Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 9 (9): 1695-1702, 2009
ISSN 1812-5654

An Extension of Multi-Response Optimization in MADM View

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Abstract: Multiple Response Surface (MRS) is the useful way to satisfy more than one output characteristic. It's originated from statistical approach to estimate relations between inputs and output variable called Response Surface Methodology (RSM). This study reviews important Multi-Response Optimization (MRO) methods and uses Multiple Attribute Decision Making (MADM) methods such as VIKOR, PROMETHEE II, ELECTRE III and TOPSIS in converting multi-response to single response in order to analyze the robust experimental design. Finally, numerical results and comparison of MADM methods are shown.

Key words: Multi-response surface optimization, robust design, multiple criteria decision making

INTRODUCTION

Setting of controllable input variables to meet a required specification of quality characteristic (or response variable) in a process is one of the common problems in the process quality control. But, generally there are more than one quality characteristics in the process and the experimenter attempts to optimize all of them simultaneously. Since, response variables are different in some properties such as scale, measurement unit, type of optimality and their preferences, there are different approaches in model building and optimization of MRS problems. Moreover, optimizing the response surfaces considering dispersion effect (variance of responses) as objective function will increase reliability and robustness. In this study, robust design and multiresponse optimization have been analyzed by MADM methods. Some earlier works in multiresponse optimization: Derringer and Suich (1980) applied a desirability function to optimize multi-response problems in a static experiment. Castillo *et al*. (1996) demonstrated the use of modified desirability functions for optimizing the multi-response problem. Layne (1995) presented a procedure that simultaneously considers three functions, the weighted loss function, the desirability function and a distance function, to determine the optimum parameter combination. Khuri and Conlon (1981) proposed a procedure based on a polynomial regression model to simultaneously optimize several responses. Logothetis and Haigh (1988) also optimized a five response process by utilizing the multiple regression technique and the linear programming approach. Pignatiello (1993) utilized a variance component and a squared deviation-from-target to form an expected loss function to optimize a multiple response problem. This method is difficult to implement. The first reason is that a cost matrix must be initially obtained and the second reason is that it needs more experimental data. Chapman (1995-1996) proposed a co-optimization approach, which uses a composite response. Leon (1996-1997) presented a method, which is based on the notions of a standardized loss function with specification limits, to optimize a multiresponse problem. However, only the Nominal-The Best (NTB) characteristic is suitable for this approach, which may limit the capability of this approach. Ames *et al*. (1997) presented a quality loss function approach in response surface models to deal with a multi-response problem. The basic strategy is to describe the response surfaces with experimentally derived polynomials, which can be combined into a single loss function by using known or desired targets. Next, minimizing the loss function with respect to process inputs locates the best operating conditions. Lai and Chang (1994) proposed a fuzzy multi-response optimization procedure to search for an appropriate combination of process parameter settings. A strategy of optimizing the most possible response values and minimizing the deviation from the most possible values is used when it considers not only the most possible value, but also the imprecision of the predicted responses. Hsieh (2006) used neural networks to estimate relation between control variables and responses. Tong *et al*. (1997) developed a Multi-Response Signal to-Noise (MRSN) ratio, which integrates the quality loss for all responses to solve the multi-response problem. The

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conventional Taguchi method can be applied based on MSRN. The optimum factor/level combination can be obtained. Su and Tong (1997) also proposed a principle component analysis approach to perform the optimization of the multi-response problem. Initially, the quality loss of each response is standardized; principle component analysis is then applied to transform the primary quality responses into fewer quality responses. Finally, the optimum parameter combination can be obtained by maximizing the summation standardized quality loss. Tong and Su (1997) proposed a procedure, which applied fuzzy set theory to Multiple-Attribute Decision-Making (MADM) to optimize a multi-responses problem. Tong *et al*. (2007) use VIKOR methods in converting Taguchi criteria to single response and then find regression model and related optimal setting. Kezemzadeh (2008) proposed a general framework for multiresponse optimization problems based on goal programming. Their study proposes a general framework in MRS problems according to some existing study and some types of related decision makers and attempts to aggregate all of characteristics in one approach. Amiri *et al*. (2008) used genetic algorithm to find best solution of Multiresponse problem in fuzzy environment. Their proposed method was combination of simulation approach, fuzzy goal programming and genetic algorithm. In viewpoint of multiple objective decision making, Bashiri *et al*. (2009) have proposed an approach in which Global Criterion (GC) have been applied to aggregate multiresponse surfaces in simulation model of probabilistic inventory model.

MULTIPLE RESPONSE SURFACE

RSM: Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving and optimizing processes. RSM also has the ability to produce an approximate function using a smaller amount of data (Yeh, 2003). However, most previous applications based on RSM have only dealt with a single-response problem and multi-response problems have received only limited attention. In today's complex manufacturing processes, call for simultaneous optimization of several quality characteristics rather than optimizing one response at a time. Studies have shown that the optimal factor settings for one performance characteristic are not necessarily compatible with those of other performance characteristics. In more general situations we might consider finding compromising conditions on the input variables that are somewhat favorable to all responses (Koksoy, 2007). More details on RSM, related designs and optimization of response surfaces are given by Kleijnen (2007, 2008), Myers and Montgomery (2002).

Multiple response optimization: Nowadays in most industrial applications, there isn't just one response and the analysts try to find operating status that satisfies all quality characteristics simultaneously. Three steps in these problems are:

- Data collection and analysis
- Model building and verification
- Optimization

Dual Response Surface (DRS) is one of MRS problems in which the mean and variance of a special quality characteristic is estimated by a polynomial surface and in the optimization stage, both variance and mean are optimized simultaneously. The characteristics of MRS problems which it is necessary to attend to the model building and optimization stages are: different importance of responses, different measuring units, different scales and magnitude, different types of optimality, different direction, different preferences of responses and also different types of decision makers (Kazemzadeh, 2008). MRO problems have been studied in several areas at different aspects. We can categorize all viewpoints in the literature into three general categories:

Desirability viewpoints: In this category, researchers try aggregate information of each responses and get one response. Then optimization is performed on single objective called desirability function.

Priority based (a.k.a classic optimization) methods: Some cases have responses with different importance, in such problem, we must consider most important response for optimization and if solutions weren't unique, then find best solution by comparing status of alternative solution in next important responses and foresaid steps is repeated till considering all responses or finding unique optimal solution. Most popular methods in this group are: utility function method, global criterion method, bounded objective function method and lexicographic method that generate a set of Pareto optimal solution.

Loss function: In this category, based on loss function (represented by Taguchi) all responses value are aggregated and convert to single one. There were wide range of researches, have been studied to develop and generalize taguchi loss function with respect to special trait of its cases.

APPLICATION OF MADM METHODS

Overview of MADM methods: Multiple attribute decision making methods are developed for selecting, ranking or rating (or sometimes categorizing) several alternative according to have several attribute which be maximized, minimized or reach a goal. Some of MADM methods use comparison of alternative for each attribute and collect these results to make a best decision such as ELECTREs, PROMETHEEs and some algorithms try to find a solution with maximum similarity to ideal and maximum dissimilarity to non ideal solution such as TOPSIS and VIKOR (Opricovic and Tzeng, 2004). In this study we focus on PROMETHEE II, VIKOR, TOPSIS and ELECTRE III to analyze special design of experiments.

MADM methods which used in this study are ELECTRE III, PROMETHEE II, VIKOR and TOPSIS. Application of these methods helps us to product one score from several responses representing aggregate score of each experiment. Summary of each algorithms are shown below:

ELECTRE III: The ELECTRE III method, like every outranking method, is based on the axiom of partial comparability, according to which preferences are simulated with the use of four binary relations: indifference (I); heavy preference (P); light preference (Q) and non-comparability (R). Furthermore, the thresholds of preference (p), indifference (q) and veto (v) have been introduced, so that relations are not expressed mistakenly due to differences that are less important. The multi-criteria model can be described as following: assuming that A is the finite group of n possible alternative solutions and m the number of the evaluation criteria (j = 1, 2,..., m). If it is assumed that the objective functions of all criteria should be maximized, the concordance matrix is defined with the elements:

$$C(a,b) = \frac{\sum_j w_j.c_j(a,b)}{\sum_j w_j} \quad (1)$$

where, w_j and c_j (a, b) are weight of jth criteria and preference level of a into b (a, b are alternatives).

$$c_j(a,b) = \begin{cases} 0 \longrightarrow p_j + a_{aj} < a_{bj} \\ \dfrac{a_{aj} - a_{bj} + p_j}{p_j - q_j} \longrightarrow q_j < a_{bj} - a_{aj} \le p_j \\ 1 \longrightarrow q_j + a_{aj} \ge a_{bj} \end{cases} \quad (2)$$

$$d_j(a,b) = \begin{cases} 1 \longrightarrow v_j + a_{aj} < a_{bj} \\ \dfrac{a_{bj} - a_{aj} - p_j}{v_j - p_j} \longrightarrow p_j < a_{bj} - a_{aj} \le v_j \\ 0 \longrightarrow p_j + a_{aj} \ge a_{bj} \end{cases} \quad (3)$$

where, p_j and q_j are the preference and indifference thresholds, respectively, which can either be constants or functions of e.g., the criteria performances. a_{bj} is performance of alternative-b-on jth criteria. The discordance matrix can be calculated as long as the veto threshold (v_j) has been defined; then credibility matrix is built from concordance and discordance matrixes.

$$S(a,b) = \begin{cases} C(a,b) \longrightarrow J(a,b) = \phi \\ C(a,b). \prod_{j \in J(a,b)} \dfrac{1 - d_j(a,b)}{1 - C(a,b)} \\ 0 \longrightarrow d_j = 1 \end{cases} \quad (4)$$

The determination of the hierarchy rank is achieved by calculating the superiority ratio for each alternative. This ratio is calculated from the credibility matrix and is the fraction of the elements' sum of every alternative's line (Q), to the sum of the elements of the alternative's respective column (W). The numerator represents the total dominance of the specific alternative over the rest and the denominator the dominance of the remaining alternatives over the former. Therefore this fraction is the score of each alternative which be maximized (Papadopoulos and Karagiannidis, 2006).

$$S_i = Q_i/W_i \quad (5)$$

TOPSIS: TOPSIS (technique for order preference by similarity to an ideal solution) method is presented by Chen and Hwang (1992), with reference to Hwang and Yoon (1981). The basic principle is that the chosen alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution. The TOPSIS procedure consists of the following steps:

- Calculate the normalized decision matrix. The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{g_{ij}}{\sqrt{\sum_{j=1}^{m} g_{ij}^2}} \quad (6)$$

where, g_{ij} is performance of alternative-i- on jth critera.

- Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as:

$$v_{ij} = w_i r_{ij}\,;\ j = 1,..., m;\ i = 1,... ,n$$

where, w_i is the weight of the ith attribute or criterion and $\Sigma_i w_i = 1$.

- Determine the ideal and negative-ideal solution

$$A^* = \{v_1^*,\ldots, v_n^*\} = \{\max_j (v_{ij})|i \in I', \min_j (v_{ij})|i \in I''\}$$
$$A^- = \{v_1^-,\ldots,v_n^-\} = \{\min_j(v_{ij})|i \in I', \max_j(v_{ij})|i \in I''\}$$

where I' is associated with benefit criteria and I'' is associated with cost criteria. Also we can convert cost criteria to benefit ($y_{ij} = x_i^* - x_{ij}|$, where, x_i^* is worst value in *i*th column) and then continue steps.

- Calculate the separation measures, using the n-dimensional euclidean distance. The separation of each alternative from the ideal solution is given as:

$$D_j^* = \sqrt{\sum_{i=1}^{n}(v_{ij} - v_i^*)^2} \quad (7)$$

Similarly, the separation from the negative ideal solution is given as:

$$D_j^- = \sqrt{\sum_{i=1}^{n}(v_{ij} - v_i^-)^2} \quad (8)$$

- Calculate the relative closeness to the ideal solution. The relative closeness of the alternative a_j with respect to A^* is defined as:

$$C_j^* = D_j^-/(Dj^* + D_j^-) \quad (9)$$

- Rank the preference order (Opricovic and Tzeng, 2004)

VIKOR methods: The VIKOR method was developed for multicriteria optimization of complex systems. It determines the compromise ranking-list, the compromise solution and the weight stability intervals for preference stability of the compromise solution obtained with the initial (given) weights. This method focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria. It introduces the multicriteria ranking index based on the particular measure of closeness to the ideal solution. Assuming that each alternative is evaluated according to each criterion function, the compromise ranking could be performed by comparing the measure of closeness to the ideal alternative. The multicriteria measure for compromise ranking is developed from the L_p-metric used as an aggregating function in a compromise programming method.

The VIKOR method includes the following steps.

- Determine the normalized decision matrix similar to TOPSIS
- Determine the ideal and negative-ideal solutions. The ideal solution A* and the negative ideal solution A^- are determined similar to TOPSIS
- Calculate the utility measure and the regret measure. The utility measure and the regret measure for each alternative are given as:

$$S_i = \sum_{j=1}^{n} w_j (f_j^* - f_{ij})/(f_j^* - f_j^-) \quad (10)$$

$$R_i = \max_j \, [w_j (f_j^* - f_{ij})/(f_j^* - f_j^-)] \quad (11)$$

where, S_i and R_i represent the utility measure and the regret measure, respectively and w_j is the weight of the jth criterion.

- Calculate the VIKOR index. The VIKOR index can be expressed as follows:

$$Q_i = v\left[\frac{(S_i - S_i^*)}{(S^- - S^*)}\right] + (1-v)\left[\frac{(R_i - R_i^*)}{(R^- - R^*)}\right] \quad (12)$$

Where:

Q_i = ith alternative VIKOR value
i = 1,…,m
S^* = $\min S_i$
S^- = $\max S_i$
R^* = $\min R_i$
R^- = $\max R_i$
v = Weight of the maximum group utility (and is usually set to 0.5)

- Rank the order of preference. The alternative with the smallest VIKOR value is determined to be the best solution (Tong *et al*., 2007)

PROMETHEE II: One other MADM studied in this research is PROMETHEE was presented in 1982 and was developed in 1985, 1994. PROMETHEE is the outranking method and use preference functions to shows alternative differences (Albadvi *et al*., 2007). PROMETHEE II is summarized in following steps:

- Collecting alternative and weighted criteria
- Determination of Preference Function for each criteria. See Chou (2007) for more information about preference functions. Figure 1 shows two usual types of preference function.

$d_j(a, b) = g_{aj} - g_{bj}$, (according to Fig. 1 and type of H(d))

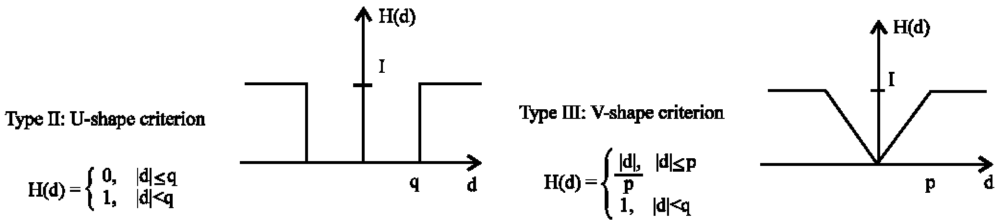

Fig. 1: Two types of preference function

- Calculation of total preference of a in respect of b as:

$$\pi(a,b) = \sum_{j=1}^{n} w_j H_j(d) \leftrightarrow \sum_{j=1}^{n} w_j = 1 \tag{13}$$

- Calculation of positive and negative flow:

$$\phi^{+}(a) = \frac{\sum_{i} \pi(a,i)}{n-1} \tag{14}$$

$$\phi^{-}(a) = \frac{\sum_{i} \pi(i,a)}{n-1} \tag{15}$$

- Find net flow that shows power of each alternatives and can be considered as alternative score

$$\varnothing(a) = \varnothing^{+}(a) - \varnothing^{-}(a) \tag{16}$$

PROPOSED METHOD

In single response surface, regression model is built from relation between controllable variables and response values but in multiresponse surface, regression model must be fitted for each response individually. In most methods (such as desirability function and weighted sum) combination of several response applied to find single response. The aim of this study is to use scores of MADM methods as one response instead of several responses achieved from experiments. For this purpose we use Φ_i, Q_i, S_i and C_i for aggregating several response data. Figure 2 shows summary of proposed methods.

There's one important notation in combination of goal programming approach and MADM tools that in most of MADM methods there are just two groups of objectives: Benefit criteria, which should be maximized and Cost criteria which should be minimize but, in GP problem, it's desired that performance values are equal to specific target value. The studied case in this study is selected from Kazemzadeh *et al.* (2008) that use goal programming to find optimal controllable variable setting. This method is more applicable and reliable than other MRO methods. For instance in comparison with desirability function and loss function, Since this method is based on decision making tools, the analyst can use other assumptions which defined and applied in other decision making science such as group decision making, fuzzy decision making, qualitative data, etc. When classic optimization methods such as goal programming, global criterion optimization and bounded objective applied in MRS optimization, the analysts had to fit response surface for each response variable and then find Pareto solution. Since fitting the regression functions have an error, foresaid method increases family error and decrease reliability, but the proposed method aggregates multiple response variables (given from experiments) to calculate only one aggregation value firstly and then fit only one regression function which simply optimized by single objective optimization methods.

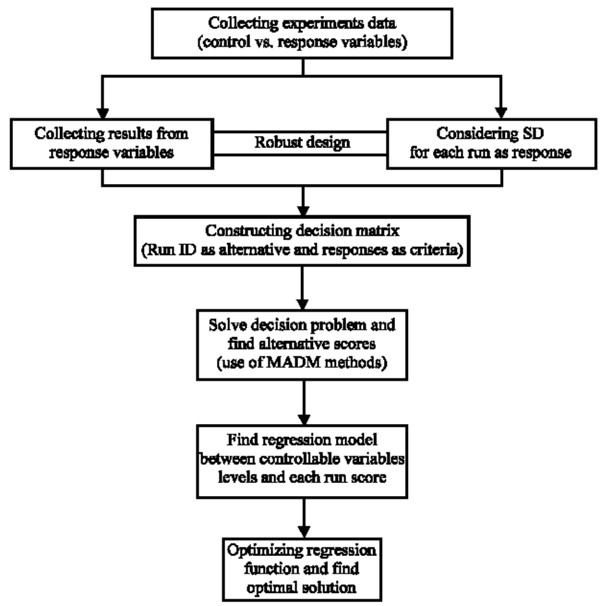

Fig. 2: Summary of proposed methods

NUMERICAL EXAMPLE

Here, Pignatiello (1993) there are two response variables (y_1, y_2) and three setting variables (x_1, x_2, x_3). A

Table 1: Experiments results

				Y_1 Replicate						Y_2 Replicate					
ID	X_1	X_2	X_3	1	2	3	4	$\hat{y}_1$*	S_1**	1	2	3	4	$\hat{y}_2$	S_2
8	1	1	1	104.45	105.03	99.79	104.92	103.55	2.52	76.90	77.03	67.99	75.77	74.42	4.33
4	1	1	-1	104.12	104.80	104.20	104.34	104.37	0.30	72.99	74.25	73.94	73.28	73.61	0.58
6	1	-1	1	98.73	99.36	102.84	94.24	98.79	3.54	67.10	63.61	68.65	62.42	65.44	2.92
2	1	-1	-1	100.19	99.63	100.27	100.60	100.17	0.40	67.03	66.18	66.58	67.94	66.93	0.76
7	-1	1	1	103.15	106.96	107.62	103.44	105.29	2.33	71.68	76.27	77.50	76.37	75.45	2.58
3	-1	1	-1	106.08	105.64	105.67	105.39	105.70	0.28	72.94	72.85	72.58	72.38	72.68	0.26
5	-1	-1	1	113.52	111.12	112.85	106.67	111.04	3.09	68.29	68.47	68.96	64.71	67.61	1.95
1	-1	-1	-1	109.90	109.76	110.70	109.77	110.03	0.45	67.70	67.24	67.96	66.93	67.46	0.46

*Average of replicate results, **SD of replicate results

Table 2: Decision matrix

DM	Y1new (CC)*	S1 (CC)	Y2new (CC)	S2 (CC)
ID-8	0.55	2.52	1.42	4.33
ID-4	1.36	0.30	0.61	0.58
ID-6	4.21	3.54	7.56	2.92
ID-2	2.83	0.40	6.07	0.76
ID-7	2.29	2.33	2.45	2.58
ID-3	2.70	0.28	0.32	0.26
ID-5	8.04	3.09	5.39	1.95
ID-1	7.03	0.45	5.54	0.46
Weight	1/3	1/6	1/3	1/6
(q, p, v)**	(0.5, 1.5, 5)	(0.3, 0.75, 2)	(0.5, 2, 5)	(0.2, 1, 2)

*Cost criteria, **ELECTREIII parameters

Table 3: Results of MADM methods

DM	X_1	X_2	X_3	TOPSIS (C_i)	ELECTRE III (S_i)	VIKOR (Q_i)	PROMETHEE II (Φ_i)
ID-8	1	1	1	0.62	1.00	0.407	0.2199
ID-4	1	1	-1	0.92	2.00	0.000	0.6667
ID-6	1	-1	1	0.29	0.67	0.995	-0.8334
ID-2	1	-1	-1	0.52	1.00	0.615	-0.2188
ID-7	-1	1	1	0.66	1.00	0.333	0.0556
ID-3	-1	1	-1	0.83	1.50	0.123	0.6668
ID-5	-1	-1	1	0.24	0.50	1.000	-0.5567
ID-1	-1	-1	-1	0.38	1.00	0.761	0.0701

2^3 design with 4 replicates were used in this example. The experimental data are shown in Table 1 that contains experiments ID, response value for each replication according to related design. In this example it is assumed that the target values of the responses (y_1, y_2) are 103 and 73, respectively.

Summary of proposed methods are as follows:

- Construction of decision matrix (Table 2)

According to robust design, we consider standard deviations(s) and y_1, y_2 as responses. Y new in Table 2 shows absolute deviations of y_i and related target (103, 73 for y_1, y_2).

- Find alternative scores by MADM methods. Table 3 shows the results of MADM methods
- Find regression model between controllable variables and scores

Table 4: Analysis of variance results for regression models by MINITAB software

Measures\ methods	TOPSIS (C_i)	ELECTRE III (S_i)	VIKOR (Q_i)	PROMETHEE II (Φ_i)
R^2 (%)	100.0	96.4	100.0	99.9
s	0.01414	0.2369	0.0198	0.0538

Table 5: Results of MADM methods

Method	Optimal solution (X_1,X_2,X_3)	Optimal responses (Y_1,S_1,Y_2,S_2)
TOPSIS (C_i)	(1, 1, -1)	(104.37, 0.3, 73.61, 0.58)
ELECTRE III (S_i)	(1, 1, -1)	(104.37, 0.3, 73.61, 0.58)
VIKOR (Q_i)	(1, 1, -1)	(104.37, 0.3, 73.61, 0.58)
PROMETHEE II (Φ_i)	(1, 1, -1)	(104.37, 0.3, 73.61, 0.58)

Table 4 shows that all regression model are meaningful at $\alpha = 0.05$ ($p<\alpha$).

$$C = 0.557500+0.03\ X_1+0.2\ X_2-0.105\ X_3-0.0175\ X_1X_2-0.0275\ X_1X_3-0.0125\ X_2X_3 \quad (17)$$

$$S = 1.08375+0.08375\ X_1+0.29125\ X2-0.29125\ X_3+0.04125\ X1X2-0.04125\ X1X3-0.08375\ X2X3 \quad (18)$$

$$Q = 0.529-0.025\ X_1-0.3135\ X_2+0.1545\ X_3+0.01275\ X_1X_2+0.04225\ X_1X_3-2.5E\text{-}04\ X_2X_3 \quad (19)$$

$$\Phi = 0.008775-0.050175\ X_1+0.393475\ X_2-0.287425\ X_3+0.09122\ X_1X_2+0.0221\ X_1X_3+0.0229\ X_2X_3 \quad (20)$$

- Optimizing fitted Function. Table 5 shows results of optimization

For Example, optimization model for TOPSIS based regression function is:

$$\text{Optimize } C = 0.557500+0.03X_1+0.2X_2-0.105\ X_3-0.0175\ X_1X_2-0.0275X_1X_3-0.0125X_2X_3$$

subject to:

$$-1 \le x_1,\ x_2,\ x_3 \le 1$$

Only for VIKOR methods, the function must be minimized but for other methods, the objective function must be maximized. Table 5 shows that, because of common approach, the all MADM method give similar results.

CONCLUSION

In this study, usage of multiple criteria decision making in MRO problem was represented. According to results (Table 3), optimal solutions of proposed method for aforesaid MADM methods have similarity. The proposed MADM based Methods are related to decision maker viewpoint about important degree of responses. In the given results it is assumed that the response-means are more important than the standard deviations. Another advantage of this method is to consider standard deviation that contributes to robust experimental design also because of fitting only one response regression function, the proposed method decreases statistical error. Since this method attempts to obtain one value from several responses; it can be categorized in desirability function approach. Future Studies on MRO problem can focus on other MADM methods application, fuzzy logic issues and comparing between multiple criteria decision making tools.

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