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Application of Rough Set Theory in Accident Analysis at Work: A Case Study

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***Abstract*— Though accident data have been collected across industries, they may inherently contain uncertainty of randomness and fuzziness which in turn leads to misleading interpretation of the analysis. To handle the issue of uncertainty within accident data, the present work proposes a rough set theory (RST)-based approach to provide rule-based solution to the industry to minimize the number of accidents at work. Using RST and RST-based rule generation algorithm Learning by Example Module: Version 2 (LEM2), 279 important rules are extracted from the accident data obtained from an integrated steel industry to analyze the incident outcomes (injury, near miss and property damage). The results of the proposed methodology explore some of the important findings which are useful for the industry perspective. Therefore, the RST-based approach can be effective and efficient as well because of its potential to produce good results in the presence of uncertainty in data.**

Keywords—Occupational accidents, Steel industry, Rough Set Theory, LEM2, Rule generation.

I. Introduction

With time, the priority for safety of the workers at workplaces has gained importance and every organization is planning different strategies for a zero-harm goal. A workplace is considered safe if it has: a good accountability, a safe environment and a good company culture. Though safety barriers present, accidents still take place at work places. On an average the estimated rate of fatal accidents is approximately 14.0 per 100000 workers. The approximate number of accidents which took place is 335000 in the whole world in the year 1994 [1]. As per the International Labour Organization, the estimated number of life lost due to diseases and accidents related to the work is nearly 2300000 and among those 360000 die of fatal accidents [1]. There is a loss of 4% in world Gross Domestic Product (GDP) due to loss in work hours, production etc. As per the EUROSTAT, the number of people losing life to occupational accidents is more than 5700. In the year of 2004, it was estimated in European Union(EU)-15 that a huge amount (0.55 Billion Euros) was used to make up for the accidents [1] and in EU-27, nearly 7 million workers or 3.2% workers faced accident at workplace[1]. This figure provides the evidence that occupation accidents is a major issue for not only the industry but the country also [1]. Thus the factors behind the accidents need to be analyzed properly. The factors are usually associated in a complicated way. The complexity of this relation can be better captured by different methods like decision tree, association rule mining, rough set theory (RST). In occupational accident analysis decision tree, association rule mining techniques are frequently used on entire dataset that leads to the generation of huge number of rules. However, these existing techniques are not able to address the inconsistencies or vagueness in the data set which may result in incorrect rule generation [2]. RST is useful to resolve this problem due to (i) it does not need any additional information about the given data, (ii) it provides efficient methods to extract hidden pattern, (iii) it automatically determines the set of decision rules, and (iv) it is easy to understand and implement.

In order to handle uncertainty in data, Fuzzy Set Theory (FST) has been adopted by many a researchers. But, the FST employs membership function which itself is uncertain in nature that leads to uncertain rule generation, as well. On the contrary, RST does not require any type of additional information to address the vagueness in data. It is defined by lower and upper approximations and it uses the indiscernibility relation to address the granularity of the knowledge [2]. The utility of RST over the existing techniques when uncertainty is present within dataset, has motivated us to carry out the present study using RST as an analytical tool in a real world industrial problem. Therefore, the objective of the present work is set to explore the utility of RST in analyzing occupational accidents scenarios by handling the issue of uncertainty within accident data. Using RST and RST-based rule generation algorithm *Learning by Example Module: Version 2* (LEM2), the analysis has been performed in this work. However, the scope of the present work is limited to a steel plant only.

The remaining part of the paper is organized in the following way: **Section II** contains related works. In **Section III**, the methodology and the basic concepts of RST have been discussed. **Section IV** explains the utility of RST using a case study. Results and discussions are presented in **Section V**. Finally, **Section VI** concludes the paper.

II. Related works

A number of analyses have been done in the field of occupation safety using RST. Some of the important works using RST have been described in this section. Nevertheless the number of studies using RST in this domain is found to be limited as compared to the application of other approaches like support vector machine [1], decision tree [3], rule mining

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[4], Bayesian Network [5], or other statistical approaches [6], [7], [8]. One similar study done by Chen et al. shows the analysis of various causes of Chinese rail accidents [9]. They have analyzed fifty significant train accidents which has led to higher number of casualties. They have integrated RST and associative rule analysis to analyze the data set [9]. They have used the RST for data preprocessing, attribute reduction and rule generation and they have used associated rules to find hidden relationships among attributes [9]. The major attributes were season, time, line, location, direction, accident type, accident causes, fatalities and injuries. The decision attribute was accident class with categories being tremendous devastating accident, considerable accident, serious accident and ordinary accident. They have found out that human error is one of the major reason in the undefined class. Most accidents took place in summer season, in the up direction in the ordinary accident class. For serious accident the summer or the spring season, main line, derailment type accident, and the down direction has major contribution. For considerable accident, the major contributors were the main line location, the winter season, collision type accident, and the down direction. For tremendous devastating accident the main line location, the collision type accident, and up line direction are important contributors [9].

Li et al, has done a major analysis on occupational accident in the using the RST [10]. In the case study, they have used combination of RST and Support Vector Machine for risk prediction. They have used RST to remove the redundant attribute and to fit the sample data or predict the sample data. Then, they have calculated the error and checked whether it is under permissible limit [10] or not.

Another important study on industrial safety using RST is fault diagnosis in Electric Power grid by Liying et al. [11]. They have used combination of the RST and Neural Network to study the fault diagnosis in the power grid. Decision rules have been obtained by using rough set approach to do the data pretreatment to guide establishment of a complete neural network structure. Thereafter, they analyzed the relation between the attributes and decision rules [11]. There were five attributes in the original data set that are people, method, environment, technology and technology. It was reduced to three attributes that are technology, people and environment [11].

Hao Zhang et al.[12] has also used the RST to address the problem of accident identification on maritime shipping route. They have used it to analyse the multidimensional accident dataset to find out the important attributes, so that they can check the number of accidents in maritime routes. The RST has been used in this paper to reduce the number of attributes present in the data set. Finally, they have used the decision tree model to determine the relation between the rules which are causing the accidents [12].

Zuowei and Lili [13] have used RST combined with the artificial neural network to address a safety assessment problem present in construction sites. In this paper, the RST is used to remove the redundant attribute from the data set without having any loss in the data set. The reduced data set is then used to determine a set of classification rules. It is also used to train a neural network. The rules generated by the RST revealed the highest degree of accuracy. The results show that the RST is a very effective tool for safety analysis and prevention of accident [13].

Another important work on RST was done by Shiau and Huang [14] in the case study regarding transportation in the Taipei City. The case study has used a sample of 610 older people. The RST was used as a qualitative approach to the problem. The RST has helped the authors to generate very useful rules regarding older people friendly transportation. The set of rules involved implication of policies for transportation facilities for the elderly [14].

A. *Research issues*

Based on the reviews on the application of RST in occupational accident domain, it is observed that there is a dearth of papers using this method. Though fuzzy methods have been used in those cases, some deficiencies still remain in the analysis regarding the inconsistencies in data that in turn leads to misleading rule interpretation.

B. *Contribution of the work*

Realizing the issues in relevant papers, the present study contributes in the following ways:

- It handles the vagueness in the accident dataset/
- It generates quality rules.
- It removes the superfluous attributes and generates the feature subset.

III. Methodology

A. *Proposed methodological flowchart*

After the collection of data, preprocessing is performed onto it. The preprocessing task includes missing value handling, inconsistency removal and useful feature selection. In feature selection technique, RST has been used to reduce the superfluous attributes and helped in rule generation using LEM2 algorithm. The whole process is depicted in Fig. 1.

B. *Rough Set Theory*

RST was developed by Zdzisaw Pawlak [2]. It can handle the problem of imperfect knowledge in a dataset. The basic concept of RST is briefly described below.

1) Basic Concept: RST can be defined using lower and upper approximations [2].

Suppose we have been given a set of objects U known as Universe. We have indiscernibility relation that is $R \subseteq U \times U$, which represents our lack of knowledge about the objects present in the universe. Assuming R is an Equivalence Relation. Let us assume Y to be a subset of the universe U. Now we will describe the set X with respect to the Relation R. We have to know the basic definitions of RST [2].

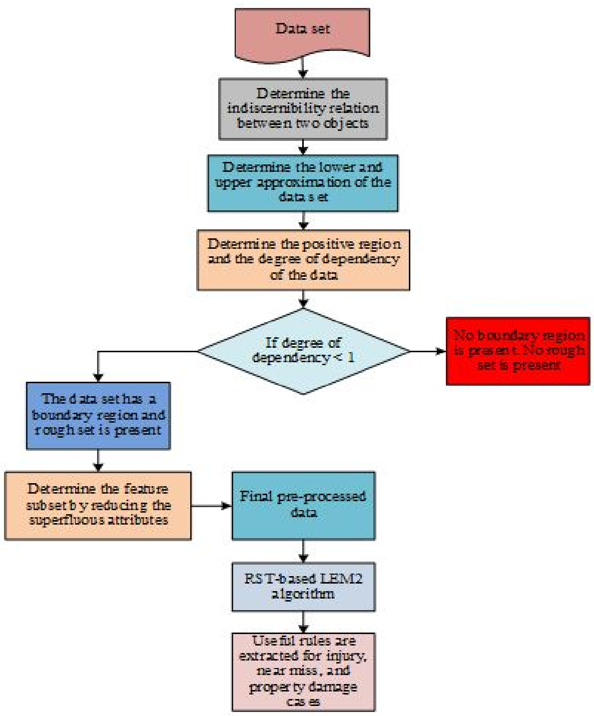

Fig. 1: Proposed methodological flowchart for rule generation using RST.

2) Approximation and boundary set: The short description of lower approximation, upper approximation and the boundary region is given below.

- The Lower Approximation - The lower approximation $P\underline{Y}$ can be defined as the set of all those objects which are certainly classified as the set Y with respect to the relation R. The lower approximation has been shown below in Eq. (1).

$$P\underline{Y} = \{y: \ [y]_P \in Y\} \tag{1}$$

- The Upper Approximation - The upper approximation $P\overline{Y}$ can be defined as the set of all those objects which can be possibly classified as the set Y with respect to the relation R. The upper approximation has been shown below in Eq. (2).

$$P\overline{Y} = \{y: \ [y]_P \cap Y \neq \emptyset\} \tag{2}$$

- The Boundary Region - The Boundary Region is defined as a set of all those objects which are neither classified as the set X nor classified as the set not-X with respect to the relation R.

3) Indiscernibility Relation: The concept of approximation is based on the similarity between two objects which is known as Indiscernibility Relation (IND). Assuming two sets U and A, where A is a set of attributes (i.e. $b: U \rightarrow b$, where V_b is the values taken by the attributes b) and U is defined as the universe of all objects. Any subset C of A which ascertains a binary relation named $I(C)$ on an Universe U is known as the indiscernibility relation(IND). It is further defined as: $pI(C)q$ only when $b(p) = b(q)$ for every $b \in C$, where $b(p)$ and $b(q)$ indicates the values of the attribute b for the objects p and q, respectively [2]. If $(p, q) \in I(C)$, then we can say that p and q are C-indiscernible. The equivalence classes for the relation I(C) are called the elementary sets. In RST, this elementary set (granules) represents the available knowledge about reality [2].

If it is found out that $IND(C) = IND(C - \{b\})$ then $b \in C$ is said to be dispensable, else b is said to be indispensable in C. Set C will be called independent if all the attributes are indiscernible [2].

4) Rough set: Let U be the universal set. Let Y be a subset of the U. If the boundary region is found to be non-empty, then the set is said to be rough set [2].

5) Positive Region: The lower approximation is also known as the positive region [2]. Suppose there are two attributes M and N which represents conditional attribute and decision attribute, respectively. The formula for calculating positive region POS is shown below in Eq. (3).

$$POS(M, N) = \bigcup_{Y \in U} \underline{P}Y \tag{3}$$

6) Degree of Dependency: Suppose $M, N \subset A$, it is defined that N is dependable on M by a degree of K, where K is a constant value with $0 \leq K \leq 1$. The formula for degree of dependency is shown below in Eq. (4).

$$K(M, N) = \|POS(M, N)\| / \|U\| \tag{4}$$

The symbol $\|.\|$ represents the cardinality of a set [15].

7) Reduct: A reduct is defined as a set of different conditional attributes which results in same values of the decision attributes as resulted by all the attributes taken together [16]. In other words, all attributes other than those representing the reduct are called the redundant attributes [16].

8) Core: The core is defined as the set of all the indispensable attributes. In other words, core is also defined as the intersection of all the reduct [16].

9) Example of application of RST with a sample data set: Let us consider a data set (shown in Table I) with records $O1, O2, O3, O4, O5, O6, O7$ and $O8$. The conditional attributes are denoted by I and J and the decision attribute is denoted by K. The values of I are z and h, J are n, z and u, and K are z and h.

From TABLE I, the two sets of records $\{O1, O4, O5, O8\}$ and $\{O2, O3, O6, O7\}$ represent the two different concepts $\{O1, O4, O5, O8\}$ shows the value h and $\{O2, O3, O6, O7\}$ shows the value z for decisional attribute. The indiscernibility relation for attributes $\{I, J\}$ are $\{O1\}$, $\{O2\}$, $\{O3\}$, $\{O4\}$, $\{O6, O7\}$ and $\{O5, O7\}$. It can be easily observed that there is inconsistency because $\{O6, O8\}$ and $\{O5, O7\}$ are not subsets of any of the above concepts. They are resulting in different values for the decisional attribute even when they have same conditional attributes.

TABLE I: A DATA SET CONSISTING OF ROUGH SET.

$Records$	I	J	K
$O1$	z	n	h
$O2$	z	z	z
$O3$	z	u	z
$O4$	h	n	h
$O5$	h	z	h
$O6$	h	u	z
$O7$	h	z	z
$O8$	h	u	h

TABLE II: NOTATIONS USED IN THE ALGORITHMS.

Symbols	Meaning of symbol
l	A set of concepts
E_i, E_j, E_{ij}	Concepts
$\{E_{ij}\}$	Indiscernible objects of concept E_i
e , e′	Object of the concepts
U_{app}	Upper approximation
L_{app}	Lower approximation
b	Set of concepts with U_{app} and L_{app}
X	A local covering for the set b, that is, it yields the smallest set of minimum rules for the whole set b
E_p	Those members of b which are either U_{app} and L_{app} of a given concept
N	Members of the E_p
D	Concept which is selected
H	The temporary storage for B
V	Set of value pair of attribute
v	$v \in$V
$[V]$	Set of those objects having attribute-pair other than v
V[H]	The value pair of attribute in objects of H
$[V$-$\{v\}]$	Set of those objects having value pair of attribute other than v
S	Members of X other than V ; S∈X-{V}

The concept $\{O2, O3, O6, O7\}$ has upper approximations $\{O2, O3, O5, O6, O7, O8\}$ and lower approximation $\{O2, O3\}$. Similarly, the concept $\{O2, O3, O6, O7\}$ has upper approximation $\{O1, O4, O5, O6, O7, O8\}$ and lower approximation $\{O1, O4\}$. The elements present in the upper approximation but not in the lower approximation can define the boundary region.

After applying RST, the dimension of data gets reduced by removing superfluous attributes and thereafter, rule generation algorithm LEM2, which is described below, is used.

C. Rule generation algorithm: LEM2

The algorithm used for rule generation in this work is *Learning by Example Module: Version 2 (LEM2)* algorithm. It is an algorithm based on RST. This algorithm works well for data set with inconsistencies [16]. The notations for algorithm is given in TABLE II. The algorithms for determining upper and lower approximation and rule generation are given in Algo. (1) and (2), respectively. Though, the complete description of the LEM2 algorithm is not provided in this paper due to the limitation in space, interested readers are requested to read its underlying concept from [16].

Algorithm 1 Computation of lower and upper approximation.

Input: set representing the concepts l ;
Output: set representing the concepts b ;

```
while l! = NULL do
    for every concept E_i ∈ l
    while l! = NULL do
        for every concept E_j ∈ l
        if E_i != E_j then
            while E_i! = NULL do
                for every object e′ ∈ E_i
                while E_i! = NULL do
                    for every object e′ ∈ E_j
                    if all the value pair of attribute of e ≡
                        all the value pair of attribute of e′
then
                        E_i is uncertain and (e,e′) is
                        uncertain pair; indiscernible objects
                        {E_ij} of the concept
                        E_j gets changed with (e,e′) ;
                    end if
                end while
            end while
        end if
        if E_i is uncertain then
            U_app is union of {E_i} and
            {E_ij}, that is U_app={E_i} ∪ {E_ij};
            L_app is subtraction of {E_i} and {E_ij}, that is,
            U_app={E_i} - {E_ij};
            change b with U_app and L_app ;
        else
            change b with E_i
        end if
    end while
end while
```

IV. CASE STUDY

A. Problem definition

The study made here is done to provide a solution to problem related to occupational accidents in an integrated steel plant in India. The dataset obtained from the steel plant contains the accident records during 2010-2013. Instead of the presence of several safety standards, the steel plant has been facing a number of accidents. A lot of interwined factors are present behind the occurrence of accidents which go unnoticed.The accident data maintained by the company often explores inconsistencies which leads to misleading and incorrect interpretation of the results from the analysis. Therefore, considering the fact of handling inconsistency in data, proper analytical method should be adopted to figure out the interrelationship among the factors leading to accidents.

B. Data set and its description

The data set used is an occupational accident data set consisting of 1062 objects, 11 conditional attributes and 1 decision attribute. The data set is categorical. The conditional attributes are ‘Day Of Incident’(Monday, Tuesday,...., Sunday), ‘Month’(January, February, March,......., December), ‘Division’(Div1, Div2,....., Div7), ‘Injury Type’(Injury Type Not

Algorithm 2 Rule Generation by LEM2.

```
Input: a set of concepts b ;
Output: a set of rules X ;

while b! = NULL do
    for every concept in b
    if uncertainty is found then
        L_app and U_app is a member of E_p
    else
        L_app= concept is the member of E_p;
    end if
    while E_p != NULL do
        for every member M ∈ E_p
        D=L_app
        H:=D
        X:=NULL
        while H != NULL do
            V := NULL
            V(G):={V|[v] ∩ H! = NULL};
            while V=NULL or [V]!=D do
                A value pair of attribute V ∈ V(G) is selected
                having highest priority in attribute
                if a tie takes place then
                    Select a v∈V(H)
                    such that |v ∩ H| is maximum;
                    if another tie takes place then
                        A v ∈ H is selected
                        with least cardinality of [v]
                        if further tie takes place then
                            select first pair;
                        end if
                    end if
                end if
                V := V ∪ {v}
                H := [v] ∩H
                V(H) := {V|[v] ∩ H! = NULL}
                V(H) := V(H) - V;
            end while
            for each v in V
            if [V-{v}]⊂ D then
                V := V - [v];
            end if
            X:= X ∪ {V}
            H := D - ⋃_{V∈X}[V]
        end while
        for each V in X ;
        if ⋃_{X−{V}} then
            X:=X-{V}
        end if
        if N is Uncertain then
            D=U_app
        end if
    end while
end while
```

Applicable (ITNA), First Aid (FA), Foreign Body (FB), Death, Fatal, Serious_Injury (Serious_I)), 'Standard Operating Procedure Combined (SOP combined)'(SOP not avaiable and not required (SNNR), SOP not available and required (SNR), SOP available and adequate and followed (SAF), SOP available and adequate and not Followed (SANF), SOP available and inadequate and followed (SIF), SOP available and inadequate and not followed (SINF)), 'Primary Cause'(Slip/Trip/Fall (STF), Crane Dashing (CD), Dashing/Collision (DC), Derailment(D), Material Handling (MH)), 'Working Condition'(Single Working (SW), Group Working(GW), Working Condition Not Applicable (WCNA)), 'Machine Condition' (Machine Idle (MI), Machine Working (MW), Machine Condition Not Applicable (MCNA)), 'Observation Type'(Unsafe Act (UA), Unsafe Act and Unsafe Condition (UAC), Unsafe Condition(UC)), 'Employee Type'(Contractor, Employee) and 'Incident Type'(Behaviour (Beh), Process (Pro)). The decision attribute is 'Incident Category'(Near Miss (NM), Property Damage (PD), First Aid Case (I), Medical Case (I)). All attributes used in this study are categorical in nature. Complete description of the data set has not been provided in this paper due to space limitation.

C. Data preprocessing

The data preprocessing plays a very important part in rule generation. Firstly, the indiscernibility relation was determined for the data set. Then, the upper and lower approximation were determined to ascertain the rough set. Finally, the positive region and the degree of dependency were determined. The degree of dependency in the data set was found to be 0.986 which certainly proves the presence of rough set in the accident data set at hand. The feature subset or superreduct that are those attributes which show the same decision rules as shown by the original dataset. The feature subset consists of 8 attributes: 'Day Of Incident', 'Month', 'Division', 'Injury Type', 'Primary Cause', 'Working Condition', 'Observation Type' and 'SOP_Combined'.

V. Results & Discussion

After the data preprocessing stage, 8 attributes are finally selected for rule extraction by LEM2 algorithm. There is a set of 279 rules extracted by using this algorithm for decisional attribute Incident Category. Only 10 rules for Near Miss (NM) cases are shown and explained in Table III. For example, in rule 1 (R1), it is observed that when SOP combined is SOP not available and also not required and observation type is unsafe condition (UC) and working condition is single working (SW), then near miss is taken place more frequently that is 42 in numbers obtained from the data set. From R2, it is observed that in Div7, unsafe act and slip/trip/fall (STF) lead to more number of near miss phenomena.Similarly, in Div7, near miss is taken place when SOP is found to be not required (refer to R3). In R4, near miss cases is observed in Div7 mostly in the presence of STF cases. In addition with this rule in Div7 near miss is also taken place when group working condition and unsafe condition are simultaneously available (refer to R5).

VI. Conclusion

The study has discussed the implementation of the RST on an occupational accident data obtained from an integrated

TABLE III: Rules extracted using RST-based LEM2 algorithm.

Rule No.	IF condition	THEN condition	Number of elements supporting the condition
R1	Injury Type is ITNA and SOP Combined is SNNR and Observation Type is UC and Working Condition is SW	NM	42
R2	Observation Type is UA and Division is Div7 and Primary Cause is STF	NM	40
R3	Injury Type is ITNA and Division is Div7 and SOP Combined is SNR	NM	29
R4	Working Condition is WCNA and Primary Cause is STF and Division is Div7	NM	29
R5	Working Condition is GW and Observation Type is UC and Division is Div7	NM	21
R6	Primary Cause is MH and Month is July	NM	10
R7	Division is Div6 and Observation Type is UC and SOP Combined is SAF and Primary Cause is STF	NM	9
R8	Working Condition is SW and Division is Div6 and SOP Combined is SANF and Observation Type is UA and Primary Cause is STF	NM	6
R9	Observation Type is UA and Primary Cause is D and Day of Incident is Friday and Month is July	NM	1
R10	Primary Cause is D and Month is June and Day of Incident is Wednesday	NM	1

steel industry. The attributes which make up the core have been identified and simultaneously the superfluous attributes are removed. The indiscernibility relation among the attributes is also found out and the degree of dependency is also computed which is an important concept to determine roughness or vagueness of a data set. Finally, some important rules have been generated which provide some important information about the occupational accident in the steel industry which in turn will help in taking important measures to check occupational accident and decrease injuries and fatalities and increase the productivity. Some of the key findings from the analysis have been listed below:

- The division Div7 is more prone to accident than the other divisions.
- Both the Div6 and Div7 experience near miss cases more due to the presence of STF primary causes.
- If the observation type is unsafe condition then there are chances of more accidents.
- Maximum number of accidents are occurred in the month of February, March and September.
- Single Working condition at workplaces is mostly attributable towards near miss incidents.

As the future scope of the current work, RST can be combined with decision tree to predict the instances of occupational accidents. Apart from the use of decision tree, other algorithms like support vector machines, artificial neural network can also be useful for this purpose of rule generation with prediction. In addition with this, more number of incident data points should be collected for better rule mining for accident cases at work.

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