An Analysis of Organizational Behaviour using k-Approximation Spaces

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Abstract: Rough set theory and Soft set theory are the two mathematical concepts that plays a vital role in decision making problems. In complex systems, the objects are equipped with various set of attributes and that will add the complexity in making decision. In this paper, we introduce k-approximation space and covering based k-soft approximation space that leads us to define k-rough set and covering based k-soft rough set. The significance of these two concepts are illustrated and compared in analyzing the Organizational behaviour of the employees in an Organization.

Keywords: Fuzzy Set Theory, Rough Set Theory, Soft Set Theory, Covering.

1. Introduction

Rough set theory[16], first proposed by Pawlak, the most important mathematical approach to deal with uncertain knowledge in information system, has basically described the indiscernible of elements by equivalence relations. Main advantage of using rough set, it does not need any additional information about data. This theory has applied to the fields of medical diagnosis, pattern recognition, data mining etc [11]. The soft set theory was introduced by Molodtsov, is a general mathematical tool for dealing with uncertainty. Many different traditional tools are there to deals with uncertainties, such as the theory of probability, the theory of fuzzy sets and the theory of rough sets, the advantage of soft set theory is that it is free from the inadequacy of the parametrization tools of those theories. According to Molodtsov, the soft set theory has been applied to various fields such as functions smoothness, game theory, riemann-integration and so on [5,6,7]. Fuzzy set theory [8,13,18] with rough set approach leads to model the strength of individual attributes and guide the search for an optimal attribute subsets. Maji and Roy [15,17] first introduced the soft set into the decision making problems with the help of the rough theory and in 2001, Maji et al.[14] introduced the concept of fuzzy soft set, the most generalized concept which is the combination of fuzzy set and soft set. Chen et al.[4] presented a new definition of soft set parameterization reduction and compared it with attributes reduction in rough set theory. Kong et al.[12] initiated the definition of normal parameter reduction into soft sets. Ali et al.[1] gave some new operations in soft set theory. Zou and Xiao[19] proposed some data analysis approaches of soft sets under incomplete information. Cagman [2,3]and Enginoglu redefined the operations of soft sets and constructed a uni-int decision making method which selected a set of optimum elements from the alternatives. Herawan and Deris[9] presented an alternative approach for mining regular association rules and maximal association rules from transactional datasets using soft set theory. Jiang et al.[10] proposed a novel approach to semantic decision making by using ontology-based soft sets and ontology reasoning.

In this paper, we define and investigate the relation between the k-rough set and covering based k-soft rough set using k-approximation space and covering based k-soft approximation space and also made an attempt to study the impact of one set of attributes over all other set of attributes. Finally, an illustrate example is worked to show the validity of these two types of rough sets approach in real time decision making problem.

2. Preliminaries

In this section, the preliminary definitions are explained which are prerequisite to study the rest of the sections.

Definition 2.1: In fuzzy sets A, each element of the universal set X is mapped to [0, 1] by the membership function $\mu_A: X \to [0, 1]$.

Definition 2.2: (Rough set) Let I = (U,A) be an information system, where U is a non-empty set of finite objects called Universe and A is a non-empty finite set of fuzzy attributes defined by $\mu_a: U \to [0,1], a \in A$ is a fuzzy set. With any $P \subseteq A$, there is an associated equivalence relation called IND(P) defined as $IND(P) = \{(x,y) \in U^2 | \forall a \in P,\ \mu_a(x) = \mu_a(y)\}$. The partition induced by IND(P) consists of equivalence classes defined by $[x]_p = y \in U \mid (x,y) \in IND(P)$. For any $X \subseteq U$, define the lower approximation space $P\_(X)$, such that $P\_(X) = \{x \in U \,|[x]_p \subseteq X\}$. Also, define the upper approximation space $P^-(X) = \{x \in U \,|[x]_p \cap X \neq \emptyset\}$. A rough set corresponding to X, where X is an arbitrary subset of U in the approximation space P, we mean the ordered pair RS(X) = ($P_{-}(X)$, $P^{-}(X)$).

Definition 2.3: (Soft set) A pair (F, E) is called a soft set (over U) if and only if F is a mapping of E into the set of all subsets of the set U.

3. K-Approximation Space

In this section, the concept of k-approximation space and k-rough set were defined and its properties were discussed.

Let U is a non-empty finite set of objects and $R_1, R_2, \dots R_k$ be k-distinct partitions on U, then $I = (U, R_1, R_2, \dots R_k)$ is called as a k-approximation space. For any $X \subseteq U$, $RS_{R_i}(X) = \left(R_{i\_}(X), R_i^{-}(X)\right)$ where $R_{i\_}(X) = \left\{x \in U \mid [x]_{R_i} \subseteq X\right\}$ and $R_i^{-}(X) = \left\{x \in U \mid [x]_{R_i} \cap X \neq \phi\right\}$, where $[x]_{R_i}$ denote the subset of U containing X with respect to the partition R_i.

In fact, each partition $R_1, R_2, \dots R_k$ induces an equivalence relation and $[x]_{R_i}$ can be viewed as the equivalence class containing X with respect to R_i. This method of defining k-approximation space will be very useful in many real time problems. When the objects of U are possessed by a k-distinct set of attributes say $A_1, A_2, \dots A_k$ where $A_i = \left\{a_{i_1}, a_{i_2}, \dots, a_{i_{n_i}}\right\}$, $i = 1,2,3 \dots k$ be the set of parameters with respect to the attributes A_i. Then $I_1 = (U, A_1), I_2 = (U, A_2) \dots I_k = (U, A_k)$ (or) $I = (U, A_1, A_2, \dots, A_k)$ be the k-information system. Each of the set of attributes $A_1, A_2, \dots A_k$ induces k-indiscernible relation and in this way also the set of objects in U will have k-partitions induced by these relations.

For any given subset X of U, the k-rough set can be defined and it can be written as $k - RS(X) = (RS_{R_1}(X), RS_{R_2}(X) \dots RS_{R_k}(X))$. Note that $R_{i\_}(X), i = 1,2, \dots k$ contains those elements of U whose corresponding partition is completely contained in U and $R_i^{-}(X)$ contains those elements of U whose corresponding partition will have a non-empty intersection with X with respect to R_i. By comparing the k-lower approximations namely $R_{1\_}(X), R_{2\_}(X) \dots R_{k\_}(X)$ and the k-upper approximations $R_1^{-}(X), R_2^{-}(X) \dots R_k^{-}(X)$, the objects of U can be classified into those sets possessing each of the k attributes A_i, $i = 1,2, \dots k$. Note that for any $[x]_{R_i}$, the partition containing the set of objects containing the attribute A_i. The rough set $RS_{R_j}\left([x]_{R_i}\right), j \neq i$ can be calculated. These rough sets will give the possible and definite objects of U possessing the attributes A_i and $A_j, j \neq i$. This can be extended to any set of objects of U possessing any attribute sets $\{A_{i1}, A_{i2}, \dots A_{ir}\}$, $\{i_1, i_2, \dots, i_r\} \subseteq \{1, 2, \dots, k\}$. In fact, $RS_{R_j}\left([x]_{R_{i_1}} \cup [x]_{R_{i_2}} \cup \dots \cup [x]_{R_{i_r}}\right)$ gives the possible and definite elements of U possessing the attributes $A_j, a_{i1}, a_{i2}, \dots a_{ir}$, where $j \neq \{i_1, i_2, \dots, i_r\}$.

Example-1:

Let $U = \{x_1, x_2, x_3\}$ and $E = \{A, B, C\}$ be the set of attributes.

Table I. Example-1: List of Parameters

Attributes	Parameters
A	$a1$=$\{x1, x2\}$
	$a2$=$x3$
B	$b1$=$\{x2, x3\}$
	$b2$=$x1$
C	$c1$=$\{x1, x3\}$
	$c2$=$x2$

A will induce partition on $R_1$and similarly, B and C will induce the partition R_2 and R_3 respectively. Now, 3-approximation space is (U, R_1, R_2, R_3). Then, for any subset X of U, the rough set will be obtained and its shown below.

- $RS_{R_1}(b_1) = (a_2, a_1 \cup a_2)$
- $RS_{R_1}(b_2) = (\phi, a_1)$
- $RS_{R_1}(c_1) = (a_2, a_1 \cup a_2)$

- $RS_{R_1}(c_2) = (\phi, a_1)$
- $RS_{R_2}(a_1) = (b_2, b_1 \cup b_2)$
- $RS_{R_2}(a_2) = (\phi, b_1)$
- $RS_{R_2}(c_1) = (b_2, b_1 \cup b_2)$
- $RS_{R_2}(c_2) = (\phi, b_1)$
- $RS_{R_3}(a_1) = (c_2, c_1 \cup c_2)$
- $RS_{R_3}(a_2) = (\phi, c_1)$
- $RS_{R_3}(b_1) = (c_2, c_1 \cup c_2)$
- $RS_{R_3}(b_2) = (\phi, c_1)$

4. Covering Based k- Soft Approximation Space

This section defines the concept of covering based k-approximation space in which a nonempty finite set of objects U is equipped with a k-disjoint set of attributes. The authors introduce k-soft set and covering based k-soft rough set which leads us to analyze the influence of one attribute over all other attributes on the elements of U.

Let $G_1 = (F_1, A_1), G_2 = (F_2, A_2) \dots G_k = (F_k, A_k)$ are the soft sets over U and $(U, C_{G_1}), (U, C_{G_2}) \dots (U, C_{G_k})$ are the covering based soft approximation space which can be written as $(U, C_{G_1}, C_{G_2}, \dots, C_{G_k})$ corresponding to the k-soft set $G = (G_1, G_2, \dots, G_k)$. Hence, $(U, C_{G_1}, C_{G_2}, \dots, C_{G_k})$ is called as the covering based k-soft approximation space with respect to the soft set $G = (G_1, G_2, \dots, G_k)$. Now, for any subset X of U, we can define the covering-based k-soft rough set as follows.

Definition 4.1

Let $I = (U, C_{G_1}, C_{G_2}, \dots, C_{G_k})$ be the covering-based k-soft rough set for any subset X of U.

$$k - CRS(X) = \left(CRS_{G_1}(X), CRS_{G_2}(X), \dots, CRS_{G_k}(X)\right)$$

where $CRS_{G_i}(X) = (CR_{G_i\_}(X), CR_{G_i}{}^{-}(X))$,
where $CR_{G_i\_}(X) = \cup_{r=1,2,\dots,n_i}\{F_i(a_i) |\, F_i(a_i) \subseteq X\}$
and $CR_{G_i}{}^{-}(X) = \cup_{r=1,2,\dots,n_i}\{F_i(a_i) |\, F_i(a_i) \cap X \neq \emptyset\}, i = 1, 2, \dots, k$.

Here, $CRS(X)$ is called as the covering-based k-soft rough set. Note that, $G_1, G_2, \dots, G_k$ represents the k-distinct coverings for the objects of U induced by $F_1, F_2, \dots, F_k$ recpectively and $CRS_{G_j}(F_i(a_{i_r}))$ is the covering based soft rough set of $F_i(a_{i_r}) \subseteq U$ possessing the attributes in G_j, for $i \neq j$.

We know that $CRS_{G_j}(X) = (CR_{G_j\_}(X), CR_{G_j}{}^{-}(X)), X \subseteq U$ and $CR_{G_j\_}(X)$ contains those subsets of U possessing the attribute A_j which are containing X and $CR_{G_j}{}^{-}(X)$ contains these subsets of U possessing the attribute A_j which are having the non-empty intersection with X. Hence $CRS_{G_j}(F_i(a_{i_r})) = \left(CR_{G_j\_}\left(F_i(a_{i_r})\right), CR_{G_j}{}^{-}\left(F_i(a_{i_r})\right)\right)$ which represents the covering based soft rough set containing the elements of U which are definitely and possibly containing the attributes in A_j and a_{i_r}.

This can be extended in the following way. For $F_{i_1}(a_{i_1 j_1}) \cup F_{i_2}(a_{i_2 j_2}) \cup \dots F_{i_r}(a_{i_r j_r}) \subseteq U$, the covering based soft rough sets $CRS_{A_j}\left(F_{i_1}(a_{i_1 j_1}) \cup F_{i_2}(a_{i_2 j_2}) \cup \dots F_{i_r}(a_{i_r j_r})\right)$ represents the elements of U containing $G_j, a_{i_1 j_1}, a_{i_2 j_2}, \dots, a_{i_r j_r}$.

From the discussion in the previous two sections, we can conclude the following. Given a finite set of objects U containing the k distinct partitions $r_1, r_2, \dots, r_k$, we can have the k-rough set defined for every subset X of U. These k-partition may be obtained by classifying the objects of U with respect to k-district set of attributes in which each attribute contains various parameters. Similarly, if U has k-distinct coverings $C_{G_1}, C_{G_2}, \dots C_{G_k}$, then the corresponding covering-based k-soft rough set can be defined for every subset X of U.

Example-2:

Let $U = \{x_1, x_2, x_3\}$ and $E = \{A, B, C, D\}$ be the set of attributes. Then, $G_1 = (F_1, A)$, $G_2 = (F_2, B), G_3 = (F_3, C)$ and $G_4 = (F_4, D)$ be the soft sets with the covering based 2-approximation spaces $(U, G_1 \cup G_2, G_3 \cup G_4)$. Then, for any subset X of U, the covering based k-soft rough set will be obtained and its shown.

Table II. Example-2: List of Parameters

Attributes	Parameters
A	$a1$=$x1$
	$a2$={$x1$, $x2$}
	$a3$=$x3$
B	$b1$={$x1$, $x2$}
	$b2$=$x3$
C	$c1$={$x1$, $x2$, $x3$}
	$c2$=$x2$
D	$d1$={$x2$, $x3$}
	$d2$={$x1$, $x3$}

- $CRS_{G_1 \cup G_2}(c_1) = (a_1 \cup a_2 \cup a_3 \cup b_1 \cup b_2, a_1 \cup a_2 \cup a_3 \cup b_1 \cup b_2)$
- $CRS_{G_1 \cup G_2}(c_2) = (\phi, a_2 \cup b_1)$
- $CRS_{G_1 \cup G_2}(d_1) = (a_3 \cup b_2, a_2 \cup a_3 \cup b_1 \cup b_2)$
- $CRS_{G_1 \cup G_2}(d_2) = (a_1 \cup a_3 \cup b_2, a_1 \cup a_2 \cup a_3 \cup b_1 \cup b_2)$
- $CRS_{G_3 \cup G_4}(a_1) = (\phi, c_1 \cup d_2)$
- $CRS_{G_3 \cup G_4}(a_2) = (\phi, c_1 \cup c_2 \cup d_1 \cup d_2)$
- $CRS_{G_3 \cup G_4}(a_3) = (\phi, c_1 \cup d_1 \cup d_2)$
- $CRS_{G_3 \cup G_4}(b_1) = (c_2, c_1 \cup c_2 \cup d_1 \cup d_2)$
- $CRS_{G_3 \cup G_4}(b_2) = (\phi, c_1 \cup d_1 \cup d_2)$

These two ways of defining the rough sets will play the major role in the classification of a finite objects containing the various attributes in a complex system. Hence, in the following sections, we illustrate these concepts in the real time problems.

5. Applications

In this section, an algorithm is defined to find the optimum solution to obtain the detailed ranking of the elements of U in accordance with the parameters and illustrates the purpose of k-approximation space and covering based k-approximation space in real time situation.

A. Algorithm

- Input k-approximation space / covering based k-approximation space.
- Construct the k-rough set / covering based k-soft rough set corresponding to the elements of one partition with respect to all other partitions.
- Calculate the fuzzy weight for each rough set using the weights of the parameter.
- Analyze the subsets of U using these weights and obtain the accurate ranking of the elements of U in accordance with the parameters.

B. Illustration

Employee value proposition (EVP) and employee engagement (EE) are the two major factors to determine the standard level of the employees in any of the organization. Age, experience and educational qualification are the categories of the employees taken for our study. The developed concepts are useful to analyze and explore the result accuracy for the categories. Let us consider a universal set U consisting of the 150 employees of an Organisation. Let $U = \{U_1, U_2 \ldots U_{150}\}$. The standard of the organisation depends on various parameters like the profile of the employees, EVP (D) and EE (E).

Table III. List of Categories

Attributes	Parameters	Notation

Age (A)	30-40 years	$a1$
	40-50 years	$a2$
	50 and above	$a3$
Experience (B)	Below 1 year	$b1$
	1-3 years	$b2$
	3-6 years	$b3$
Qualification (C)	Diploma	$c1$
	UG	$c2$
	PG	$c3$
	Others	$c4$

In the following example, we give a detailed analysis of the influence of these factors in the Organisation using our proposed methods of k-approximation space and Covering based k-soft approximation space.

The profile of the employees includes Age(A), Educational Qualification(B) and Experience(C). The main objective is to get the equivalence classes induced by A, B, C, D and E on U. To achieve this, age(A) is classified into three categories 30-40 years(a_1), 40-50 years(a_2) and 50 above(a_3) and educational qualification(B) into three categories namely b_1, b_2 and b_3. Similarly, experience(C) is classified into four categories c_1, c_2, c_3 and c_4. (shown in table-III)

A will induce a partition R_1on U by grouping the employees who fall in a_1, a_2 or a_3. Similarly, B and C will induce on partition R_2 and R_3 respectively. By taking into an account the parameters influencing EVP. We have a partition R_4 on U corresponding to EVP values of 0.3, 0.4, 0.5 and 0.6. Similarly, from the data obtained EE will also induces a partition R_5 on U corresponding to EE values of 0.3, 0.4, 0.5 and 0.6.

Table IV. Details about employee engagement and employee value proposition

	Parameters	**Weights**
Employee value proposition (D)	$d1$	0.3
	$d2$	0.4
	$d3$	0.5
	$d4$	0.6
Employee engagement (E)	$e1$	0.3
	$e2$	0.4
	$e3$	0.5
	$e4$	0.6

Now, we have a five-approximation space $(U, R_1, R_2, R_3, R_4, R_5)$. Now, for any subset X of U, the k-rough set can be obtained which will effectively reflect the set of employees with a given age group, educational qualification, experience and having the EVP and EE who fall definitely and possibly into X. We exhibit this by taking the set a_1 as

$$5\,RS(a_1) = (RS_{R_1}(a_1), \quad RS_{R_2}(a_1), \quad RS_{R_3}(a_1), \quad RS_{R_4}(a_1), \quad RS_{R_5}(a_1))$$

This means that the employees who fall into 30-40 years of age will have $R_{1\_}(a_1), R_{2\_}(a_1), R_{3\_}(a_1), R_{4\_}(a_1)$, $R_{5\_}(a_1)$ and possibly will have $R_1^{-}(a_1)$, $R_2^{-}(a_1)$, $R_3^{-}(a_1)$, $R_4^{-}(a_1)$, $R_5^{-}(a_1)$.

We can also rank the employees who fall into $a_1$with respect to their EVP and EE. This can be achieved by taking R_1, R_4 and R_5. That is by finding 3-$RS(a_i), i = 1,2,3$. The ranking of profile of the set of employees with respect to their EVP and EE are showing in the following table-V

Table V. K- Rough Sets

X	**RS(X) with respect to EVP**	**RS(X) with respect to EE**

a1	$(\phi, d2 \cup d3)$	$(\phi, e2 \cup e3 \cup e4)$
a2	$(d1, d1 \cup d2 \cup d3)$	$(\phi, e1 \cup e2 \cup e3)$
a3	$(d4, d2 \cup d3 \cup d4)$	$(e1, e1 \cup e2 \cup e3 \cup e4)$
b1	$(d4, d2 \cup d3 \cup d4)$	$(\phi, e2 \cup e3 \cup e4)$
b2	$(\phi, d1 \cup d2 \cup d3)$	$(\phi, e2 \cup e3 \cup e4)$
b3	$(\phi, d1 \cup d2 \cup d3)$	$(\phi, e1 \cup e2 \cup e4)$
c1	$(\phi, d2 \cup d3)$	$(\phi, e3)$
c2	$(d4, d2 \cup d3 \cup d4)$	$(\phi, e2 \cup e3 \cup e4)$
c3	$(d1,\ d1 \cup d2 \cup d3$	$(\phi, e2 \cup e3 \cup e4)$
c4	$(\phi, d2)$	$(\phi, e1 \cup e2 \cup e3)$

By analyzing table-V, we can say that employees with UG and PG qualifications are satisfied with EVP and have been satisfied with both EVP and EE by employees over 50 years of age. Employees with one year's experience have been pleased with EVP. Employees with a diploma in education were not satisfied with their experiences both in the EVP and the EE.

In the following discussion, we are using the covering based k-soft approximations for the same dataset and our aim to obtain the optimal ranking. Covering based k-soft rough set is the extension of soft rough sets by relaxing the partitions arising from equivalence relation to coverings.

We generate the soft sets $G_1 = (F_1, A), G_2 = (F_2, B), G_1 = (F_3, C), G_4 = (F_4, D)$ and $G_5 = (F_5, A)$ on the same universe U which are based on age, experience, educational qualification, EVP and EE, where $F_1: A \to P(U)$ is defined as $F_1(x) =$ set of employees categories by age. Similarly, other functions will be defined. First, let us consider the coverings, $G_3 \cup G_4 = (F_3 \cup F_4, C \cup D)$, where $\{F_3(x), F_4(y) | x \in C, y \in D\}$ is a covering on U and let as consider the another covering$G_3 \cup G_5 = (F_3 \cup F_5, C \cup E)$, where $\{F_3(x), F_5(y) | x \in C, y \in E\}$ is a covering on U. Therefore, we generate covering based 2-soft approximation space $G = (U, G_3 \cup G_4, G_3 \cup G_5)$. Now, for each a_1, a_2, a_3, b_1, b_2 and b_3 we find the covering based 2-soft rough set. i.e)

$$2 - CRS_{G_3 \cup G_4}(a_1) = \left(CR_{G_3 \cup G_4 \_}(a_1), CR_{G_3 \cup G_4}{}^{-}(a_1)\right) \text{ and}$$

$$2 - CRS_{G_3 \cup G_5}(a_1) = \left(CR_{G_3 \cup G_5 \_}(a_1), CR_{G_3 \cup G_5}{}^{-}(a_1)\right)$$

Now, for any subset X of U, the covering based k-soft rough set can be obtained. We can analysis the set of employees according to their experience and educational qualification with respect to EVP and EE (tabulated in table-IV).

Table VI. Covering based k-soft rough sets

X	CRS(X) with respect to B and D
a_1	$(\phi, b_2 \cup b_3 \cup d_2 \cup d_3)$
a_2	$(d_1, b_1 \cup b_2 \cup b_3 \cup d_1 \cup d_2 \cup d_3)$
a_3	$(\phi, b_1 \cup b_2 \cup b_3 \cup d_2 \cup d_3 \cup d_4)$
c_1	$(\phi, b_1 \cup d_2 \cup d_3)$
c_2	$(d_4, b_1 \cup b_2 \cup b_3 \cup d_2 \cup d_3 \cup d_4)$
c_3	$(\phi, b_2 \cup b_3 \cup d_2 \cup d_3 \cup d_4)$
c_4	$(\phi, b_2 \cup b_3 \cup d_2)$
X	**CRS(X) with respect to B and E**
a_1	$(\phi, b_2 \cup b_3 \cup e_2 \cup e_3 \cup e_4)$
a_2	$(\phi, b_1 \cup b_2 \cup b_3 \cup e_1 \cup e_2 \cup e_3)$
a_3	$(e_1, b_1 \cup b_2 \cup b_3 \cup e_1 \cup e_2 \cup e_3 \cup e_4)$
c_1	$(\phi, b_1 \cup e_3)$
c_2	$(\phi, b_1 \cup b_2 \cup b_3 \cup e_2 \cup e_3 \cup e_4)$
c_3	$(\phi, b_2 \cup b_3 \cup e_2 \cup e_3)$
c_4	$(\phi, b_2 \cup b_3 \cup e_1 \cup e_2 \cup e_3)$
X	**CRS(X) with respect to C and D**
a_1	$(\phi, c_2 \cup c_3 \cup c_4 \cup d_2 \cup d_3)$
a_2	$(d_1, c_2 \cup c_3 \cup c_4 \cup d_1 \cup d_2 \cup d_3)$
a_3	$(c_1, c_1 \cup c_2 \cup c_3 \cup c_4 \cup d_2 \cup d_3 \cup d_4)$

b_1	$(c_1 \cup d_4, c_1 \cup c_2 \cup d_2 \cup d_3 \cup d_4)$
b_2	$(\phi, c_2 \cup c_3 \cup c_4 \cup d_1 \cup d_2 \cup d_3)$
b_3	$(\phi, c_2 \cup c_3 \cup c_4 \cup d_1 \cup d_2 \cup d_3)$
X	**CRS(X) with respect to C and E**
a_1	$(\phi, c_2 \cup c_3 \cup c_4 \cup e_2 \cup e_3 \cup e_4)$
a_2	$(\phi, c_2 \cup c_3 \cup c_4 \cup e_1 \cup e_2 \cup e_3)$
a_3	$(c_1 \cup e_1, c_1 \cup c_2 \cup c_3 \cup c_4 \cup e_1 \cup e_2 \cup e_3 \cup e_4)$
b_1	$(c_1, c_1 \cup c_2 \cup e_2 \cup e_3 \cup e_4)$
b_2	$(\phi, c_2 \cup c_3 \cup c_4 \cup e_2 \cup e_3 \cup e_4)$
b_3	$(\phi, c_2 \cup c_3 \cup c_4 \cup e_1 \cup e_2 \cup e_4)$

From the table-6, We can say that employees with UG qualifications, 6 months to 1 year of experience and over 50 years of age were satisfied with EVP and EE. Employees with diploma and other qualifications have not been satisfied with their EVP and EE.

C. Comparative Analysis

In this work, we have defined and discussed the two types of rough sets, one is k-rough set and the other is covering based k-soft rough set. We illustrated the algorithm for these two types of rough sets by using the same data sets. As a result, the method with the covering based k-soft rough set is more reliable than the k-rough set when solving the real time problem. Figure-1, 2 and 3 illustrate the values and efficiencies of the defined methods.

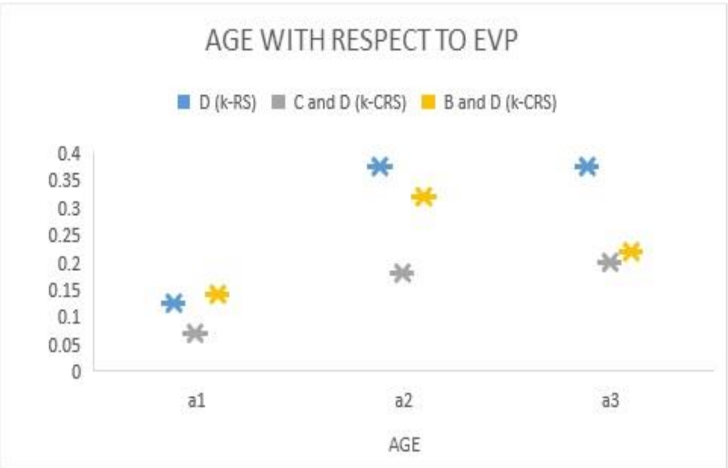
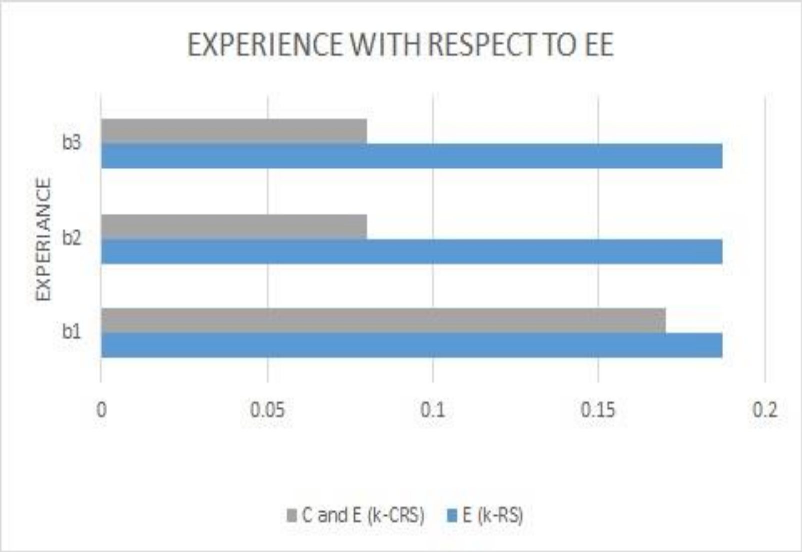


Fig. 1. Comparative analysis of the attribute age



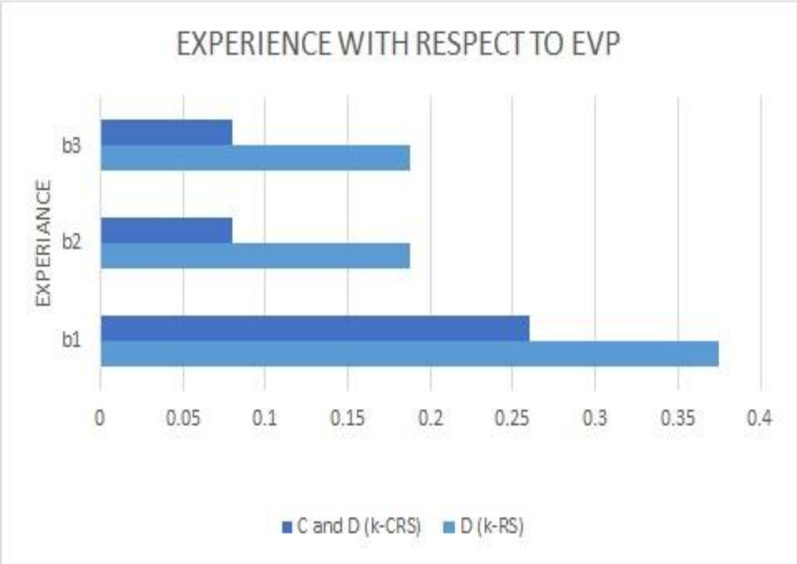


Fig. 2. Comparative analysis of the attribute experience

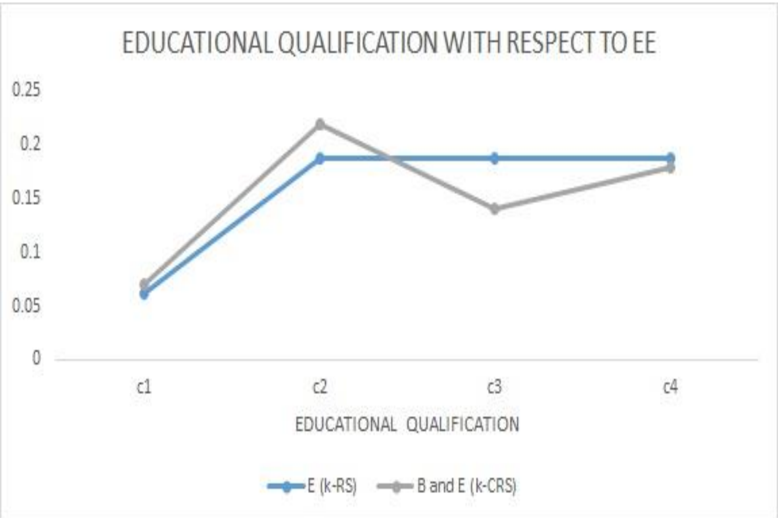


Fig. 3. Comparative analysis of the attribute educational qualification

6. Conclusion

In this paper, we have defined k-approximation space, covering based k-soft approximation space which leads to define k-rough set and covering based k-soft rough set. The method of finding the k-rough sets and covering based k-soft rough sets can be applied to real time problems. Therefore, we have illustrated our proposed model in a comparative study of Organizational behaviour of the employees in an organization by taking into account the significant parameters like age, experience, qualification, EVP and EE. The future work is to investigate the properties of these k-rough set and covering based k-soft rough sets and their applications.

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References

1. Das, T.K. and Acharjya, D.P. (2014). A decision making model using soft set and rough set on fuzzy approximation spaces. *Inform. Sci.*, 13(3), 170–18.
2. Feng, F., Liu, X., Violeta, F.L. and J. B. Young. (2011). Soft sets and soft rough sets. *Inform. Sci.*, 181, 1125-1137.
3. Feng, F. (2011). Soft rough sets applied to multicriteria group decision making. *Ann.Fuzzy Math.Inform*., 2, 69-80.
4. George.J.Klir and Bo Yuan. (1995). Fuzzy sets and Fuzzy logic theory and Applications.
5. Kwang. H. Lee. (2005). First Course on Fuzzy Theory and Applications, *Springer*.
6. Maji, P.K., Roy, A. R. and Biswas, R. (2001). Fuzzy soft sets. *J.FuzzyMath.*, 9, 589- 602.
7. Pawlak, Z. (1982). Rough Sets, *Int. J. Inf. Comp Sci.*, 11, 341-356.
8. Zadeh, L.A. (1965). Fuzzy sets. *Inform. Control.*, 8, 338-353.
9. Jacek Jelonek, Krzysztof Krawiec and Roman Slowinsk. (1995). Rough set reduction of attributes and their domains for Neural Networks. *Computational Intelligence*, 11(2).
10. Ling Sun, Jia-Yu Chi and Zhong-Fei Li. (2006). A Study on Reduction of attributes based on variable precision rough set and information entrop. *Proceedings of the Fifth International Conference on Machine Learning and Cybernetics, Dalian.*