Naseer Ahmad[1,2], Shahid Kamal[1], Zulfiqar Ali Raza[2,*], Muhammad Zeshan[2], Sharjeel Abid[3], Zafar Javed[4], Mehmet Karahan[5,]**

Comparative Analysis of the Performances of Six Taguchi-Based Multi-Response Optimisation Techniques for Product Development in Textiles

DOI: 10.5604/01.3001.0014.9312

[1] **University of the Punjab, College of Statistical and Actuarial Sciences,** Lahore, Pakistan

[2] **National Textile University, Department of Applied Sciences,** Faisalabad-37610, Pakistan,
* e-mail: zarazapk@yahoo.com

[3] **National Textile University, School of Engineering and Technology, Department of Textile Engineering,** Faisalabad-37610, Pakistan

[4] **National Textile University, School of Arts & Design,** Faisalabad, Pakistan

[5] **Bursa Uludağ University, Vocational School of Technical Sciences,** Görükle-Bursa, Turkey,
** e-mail: mkarahan@uludag.edu.tr

Abstract
Researchers are using different statistical techniques for process optimisation and product development both in academia and industries. Similarly, several statistical tools are being employed in the textile industry for process optimisation during the manufacturing of different products. The purpose of this study was to analyse different Taguchi-based techniques in the multi-response optimisation of selected industrial processes and then to generalise the outcomes. Herein, six different Taguchi-based multi-response optimisation techniques, including grey relational analysis (GRA), the weighted signal-to-noise (WSN) ratio, principal component analysis, VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), the multiple response signal-to-noise ratio, and Fuzzy logic were compared against three data sets of industrial processes. The researchers herein optimised cotton dyeing, the finishing of textile to make them oleo-hydrophobic, and the production of rhamnolipids (bio-surfactants). The results demonstrated that the Fuzzy logic-based Taguchi method gave the best optimisation amongst all the other approaches, followed by GRA and WSN for all the selected processes. The said statistical techniques were applied to specific textile and biotechnological processes. The outcomes of this study can help researchers in practical implementation in industrial sectors. In this study, a comparative analysis of the performances of six Taguchi-based multi-response optimisation techniques was conducted for potential industrial processes, particularly textile processing .

Key words: *Fuzzy logic, grey relational analysis, optimisation, Taguchi method, textile.*

Introduction

In the manufacturing sector, variability of the process is the main hurdle in achieving the desired quality of products. Different researchers have developed various statistical techniques not only for improving the quality of products but also for reducing defect percentage in the final products through process optimisation and the reduction of variability in the process. For instance, Taguchi methodology changed the direction of quality engineering by introducing the concept of loss function, system parameters, and the tolerance design approach to achieve a robust (insensitive-to-noise factors) process [1]. The orthogonal array (OA) and signal-to-noise (SN) ratios are the key tools in Taguchi methodology [2] which requires a number of combinations of experiments that are time, cost and labor intensive. The Taguchi method of design of experiments is a simple statistical tool involving a system of tabulated designs (arrays. Here, the SN ratio is the ratio of sensitivity to variability and is used to examine the effect of control parameters on the product yield and process efficiency. Conceptually, the SN is used in terms of the magnitude of voice in the communications industry and is expressed in decibels (dB) [3].

Taguchi methodology has proved its effectiveness in improving the off-line quality of processes and products in the industry. However, by this methodology, the setting of process parameters can be optimised concerning a single quality characteristic of the process of a product, whereas researchers are usually required to find out the optimal settings of process parameters of multiple responses at the same time [4]. For this purpose, the Taguchi method was coupled with other multi-response approaches to analyse and optimise such problems that involve more than one response. In the recent era, researchers have developed multi-response optimisation techniques based on the SN ratios for the optimal settings of process parameters. The effectiveness of all these approaches for multi-response optimisation has been verified [5]. The people working in academia and industry are trying to figure out which approach is the most suitable for reducing variation and improving the quality of products. In this study, a performance-based comparative analysis of six multi-response optimisation techniques: grey relational analysis (GRA), the weighted signal-to-noise (WSN) ratio, PCA, VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), the multiple response signal-to-noise (MRSN) ratio, and Fuzzy logic were performed.

For this purpose, three sets of experimental data containing multiple responses were taken and the process parameter settings of each data set were evaluated using the six multi-response optimization techniques mentioned above. Multi-response optimisation methodologies, especially the GRA [6], PCA [7], AHP (Analytic Hierarchy Process) [8] manułfacturing firms require to meet demand, increase quality, and decrease cost due to continuous changes in the market. Because of the importance of flexible manufacturing system, the optimum operator allocation problem in cellular manufacturing systems (CMSs, WSN [9] some of which are correlated. For example, material removal rate and tool wear rate are highly correlated). Although in the recent past several methods have been proposed in the literature to resolve the multi-response optimization problems, only a few of them take care of the possible correlation between the responses.

Ahmad N, Kamal S, Raza ZA, Zeshan M, Abid S, Javed Z, Karahan M. Comparative Analysis of the Performances of Six Taguchi-Based Multi-Response Optimisation Techniques for Product Development in Textiles. *FIBRES & TEXTILES in Eastern Europe* 2021; 29, 5(149): 100-108. **DOI:** 10.5604/01.3001.0014.9312

All these methods primarily make use of principal component analysis (PCA, ANN (Artificial Neural Networks) [10], Fuzzy logic [11], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [12], and DEA (Data Envelopt ment Analysis) [13] can be coupled with Taguchi methodology to solve complex multi-attribute optimisation problems. Deng recommended the GRA method coupled with the Taguchi method for assessing the performance of complex problems involving multiple responses by introducing a grey relational grade based on the SN ratios of each response [6]. A group of researchers [14] compared four quantitative methods for the simultaneous optimization of multiple responses using the concept of distance metric. Another group studied the performance of four Taguchi-based techniques: GRA, MRSN, WSN, and VIKOR, and reported the WSN ratio method to be the best one [15] researchers have attempted several systematic procedures for optimising the multiple responses of WEDM processes. However, most of these approaches use complex statistical/mathematical tools and are, therefore, impractical for application by the engineers who may not have a strong background in mathematics. Only a few methods, e.g., grey relational analysis and multiple response signal-to-noise ratio approaches use relatively simpler computational procedures. On the other hand, the computational procedures for the weighted signal-to-noise (WSN). Gauri and Pal [16] this method has been developed to optimize single-response processes. But, in many situations, the engineers are required to determine the process settings that can simultaneously optimize multiple responses. In the recent past, researchers have proposed several systematic procedures for multi-response optimization. Most of these methods use complicated statistical/mathematical models and are, therefore, not easily comprehendible to the engineers who do not have a strong background in mathematics. Only a few methods, e.g. weighted signal-to-noise (WSN) performed a result-based comparison of five Taguchi-based multi-response optimisation techniques, including PCA; in that study, they also recommended WSN as the leading one performance-wise. In this study, six Taguchi-based methodologies were used and a comparison made based on their performances. From an engineering perspective, it is very important to know which methodology is appropriate and efficient amongst several available approaches in determining optimum process parameters.

Materials and methods

GRA, WSN, PCA, VIKOR, MRSN, and Fuzzy logic methodologies

The Taguchi method is a practical approach in statistics for solving quality problems in various disciplines of engineering and sciences. In this method, desirable variables are converted into corresponding SN ratios. SN ratios are generally classified as nominal-the-better, lower-the better, and higher-the better.

For nominal-the-better,

$$\eta_{ij} = -10log_{10}(\bar{y} - T)^2 + S^2 \quad (1)$$

For higher-the-better,

$$\eta_{ij} = -10\log_{10}\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_{ijk}^2} \quad (2)$$

For lower-the-better,

$$\eta_{ij} = -10log_{10}\frac{1}{n}\sum_{i=1}^{n}y_{ijk}^2 \quad (3)$$

Where, $\bar{y} = \sum_{k=1}^{n} y_{ijk}$, $S^2 = \frac{1}{n-1}\sum_{k=1}^{n}\left(y_{ijk} - \bar{y}\right)^2$; n is the number of runs, η_{ij} the SN ratio of the jth response and ith trial, and *yijk* the observed value of the ith experimental run, jth response, and kth repetition. The unit of SN is dB, and T is the targeted value. The SN ratios are normalised (scaled) into the range of 0 to 1 to reduce any variability, distribute the data evenly, and avoid the effect of different units used in the responses. The normalised equations of SN ratios as nominal-the-better (***Equation (4)***), higher-the-better (***Equation (5)***), and lower-the-better (***Equation (6)***), respectively, are given below.

The quality loss function values of SN ratio values of desirable responses are converted into normal SN ratios scaled into a (0, 1) interval before further analysis so that the variability among the different responses may be reduced.

The following three steps are generic for all selected six methodologies to achieve the objective of optimisation:

Step 1: Transform multiple responses into a single response, named as the multi-response performance index (MRPI), using the respective procedure of each approach for optimisation.

Step 2: Convert MRPIs to a factor level table to determine the optimum level of each factor.

Step 3: Predict the SN ratio value for each response under the optimal conditions from step 2.

All six methodologies vary concerning the first step in determining the MRPIs by employing the different methodologies.

Experimental methodologies for the conversion of multiple responses into a single performance index

The six methodologies, i.e., GRA, WSN, PCA, VIKOR, MRSN, and Fuzzy logic mainly vary concerning the first step in converting the multiple responses into single performance indices (MRPIs). The procedures adopted in the GRA, WSN, PCA, VIKOR and MRSN methodologies are thoroughly described by Krishnainah and Shahabudeen [17]. Taguchi-based fuzzy logic optimisation methodology is described by Pandey and Dubey in their study [11]. Corresponding to the different levels of process parameters, the average MRPI is calculated; the highest average value of MRPI of the level implies the optimum level for that factor. The value of MRPI lies between 0 and 1, wherein close to 0 means less critical quality.

Analysis of variance

The analysis of variance (ANOVA) method is a well-known series of statistical methods developed by Fisher [18] and is used to identify influential process parameters in the development of a model. In this study, ANOVA was carried out

$$Z_{ij} = \frac{|\eta_{ij}-T| - \left(|\eta_{ij}-T|^{min},\ i=1,2,\cdots,n\right)}{\left(|\eta_{ij}-T|^{max},\ i=1,2,\cdots,n\right) - \left(|\eta_{ij}-T|^{min},\ i=1,2,\cdots,n\right)} \quad (4)$$

$$Z_{ij} = \frac{\eta_{ij} - \left(\eta_{ij}^{min},\ i=1,2,\cdots,n\right)}{\left(\eta_{ij}^{max}, i=1,2,\cdots,n\right) - \left(\eta_{ij}^{min}, i=1,2,\cdots,n\right)} \quad (5)$$

$$Z_{ij} = \frac{\left(\eta_{ij}^{max},\ i=1,2,\cdots,n\right) - \eta_{ij}}{\left(\eta_{ij}^{max},\ i=1,2,\cdots,n\right) - \left(\eta_{ij}^{min},\ i=1,2,\cdots,n\right)} \quad (6)$$

Equations (4)-(6).

Table 1. SN ratios and normalised SN ratios for data set 1.

	Factors			SN ratio							Normalised SN ratio						
Run	A	B	C	WCA	OCA	AP	CRA	Stiff-ness	Tear strength	Tensile strength	WCA	OCA	AP	CRA	Stiff-ness	Tear strength	Tensile strength
1	1	1	1	40.880	37.600	49.550	44.700	-11.510	64.740	59.730	0.014	0.058	0.780	0.187	0.010	0.874	0.445
2	1	2	2	40.860	39.210	49.950	45.330	-11.580	64.480	59.700	0.000	0.666	0.887	0.871	0.161	0.779	0.423
3	1	3	3	41.270	38.550	49.520	45.440	-11.600	62.310	59.123	0.368	0.418	0.774	0.986	0.220	0.000	0.000
4	2	1	2	41.740	39.390	49.760	45.020	-11.540	64.900	59.770	0.798	0.735	0.836	0.538	0.075	0.932	0.475
5	2	2	3	41.680	37.440	50.290	45.160	-11.510	63.860	59.763	0.742	0.000	0.974	0.681	0.009	0.556	0.468
6	2	3	1	41.070	39.360	49.700	44.520	-11.680	64.620	60.490	0.187	0.723	0.819	0.000	0.402	0.831	1.000
7	3	1	3	41.340	39.720	46.570	44.890	-11.510	64.170	60.130	0.435	0.859	0.000	0.398	0.000	0.668	0.734
8	3	2	1	41.370	40.090	50.390	44.520	-11.920	65.090	59.850	0.458	1.000	1.000	0.004	1.000	1.000	0.534
9	3	3	2	41.960	39.730	50.180	45.450	-11.870	63.850	59.460	1.000	0.862	0.947	1.000	0.865	0.553	0.243

Table 2. Various MRPIs for data set 1.

	Multi-response performance index (MRPI)					
	GRA	WSN	PCA	VIKOR	MRSN	FMPI
1	0.6320	0.3384	-0.1779	0.9790	4.7057	0.688
2	0.7187	0.5411	-0.1572	0.7713	2.6673	0.498
3	0.6583	0.3951	0.1244	0.9360	4.0328	0.501
4	0.7540	0.6272	-0.3977	0.5190	2.0260	0.895
5	0.6965	0.4901	-0.1051	0.8288	3.0970	0.497
6	0.7375	0.5659	-0.4847	0.7432	2.4724	0.511
7	0.4420	0.6686	3.5458	0.8831	-0.5215	0.500
8	0.7136	0.8330	1.4655	0.5691	-0.3883	0.751
9	0.7815	0.8529	1.0710	0.0000	-0.1186	0.748

for MRPIs computed from the six methods to identify the significant factors for which the p-value was less than the level of significance; 5% in our study, and these factors might be considered as significant factors.

Validation test of the selected influencing factor – a level combination

The validation of selected influencing factors lies in the prediction of SN ratios under optimal conditions computed from each method.

Application of finish on dyed samples

Some oleo-hydrophobic finishing experiments were conducted on dyed cotton fabric to track any shade changes after application of the finish. For that purpose, the dyeing of bleached cotton fabric was performed using the isothermal exhaust method. The ready-for-dyeing fabric was dyed with Remazol Red B (Molecular mass 560.74 g/mol) at 2% shade with 60 g/l of common salt (NaCl, an exhaustion agent) and 20 g/l of sodium carbonate (fixing agent) in a lab-scale dyeing machine with a materials-to-goods ratio of 1:20 using the isothermal dyeing method at 60 °C for 1 h. Finally, the dyed sample was removed and washed in cold and then hot water to remove any residual auxiliaries and unfixed dyes, and subsequently dried at room temperature. In the second step, the dyed fabric underwent oleo-hydrophobic finishing considering three input variables, *viz*. A: concentrations of the finish (Oleophobol CP-C®), B: concentration of cross-linking agent (Knittex FEL®), and C: curing temperature. The finishing process of the dyed cotton fabrics was performed under optimised Taguchi based on WSN ($A_3B_2C_2$) and FMPI ($A_3B_1C_2$). The responses included the water contact angle (WCA), oil contact angle (OCA), air permeability (AP), crease recovery angle (CRA), stiffness, and tear and tensile strengths of the finished dyed fabric.

Measurement of colour coordinates

A spectrophotometer (7000A, ColorEye, USA) was used to determine the CIELab (international commission on illumination) values using dCIELab.D55-10 software to observe any changes in the shade after the application of the finish. Minimum or no change of shade is one of the unavoidable requirements after finishing as compared to the unfinished dyed sample.

Results and Discussion

For the performance-based comparison of the six methods i.e. GRA, WSA, PCA, VIKOR, MRSN, and Fuzzy logic, the above-mentioned three sets of experimental data were analysed.

Weighting scheme

In the computation of MRPIs of the GRA, WSN, VIKORE, and MRSN methods, it is required to assign a weight to each response at some stage of analysis. In this study, all the responses were weighted equally. Whereas in the PCA method the weights were applied using eigenvalues.

For the computation of MRPIs of the GRA, WSN, VIKOR methods, in the first step, SN and normalised SN ratios of each response are evaluated by using ***Equations (1)-(6)*** which are shown in ***Table 1***. For the calculation of MRPIs of PCA, the procedure is carried out for normalised SN ratios of the responses using the standard method, described in our early study [19]. The PCA results, including principal components corresponding to each trial, eigenvalues of each component, the proportion of variation explained by each component, and the eigenvector corresponding to each eigenvalue of normalised SN ratios of Ahmad et al.'s data were computed [20]. From this analysis, three principal components of this data set had an eigenvalue more significant than one, and thus taken for further analysis. Further, ***Table 2*** shows the MRPIs for Ahmad et al.'s data [20], whereas the Fuzzy logic MRPIs were computed using the standard method, given in the experimental section. All MRPIs of the six approaches are given in ***Table 2***.

Figure 1.a graphically shows input linguistic variables with seven membership values of Fuzzy rules, and ***Figure 1.b*** represents the membership function for linguistic variables for Ahmad et al.'s experimental data [20]. Membership plots for the input and output variables using the triangular membership functions of Ahmad et al.'s experimental data [20] and a typical plot are shown in ***Figure 1.b***.

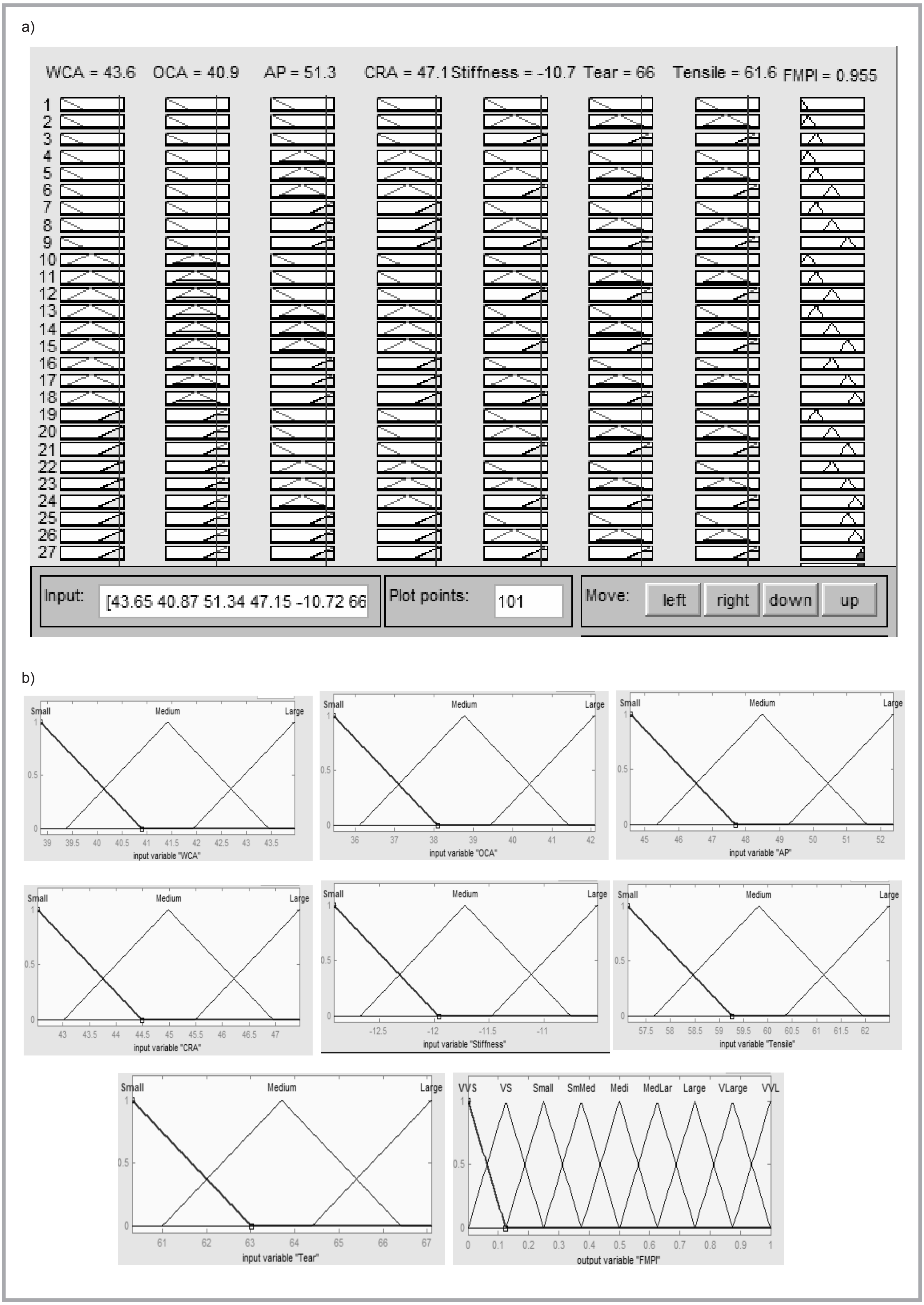

Figure 1. a) Rule viewer of data set, b) membership function plot of input and output variables for data set 1.

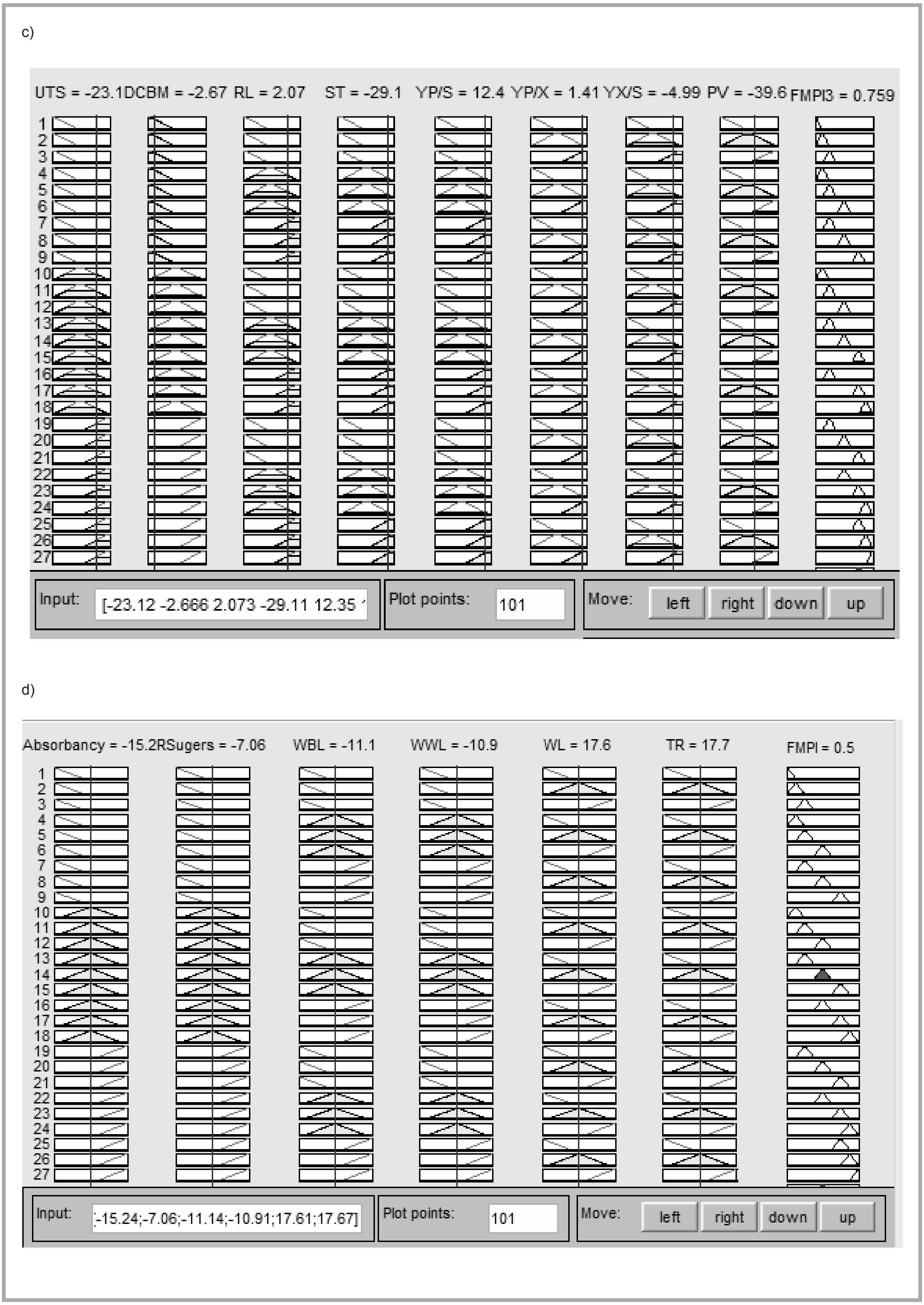

Figure 1. *c) rule viewer of data set 2, d) rule viewer of data set 3.*

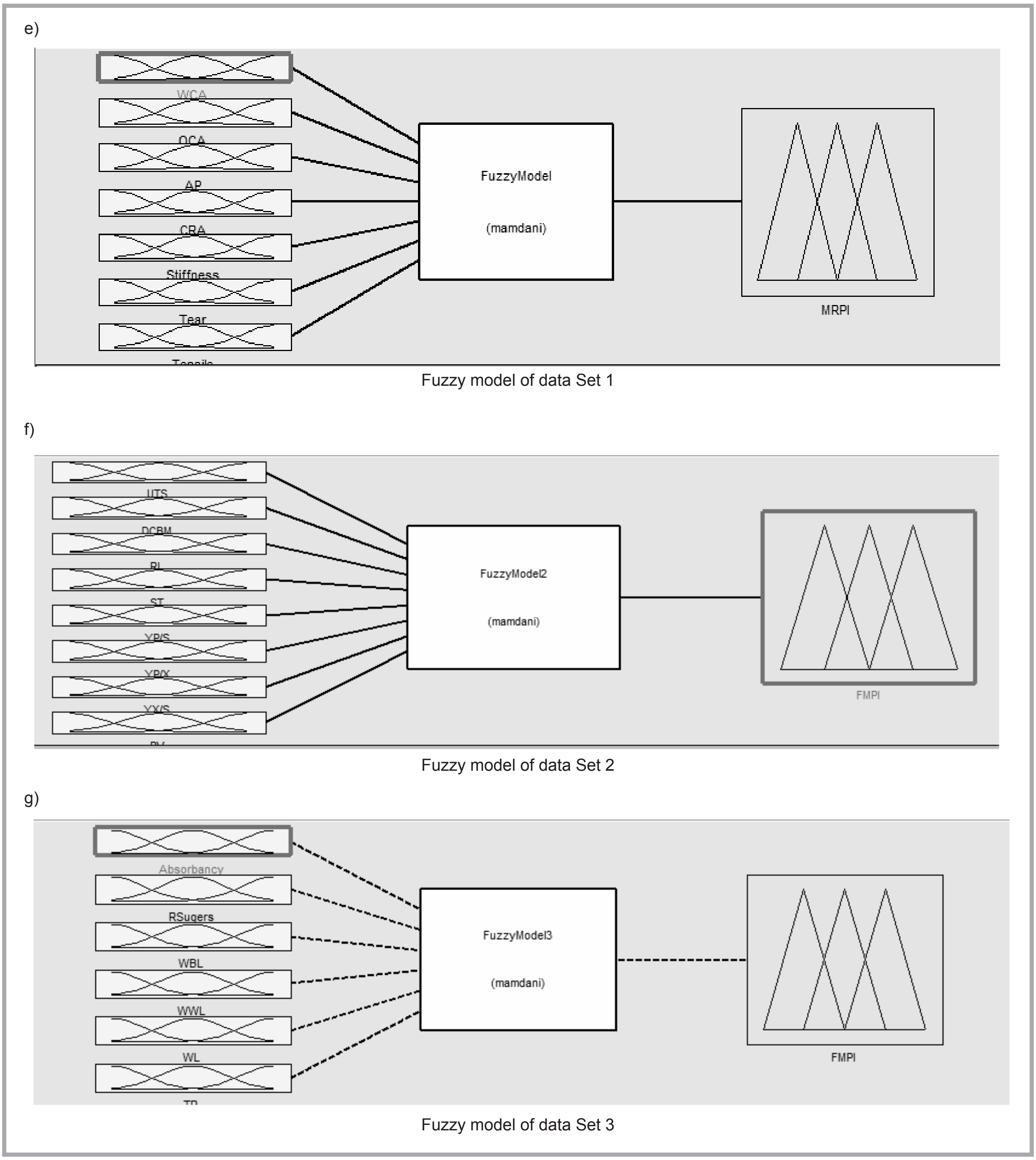

Figure 1. *e) block diagram of Fuzzy model for FMPI of data set 1, f) block diagram of Fuzzy model for FMPI of data set 2, and g) block diagram of Fuzzy model for FMPI of data set 3.*

Table 3. *Summary results of ANOVA for WSN, GRA, MRSN, VIKOR, and PCA for data set 1.*

Factor	GRA		WSN		PCA		VIKOR		MRSN		FMPI	
	SS	F-Test	SS	F-Test	SS	F-Test	SS	F-Test	SS	F-Test	SS	F-Test
A	0.0199	8.2	0.0745	12.3	0.1415	1.42	0.2539	4.28	5.0165	14.09	0.1074	1.96
B	0.0084	3.45	0.0251	4.14	0.0679	0.68	0.0864	1.46	1.8561	5.21	0.009	0.16
C	0.0154	6.34	0.0647	10.68	0.0525	0.53	0.3302	5.56	4.06	11.4	0.0949	1.73
Error	0.0024		0.0061		0.1		0.0593		0.3561		0.0548	
Total	0.0461		0.1703		0.3619		0.7299		11.2886		0.2661	

__Table 4.__ Main effects on MRPIs of GRA, WSN, PCA, VIKOR, MRSN, and Fuzzy logic for data set 1.

Technique	Factors	A	B	C
GRA ($A_3B_3C_2$)	Level 1	0.6697	0.6849	0.7342
	Level 2	0.7293	0.7494	**0.7752**
	Level 3	**0.7848**	**0.7496**	0.6745
WSN ($A_3B_2C_2$)	Level 1	0.4249	0.4692	0.5393
	Level 2	0.5611	**0.5816**	**0.6499**
	Level 3	**0.6457**	0.5808	0.4424
PCA ($A_1B_3C_3$)	Level 1	**-0.0703**	-0.3657	-0.3503
	Level 2	-0.3292	-0.2169	-0.2245
	Level 3	-0.3428	**-0.1596**	-0.1674
VIKOR ($A_3B_3C_2$)	Level 1	0.8954	0.7937	0.7638
	Level 2	0.697	0.723	**0.4301**
	Level 3	**0.484**	**0.5597**	0.8826
MRSN ($A_1B_1C_3$)	Level 1	**3.8019**	**3.4258**	2.8812
	Level 2	2.5318	2.41	1.9214
	Level 3	2.0274	2.5254	**3.5585**
Fuzzy logic ($A_3B_1C_2$)	Level 1	0.562	**0.694**	0.65
	Level 2	0.634	0.582	**0.714**
	Level 3	**0.666**	0.587	0.499

All the seven input linguistic variables with three linguistic values *viz*.: S: Small, M: Medium, and H: High were taken, whereas for the output linguistic variable, nine linguistic values viz.: VVS: Very very small, VS: Very small, S: Small, SM: Small-medium, MH: Medium-high, H: High, VH: Very high, and VVH: Very very high were taken as elaborated in ***Figure 1.b***.

For the Fuzzy logic method, the MRPIs were computed by employing the procedure mentioned in the experimental section for each experimental run of Ahmad et al.'s [20] experimental data, which are shown in ***Table 2***. In this method, normalised SN ratio variables were considered as linguistic variables, and these were fuzzified by employing a triangular membership function and then applying centroid defuzzification to get a non-fuzzification output. Finally, MRPIs of Ahmad et al.'s [20] experimental data were computed. In Fuzzy logic, input and output parameters are known as linguistic variables. The ANOVA test was conducted to analyse the effect of process parameters on the MRPIs obtained from the GRA, WSN, PCA, VIKOR, MRSN, and Fuzzy logic methods for Ahmad et al.'s [20] experimental data; the results are shown in ***Table 3***. The critical F-value of factor A (concentration of O-CPC) for all the methods, except the VIKOR method, concerning all types of MRPIs at a 95% confidence level is significantly high. The second important factor is C (curing temperature).

Table 4 shows the main effects of all MRPIs of all the six methods for each experimental run. Optimum settings of process parameters for the Fuzzy logic method were obtained i.e. A_3, B_1, and C_2 for Ahmad et al.'s [20] experimental data, i.e., the optimum setting of the process parameters for the Fuzzy logic method concerning simultaneous optimisation of the seven responses were found to be A_3 B_1 C_2, which is shown in ***Table 4***; whereas the optimal conditions of factors A, B, and C for the GRA, WSN, PCA, VIKOR, and MRSN methods were set as $A_3B_3C_2$, $A_3B_2C_2$, $A_1B_3C_3$, $A_3B_3C_2$, and $A_1B_1C_3$, respectively. It was interesting to note that the GRA and VIKOR methods showed the same optimal conditions. As discussed earlier, the final target of the researcher is to minimise the quality loss function of the product manufactured or process, i.e., to maximise SN ratios of the responses of interest. For this purpose, SN ratios of optimised conditions derived by the methods were predicted, accordingly. For these optimal conditions, the predicted SN ratios are given in ***Table 5***, which shows that the optimal condition derived from the WSN method gave the highest total predicted SN ratio of 289.86 dB, followed by the Fuzzy logic method exhibiting the second highest total predicted SN ratio of 289.11 dB, with GRA with a 289 dB total SN ratio in third position.

Raza et al. [21] and Rehman et al.'s [22] experimental data

The Taguchi-based L_9 orthogonal array experimental runs along with computed SN and normalized SN ratios for various responses obtained from Raza et al. [21] and Rehman et al.'s [22] experimental data are shown in ***Tables 1.S*** and ***6.S***, respectively. MRPIs for the GRA, WSA, VIKOR, and MRSN methods computed using normalised SN ratios for Raza et al. [21] and Rehman et al.'s [22] experimental data are given in ***Tables 2.S*** and ***7.S***, respectively. The normalised SN ratio values of multiple responses of Raza et al. [21] and Rehman et al.'s [22] experimental data were taken as the input variables to compute MRPIs of the PCA and Fuzzy logic methods by employing the standard set procedure [22]. In the PCA

__Table 5.__ Predicted SN ratios of the six methods under optimum conditions for data set 1.

Response	GRG (dB) $A_3B_3C_2$	PCA (dB) $A_1B_3C_3$	VIKOR (dB) $A_3B_3C_2$	MRSN (dB) $A_1B_1C_3$	Uncoloured specimens		Coloured specimens	
					WSN (dB) $A_3B_2C_2$	FMPI (dB) $A_3B_1C_2$	WSN (dB) $A_3B_2C_2$	FMPI (dB) $A_3B_1C_2$
WCA	41.81	41.16	41.81	41.05	41.68	41.75	41.28	41.34
OCA	40.48	38.21	40.48	37.91	40.18	39.36	40.52	40.43
AP	49.72	49.18	49.72	48.00	50.13	50.59	50.12	50.85
CRA	45.36	45.45	45.36	45.18	45.22	45.3	44.83	44.41
Stiffness	-11.87	-11.55	-11.87	-11.35	-11.83	-11.68	-11.59	-11.96
Tear strength	63.92	62.43	63.92	63.44	64.81	64.01	64.52	64.72
Tensile strength	59.58	59.32	59.58	59.51	59.67	59.78	59.67	59.67
Total	**289.00**	**284.21**	**289.00**	**283.73**	**289.86**	**289.11**	**289.35**	**289.46**

method, PCA for the normalised values of multiple responses of Raza et al. [21] and Rehman et al.'s [22] experimental data was carried out using Minitab 17® software, and the respective eigenvalues and proportion of the variation of principal components as well as the eigenvector of each eigenvalue of both data sets were obtained [22]. The MRPIs of all six methods computed from Raza et al. [21] and Rehman et al.'s [22] experimental data are given in ***Table 2.S*** and ***Table 7S***, respectively [22]. Figure 1(c) shows the fuzzified rule viewer for MRPIs for Raza et al.'s experimental data [21], which could accept any value of 8 multiple output responses of UTS, DCBM, RL, ST, YP/S, YP/X, YX/S, and PV, and similarly ***Figure 1.d*** represents the fuzzified rule viewer for MRPIs for Rehman et al.'s experimental data [22], which could accept any value of 6 multiple output responses of absorbency: RS, WBL, WWL, WL, and TR. ***Figures 1.e***, ***1.f*** and ***1.g*** show block diagrams of the Fuzzy model for FMPI for Raza et al. [21], Ahmad et al. and Rehman et al.'s [22] experimental data, respectively.

For the Fuzzy logic method, the MRPIs are computed by employing the procedure mentioned in the experimental section for each experimental run of Raza et al. [21] and Rehman et al.'s [22] experimental data, which are shown in ***Tables 2.S*** and ***7.S***, respectively. ***Table 9.S*** reveals the main effects computed from Rehman et al.'s experimental data [22] for various MRPIs of the six methods.

ANOVA was carried out on the MRPIs of both data sets corresponding to each method separately. A summary of the results of ANOVA for the GRA, WSN, PCA, VIKOR, MRSN and Fuzzy logic methods for Raza et al. [21] and Rehman et al.'s [22] experimental data is given in ***Tables 4.S*** and ***8.S***, respectively. It was noted from ***Table 4.S*** that factor A was the most significant process parameter concerning GRA (F-value: 4.44), WSN (F-value: 3.97), PCA (F-value: 18.83), and Fuzzy (F-value: 3.01) indexes, with factor C being the second most promising factor. Whereas according to the VIKOR method, factor C was the most influencing process parameter; whiles B was the second most influencing factor. Similarly, Table 8S reveals that factor C was the most influencing factor with respect to all six indexes, i.e., GRA (F-value: 4.56), WSN (F-value: 4.56), PCA (F-value: 7.38), VIKOR (F-value: 3.95), MRSN (F-value: 5.37), and Fuzzy Logic (F-value: 114.24), with factor A being the second most influencing factor with respect to GRA (F-value: 2.75), WSN (F-value: 4.00), VIKOR (F-value: 3.16), MRSN (F-value: 4.72), and Fuzzy Logic (F-value: 6.20). While factor B had the second highest effect on the PCA (F-value: 1.65) index and MRPIs.

Table 3.S shows the level averages of MRPIs (main effects) computed from Raza et al.'s experimental data [21] based on the six methods, where the larger the level average values (main effects) of the process parameters for the different MRPIs, the better the quality. Finally, the optimum condition of the process parameters for Raza et al.'s experimental data [21] for GRA, WSN, PCA, VIKOR, MRSN, and Fuzzy logic could be observed as $A_2B_3C_1$, $A_2B_3C_1$, $A_2B_2C_1$, $A_1B_1C_3$, $A_1B_2C_2$, and $A_2B_3C_1$, respectively. It was observed that GRA, WSN, and Fuzzy Logic had the same optimal conditions. To compare these methods, predicted SN rations for Raza et al.'s experimental data [21] were computed for each of these six optimal conditions of the respective methods. The predicted SN ratios are given in ***Table 5.S***. From these total predicted SN ratios, it was observed that GRA, WSN, and Fuzzy logic led to maximum predicted SN ratios, given in ***Table 5.S***. Similarly, the optimum condition of the process parameters for Rehman et al.'s experimental data [22] for GRA, WSN, PCA, VIKOR, MRSN, and Fuzzy logic could be noted as $A_1B_2C_3$, $A_1B_2C_3$, $A_3B_1C_1$, $A_1B_3C_3$, $A_3B_3C_2$, and $A_1B_2C_2$, respectively.

It was also interesting to note that GRA and WSN showed the same optimal conditions of process parameters for the highest main effect (***Table 9.S***). Consequently, the optimum conditions were applied to compute the predicted SN ratios for each method (***Table 10.S***). Fuzzy logic led to the maximum predicted SN ratio, followed by the WSN and GRA approaches. It could be stated that no method gives a better result than the Taguchi-based Fuzzy logic multi-response optimizstion technique. Fuzzy logic, due to its nature of including multiple values of linguistic variables, offers a broader and richer field of resources for assessing more accurate MRPIs of data sets for simultaneous optimizstion solutions. With the change in the level of complexity of the data set, a variation in the performance of the methods was observed, except for Fuzzy logic. It is also expected that the same method would perform better in the case of other complex processes under the domain of manufacturing of multi-featured product optimizstion.

Colour coordinates of finished dyed fabric

LAB values of the samples are shown in Table 11S. The results demonstrated that both finished samples show only a slight change in the shade and passed the shade criteria (acceptable). Sample S-1 was slightly lighter than the untreated one (dyed), whereas the S-2 sample was slightly darker than the untreated one. Sample S-1 showed only marginal red and yellowness as compared to the untreated one, whereas sample S-2 was slightly greener and yellower. This might be attributed to the slight yellow colour of the resin. The results demonstrated that after finishing, the samples are within the acceptable limits of change in shade.

There is contradictory literature available on the change of shade after the application of resin to cotton fabrics. Researchers reported a significant shade change with resin on reactive dyed 100% cotton fabric [23, 24]. However, less change of shade was reported after the application of resin on blended cotton fabrics [25]. In general, less change of shade is of utmost importance in the industry for reproducibility. Our results showed almost no change of shade after the application of the resin, which is promising for the industry.

Other parameters of finished dyed fabric

Finally, the WCA, OCA, AP, CRA, stiffness, and tear and tensile strengths of both dyed finished fabrics (S-1 and S-2) were measured according to their respective standard methods described in the literature [26]. The predicted S/N ratios of the responses measured are given in ***Table 5***, which demonstrates that no significant change in the response values of the dyed fabric was observed; thus, the hydrophobicity and oleophobicity were found to be equally valid for both dyed and un-dyed treated fabrics in contact angle measurements.

Conclusions

As there are various multi-response optimisation techniques available, it becomes confusing as to which to choose for the best possible results. Therefore, in the present study, the performance efficiency for six promising Taguchi-based multi-response optimisation techniques, e.g., grey relational analysis, the weighted signal-to-noise ratio, principal component analysis, VIKOR, the multi-response signal-to-noise ratio, and Fuzzy logic were standardised. Three sets of experimental data were analysed at optimised conditions suggested by these standardised methods (reported in the respective literature), and the predicted signal-to-noise ratios were computed. The methods were applied for the dyeing of cotton fabric, the application of finishing, and biotechnological study. The predicted optimisation performance of these methods was judged. Based on the predicted optimisation performance, it was found that no method other than Fuzzy logic could give better performance in the simultaneous optimisation problem. The WSN method was the second most leading procedure in this regard. This study would set up a road map not only for other textile processes but also in other materials-based sectors of science and technology.

References

1. Ardakani MK, Noorossana R. A New Optimization Criterion for Robust Parameter Design – The Case of Target is Best. *Int J Adv Manuf Technol* 2008; 38: 851-859.
2. Rao RS, Kumar CG, Prakasham RS, et al. The Taguchi Methodology as a Statistical Tool for Biotechnological Applications: A Critical Appraisal. *Biotechnology Journal* 2008; 3: 510-523.
3. Ryan TP. *Taguchi's Quality Engineering Handbook*. Epub Ahead of Print 2005. DOI: 10.1080/00224065.2005.11980326.
4. Wang Y, Zhao YF. Investigation of Sintering Shrinkage in Binder Jetting Additive Manufacturing Process. *Procedia Manuf* 2017; 10: 779-790.
5. Chang C-L, Hsu C-H. Multi-Criteria Analysis via the VIKOR method for Prioritizing Land-Use Restraint Strategies in the Tseng-Wen Reservoir Watershed. *J Environ Manage* 2009; 90: 3226-3230.
6. Chiang JS, Wu PL, Chiang SD, et al. *Introduction to Grey System Theory*, 1998.
7. John B. Simultaneous Optimization of Multiple Performance Characteristics of Carbonitrided Pellets: A Case Study. *Int J Adv Manuf Technol* 2012; 61: 585-594.
8. Azadeh A, Nazari-Shirkouhi S, Hatami-Shirkouhi L, et al. A Unique Fuzzy Multi-Criteria Decision Making: Computer Simulation Approach for Productive Operators' Assignment in Cellular Manufacturing Systems with Uncertainty and Vagueness. *Int J Adv Manuf Technol* 2011; 56: 329-343.
9. Gauri SK, Chakravorty R, Chakraborty S. Optimization of Correlated Multiple Responses of Ultrasonic Machining (USM) Process. *Int J Adv Manuf Technol* 2011; 53: 1115-1127.
10. Khaw JFC, Lim BS, Lim LEN. Optimal Design of Neural Networks using the Taguchi Method. Neurocomputing 1995; 7: 225-245.
11. Pandey AK, Dubey AK. Taguchi Based Fuzzy Logic Optimization of Multiple Quality Characteristics in Laser Cutting of Duralumin Sheet. *Opt Lasers Eng* 2012; 50: 328-335.
12 Yang T, Chou P. Solving A Multiresponse Simulation-Optimization Problem with Discrete Variables using a Multiple-Attribute Decision-Making Method. *Math Comput Simul* 2005; 68: 9-21.
13. Liao HC. A Data Envelopment Analysis Method for Optimizing Multi-Response Problem with Censored Data in the Taguchi Method. In: *Computers And Industrial Engineering. Elsevier Ltd* 2004; pp. 817-835.
14. Wurl RC, Albin SL. A Comparison of Multiresponse Optimization Sensivity to Parameter Selection. *Qual Eng* 1999; 11: 405-415.
15. Gauri SK, Chakraborty S. A Study on the Performance of some Multi-Response Optimisation Methods for WEDM Processes. *Int J Adv Manuf Technol* 2010; 49: 155-166.
16. Gauri SK, Pal S. Comparison of Performances of Five Prospective Approaches for the Multi-Response Optimization. *Int J Adv Manuf Technol* 2010; 48: 1205-1220.
17. Krishnaiah K, Shahabudeen P. Applied Design of Experiments and Taguchi Methods, https://books.google.com.pk/books?id=hju9JYVhfV8C&printsec=frontcover#v=onepage&q&f=false (2012, accessed 10 September 2020).
18. Ahmad N, Kamal S, Raza ZA, et al. Multi-Objective Optimization in the Development of Oil and Water Repellent Cellulose Fabric Based on Response Surface Methodology and the Desirability Function. *Mater Res Express* 2017; 4: 035302.
19. Umair M, Shaker K, Ahmad N, et al. Simultaneous Optimization of Woven Fabric Properties Using Principal Component Analysis. *J Nat Fibers* 2017; 14: 846-857.
20. Ahmad N, Kamal S, Raza ZA, et al. Multi-Response Optimization in the Development of Oleo-Hydrophobic Cotton Fabric using Taguchi Based Grey Relational Analysis. *Appl Surf Sci* 2016; 367: 370-381.
21. Raza ZA, Rehman A, Hussain MT, et al. Production of Rhamnolipid Surfactant and Its Application in Bioscouring of Cotton Fabric. *Carbohyd Res* 2014; 391: 97-105.
22. Rehman A, Raza ZA, Masood R, et al. Multi-Response Optimization in Enzymatic Desizing of Cotton Fabric Under Various Chemo-Physical Conditions Using a Taguchi Approach. *Cellulose* 2015; 22: 2107-2116.
23. Kabir SM, Tania IS, Uddin Z. Effects of Resin Treatments on the Quality of Cotton Fabric Dyed with Reactive Dye. *FIBRES & TEXTILES in Eastern Europe* 2018; 26, 1(127): 102-107. DOI: 10.5604/01.3001.0010.7804.
24. Abid S, Hussain T, Nazir A, et al. Simultaneous Fixation of Wrinkle-Free Finish and Reactive Dye on Cotton Using Response Surface Methodology. *Cloth Text Res J* 2018; 36: 119-132.
25. Mukthy AA, Yousuf A, Anwarul M. Effects of Resin Finish on Cotton Blended Woven Fabrics. *Int J Sci Eng Technol* 2014; 990: 983-990.

Received 19.10.2020 Reviewed 15.03.2021