The Rougt Set Theory Applied to a Set of the New Severity Indices

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***Abstract*— In this paper it is presented a study were the Rough Set Theory is applied to a set of the new severity index. The developed methodology produces a classification of the system operation in four possible states: normal, alert, emergency I and emergency II. The states can be classified horizontally as secure, that correspond to the normal state and insecure for the remaining ones. Severity indices are used to represent the impact of the reliable contingencies in electric power system Security studies. In this study the severity index is considered for classification and ranking the contingencies. This methodology was applied to the 118IEEE busbar test power network, and the results obtained are analyzed. Finally, some conclusions that provide a valuable contribution to the understanding of the power system security analysis are pointed out.**

Keywords-component; Rougt set theory; security analysis; contingencies analysis, electric power systems

I. INTRODUCTION

Steady state contingency analysis is on the most important to assessment of the risk to happened same contingencies in an electrical power system network [1]. This is a particularly important task of network operators, especially as network security issues become of prime importance in the current era of electricity deregulation [1]. Continuity of service in case of contingency affecting the system can only be guaranteed if certain conditions are fulfilled in terms of system structure on the one hand, and in terms of organization of the system on the other [3]. This paper focuses on the analysis of 118IEEE test power Network experimental data that are produced through operating point simulation, contingency application, Rough Set Theory validation with a new set of the severity index (new attributes), to point out the "nature" of given contingencies. Experimental statistical results of contingency prediction and selected network state indicators are translated to electric network data in an effort to further interpret the "nature" of each contingency and produce effective predicting algorithms that support operators [2]. In this paper, a more extended contingency analysis study is presented, where the contingencies examined can be classified in four groups of interest, in Normal, Alert, Emergency I and Emergency II. Experimental data demonstrate that combinations of contingencies tend to produce behavior of incremental nature in what concerns their predictability when Data Mining tools are used. The complexity of security analysis procedure increases with system size and is based on multiple power flows simulations, for all credible outages, at frequent intervals, and becomes a difficult computation task [4]. Therefore, the computer programs used in off line security studies, may not be suitable for on line application, since a large number of contingencies must be simulated in a short period of time. In this case a fast filtering and ranking technique should be used, instead of a detailed simulation of all contingencies [5]. The need to perform real-time steady-state security analysis is highly recognized. So, a smaller number of credible critical contingencies should be identified and analyzed to assess the security of the system operation point.

The Rough Sets Theory has been used effectively to handle efficiently problems where large amounts of data are produced [6]. Rough Sets theory constitutes a framework for inducing minimal decision rules [7]. These rules, in turn, can be used to perform a classification task. The main goal of the rough set analysis is to search large databases for meaningful decision rules and finally acquire new knowledge. This approach is based on four main topics: indiscernibility, approximation, reducts and decision rules [6]. A reduct is a minimal set of attributes from the whole attributes set that preserves the partitioning of the finite set of objects and therefore the original classes. It means that the redundant attributes are eliminated. When the reducts are found, the task of creating definite rules for the value of the decision attribute of the information system is practically performed. Decision rules are generated combining the attributes of the reducts with the values. Decision rules extract knowledge, which can be used when classifying new objects, not in the original information system [6].

II. FORMULATION THE PROBLEM

The proposed methodology for the study of the steady-state security of an electric power network is divided in three modules. The first one requires the evaluation of the line outage distribution factors as well as the generation shift factors in order to discard the uninteresting contingencies as fast as possible. This module produces two lists, one with the harmless contingencies and the other with the dangerous or potentially dangerous contingencies. The second module uses the results produced by the first iteration of the Fast Decoupled Load Flow to screen the list of the harmful contingencies. All simulated contingencies that are not severe to the system security are classified as harmless (ND). The other ones are ordered as dangerous (D) or potentially dangerous ones (PD) in accordance with the performance index value. Finally, the third module analyses in detail the last established contingency list, using an accurate power flow formulation based on the Newton-Raphson method. In order to combine computational efficiency with reliability (ability to capture all dangerous contingencies) all the filtering modules use performance indices to evaluate the overload impact in the transmission lines and busbar out-of-limit voltage.

A. Severity Indices Related to the Power and Voltage

The power severity indices that were used to evaluate the overload impact in the network devices are obtained using the following expression [1]:

$$\eta_p = \sum_{i=1}^{n_r} \omega_{pk} \left(\frac{S_k}{S_k^{\max}} \right)^{2m} \tag{1}$$

where η_P is the overload performance index; η_V is the number of branches; ω_{Pk} is a weighting factor; S_k is the branch load; S_k^{max} is the overload limit; m is the exponent of the η_P function.

The voltage severity indices that characterized emergency operating conditions where voltage limits violations may occur can be obtained using the following expression [1]:

$$\eta_v = \sum_{i=1}^{n_b} \omega_{vi} \left(\frac{V_i - V_i^{\mathrm{sp}}}{\Delta V_i^{\lim}} \right)^{2n} \tag{2}$$

where η_V is the out-of-limit voltage performance index; n_b is the number of busbars; ω_{vi} is a weighting factor; V_i is the voltage magnitude at busbar i; V_i^{sp} is the specified or rated voltage magnitude at busbar i; ΔV_i^{lim} is the voltage deviation limit; n is the exponent of the η_v function. The exponents m and n aim at reducing masking effects [1]. The weighting factors accommodate de influence of the power network devices, based on the engineering judgment of the power system operators.

B. Severity Indices Related to the Losses

These security performance indices are based on the power losses and are evaluated using the following equations [4]:

$$P_{LV} = \sum_{i=1}^{n_b-1} \sum_{k=i+1}^{n_b} -\left[G_{ik} \left(V_i - V_k \right)^2 \right] \tag{3}$$

$$P_{L\delta} = \sum_{i=1}^{n_b-1} \sum_{k=i+1}^{n_b} -\left[G_{ik} V_i V_k \left(\delta_i - \delta_k \right)^2 \right] \tag{4}$$

where P_{LV} and $P_{L\delta}$ are the power severity indices related to the voltage magnitude and to the voltage phase respectively, G_{ik} denotes the conductance of the branch *i-k*, δ_i and δ_k stand for the voltage phase at busbar *i* and *k* respectively. The above indices in (3) and (4) are calculated considering two components that are coupled whit *P-δ* and *Q-V* respectively.

C. Severity Indices Related to the Overloads

This security indices is based on the overloads in the transmition lines and are evaluated using the following equation [8]:

$$SI_{OL} = \sum_{\substack{i=1 \\ i\in OL}}^{NL} \left(\frac{S_i - S_i^{Lim}}{S_i^{Lim}} \times 100 \right)^2 \tag{5}$$

where NL is the number of the transmition lines; OL is the set of the transmission lines in overload; S_i is the power in *MVA* in the overload line *i*, and S_i^{lim} is the limit power in *MVA* in the transmission lines in overload *i*.

D. Severity Indices Related to real edge of the Active and Reactive power

The real edge of the active power on the generators in any operation point is calculated with the capacity curves for each generator [8]. The severity indices related to the real edge of the active power are evaluated using the following equation [8]:

$$SI_{Pmar} = 100 \times \sum_{\substack{i=1 \\ i\in PV}}^{NB} \left(\frac{P_{\max i} - P_i}{P_{\max i}} \times 100 \right)^{-2} \tag{6}$$

where NB is the number of busbars; Pi is the active power generated in the busbar i; P_{maxi} is the maximum active power available in the busbar i, PV is the set of the generators busbar *(PV).*

The real edge of the reactive power on the generators in any operation point is calculated with the capacity curves for each generator. The severity indices related to the real edge of the reactive power are evaluated using the following equation [8]:

$$SI_{Q\max} = 100 \times \sum_{\substack{i=1 \\ i\in PV}}^{NB} \left(\frac{Q_{\max i} - Q_i}{Q_{\max i}} \times 100 \right)^{-2} \tag{7}$$

where NB is the number of busbars; Qi is the reactive power generated in the busbar i; Q_{maxi} is the maximum active power available in the busbar i, PV is the set of the generators busbar *(PV).*

III. THE ROUGH SET THEORY

To arrange incomplete and uncertainty problem the Rough Set Theory (RST), a new mathematical tool, was used recently [6]. The Rough Set model has several advantages to data analysis. It is just based on the original data and does not need any external information. Moreover, no assumptions about data are necessary and it is suitable for analyzing both quantitative and qualitative features. The RST works with lower and upper approximation of a set as it is represented in figure 1. The starting point of rough set theory is the indiscernibility relation, which is generated by information about objects of interest. The indiscernibility relation expresses the fact that due to a lack of information it is difficult to discern some objects employing available information or knowledge. The discernibility relation is used for two basic operations in RST i.e. upper $\overline{R}X$ and lower $\underline{R}X$ approximations, which defines crisp and vague manner in the sets. If any concept of the universe can be formed as a union of some elementary sets, it is referred to as crisp (precise). On the contrary, if the concept cannot be presented in such a way, it is referred to as vague (imprecise, rough). $\overline{R}X$ is defined as the collection of cases whose equivalence classes are at least partially contained in (i.e. overlap with) the set of cases to approximate $\underline{R}X$ is defined as the collection of cases whose equivalence classes are fully contained in the set of cases to approximate [7]. So, there are five regions of interest: $\overline{R}X$ and $\underline{R}X$, and $POS_R(X)$, $BN_R(X)$ and $NEG_R(X)$. These sets are defined as shown below [7]. Let a set $X \subseteq U$, R be an equivalence relation and knowledge. Two subsets base can be associated:

i) R - Lower: $\underline{R}X = U\{Y \in U/R : Y \subseteq X\}$

ii) R - Upper: $\overline{R}X = U\{Y \in U/R : Y \cap X \neq \phi\}$

It means that the elements belong to $\underline{R}X$ set can be with certainly classified as elements of X ; while the elements belong to $\overline{R}X$ set can be possibly classified as elements of X . In the same way, $POS_R(X)$, $BN_R(X)$ and $NEG_R(X)$ are defined below [7].

iii) $POS_R(X) = \underline{R}X \Rightarrow$ certainly member of X

iv) $NEG_R(X) = U - \overline{R}X \Rightarrow$ certainly non member of X

v) $BN_R(X) = \overline{R}X - \underline{R}X \Rightarrow$ possibly member of X

Due to the granularity of knowledge, rough sets cannot be characterized by using available knowledge. Consequently, with every rough set there are associate two crisp sets, called lower and upper approximation. Logically, the lower approximation of a set consists of all elements that surely belong to the set, whereas the upper approximation of the set constitutes of all elements that possibly belong to the set, and the boundary region of the set consists of all elements that cannot be classified uniquely to the set or its complement, by employing available knowledge [7].

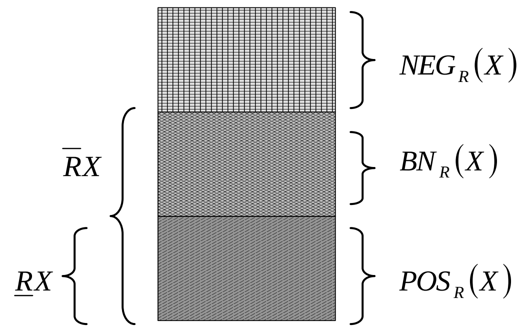

Figure1. Definition of *R*-approximation sets and *R*-regions

It is necessary to define two major concepts in RST, reduct and core previous to the presentation of the algorithm. These concepts are important in the knowledge base reduction. The algorithm of the reduction of a decision table is shown in figure 2, [7].

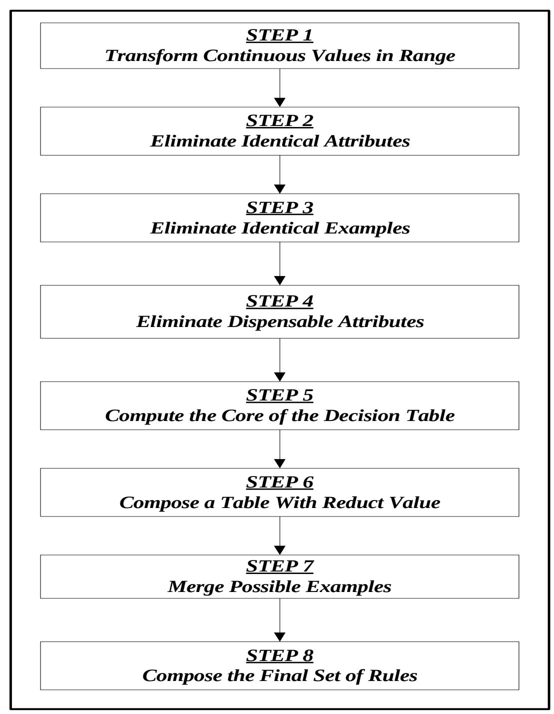

Figure2. Algorithm of reduction

The process of finding a reduced set of attributes with the similar or approximate classificatory strength as the original set is called attribute reduction. Some attributes in an information system may be redundant and consequently can be eliminated without losing essential classificatory information. Let R be a family of equivalence relations. The reduct of R, *RED(**R**)*, is defined as a reduced set of relations that conserves the same inductive classification of set R. The core of R, *CORE(**R**)*, is the set of relations that appears in all reduct of R, i.e., the set of all indispensable relations to characterize the relation R. As the core is the intersection of all reducts, it is included in every reduct, i.e., each element of the core belongs to some reduct. Therefore, in a sense, the core is the most important subset of attributes, since none of its elements can be removed without affecting the classification strength of attributes. Definitely, the geometry of reducts can be more compounds. The core can be empty but there can exist a partition of reducts into a few sets with non-empty intersection. The approximation of classification is a simple extension of the definition of approximation of sets. Namely if $F=\{X_1, X_2,..., X_n\}$ is a family of non empty sets, then $\underline{R}F=\{\underline{R}X_1, \underline{R}X_2,..., \underline{R}X_n\}$ and $\overline{R}F=\{\overline{R}X_1, \overline{R}X_2,..., \overline{R}X_n\}$, are called the $\underline{R}F$ – lower and the $\overline{R}F$ – upper approximation of the family F [7].

Two measures can be defined to describe inexactness of approximate classification.

The first one is the extension of the measure defined to describe accuracy of approximation sets.

The accuracy of approximation of F by R is defined as [7]:

$$\alpha R(F)=\frac{\sum \mathrm{card}\underline{R}X_i}{\sum \mathrm{card}\overline{R}X_i} \qquad (8)$$

where card(X) denotes the cardinality of $X=\varnothing$.

The accuracy of approximation can be used to measure the quality of approximation of decision classes on the universe U. It is possible to use another measure of accuracy defined by $1-\alpha R(X)$. Some other measures of approximation accuracy are also used based on entropy or some more specific properties of boundary regions. The choice of a relevant accuracy of approximation depends on a particular data set. The accuracy of approximation of X can be tuned by R [7].

The second measure, called the quality of approximation of F by R, is the following [7]:

$$\gamma R(F)=\frac{\sum \mathrm{card}\underline{R}X_i}{\mathrm{card}\, U} \qquad (9)$$

The accuracy of classification expresses the percentage of possible correct decision, when classifying objects, employing the knowledge R. The quality of classification expresses the percentage of objects which can be correctly classified to classes of F employing knowledge R. By selecting a proper balance between the accuracy of classification and the description size it is expect to find the classifier with the high quality of classification also on unseen objects [7]. One of the most important applications of RST is the generation of decision rules for a given information system for the prediction of classes for new objects which are beyond observation. The rules are presented in an “If condition(s) then decision(s)” format.

IV. APPLICATION EXAMPLE

As an application example was used the 118 IEEE test power network (Figure 1), (54 generators, 194 branches and 91 loads) for the security assessment [9]. A first order contingency study was carried out for all the transmission lines, transformers and generators. The input numerical values were obtained using the software package ***SecurMining1.0***, developed. It was simulated a first order contingency in transmission lines and transformers. In every case it was used normalized severity indices.

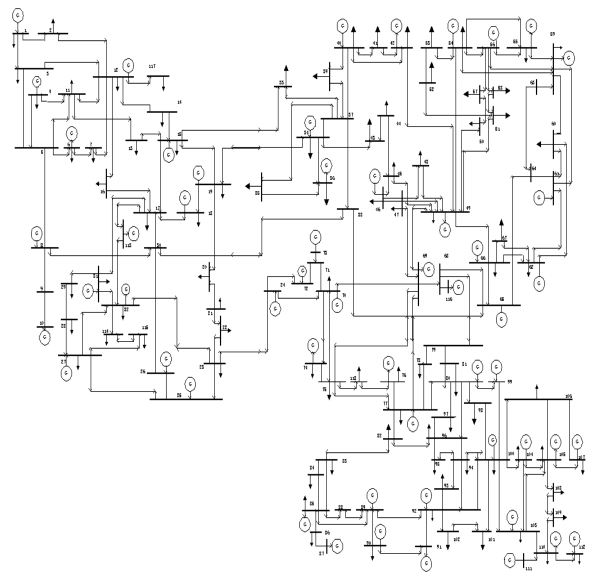

Figure 3 . 118IEEE Test power network

V. RESULTS

In this section are presented the final results produced by the proposed contingency screening and ranking algorithm for assessment and classification contingencies of an Electric Power System using the Rough Set theory. Due to large number of results produced, only some of the most significant are shown. A first order contingency study was carried out and it was obtained a list of 184 contingencies that allows the construction a contingency control database.

The specified attributes are as follows:

A_1 – overloads in the transmission lines;
A_2 – number of overload transmission lines;
A_3 – severity indices related to the power;
A_4 - severity indices related to the voltage;
A_5 – power severity indices related to the voltage magnitude
A_6 - power severity indices related to the voltage phase
A_7 – severity indices related to the overloads
A_8 - severity indices related to the real power margin
A_9 – Severity indices related to the reactive power margin
Dec. – Security

The decision attribute (Dec.) is divided in four states, Normal, Alert, Emergency I and Emergency II. Table I presents a set of information related to a contingency control database.

TABLE I
THE ATTRIBUTES REPRESENTED BY THE SET

Cont. Nº	Attributes									
	A1	A2	A3	A4	A5	A6	A7	A8	A9	Dec.
1	1	1	3	3	2	1	1	1	1	N
2	1	1	4	3	2	2	1	2	4	A
3	1	1	4	4	2	2	1	1	1	A
4	3	2	4	3	2	4	3	3	4	E1
5	1	1	3	3	2	1	1	1	1	N
6	4	2	4	1	4	4	4	2	1	E2
7	3	2	4	1	4	2	3	1	3	E1
8	3	2	4	1	4	4	3	2	3	E1
9	4	4	4	4	4	4	4	4	4	E2
10	3	2	4	1	4	2	3	1	3	E1
11	1	1	3	1	4	2	1	1	3	A
12	1	1	3	1	4	1	1	1	1	A
13	3	2	4	3	2	4	3	2	3	E1
14	3	2	3	2	4	1	2	1	1	E1
15	1	1	3	4	4	2	1	1	4	E1
...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...
170	4	2	4	3	4	4	4	4	3	E2
171	1	1	3	3	2	4	1	1	1	N
172	1	1	4	3	2	4	1	1	1	A
173	1	1	4	1	4	2	1	1	1	A
174	1	1	3	1	2	2	1	1	1	N
175	1	1	4	2	2	2	1	1	1	N
176	1	1	4	1	2	4	1	3	1	A
177	1	1	3	3	4	2	1	1	1	N
178	1	1	3	3	4	1	1	1	1	N
189	1	1	4	2	4	2	1	1	1	A
180	1	1	3	2	4	2	1	1	1	N
181	1	1	3	1	4	2	1	1	1	N
182	1	1	3	1	4	2	1	1	1	N
183	1	1	2	1	4	1	1	1	1	N
184	1	1	3	1	4	1	1	1	1	N

Table II shows the chosen range for the coded qualitative attributes. The condition attributes are coded into four qualitative terms: Low, Medium and High. The decision attribute is coded into four qualitative terms: Normal, Alert, Emergency I and Emergency II.

Due to large amount of information only the final rules are presented, since it was used a powerful interface between the ***SecurMining1.0*** software package and the ROSE computer programme [10]. Using the above computer software packages it can verify that the attributes A_1, A_3, A_4, A_6, A_7 and A_9 are the Core and the Reduct of the set of contingencies. The quality of classification for all conditions and the attributes in the core was 0.9185.

TABLE II
DEFINITION OF RANGE ATTRIBUTES CODING

Attrib.	**Codes**			
	1	2	3	4
A_1	95% <	95% < a <100%	100 % ≤ a ≤ 110 %	> 110 %
A_2	0	2 ≤	3 ≤ b ≤ 4	> 4
A_3	0,980 <	0,980<c<0,990	0,990 ≤ c ≤ 1,00	> 1,00
A_4	0,980 <	0,980<d<0,990	0,990 ≤ d ≤ 1,00	> 1,00
A_5	0,900 <	0,900<e<0,963	0,963 ≤ e ≤ 0,980	> 0,980
A_6	0,003 <	0,003<f<0,004	0,004 ≤ f ≤ 0,980	> 0,100
A_7	0,00013 <	0,00013<g<0,05647	0,05647 ≤ g ≤ 1,000	> 1,000
A_8	1,00088 <	1,00088<h<1,00089	1,00089≤ h≤ 1,0009	>1,0009
A_9	0,828 <	0,828<i<0,829	0,829 ≤ i ≤ 0,850	> 0,850
S	N	A	E_1	E_2

The table III showed the approximation of the objects in the Decision levels.

TABLE III
APPROXIMATION OF THE OBJECTS

Decision Level	Nº of objects	Approximation Upper	Approximation Lower	Precision the approx. of classification
Normal	89	90	75	0.8333
Alert	57	71	56	0.7887
Emergency I	27	27	27	1.0000
Emergency II	11	11	11	1.0000

According to the algorithm described previously, and using logical arithmetic, it is possible to compose the above set of rules. Also, incorporating the range values the final set of rules and approximate rules that contains the knowledge of a initial database range values obtained with the SecurMining1.0 software package. The Rules are divided in four sets. The first set contains the rules for Normal State; this set is too composed with 12 (twelve) exact rules. The second set contain the rules for Alert State, this set contain to 12 (twelve) exact rules. The thirty set is composed for 8 (eight) exact rules and characterized the Emergency I State. Finally the last set of rules characterized the Emergency State II, and it is composed for 2 (two) exact rules. In this study we have one approximate rule. The L is a Low value, M is Medium value, H is a high value and F is a Full value. Due to large amount of information only the some final rules are presented.

Exact Rules for Normal State:

1 – If (A_1 is L and A_3 is H and A_9 is M) then S = N

2 – If (A_1 is L and A_3 is H and A_4 is H and A_8 is L) then S = N

3 – If (A_1 is L and A_3 is H and A_7 is M and A_9 is L) then S = N

4 – If (A_1 is L and A_4 is L and A_6 is M and A_7 is M) then S = N

5 – If (A_8 is H and A_9 is H) then S = N

6 – If (A_1 is L and A_6 is H) then S = N

7 – If (A_3 is H and A_4 is M and A_9 is L) then S = N

8 – If (A_1 is L and A_3 is M) then S = N

9 – If (A_4 is M and A_6 is M) then S = N

10 – If (A_1 is L and A_6 is M and A_9 is M) then S = N

11– If (A_7 is L and A_9 is H) then S = N

12 – If (A_6 is M and A_7 is L and A_9 is L) then S = N

Exact Rules for Alert State:

1 – If (A_3 is F and A_6 is F and A_7 is M and A_9 is L) then S = A

2 – If (A_1 is M and A_8 is L) then S = N

3 – If (A_1 is L and A_3 is F and A_7 is L) then S = A

4 – If (A_4 is F and A_6 is M and A_9 is L) then S = A

5 – If (A_3 is F and A_4 is H and A_7 is M and A_9 is F) then S = A

6 – If (A_3 is H and A_6 is F and A_7 is F) then S = A

7 – If (A_3 is F and A_4 is H and $A_6$is M and A_9 is L) then S = A

8 – If (A_6 is L and A_7 is H) then S = A

9 – If (A_6 is F and A_7 is H and A_8 is L) then S = A

10 – If (A_3 is F and A_6 is M and A_7 is F and A_9 is L) then S = A

11– If (A_1 is H and A_9 is M) then S = A

12 – If (A_3 is H and A_7 is M and A_9 is H) then S = A

Exact Rules for Emergency I State:

1 – If (A_1 is L and A_3 is F and A_6 is F and A_7 is F) then S = E_1.

2 – If (A_1 is H and A_7 is F) then S = E_1.

3 – If (A_9 is H) then S = E_1.

4 – If (A_2 is L and A_8 is F) then S = E_1.

5 – If (A_1 is H and A_9 is L) then S = E_1.

6 – If (A_7 is H and A_9 is H) then S = E_1.

7 – If (A_4 is F and A_7 is M and A_9 is F) then S = E_1.

8 – If (A_2 is M and A_7 is L) then S = E_1.

Exact Rules for Emergency II State:

1 – If (A_1 is F and A_8 is F) then S = E_2.

2 – If (A_1 is F and A_7 is F and A_8 is M) then S = E_2.

Approximate Rules:

1 – If (A_1 is L and A_3 is H and A_4 is L and A_6 is F and A_7 is L and A_9 is L) then S = N or S = A.

VI. CONCLUSIONS

In this paper, we have proposed a new learning approach to derive rules from incomplete data sets based on the Rough Set Theory. This theory was used for study and analyse the steady–state contingency classification. The knowledge acquisition process is a complex task, since the experts have difficulty to explain how to solve a specified problem. The study presents a systematic approach to transform examples in a reduced set of rules. The results that were produced using the Rough Set Theory are a set of rules for the four scenarios proposed, Normal, Alert, Emergency I and Emergency II and showing the importance of the chosen range for the coded qualitative attributes.

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