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ANALYSIS OF SOIL FERTILITY FOR WHEAT CROP: A ROUGH SET BASED MODEL

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ABSTRACT

Rough Set Theory is an emerging mathematical tool that deals with the Knowledge Discovery, Pattern Recognition and Data Mining. The attribute reduction of the theory relies upon the discernibility matrix. Soil fertility is the major factor which contributes in yielding optimum crop production and therefore proper knowledge of the nutritional values required by soil is important. Due to many reasons such as lack of knowledge or improper guidance, farmers are deficient in proper nutritional management. The paper proposes a model for optimum usage of fertilizers required accordingly for Wheat Crop. Support, Strength, Certainty Factor and Coverage Factor prove the efficiency of the rules so generated.

Keywords: Certainty Factor, Coverage Factor, Decision rules, Discernibility matrix, Rough Set, Soil Fertility.

1. Introduction

Our country's economy is largely influenced by agriculture. It contributes a large part in Gross Domestic Product. Most of the people of rural area of India are indulged into the practices of agriculture and also earn their livelihood from it. India comes on second position when the production of wheat crop is concerned. So it becomes important for farmers to have a proper plan from preparation of land to harvesting the crop. There are many factors that affect the crop yield like Crop Variety, Soil Type, Soil Fertility, Climate, and so on. Among these factors, Soil

Fertility is the major factor. But most of the farmers be deficient in proper management due to lack of knowledge and improper information conveyed by informal sources like fertilizer dealers.

There are many techniques in soft computing which are being used by researchers to hi-tech the agricultural field. It is found that crisp and traditional scientific methods are somewhat difficult to implement on large data sets. Scientific methods sometimes generate flawed results because of statistical constraints and data inconsistencies. Also, when it comes to real-world data, it becomes complex to apply traditional and crisp methods. To overcome these problems many researchers are heading towards the concept of vagueness and imperfection for knowledge discovery and data mining. One of these concepts, Rough Set Theory (RST) has been emerging with its fascinating properties. In 1982, Z. Pawlak (Pawlak, 1982) introduced the concept of Rough Set[1] (RS) that is employed for Data Mining, Knowledge Discovery and Attribute Reduction. The theory has many applications such as in the field of banking, medicine, engineering, agriculture, acoustics, material science, and so on (Pawlak, 1997). In agricultural field various techniques are available viz., support vector machines (SVM), k- nearest neighbor, ID3 algorithms, k-means, and artificial neural networks (Yethiraj, 2012). Hidden information can be derived from large agricultural dataset with the help of RS (Liu & Xiao-Zhang, 2009). With the use of RS, Decision Tree (DT) and clustering level of soil fertility is evaluated in (Chen & Ma, 2011). In 2014 (Lavanya & Iyengar, 2014) a model for nutrient management for rice based on RS was proposed. The authors analyzed various growth factors to determine the Nitrogen, Phosphorous, and Potassium (NPK) supplies for site specific crops. In (Chen, Liu, & Wan, 2014) the authors proposed attribute reduction algorithm for agricultural diseases and pests.

This paper states the condition of required dose of nutritional supplement for wheat crop on the data of two states viz. Madhya Pradesh and Maharashtra. The theory allows preprocessing of data, reduction of inconsistent data and generation of rules from the reduced attributes. In order to preprocess the data, some codes are assigned to the original value. The study considers Soil Type, Target Yield, Crop Variety and Soil Test Value (NPK available in soil) as conditional attributes and Recommended Dose of fertilizer nutrients N, P_2O_5, and K_2O as decision attribute. Further on the basis of discernibility matrix core is computed and the decision rules are generated.

[1] Z. Pawlak firstly introduced the concept of Rough Set in the Report 431 at Institute of Computer Science, Polish Academy of Sciences (1981) and later the concept was published in 1982 (Pawlak, 1982).

2. Preliminaries

Rough set introduced by Pawlak is popular tool for dealing the data with vagueness and imperfection (Pawlak, 1982). Approximation is the key concept of RS. RS is a formal approximation of a crisp set consisting of the lower and the upper approximation of the original set (Walczak & Massart, 1999).

2.1. Information system/ Decision table: An information system IS (or approximation space) is defined as a pair IS = (*U, I, E, F*) where *U* = non-empty finite set called the universe, *I*= non-empty finite set of attributes, *E* = subset of *I* called Conditional attribute, *F* = subset of *I* called Decision attribute. Each attribute of *I* i.e., $a \in I$ defines an information function $f_a : U \to V_a$, where V_a called as domains the set of values of *a*.

2.2. Indiscernibility relation: Indiscernibility relation *Ind(M),* where $M \subset I$, is defined as: two objects y_i and y_j, are indiscernible by the set of attributes *M*∈*I*, if $m(y_i) = m(y_j)$ for every $m \in M$. Every subset (or equivalence class) of *Ind(M)* is known as elementary set in *M* because it represents the smallest indiscernible group of objects. The equivalence class is denoted by $[y_i]_{IND(M)}$.

2.3. Lower and Upper Approximations: Let *Y* denote the subset of elements of the universe *U*. The *lower approximation* of a set contains all the elements that doubtlessly belong to the set. The *lower approximation* of *Y* in $M(M \subseteq I)$ is defined as the union of all the elementary sets which are contained in *Y*. It is denoted by $\underline{MY}$. Mathematically, $\underline{MY} = \{y_i \in U \mid [y_i]_{IND(M)} \subset Y\}$.

The *upper approximation* of a set contains all the elements that possibly belong to the set. The *upper approximation* of *Y* in $M(M \subseteq I)$ is defined as the union of all the elementary sets which have a non-empty intersection with *Y*. It is denoted by $\overline{MY}$. Mathematically, $\overline{MY} = \{y_i \in U \mid [y_i]_{IND(M)} \cap Y \neq \phi\}$.

The *boundary* of *Y* in *U* is defined as the difference of the *upper* and *lower approximation* i.e., $Boun(Y) = \overline{MY} - \underline{MY}$.

2.4. Accuracy of approximation: For any set *Y* in $M \subseteq I$, accuracy can be defined as follows:

$$\alpha_M(Y) = \frac{cardinality\ of\ lower\ approximation}{cardinality\ of\ upper\ approximation} = \frac{|\underline{MY}|}{|\overline{MY}|}$$

If $\alpha_M(Y) = 1$, *Y* is *crisp* with respect to *I* and if $\alpha_M(Y) = 0$, *Y* is *rough* with respect to *I*.

2.5. Core and Reduct: Core and reduct are the two central concepts of RST. The subset of attributes which discern all objects discernible by the original IS is called *reduct*. It is denoted by $Red(E)$.The intersection of all reducts is called core. It is denoted by $Core(E)$ and is defined as $Core(E) = \cap Red(E)$. For computation of core and reduct discernibility matrix is used.

Some more definitions based on probabilities (Pawlak, 2002) are as follows:

2.6. Support of the decision rule: The *support* of the decision rule $E \rightarrow_y F$ is the number defined by $supp_y(E,F) = |E(y) \cap F(y)|$ where $E = \{e_1, e_{2, \ldots\ldots,} e_n\}$ is the set of conditional attributes and $F = \{f_1, f_{2}, \ldots\ldots, f_n\}$ is the set of decision attributes.

2.7. Strength of the decision rule: The *strength* of the decision rule $E \rightarrow_y F$ is the number defined by $\sigma_y(E,F) = \frac{supp_y(E,F)}{|U|}$ where $|U|$ is the cardinality of the objects.

2.8. Certainty Factor and Coverage Factor: The *certainty factor* of the decision rule $E \rightarrow_y F$ is defined by $cer_y(E,F) = \frac{supp_y(E,F)}{|E(x)|}$. If $cer_y(E,F) = 1$, then $E \rightarrow_y F$ will be called a c*ertain decision* rule and if $0 < cer_y(E,F) < 1$ the decision rule will be referred to as an *uncertain decision rule*. The *coverage factor* of the decision rule $E \rightarrow_y F$ is defined by $cov_y(E,F) = \frac{supp_{.y}(E,F)}{|F(x)|}$.

3. Information System

The various data was taken from AICRP[1] on Soil Test Crop Response Correlation issued by Indian Institute of Soil Science, Bhopal[2]. The report describes crop wise the recommended dose of fertilizer nutrients (kg ha^{-1}) against the Soil Type, Crop Variety, Target Yield (q ha^{-1}) and Soil Test Values (kg ha^{-1}). In this paper, the study is conducted on the dataset of wheat crop for M.P. and Maharashtra. The various conditions and the fertilizer prescription based on varying soil test values for wheat crop of districts of M.P. are presented in Table 1 and Table 2 respectively.

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[1] All India Coordinated Research Projects (AICRP) are regulated by Indian Council of Agricultural Research. Initially these projects were conducted under Indian Agricultural Research Institute but now these are conducted by various institutes of India.

[2] "Four Decades of STCR Research - Crop Wise Recommendations", available at: http://www.iiss.nic.in/downloads/stcr%20Crop%20wise%20Recommendations.pdf

Table 1: Wheat Crop Specification in some districts of M.P.

Crop:	Wheat
Soil Type:	Shallow, Medium black and Deep black soils
Varieties:	Narmada -4, Kalyan sona, Lok-1, Shera, GW 272
Yield (q ha^{-1}):	30 – 60
Applicability:	Range of soil test values (Kg ha^{-1})**;** N: 100- 500; P: 5- 25 K: 100-500
Districts:	Bhopal, Dhar, Jabalpur, Indore, Khandwa, Khargone, Mandsaur, Narsinghpur, Powarkheda, Rewa, Satna, Sagar, Sehore, Ujjain.

Table 2: Soil Values for Wheat Crop in the mentioned districts of M.P.

Soil test values (kg ha^{-1})			Fertilizer nutrient requirement (kg ha^{-1}) for yield target (q ha^{-1})					
			35			40		
N	P	K	N	P2O5	K2O	N	P2O5	K2O
100	5	200	114	57	136	136	131	69
150	10	250	94	83	49	116	103	61
200	15	300	74	54	41	96	74	53
250	20	350	54	25	33	76	45	45
300	25	400	34	-	25	56	17	37

Equation for calculating the fertilizer nutrient Requirement

$x = 4.40t - 0.40x_1 \qquad y = 4.00t - 4.58y_1 \qquad z = 2.53t - 0.16z_1$

where x = recommended dose of N, y = recommended dose of P_2O_5, z = recommended dose of K_2O, x_1 = soil test value of N, y_1 = soil test value of P_2O_5, z_1 = soil test value of K_2O, t = target yield.

The various conditions and the fertilizer prescription based on varying soil test values for wheat crop of districts of Maharashtra are presented in Table 3 and Table 4 respectively.

Table 3: Wheat Crop Specifications in some districts of Maharashtra

Crop:	Wheat (Rabi)
Variety:	HD-2189
Soil Type:	Vertic Haplustepts
Situation:	Irrigated
Districts:	Ahmednagar, Pune, Jalgaon, Nasik, Aurangabad, Parbhani, Jalna, Akola, Buldhana, Wardha, Yawatmal, Satara, Sangli, Kolhapur, Dhule, Nandurbar.

Table 4: Soil Values for Wheat Crop in the mentioned districts of Mahrashtra

Soil test values (kg ha^{-1})			Fertilizer nutrient requirement (kg ha^{-1}) for yield target (q ha^{-1})					
			40			50		
N	P	K	N	P2O5	K2O	N	P2O5	K2O
100	6	250	237	59	45	303	78	69
120	8	275	222	53	40	288	72	64
140	10	300	207	47	34	273	66	58
160	12	325	193	41	29	259	60	53
180	14	350	178	36	23	244	55	47
200	16	375	163	30	18	229	49	42
220	18	400	149	25*	25*	214	43	36
240	20	425	133	25*	25*	199	37	31
260	22	450	118	25*	25*	185	32	25
280	24	475	103	25*	25*	170	26	20
300	26	500	80	25*	25*	155	20	15

* Minimum dose of P2O5 and K2O

The targeted yield equations for the wheat crop of districts of Maharashtra are given by:

$$p = 7.54t - 0.74p_1 \qquad q = 1.90t - 2.88q_1 \qquad r = 2.49t - 0.22r_1$$

where p = recommended dose of N, q = recommended dose of P_2O_5, r = recommended dose of K_2O, p_1 = soil test value of N, q_1 = soil test value of P_2O_5, r_1 = soil test value of K_2O, t = target yield.

The categorization of N, P, and K defined in (Motiramani & Wankhede, 1964) is defined in Table 5:

Table 5: Categorization of N, P, K

Category	*N(kg ha^{-1})*	*P(kg ha^{-1})*	*K(kg ha^{-1})*
Low	< 272	< 12.4	137
Medium	272– 540	12.4 – 22.4	137 – 337
High	>544	>22.4	>337

4. Computation

The information system consists of four conditional attributes and a decision attribute. The study is conducted on dataset of 32 elements. The different attribute types are mapped into some domain values. The Table 6 depicts the various attributes and their domain values.

Table 6:Attributes and Their Domain Values

Attributes	Attribute Types	Attribute Values
a_1 (Soil Type)	Black Soil	1
	Vertic Haplustepts	2
a_2 (Target Range)	35 q ha^{-1}	1
	40 q ha^{-1}	2
	50 q ha^{-1}	3
a_3 (Crop Variety)	Narmada-4, Lok-1, Kalyan sona, Shera, GW 272	1
	HD-2189	2
a_4 (Soil Test Values N:P:K)	low: low: medium	1
	low: medium: medium	2
	medium: medium: high	3
	medium: high: high	4
	low: medium: high	5
d (Recommended Dose of $N:P_2O_5:K_2O$)	low: high: low	1
	low: low: low	2
	low: medium: low	3
	medium: high: low	4

On the basis of above classification, the data set is depicted in the Table 7. For further calculation equivalence classes based on Ind(B) = $\{a_1, a_2, a_3, a_4, d\}$ are presented in Table8. The lower and upper approximations based on decision attribute values i.e. {1, 2, 3, 4} with boundary region and accuracy are calculated as in Table 9.

Table 7: Information System

Attributes	a_1	a_2	a_3	a_4	d
A_1	1	1	1	1	1
A_2	1	1	1	1	1
A_3	1	1	1	2	1
A_4	1	1	1	3	1
A_5	1	1	1	4	2
A_6	1	2	1	1	1
A_7	1	2	1	1	1
A_8	1	2	1	2	1
A_9	1	2	1	3	1
A_{10}	1	2	1	4	3
A_{11}	2	3	2	1	4
A_{12}	2	3	2	1	4

A_{13}	2	3	2	1	4
A_{14}	2	3	2	1	1
A_{15}	2	3	2	5	1
A_{16}	2	3	2	5	1
A_{17}	2	3	2	5	1
A_{18}	2	3	2	5	1
A_{19}	2	3	2	5	1
A_{20}	2	3	2	4	1
A_{21}	2	3	2	4	1
A_{22}	2	2	2	1	1
A_{23}	2	2	2	1	1
A_{24}	2	2	2	1	1
A_{25}	2	2	2	1	1
A_{26}	2	2	2	5	1
A_{27}	2	2	2	5	1
A_{28}	2	2	2	5	1
A_{29}	2	2	2	5	1
A_{30}	2	2	2	5	1
A_{31}	2	2	2	4	1
A_{32}	2	2	2	4	1

Table 8: Sets Based on Equivalence Class

Objects	a_1	a_2	a_3	a_4	d
$\{A_1, A_2\}$	1	1	1	1	1
$\{A_3\}$	1	1	1	2	1
$\{A_4\}$	1	1	1	3	1
$\{A_5\}$	1	1	1	4	2
$\{A_6, A_7\}$	1	2	1	1	1
$\{A_8\}$	1	2	1	2	1
$\{A_9\}$	1	2	1	3	1
$\{A_{10}\}$	1	2	1	4	3
$\{A_{11}, A_{12}, A_{13}\}$	2	3	2	1	4
$\{A_{14}\}$	2	3	2	1	1
$\{A_{15}, A_{16}, A_{17}, A_{18}, A_{19}\}$	2	3	2	5	1
$\{A_{20}, A_{21}\}$	2	3	2	4	1
$\{A_{22}, A_{23}, A_{24}, A_{25}\}$	2	2	2	1	1
$\{A_{26}, A_{27}, A_{28}, A_{29}, A_{30}\}$	2	2	2	5	1
$\{A_{31}, A_{32}\}$	2	2	2	4	1

Table 9: Classification of Data

Decision Class	Lower Approximation	Upper Approximation	Boundary	Accuracy
d = 1	{A_1, A_2, A_3, A_4, A_6, A_7, A_8, A_9, A_{14}, A_{15}, A_{16}, A_{17}, A_{18}, A_{19},A_{20}, A_{21}, A_{22}, A_{23}, A_{24}, A_{25}, A_{26}, A_{27}, A_{28}, A_{29}, A_{30}, A_{31}, A_{32}}	{ A_1, A_2, A_3, A_4, A_6, A_7, A_8, A_9, A_{11}, A_{12}, A_{13},A_{14}, A_{15}, A_{16}, A_{17}, A_{18}, A_{19},A_{20}, A_{21}, A_{22}, A_{23}, A_{24}, A_{25}, A_{26}, A_{27}, A_{28}, A_{29}, A_{30}, A_{31}, A_{32}}	{A_{11}, A_{12}, A_{13}}	0.9
d = 2	{A_5}	{A_5}	ϕ	1
d = 3	{A_{10}}	{A_{10}}	ϕ	1
d = 4	{A_{11}, A_{12}, A_{13}}	{A_{11}, A_{12}, A_{13},A_{14}}	{A_{14}}	0.75

From the above boundary regions it can be concluded that the equivalence classes {A_{11}, A_{12}, A_{13}} and {A_{14}} cannot be classified as they have different decision despite of having similar conditions. Hence the reduced data set will take the form as in Table 10:

Table 10: Reduced Data set

Objects	a_1	a_2	a_3	a_4	d
{A_1, A_2}	1	1	1	1	1
{A_3}	1	1	1	2	1
{A_4}	1	1	1	3	1
{A_5}	1	1	1	4	2
{A_6, A_7}	1	2	1	1	1
{A_8}	1	2	1	2	1
{A_9}	1	2	1	3	1
{A_{10}}	1	2	1	4	3
{A_{15}, A_{16}, A_{17}, A_{18}, A_{19}}	2	3	2	5	1
{A_{20}, A_{21}}	2	3	2	4	1
{A_{22}, A_{23}, A_{24}, A_{25}}	2	2	2	1	1
{A_{26}, A_{27}, A_{28}, A_{29}, A_{30}}	2	2	2	5	1
{A_{31}, A_{32}}	2	2	2	4	2

To infer decision rules from the data set, reduct and core are needed. For the calculation of reduct and core, discernibility matrix is used. Elementary sets with some specific notations are: $O_1 = \{A_1, A_2\}$, $O_2 = \{A_3\}$, $O_3 = \{A_4\}$, $O_4 = \{A_5\}$, $O_5 = \{A_6, A_7\}$, $O_6 = \{A_8\}$, $O_7 = \{A_9\}$, $O_8 = \{A_{10}\}$, $O_9 = \{A_{15}, A_{16}, A_{17}, A_{18}, A_{19}\}$, $O_{10} = \{A_{20}, A_{21}\}$, $O_{11} = \{A_{22}, A_{23}, A_{24}, A_{25}\}$, $O_{12} = \{A_{26}, A_{27}, A_{28}, A_{29}, A_{30}\}$, $O_{13} = \{A_{31}, A_{32}\}$. Table 11 shows the discernibility matrix for these elementary sets.

Table 11: Discernibility matrix

Objects	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	O_{10}	O_{11}	O_{12}
O_1												
O_2	a_4											
O_3	a_4	a_4										
O_4	a_4	a_4	a_4									
O_5	a_2	a_2, a_3	a_2, a_3	a_2, a_4								
O_6	a_2, a_4	a_2	a_2, a_4	a_2, a_4	a_4							
O_7	a_2, a_4	a_2, a_3	a_2	a_2, a_4	a_4	a_4						
O_8	a_2, a_4	a_2, a_4	a_2, a_4	a_2	a_4	a_4	a_4					
O_9	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4				
O_{10}	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1,a_2, a_3	a_4			
O_{11}	a_1, a_2, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1,a_2	a_1,a_3,a_4	a_1, a_3,a_4	a_1, a_3,a_4	a_2,a_4	a_2, a_4		
O_{12}	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_3,a_4	a_1,a_3,a_4	a_1, a_3,a_4	a_1, a_3,a_4	a_2	a_2, a_4	a_4	
O_{13}	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3, a_4	a_1, a_2, a_3	a_1,a_3, a_4	a_1, a_3,a_4	a_1, a_3,a_4	a_1,a_3	a_2, a_4	a_2	a_4	a_4

Now, for further process the discernibility function of the discernibility matrix (Table 11) is constructed. With the help of absorption law the discernibility function is simplified to get the reducts.

$$a_4 \times a_4 \times a_4 \times a_2 \times (a_2 + a_4) \times (a_2 + a_4) \times (a_2 + a_4) \times (a_1 + a_2 + a_3) \times (a_1 + a_2 + a_3 + a_4) \times$$
$$(a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times a_4 \times a_4 \times$$
$$(a_2 + a_3) a_2 \times (a_2 + a_3) \times (a_2 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 +$$
$$a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times a_4 \times (a_2 + a_3) \times (a_2 + a_4) \times a_2 \times (a_2 +$$
$$a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times$$
$$(a_1 + a_2 + a_3 + a_4) \times (a_2 + a_4) \times (a_2 + a_4) \times (a_2 + a_4) \times a_2 \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2$$
$$+ a_3) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3) \times a_4 \times a_4 \times a_4 \times (a_1 + a_2 +$$
$$a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2) \times (a_1 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times a_4 \times a_4 \times (a_1 +$$
$$a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times a_4$$

$$(a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times$$
$$(a_1 + a_2 + a_3 + a_4) \times (a_1 + a_2 + a_3) \times (a_1 + a_3 + a_4) \times (a_1 + a_3 + a_4) \times (a_1 + a_3) \times a_4 \times (a_2 +$$
$$a_4) \times a_2 \times (a_2 + a_4) \times (a_2 + a_4) \times (a_2 + a_4) \times a_2 \times a_4 \times a_4 \times a_4$$
$$= a_1 a_2 a_4 + a_2 a_3 a_4$$

$\{a_1, a_2, a_4\}$ and $\{a_2, a_3, a_4\}$ are two *Reducts* for the given information table. The core is the set of common attributes among all of the reducts. In this case *Core* will be $\{a_2, a_4\}$. Now with the use of core candidate rules are generated (Table 12).

Table 12: Candidate Rules

Rules	a_2	a_4	d
R_1	1	1	1
R_2	1	2	1
R_3	1	3	1
R_4	1	4	2
R_5	2	1	1
R_6	2	2	1
R_7	2	3	1
R_8	2	4	3
R_9	3	5	1
R_{10}	3	4	1
R_{11}	2	5	1
R_{12}	2	4	1

Following decision rules are drawn from the above described candidate rules:

- If $(a_2,1)\wedge\{(a_4,1)\vee(a_4,2)\vee(a_4,3)\}\rightarrow(d,1)$.
- If $(a_2,1)\wedge(a_4,4)\rightarrow(d,2)$.
- If $(a_2,2)\wedge\{(a_4,1)\vee(a_4,2)\vee(a_4,3)\vee(a_4,5)\}\rightarrow(d,1)$.
- If $(a_2,2)\wedge(a_4,4)\rightarrow\{(d,3)\vee(d,1)\}$.
- If $(a_2,3)\wedge\{(a_4,4)\vee(a_4,5)\}\rightarrow(d,1)$.

The following conclusions are drawn from the above decision rules:

1. The recommended dose of $N:P_2O_5:K_2O$ is low: high: low, if
   - Target yield is 35 q ha^{-1} and soil test value of N:P:K is low: low: medium or low: medium: medium or medium: medium: high.

- Target yield is 40 q ha^{-1} and soil test value of N:P:K is low: low: medium or low: medium: medium or medium: medium: high or medium: high: high or low: medium: high.
- Target yield is 50 q ha^{-1} and soil test value of N:P:K is low: low: medium or medium: high: high or low: medium: high.

2. The recommended dose of $N:P_2O_5:K_2O$ is low: low: low, if
   - Target yield is 35 q ha^{-1} and soil test value of N:P:K is medium: high: high.
3. The recommended dose of $N:P_2O_5:K_2O$ is low: medium: low, if
   - Target yield is 40 q ha^{-1} and soil test value of N:P:K is medium: high: high.

The Table 13 shows the efficiency of rules in terms of support, strength, certainty factor, and coverage factor.

Table 13: Efficiency of Rules

Decision Rules	*Support*	*Strength*	*Certainty*	*Coverage*
R_1	2	0.06	1	0.07
R_2	1	0.03	1	0.04
R_3	1	0.03	1	0.04
R_4	1	0.03	1	1
R_5	6	0.19	1	0.22
R_6	1	0.03	1	0.04
R_7	1	0.03	1	0.04
R_8	1	0.03	0.33	1
R_9	5	0.16	1	0.19
R_{10}	2	0.06	1	0.07
R_{11}	5	0.16	1	0.19
R_{12}	2	0.06	0.67	0.07

Support of a decision rule states the number of elements which follows the corresponding rule. The part of the data set covered by any particular rule is expressed in terms of its Strength. Certainty Factor provides the level of accuracy of decision rule on the basis of conditional attributes. Rule with certainty equals to 1 shows accuracy of 100%. Coverage Factor defines efficiency of the rule under consideration of the decision attribute. It shows the strength of rule with respect to same decision value. The Table 13 shows the efficiency of rules.

From Table 13, it is clear that the maximum number of elements support the rule R_5that defines as a certain rule with highest strength and medium coverage among all the rules. R_2, R_3, R_4, R_6, R_7 are certain rules with minimum support, strength and coverage (except R_4, having greatest coverage). R_8 is an uncertain rule with minimum support, strength and highest coverage. R_1, R_9,

R_{10}, and R_{11} are certain rules with medium support, strength and coverage. R_{12} is an uncertain rule with medium support, strength and coverage.

5. Conclusion

To maintain the better yield of wheat crop, it is necessary to balance the entire growth supporting factor. The basic nutritional requirements of soil for growing crops are Nitrogen (N), Phosphorus (P), and Potassium (K). But these supplements vary for different Soils, Crops, Crop Varieties, Climate, Target Yield, Soil Test Values, and so on. The present study consists of the analysis of recommended dose of N:P:K in terms of N: P_2O_5: K_2O as Phosphorus and Potassium are found in the form of oxides in fertilizers. In this study, Rough Set approach is applied for finding the possibilities to enhance the Soil Fertility on the basis of available growth factors. The generated core is further converted into decision rules. And with these possibilities, the efficiency of every decision rules so generated is presented in terms of Support, Strength, Certainty Factor, and Coverage Factor.

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