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DOI 10.1007/s12046-016-0569-5

Mahalanobis Taguchi system based criteria selection tool for agriculture crops

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MS received 18 January 2016; revised 6 May 2016; accepted 8 June 2016

Abstract. Agriculture crop selection cannot be formulated from one criterion but from multiple criteria. A list of criteria for crop selection was identified through literature survey and agricultural experts. The identified criteria were grouped into seven main criteria namely, soil, water, season, input, support, facilities and threats. In this paper, Mahalanobis Taguchi system based tool was developed for identification of useful set of criteria which is a subset of the original criteria, for taking decision on crop selection in a given agriculture land. The combination of Mahalanobis distance and Taguchi method is used for identification of important criteria. Matlab software was used to develop the tool. After entering the values for each main criteria in the tool, it will process the value and identify the useful sub-criteria under each main criteria for selecting the suitable crop in a given agriculture land. Instead of considering all criteria, one can use these useful set of criteria under each main criteria for taking decision on crop selection in agriculture.

Keywords. Dimension reduction; Mahalanobis distance; measurement scale; orthogonal array; signal-to-noise ratio; agriculture.

1. Introduction

Despite the focus on industrialization, agriculture remains a dominant sector of the Indian economy both in terms of contribution to gross domestic product (GDP) as well as a source of employment to millions across the country. About 65% of Indian population still depend on agriculture for employment and livelihood. India is the first in the World in the production of many agriculture crops such as rice, wheat, sugarcane, groundnut and vegetables [1]. Owing to the ever increasing population, advanced technologies need to be introduced in agriculture crop production. Proper planning and management need to be done to improve agriculture crop yield. Land suitability is primary factor to be considered in agriculture development. Apart from land suitability analysis, a key factor in improving agriculture crops is to develop methods for selecting suitable crop for cultivation in a given land [2]. The crop selection cannot be done with one criterion rather multiple criteria need to be considered. Since all the criteria may not be necessary for taking decision on crop selection, it is mandatory to identify the prime set of criteria which is a subset of the original criteria. In order to identify the prime set of criteria for agriculture crop selection, Mahalanobis Taguchi system (MTS) based tool was developed.

MTS is a multivariate diagnosis method for developing multidimensional measurement scale which is up to date with the recent trends. It uses procedures that are data analytic and are independent of the distribution of the characteristics that define the system [3]. Several experimental designs have been developed to identify prime set of criteria which are complex and difficult to use. MTS is an alternative approach to the experimental design which can be used for dimension reduction [4].

Mahalanobis Taguchi system is a statistical method widely applied for prediction, classification and other decision making problems. MTS has been successfully applied in many applications such as finance, medicine, statistics, and general science in order to improve the performance of the product and process [5]. MTS-based tool was developed to select prime set of criteria for the identification of optimal location in shrimp aquaculture [6]. The principles of Taguchi method were used to screen the important criteria for the identification of a suitable training institution [7]. A multiclass Mahalanobis-Taguchi system (MMTS) was developed for multiclass classification and feature selection. The developed model was validated using health care dataset [8]. MTS was successfully applied to accurately predict the drill-bit breakage which ensures high tool life utilization [9]. A multi-sensor based decision making tool for centrifugal pump failures was developed using MTS. The developed tool was used for fault detection, isolation and prognostics scheme [10]. MTS was

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Published online: 19 November 2016

applied as diagnosis and forecasting tool for vehicle handling and was compared with a standard statistical approach [11].

Mahalanobis Taguchi system was applied to predict the financial crisis in Taiwan's electronic sector [12]. An MTS-based system was developed to predict faults in heavy duty vehicles and for multiclass classification problem [13]. It has been found that MTS can be used to identify useful set of variables from the given dataset in less time and future diagnosis can be done with the useful variables identified [14]. A single decision making tool was developed using MTS to detect, isolate and forecast the faults. The tool used Mahalanobis distance (MD) based fault clustering method for the classification of faults into various categories [10]. A comparative study was adopted to design the questionnaire on audit quality for government procurement agencies and to find reduced questionnaire model with high accuracy using MTS, logistic regression and neural networks [15].

Until now, MTS has not been applied to identify the useful set of criteria for crop selection in agriculture development. In this paper, MTS-based decision tool was developed to identify prime set of criteria for agriculture crop selection.

2. Materials and methods

2.1 *Criteria and sub-criteria*

A list of 27 criteria was identified by reviewing the literature and taking several experts opinion who are all working in agriculture field [2, 5, 16]. The selected criteria are then grouped into seven main criteria, namely, soil (11 sub-criteria), water (2 sub-criteria), season (has no sub-criteria), input (6 sub-criteria), support (2 sub-criteria), facilities (3 sub-criteria) and threats (2 sub-criteria). Out of 27 criteria, 26 were applied to MTS, leaving main criteria season that has no sub-criteria. MTS need not be applied to criteria which has no sub-criteria [4].

2.2 *Study area and datasets*

The required data for this study was collected from various villages such as Kattampoondi, su. Palliyampattu, Veraiyur, Thalayampallam, and Andampallam in Tiruvannamalai block in the state of Tamil Nadu, India. This district lies between the latitude of 12°15′N and the longitude of 79°07′E. This district was selected because agricultural crops such as paddy, ground nut, sugarcane, maize, and pearl millet are major economic crops in these areas. The major crops cultivated in the study area were taken for investigation.

2.3 *Normal and abnormal observations*

The datasets used in this experimental study were collected from 40 randomly selected agriculture sites. The normal group called Mahalanobis space was calculated based on datasets collected from 20 farms which are considered to be suitable and moderate for cultivating the major crops in that area. The abnormal group was calculated based on 20 farms which are considered to be unsuitable to cultivate any crop.

2.4 *Suitability ratings*

The suitability ratings of the criteria for the identified crops in the study area were taken from agriculture soil testing manual and fertilizer recommendation manual for Tiruvannamalai block. The suitability ratings for the identified criteria for agriculture crop selection were taken from different literatures with some modification to suit the experimental land environment based on the opinion of 15 researchers who are working in the agriculture field. The final decision from the group was taken through majority [17].

The sub-criteria under soil main criteria to select a suitable crop for cultivation are electrical conductivity (EC), PH, available N, available P, available K, available Zn, available Cu, available Fe, available Mn, lime status and soil texture. The suitability ratings for these sub-criteria were taken from soil testing manual for the experimental land. There are various soil textures available for crop cultivation. Sandy loam and sandy clay loam are the only two suitable soil textures found in the experimental area. The unsuitable value for texture variable (SO11) is greater than 2, as there are many soil textures (example sandy) which are not suitable for crop cultivation. The sub-criteria under water the main criteria are electrical conductivity (EC) and PH. The suitability value for main criteria season was given with respect to the crops cultivated in various seasons in the experimental land. As the main criteria season does not contain any sub-criteria, prime set of sub-criteria need not be identified for this main criteria. The sub-criteria under input main criteria are nitrogen, urea, P_2O_5, single super phosphate (SSP), K_2O and muriate of potash (MOP). The suitability values for these sub-criteria were taken from fertilizer recommendation manual for the identified crops in the study area. The suitability ratings for the sub-criteria of support and facilities were assigned using various experts' opinion to suit the experimental land. The sub-criteria of threats main-criteria are flood and winter rain. The suitability ratings for threats main-criteria were identified particularly for the study area. The sub-criteria before MTS and final selection of sub-criteria with their suitability ratings and notations for the implementation are given in table 1.

Table 1. Suitability ratings and the notations for the sub-criteria under each main criteria.

S. no.	Sub-criteria before MTS	Suitability ratings: Suitable	Suitability ratings: Unsuitable	Notations	Final selection of sub-criteria
Soil					
1	EC	0.1–3.0	>3	SO1	EC
2	PH (ppt)	0–8.5	>8.5	SO2	PH
3	Available N (kg)	≥42	<42	SO3	Available N
4	Available P (kg)	≥1	<1	SO4	Available P
5	Available K (kg)	≥48	<48	SO5	Available K
6	Available Zn (kg)	1.2–5	<1.2	SO6	Available Zn
7	Available Cu (kg)	1.2–5	<1.2	SO7	Available Cu
8	Available Fe (kg)	8.1–24	<8	SO8	Available Fe
9	Available Mn (kg)	2.01–12	<2	SO9	Available Mn
10	Lime status	1–2 (1, nil; 2 medium)	>2	SO10	Lime status
11	Texture	1–2 (1, sandy loam; 2, sandy clay loam)	>2	SO11	Texture
Water					
12	EC	0.1–2	>2	W1	EC
13	PH	0–8.5	>8.5	W2	PH
14	Season	1–5 (1. Rabi, 2. Kharif, 3. Sornavari, 4. Rabi and Kharif, 5. Rabi, Kharif and Sornavari)	>5	S1	Season
Input					
15	N (kg)	≥0.1	<0.1	IP1	N
16	Urea (kg)	≥0.1	<1	IP2	Urea
17	P_2O_5 (kg)	≥0.1	<1	IP3	P_2O_5
18	SSP (kg)	≥0.1	<1	IP4	SSP
19	K_2O (kg)	≥0.1	<1	IP5	–
20	MOP (kg)	≥0.1	<1	IP6	–
Support					
21	Distance to agriculture extension centres (m)	≤3000	≥5000	SP1	Distance to agriculture extension centres
22	Distance to research centres (m)	≤5000	≥7000	SP2	Distance to research centres
Facilities					
23	Distance to roads (m)	≤2000	≥3000	F1	–
24	Distance to markets (m)	≤1000	≥2000	F2	Distance to markets
25	Distance to seed processing plants (m)	≤3000	≥4000	F3	Distance to seed processing plants
Threats					
26	Flood	0 (0, no flood)	>0 (1, medium; 2, severe)	T1	–
27	Winter rain (mm)	≤200	≥400	T2	Winter rain

2.5 *Mahalanobis-Taguchi system based tool*

In this paper, the identification of prime set of sub-criteria under each main criteria was calculated iteratively using the following steps [3, 18, 19].

Step 1: Construction of measurement scale with Mahalanobis Space (MS) as the reference

The first step in the construction of measurement scale was the collection of normal and abnormal observations. Then the normal observations were normalized by using their mean and standard deviation. The Mahalanobis distances corresponding to these observations were computed using the inverse of the correlation matrix [18]. The formula used for finding the MD is

$$MD_j = \frac{1}{k} Z_{ij}^T C^{-1} Z_{ij} \tag{1}$$

where k is the total number of sub-criteria, Z_{ij} is the normalized matrix explained below, C is the correlation matrix for normalized data and C^{-1} is the inverse of correlation matrix. i is the number of sub-criteria and j is the number of alternatives.

The detailed steps to calculate normalized matrix Z_{ij} and its transpose are given below:

1. Calculate the mean $\overline{x_i}$ for each sub-criteria under each alternative in the normal observation using the formula

$$\overline{x_i} = \frac{\sum_{j=1}^{n} X_{ij}}{n} \quad (2)$$

where X_{ij} is the value of ith sub-criteria in jth alternative, n is the number of alternatives.

2. Calculate the standard deviation S_i for each sub-criteria under each alternative for the normal observation using the formula

$$S_i = \sqrt{\frac{\sum_{j=1}^{n} \left(X_{ij} - \overline{x_i}\right)^2}{n-1}}. \quad (3)$$

3. Normalize the observation values to calculate the normalized matrix Z_{ij} using the formula given below and find the transpose of Z which is Z_{ij}^T.

$$Z_{ij} = \frac{(X_{ij} - \overline{x_i})}{S_i}. \quad (4)$$

Thus calculated MDs were used to define the normal group. This group is called as Mahalanobis space [19]. We found that the average MD value calculated for each main criteria in the normal observation was close to the theory of Mahalanobis Taguchi strategy (i.e. 1) [18].

Step 2: Validation of measurement scale

The validation of measurement scale was done by calculating the MDs of abnormal observations. The abnormal observations were normalized using the mean and standard deviation calculated from normal observations. The MDs of abnormal observations were calculated using the correlation matrix of normal observations obtained in previous step using Eq. (1). If the MDs of the abnormal observations are higher, then the measurement scale is said to be good. Here the MDs of the abnormal observation were higher than the MDs of the normal observations. Hence the measurement scale was validated.

Step 3: Identification of prime set of sub-criteria

The prime set of sub-criteria which is subset of given sub-criteria under each main criteria was identified by using orthogonal arrays (OA) and signal-to-noise ratios (S/N ratio). An orthogonal array is a table that actually gives the combination of criteria, which allows us to test the outcome of the presence or absence of a criteria. The orthogonal arrays are used so that the interactions between the factors are evenly distributed to other columns of the OAs and confounded to various main effects [20]. Orthogonal array and S/N ratios are used to reduce the number of variables without reducing the system performance in multivariate systems [10].

The size of the orthogonal array is determined by the number of criteria and the levels. The suitable OA was selected based on the total degrees of freedom required for the individual sub-criteria. The number of degrees of freedom is always one less than the number of levels [21]. Each row in orthogonal array represents the experimental run.

OAs are used to minimize the number of variable combinations by allocating the variables to the columns of the array. Two level arrays are used in which the presence and the absence of the variables are considered at the levels. In OA, level 1 in the column represents the presence of a sub-criteria and level 2 represents the absence of that sub-criteria [19]. For example, there are 11 sub-criteria under soil main criteria. Therefore OA selected for soil main criteria is $L_{12}(2^{11})$, 12 is the number of experimental runs and 11 denotes the sub-criteria. Thus orthogonal arrays used for the main criteria are $L_{12}(2^{11})$ for soil, $L_4(2^3)$ for water, support, facilities and threats, $L_8(2^7)$ for input. The orthogonal arrays for the main criteria are shown in tables 2, 3, and 4. For the experimental combination run in OA, MDs for the abnormal observations were calculated using Eq. (1).

After obtaining the MDs of the abnormal observations corresponding to the various combinations of OA, S/N ratios are computed for all these combinations to find the useful set of variables. S/N ratios are important to improve the accuracy of the measurement scale and reduce the cost of diagnosis [19].

Two S/N ratios are calculated for each criteria using the formula given below:

$$S/_N \,\text{ratio} = -10\log_{10}\left[\left(\frac{1}{t}\right)\sum_{i=1}^{t}\frac{1}{MD_i^2}\right] \quad (5)$$

where t is the number of sub-criteria present in the given combination of experimental run.

One S/N ratio is used to represent the average S/N ratio from the experimental runs when the criteria is included and another S/N ratio represents the average S/N ratio from the experimental runs when the criteria is excluded. Thus S/N ratios are used to compare the effectiveness of including and excluding a criteria. Gain is calculated as difference between the average S/N ratio when the criteria is included and when the criteria is excluded using the formula given below:

$$\text{Gain} = (\text{average of S/N ratio})_{\text{level 1}} - (\text{average of S/N ratio})_{\text{level 2}} \quad (6)$$

Therefore when the gain is positive for a criteria that criteria is considered as useful and if the gain is negative, the criteria can be excluded [22].

The 22 prime set of sub-criteria identified in this step are electrical conductivity (EC), PH, available N, available P, available K, available Zn, available Cu, available Fe, available Mn, lime status and soil texture under soil main criteria (11); electrical conductivity (EC) and PH under water main criteria (2); nitrogen, urea, P_2O_5, and single super phosphate (SSP), under input main criteria (4);

Table 2. $L_{12}(2^{11})$ orthogonal array and average S/N ratio for soil main criteria.

Run	1 (SO1)	2 (SO2)	3 (SO3)	4 (SO4)	5 (SO5)	6 (SO6)	7 (SO7)	8 (SO8)	9 (SO9)	10 (SO10)	11 (SO11)
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1
Level 1	33.29	32.74	31.80	33.01	31.68	32.62	31.43	31.88	31.73	31.61	32.06
Level 2	29.89	30.45	31.39	30.18	31.50	30.57	31.76	31.31	31.46	31.58	31.13
Gain	3.40	2.29	0.41	2.83	0.18	2.05	−0.32	0.57	0.27	0.04	0.93

Table 3. $L_8(2^7)$ orthogonal array and average S/N ratio for input main criteria.

Run	1 (IP1)	2 (IP2)	3 (IP3)	4 (IP4)	5 (IP5)	6 (IP6)	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2
Level 1	40.07	39.01	55.97	42.80	35.98	34.61	
Level 2	35.38	36.44	19.48	32.65	39.47	40.84	
Gain	4.70	2.56	36.50	10.14	−3.50	−6.24	

distance to agriculture extension centres and distance to research centres under support main criteria (2); distance to markets and distance to seed processing plants under facilities main criteria (2); and winter rain under threats main criteria (1).

The confirmation run is the next step to validate the results that we get in previous step, i.e. to validate the prime set of sub-criteria identified using OA and S/N ratio.

Step 4: Confirmation run

A confirmation run was conducted on the prime set of sub-criteria selected in the previous step. The average MD of abnormal group with prime set of sub-criteria and the average MD of abnormal group with all sub-criteria were calculated. If the average MD with prime set of sub-criteria was greater than the average MD with all sub-criteria, then remove the sub-criteria with negative gain identified in the previous step. Otherwise retain the sub-criteria and include it to the prime set of sub-criteria for agriculture crop selection.

3. Results and discussions

The experiment was conducted by collecting 20 normal observations and 20 abnormal observations from the study area. Twenty normal observations were used for constructing the original measurement scale. Twenty abnormal observations were used for validation purpose. The abnormal observations were normalized using the mean and standard deviation obtained from the normal observation. The MDs were calculated for the abnormal observations using the correlation matrix of the normal group. Since the average MD of the abnormal observation is higher than the average MD of normal observation, the measurement scale constructed was good. For example average MD of abnormal observation and normal observation is shown for soil main criteria in figure 1.

Identification of prime set of sub-criteria was done using orthogonal array and S/N ratio. The orthogonal arrays used for the main criteria are $L_{12}(2^{11})$ for soil, $L_4(2^3)$ for water,

Table 4. $L_4(2^3)$ orthogonal array and average S/N ratio for water, facilities, support and threats main criteria.

Run	1	2	3
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1
Water	W1	W2	
Level 1	20.30	21.03	
Level 2	20.09	18.63	
Gain	0.21	2.40	
Facilities	F1	F2	F3
Level 1	30.91	36.55	35.93
Level 2	31.46	25.82	26.44
Gain	−0.55	10.73	9.50
Support	SP1	SP2	
Level 1	37.81	26.92	
Level 2	15.55	37.33	
Gain	22.26	−10.41	
Threats	T1	T2	
Level 1	17.59	25.99	
Level 2	27.33	10.52	
Gain	−9.75	15.47	

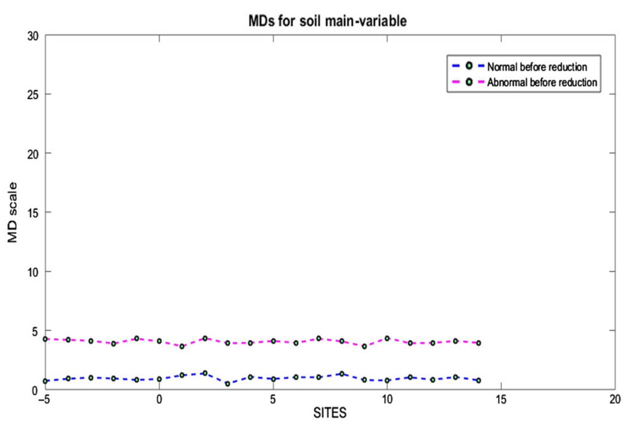

Figure 1. MDs of normal and abnormal observation for soil main criteria.

support, facilities and threats, $L_8(2^7)$ for input shown in tables 2, 3 and 4. There are 11 sub-criteria under soil main criteria. Therefore OA selected for soil main criteria is $L_{12}(2^{11})$, 12 is the number of experimental runs and 11 denotes the sub-criteria. There are six sub-criteria under input main criteria. Therefore OA selected for soil main criteria is $L_8(2^7)$, eight is number of experimental runs and seven denotes the number of columns. The six sub-criteria were allocated to the first six columns of this array. There

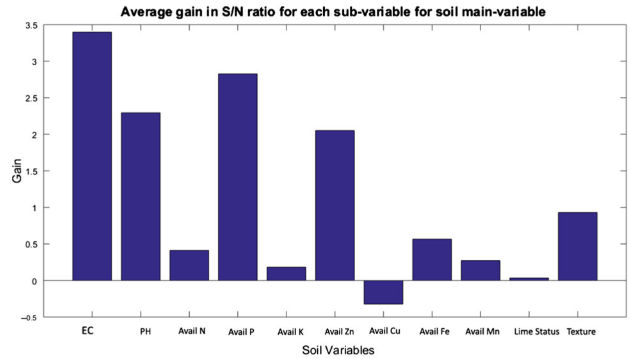

Figure 2. Average S/N ratio and gain for soil main criteria.

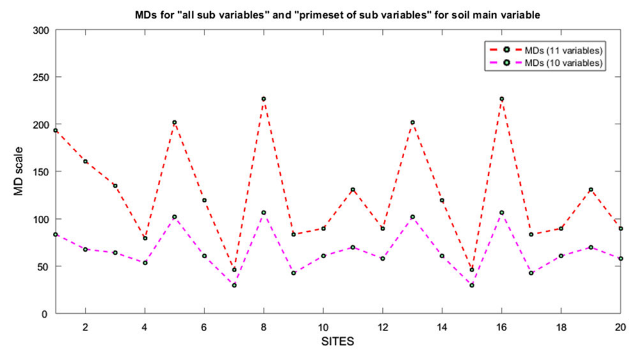

Figure 3. MDs of all sub-criteria and reduced sub-criteria for soil main criteria.

are two sub-criteria under water, support, threats main criteria and three sub-criteria under facilities main criteria. Therefore OA selected for all these main criteria is $L_4(2^3)$, four denotes the number of experimental runs and three denotes the number of columns. The two sub-criteria were allocated to the first two columns of this array for water, support and threats main criteria. And three sub-criteria were allocated to the first three columns of this array for facilities main criteria.

The results of average S/N ratio and gain for each main criteria is shown in tables 2–4. In these tables, level 1 indicates inclusion of the sub-criteria and level 2 represents exclusion of the sub-criteria. Average S/N ratio was calculated for each sub-criteria under main criteria at level 1 and level 2. Then gain was calculated by subtracting the S/N ratio at level 2 from S/N ratio at level 1. The sub-criteria which have positive gain can be retained and the sub-criteria with negative gain can be excluded. And the confirmation run can be conducted on the prime set of sub-criteria. In table 3, for soil main criteria, it has been identified that the sub-criteria SO1, SO2, SO3, SO4, SO5, SO6, SO8, SO9, SO10 and SO11 have positive gains. Hence these sub-criteria were found to be useful and SO7 sub-criteria can be reduced. Figure 2 shows the average S/N ratio and gain for soil main criteria with sub-criteria SO7 with negative gain.

Table 5. MDs of normal and abnormal group for each main criteria.

MDs	Soil	Water	Input	Support	Facilities	Threats
Normal						
Range	0.5–1.36	0.18–2.98	0.3–2.81	0.16–2.23	0.21–2.85	0.38–1.72
Average	0.95	0.96	0.95	0.95	0.97	0.95
Abnormal (all)						
Range	46.21–226.44	13.61–23.33	6.6–6.73	21.12–219.49	2.00–2.32	4.02–6.69
Average	127.31	16.87	6.65	146.97	2.11	5.15
Abnormal (reduced)						
Average	66.5	16.87	**7.46**	112.35	**13.48**	**9.53**

The average MD values of reduced sub-criteria identified is greater than the average MD values of abnormal group with all criteria is highlighted in bold.

Tables 2, 3 and 4 have sub-criteria with negative gain. In table 2, sub-criteria SO7 has negative gain. In table 3, sub-criteria IP5 and IP6 have negative gain and in table 4, sub criteria F1, SP2, and T1 have negative gain. Confirmation run was conducted for the prime set of sub-criteria identified.

In confirmation run step, MDs of abnormal observations with all sub-criteria and MDs of abnormal observations with reduced set of sub-criteria were calculated. Figure 3 shows the MDs of abnormal observations for all sub-criteria and reduced set of sub-criteria in soil main criteria. Average MD of abnormal group for all sub-criteria and prime set of sub-criteria is given in table 5. The average MD values of normal observation for all main criteria are found to be close to 1 according to MTS theory (table 5). From table 5, it has been identified that the main criteria input, facilities and threats have higher average MD of abnormal group with reduced sub-criteria greater than the average MD of abnormal group with all sub-criteria. Hence the sub-criteria with negative gain in the main criteria input (IP5, IP6), facilities (F1) and threats (T1) can be reduced. The sub-criteria which are reduced after applying MTS is given in table 1. Out of 26 criteria, four sub-criteria were reduced using MTS based tool. The 22 prime set of sub-criteria selected by the developed tool can be used for Agriculture crop selection.

4. Conclusion

The Mahalanobis Taguchi based decision tool was developed using MATLAB software. As agriculture crop selection cannot be done using single criteria, 27 criteria were selected initially for making decision and 26 were applied to MTS (criteria season has no sub-criteria). During the first phase of MTS based decision tool, six sub-criteria were found to have negative gain. In confirmation run, since main criteria input, facilities and threats have higher average MD of abnormal group with reduced sub-criteria greater than the average MD of abnormal group with all sub-criteria, four sub-criteria under these main criteria can be reduced. Finally 22 prime set of sub-criteria out of 26 sub-criteria were identified for agriculture crop selection using MTS based decision tool. The prime set of criteria selected using this tool was validated by agriculture experts working in the field. The developed MATLAB program can be used to find useful criteria for any problem by providing sufficient input. Irrelevant and redundant data can be removed using the developed tool using orthogonal arrays and signal-to-noise ratios. Researchers can identify useful criteria using this generic tool in the preliminary step of their research.

Acknowledgements

This work forms part of the R&D activities of TIFAC-CORE in Automotive Infotronics located at VIT University, Vellore. The authors would like to thank DST, Government of India for providing necessary hardware and software support for completing this work successfully.

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