-129)	(145-147)	(89-94)	bad

Table 7. The ordered decision table

	T 1	T2	T3	T4	Quality
x1	(50-56)	(123-126)	(145-147)	(85-88)	good
x4	(50-56)	(130-134)	(148-150)	(95-99)	good
x6	(50-56)	(130-134)	(145-147)	(95-99)	good
x7	(57-62)	(130-134)	(151-155)	(85-88)	good
x2	(50-56)	(127 - 129)	(148-150)	(85-88)	bad
x3	(50-56)	(127 - 129)	(151-155)	(89-94)	bad
x5	(50-56)	(123-126)	(148-150)	(95-99)	bad
x8	(57-62)	(127-129)	(145-147)	(89-94)	bad

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		Tal	ole 8. The discern	ibility matrix				
	x1	x6	x4	x7	x2	x3	x5	x8
x1	0							
x6	0	0						
x4	0	0	0					
x7	0	0	0	0				
x2	T 2;T 3	2	T 2;T 3; T 4	T 2; T 4	T 1; T 2;T 3	0		
x3	T 2;T 3; T 4	T 2;T 3; T 4	T 1; T 2;T 4	0	0			
x5	T 3;T 4	T 2;T 3	Т2	T1;T2; T3;T4	0	0	0	
x8	T1; T 2; T 4	T 1; T2; T 4;	T 1; T 2; T3; T4	T2;T3;T4	0	0	0	0

6. Conclusions

Usually, the processing systems have a very complex control structure and a huge database describing its operation. The rough set method selects the most important attributes and creates rules between them and the decisions. In this paper, the rough set method has been used for the improvement of the control structure of an FCC unit. The main findings are:

The increase of the number of intervals augments the number and the accuracy of rules.

The optimal number of intervals is between 6-8.

Temperature of the catalyst is a very important attribute in the FCC unit control system.

Temperature of catalyst can be controlled by the feed flow of BMC.

The application of rough sets has lead to the determination of the control structure of FCC unit as presented in Fig. 7. The proposed improvement is accepted by industrial experts and under implementation in the industrial unit.

List of Symbols

A	non-empty set of attributes
B	indiscernibility relation
BMC	bottom product of the main distillation column
CC	composition control
Fair	stripper steam flow (t/h)
Fdispersion	dispergating steam flow (t/h)
F _{stripper}	stripper steam flow (t/h)
FC	flow control

Н	enthalpy (kJ/mole)
HS	high selector
LC	level control
MON	motor octane number
0	consists of elements not belonging to X
R	binary relation
S	information system
Tair	air temperature (°C)
Tcatalyst	catalyst temperature (°C)
Toil	feed temperature (°C)
T_{1-4}	attribute or a decision
TC	temperature control
TT	temperature transmitter
U	non-empty, finite set called the universe of objects
х	elements of discernibility matrix
x1-8	elements of discernibility matrix
X	class of the objects under consideration
У	elements of discernibility matrix
Z	elements of discernibility matrix
V_a	domain of a
$\alpha_B(\mathbf{X})$	accuracy of approximation

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