Proc. ICCS-11, Lahore, Pakistan
December 19-22, 2011, Vol. 21, pp. 209-222

A DATA ENVELOPMENT ANALYSIS METHOD FOR OPTIMIZING MULTI-RESPONSE PROBLEM BY DYNAMIC TAGUCHI METHOD

Majid Jalili, Mahdi Bashiri and **Amirhossein Amiri**
Department of Industrial Engineering, Faculty of Engineering,
Shahed University, Tehran, Iran.
Email: mjalili@shahed.ac.ir, bashiri@shahed.ac.ir, amiri@shahed.ac.ir

ABSTRACT

The Taguchi method is a useful technique to improve the performance of products or processes at a lower cost and in less time. This procedure is categorized to the static and dynamic quality characteristic.

The optimization of multiple responses has received increasing attention over the last few years in many manufacturing organizations. Several approaches dealing with multiple static quality characteristic problems have been reported. However, little attention has been focused on optimizing the multiple dynamic quality characteristics. As a result, Taguchi method is not appropriate to optimize a multi-response problem.

In this paper, we investigate multivariate Taguchi dynamic problem and propose a method based on Data Envelopment Analysis (DEA). Among the advantages of the proposed approach over traditional Taguchi method is the non-parametric, non-linear way in evaluation of all factor combinations. Simulated data shows that proposed method could increase robustness of the dynamic Taguchi method.

KEYWORDS

Data Envelopment Analysis (DEA); Taguchi Dynamic Problem; Multi Response Optimization; Signal to noise ratio; Robust parameter design.

1. INTRODUCTION

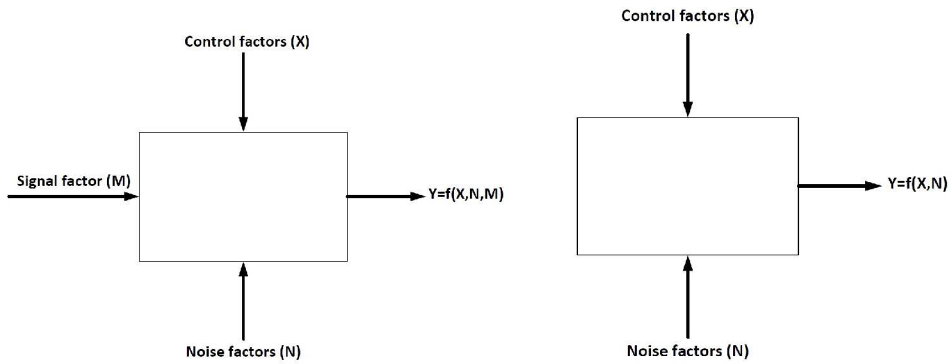
The robust design has been successfully applied to a variety of industry problems for upgrading product quality since Taguchi (1987) first introduced this method in 1980. The objective of robust design is to reduce response variation in products or processes by selecting the settings of control factors, which provide the best performance and the least sensitivity to noise factors. This act is done by using interaction between control and noise factors.

To execute the robust design, Taguchi employs an orthogonal array (OA) to arrange the experiments and uses the signal-to-noise ratio (SNR) to measure the performance of each experimental run. He proposed the dynamic SN ratio formula as follows:

$$SN = 10\log\left(\frac{\beta^2}{\sigma^2}\right) \tag{1}$$

The β and σ are evaluated for different combination of control factors. *SNR* desires to be maximized. A two-step optimization procedure is then used to determine the optimal factor combination to simultaneously reduce the response variation and bring the mean close to the target value.

Taguchi divided the RPD methodology into two categories: static and dynamic characteristics. Static systems are defined as those desired output of the system has a fixed target value and problem attempts to obtain the value of a quality characteristic of interest as close as possible to a single specified target value. Whereas dynamic systems are those target values depends on the input signal set and there is a relationship between response (output) and signal (input). This signal-response relationship is of primary importance to the performance of the system. Figure 1(a-b) denote dynamic and static systems.



(a) (b)

Fig.1: (a) Dynamic system (b) Static system

Miller and Wu (1996) criticized the terminology of Taguchi and labeled the static system, simple response system and the dynamic system, signal-response system. They said that static and dynamic systems are applied for systems, which concerned with time whereas the simple response system and signal-response systems can concern with others. They divided signal-response system into two categories, multiple target systems and measurement systems. Wu and Hamada (2000) introduced the third category as control systems.

Because the signal-response concept plays an important role in product/process development, robust parameter design of signal-response systems (also called dynamic parameter design in Taguchi's terminology) is an effective and powerful tool for quality improvement.

Signal-response systems ideally suppose that there exist a linear relationship between the response and the signal factor. Moreover, dispersion and sensitivity are two important aspects of the signal-response system which are considered with an index such as SNR [3]. According to the linear assumption of relationship function, the simple linear regression model can be written as follows:

$$y = \alpha + \beta M + \varepsilon \tag{2}$$

where, M is the signal factor with predefined p levels with the value of m_i in ith level, y_i is the response value for ith level of signal factor, $E(\varepsilon)=0$ and $Var(\varepsilon)=\sigma^2$. A performance measure, which converts σ^2 and β in to a single measure is

$$\omega = \ln\left(\frac{\beta^2}{\sigma^2}\right) \tag{3}$$

In contrast to Taguchi's dynamic *SNR* and two-step optimization procedure, Miller and Wu [2] develop response function modeling (RFM) to optimize signal-response systems. RFM uses the experimental data to model the signal-response relationship as a function of the control and noise factors. The specified performance measure is then evaluated with respect to the fitted regression models. This method is an extension of the response modeling approach first recommended by Welch et al. (1990) and Shoemaker et al. (1991) for simple response applications.

Wasserman (1996) presents a case study of the parameter design with dynamic characteristics by using multiple regression models. Khattree (1996) provides a method for estimation in the robust parameter design in the situation in which all the noise variables cannot be studied simultaneously. He used response surface approach. Lunani et al. (1997) note that using SNR as a quality performance measure might produce inaccuracies due to a mistake to evaluate dispersion effect. They developed two graphical methods for identifying appropriate measures of dispersion, thereby avoiding interactions between the dispersion and sensitivity effects for a dynamic problem.

Miller (2002) compares three methods of analyzing signal-response applications, including Miller and Wu's (1996) approach, Taguchi method and a graphical approach devised by Lunani et al. (1997). He introduces a new graphical technique, the joint effects plot and demonstrated usefulness of his proposed method. Lesperance and Park (2003) propose a joint generalize the linear model to evaluate the robust design of dynamic characteristics, which is based on standard regression modeling techniques.

Roshan and Wu (2002) describe the application of *SNR* in the analysis of the multiple target systems.

Roshan and Wu (2002) give a theoretical formulation for multiple target systems and develop a practical approach for optimization that and overcome some limitations.

Wu and Yeh (2005) present an approach to optimizing multiple dynamic problems based on quality loss. The objective is to minimize the total average quality loss for the multiple dynamic quality characteristic's experiments. Zhiyu et al. (2006) propose a new desirability function method for multiple robust parameter design. The proposed method can yield better results than traditional desirability function approach.

Gupta et al. (2010) propose a split-plot approach to the signal-response system characterized by two variance components. They demonstrate that explicit modeling of variance components using GLMMs leads to more precise point estimates of important model coefficients with shorter condense intervals within-profile variance and between-profile variance. Dasgupta et al. (2010) presented a robust design of measurement systems. They developed an integrated approach for estimation and reduction of measurement variation through a single parameter design experiment.

In general several researches have addressed multiple static quality characteristics problems such as Khuri and Conlon (1981), Lin et al. (2002), Su and Tong (1997), Lu and Antony (2002), Elsayed and Chen (1993), Wu (2002), Derringer and Suich (1980), Vining (1998), Tsui (1999), Tong et al. (1997) and Logothetis and Haigh (1988).

Several publications have studied the robust design problem concerning the dynamic systems such as Wasserman (1996), Lunani (1996), Miller and Wu (1996), Su and Hsieh (1998), Tsui (1997), McCaskey and Tsui (1997) and Chang (2008).

However, few studies have been concerned with optimizing the parameter design for multiple dynamic quality characteristics. Chang (2008) proposed a procedure based on desirability function to optimize multiple dynamic quality characteristics. He used Simulated Annealing to find best factor setting.

The rest of the paper is organized as follows: The proposed method is discussed in Section 2. In Section 3, a simulated dataset is applied and the performance of the proposed method is evaluated. Our concluding remarks and some future researches are given in the final section.

2. PROPOSED METHOD

DEA is a linear programming based technique for measuring the relative efficiency of a set of competing decision-making units (DMU) where comparison between inputs and outputs are difficult (Dyson et al. (1990)).

The relative efficiency of the 'multiple inputs and outputs' in DMU is defined as a ratio of the weighted sum of the DMU's outputs divided by the weighted sum of the DMU's inputs. So, if the higher performance for a DMU can be obtained, the input data of the ratio must have lower values, and the output data of the ratio must have higher values. In this article, we use DEA to select best setting of control factors in Taguchi method. Hence multiple response of signal-response system converts to the single measurement (DEA) in each level of the signal factor.

The general efficiency measure used by DEA is summarized as the following:

$$\text{Max } Z_j = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \tag{4}$$

$$u_r, v_i \geq 0$$

where Z; the efficiency measure of DMU j;

y_r ; The values of output y for DMU j;

x_i ; The values of input x for DMU j;

u_r ; The weights assigned to trial DMU k for output y;

v_i ; The weights assigned to trial DMU k for input x:

This nonlinear programming formulation (4) is equivalent to the following linear programming (LP) formulation (5) by setting its denominator equal to 1 and by maximizing its numerator.

$$\text{Max } Z_j = \sum_{r=1}^{s} u_r y_{r0}$$

$$\sum_{i=1}^{m} v_i x_{ij} = 1 \tag{5}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 1$$

$$u_r, v_i \geq 0$$

In the basic DEA (CCR model), which developed by Charnes, Cooper, and Rhodes (1978), the objective is to maximize the relative efficiency value of a trial DMU among a reference set of DMUs; by selecting the optimal weights associated with the input and output measures. The relative efficiency value for a Taguchi dynamic problem considered as *SNR*. For a multivariate dynamic problem, *SNR* obtained as follows:

$$SNR = -10 \log\left[\frac{1}{m}\sum_{k=1}^{m} y_{ijk}^2\right], \quad 0 \leq y_{ijk} < \infty \tag{6}$$

(for the smaller-the-better response)

$$SNR = -10\log\left[\frac{1}{m}\sum_{k=1}^{m}\frac{1}{y_{ijk}^{2}}\right],\quad 0 \le y_{ijk} < \infty \tag{7}$$

(for the larger-the-better response)

$$SNR = 10\log\left(\frac{\bar{y}^{2}}{S^{2}}\right) \tag{8}$$

(for the nominal-the-best response)

where y_{ijk} is observed data for the *i*th response at the *j*th trial.

Steps of the proposed method are expressed as:

Step 1: Calculate *SNR* for each levels of signal factor.

Step 2: Normalize the *SNR* for the *i*th response in the *j*th experiment. Because the *SNR* desire to be maximized, Equation (9) is useful.

$$Z_j = \frac{SNR_j - SNR_{j\min}}{SNR_{j\max} - SNR_{j\min}} \tag{9}$$

Step 3: Estimate the relative efficiency of in each level of the signal factor for each DMU. Each treatment in the orthogonal array is regarded as a DMU when applying DEA. After that General Index (GI) is calculated as follows:

$$GI_i = \sqrt[m]{U_{i1} \times U_{i2} \times \ldots \times U_{ij}} \tag{10}$$

where U_{im} is obtained efficiency for *i*th DMU in *j*th levels of signal factor. *m* is number of signal factor levels.

Step 4: According to the calculated GI, best setting of controllable factors are selected. This setting of the control factors introduces the efficiency treatment between trials of an experiment. Note that this treatment can be an initial solution for any optimization method.

3. NUMERICAL EXAMPLE

We investigate the proposed index by simulated dataset. Suppose there are two responses Y_1 and Y_2. The example, including five control factors, x_1, x_2, x_3, x_4, x_5, one noise factor *N* and a signal factor *M*. To consider an example, a combined array with resolution *VI* is used (see Table 1). Target values for each level of the signal factor for Y_1 are 0.1, -0.1 and 0.1 respectively. And these values for Y_2 are -0.2, 0.1 and 0.2.

Table 1:
Combined array 2_{VI}^{6-1} as the designed experiment in the numerical example

No.	A	B	C	D	E	N
1	-1	-1	-1	-1	-1	-1
2	1	-1	-1	-1	-1	1
3	-1	1	-1	-1	-1	1
4	1	1	-1	-1	-1	-1
5	-1	-1	1	-1	-1	1
6	1	-1	1	-1	-1	-1
7	-1	1	1	-1	-1	-1
8	1	1	1	-1	-1	1
9	-1	-1	-1	1	-1	1
10	1	-1	-1	1	-1	-1
11	-1	1	-1	1	-1	-1
12	1	1	-1	1	-1	1
13	-1	-1	1	1	-1	-1
14	1	-1	1	1	-1	1
15	-1	1	1	1	-1	1
16	1	1	1	1	-1	-1
17	-1	-1	-1	-1	1	1
18	1	-1	-1	-1	1	-1
19	-1	1	-1	-1	1	-1
20	1	1	-1	-1	1	1
21	-1	-1	1	-1	1	-1
22	1	-1	1	-1	1	1
23	-1	1	1	-1	1	1
24	1	1	1	-1	1	-1
25	-1	-1	-1	1	1	-1
26	1	-1	-1	1	1	1
27	-1	1	-1	1	1	1
28	1	1	-1	1	1	-1
29	-1	-1	1	1	1	1
30	1	-1	1	1	1	-1
31	-1	1	1	1	1	-1
32	1	1	1	1	1	1

10 replicates are simulated in each treatment. Mean and variance-covariance matrix of two responses and obtained DEA value in each level of the signal factor (0.1, 0.2 and 0.3) are presented in Table 2.

Table 2:
Experimental results for the designed experiment of the numerical example

No.	M1=0.1 Mean (Y1)	M1=0.1 Mean (Y2)	M1=0.1 Var.-Cov. Matrix		M2=0.2 Mean (Y1)	M2=0.2 Mean (Y2)	M2=0.2 Var.-Cov. Matrix		M3=0.3 Mean (Y1)	M3=0.3 Mean (Y2)	M3=0.3 Var.-Cov. Matrix		M1=0.1	M2=0.2	M3=0.3
1	2.25	-1.83	1.12	0.60	2.87	-2.04	1.51	0.46	2.61	-1.53	1.15	0.27	0.17	0.29	0.18
			0.60	0.96			0.46	1.21			0.27	0.63			
2	2.18	0.70	0.45	-0.12	1.47	0.97	0.87	0.07	1.12	1.27	0.44	-0.17	0.37	0.44	0.54
			-0.12	1.23			0.07	1.22			-0.17	0.87			
3	-1.49	-2.89	0.92	0.35	-1.38	-3.01	0.50	0.08	-0.81	-3.40	1.56	0.05	0.17	0.28	0.33
			0.35	1.38			0.08	0.70			0.05	1.13			
4	-3.53	-3.63	1.02	0.48	-4.18	-2.40	0.63	0.01	-5.05	-1.79	0.70	-0.01	0.29	0.18	0.48
			0.48	1.26			0.01	0.83			-0.01	0.92			
5	0.91	-1.68	1.08	-0.22	0.62	-2.23	1.23	0.14	0.09	-3.16	0.37	0.05	0.11	0.13	0.25
			-0.22	2.58			0.14	0.46			0.05	0.97			
6	11.32	5.56	1.30	-0.09	10.77	5.57	1.15	-0.44	10.78	5.83	1.69	0.04	0.86	0.15	0.98
			-0.09	0.94			-0.44	0.41			0.04	0.46			
7	-5.94	-7.26	0.63	0.11	-6.09	-7.55	0.86	0.27	-6.15	-7.18	0.66	0.01	0.87	0.90	0.94
			0.11	1.86			0.27	1.15			0.01	0.59			
8	-6.04	-1.54	1.33	0.53	-5.56	-0.97	0.96	0.07	-6.28	-2.54	0.86	0.05	0.12	0.24	0.22
			0.53	1.34			0.07	0.69			0.05	0.34			
9	-5.75	-3.40	0.74	0.46	-5.78	-3.87	0.37	-0.14	-6.20	-4.64	1.69	0.21	0.16	0.18	0.17
			0.46	1.14			-0.14	0.91			0.21	0.74			
10	1.59	-2.85	0.69	-0.23	1.04	-2.24	0.44	0.03	1.47	-1.52	0.58	0.36	0.28	0.27	0.35
			-0.23	0.75			0.03	1.97			0.36	0.62			
11	5.54	2.3	0.94	0.14	6.15	0.99	1.10	-0.23	6.12	1.50	0.76	0.12	0.84	0.88	0.67
			0.14	1.44			-0.23	0.65			0.12	1.22			

Table 2 (Contd….)

No.	M1=0.1				M2=0.2				M3=0.3				M1=0.1	M2=0.2	M3=0.3
	Mean (Y1)	Mean (Y2)	Var.-Cov. Matrix		Mean (Y1)	Mean (Y2)	Var.-Cov. Matrix		Mean (Y1)	Mean (Y2)	Var.-Cov. Matrix				
12	-7.70	-2.58	0.45	-0.20	-7.85	-3.71	1.02	0.22	-8.61	-3.26	0.75	-0.20	0.32	0.36	0.57
			-0.20	0.92			0.22	0.53			-0.20	0.33			
13	4.69	7.70	0.63	0.38	5.25	6.76	0.84	-0.33	5.70	6.64	0.59	0.08	0.19	0.23	0.29
			0.38	1.76			-0.33	0.77			0.08	0.99			
14	-1.82	5.15	0.77	-0.15	-1.75	5.08	0.75	0.55	-2.86	5.58	0.69	0.49	0.39	0.24	0.17
			-0.15	1.01			0.55	1.42			0.49	1.78			
15	1.96	-0.55	1.49	1.29	1.93	-0.14	0.63	-0.26	1.69	-0.39	1.33	0.05	0.92	0.96	0.92
			1.29	1.88			-0.26	0.78			0.05	0.11			
16	4.37	7.95	1.10	0.27	5.04	7.93	1.65	-0.10	5.24	7.91	1.48	-0.41	0.17	0.18	0.15
			0.27	0.63			-0.10	0.41			-0.41	1.33			
17	7.08	10.63	1.63	0.21	8.36	10.69	0.25	-0.04	8.72	11.23	2.08	-0.37	0.28	0.35	0.30
			0.21	0.37			-0.04	0.72			-0.37	0.92			
18	-6.16	-5.26	1.57	-0.01	-6.58	-5.44	0.98	0.03	-6.33	-4.92	1.00	0.30	0.76	0.88	0.79
			-0.01	1.18			0.03	0.99			0.30	1.10			
19	-1.63	-5.00	0.82	0.35	-0.98	-4.95	0.97	0.23	-1.55	-5.14	1.31	0.15	0.84	0.74	0.94
			0.35	0.80			0.23	1.18			0.15	0.35			
20	4.30	-1.65	1.34	-0.15	3.88	-0.74	1.43	0.62	3.80	0.07	1.03	0.45	0.27	0.17	0.09
			-0.15	0.65			0.62	1.61			0.45	1.50			
21	-3.59	2.75	0.42	0.12	-3.29	2.23	1.67	-0.05	-3.23	1.85	0.92	0.60	0.55	0.73	0.66
			0.12	1.83			-0.05	1.14			0.60	0.75			
22	1.69	-0.37	0.79	0.12	2.00	0.39	1.75	0.11	2.38	0.13	0.43	-0.18	0.27	0.52	0.65
			0.12	0.53			0.11	0.95			-0.18	2.16			
23	-4.33	3.28	0.52	0.00	-4.84	2.4	1.21	0.63	-5.90	2.93	0.77	-0.03	0.43	0.65	0.57
			0.00	0.49			0.63	1.05			-0.03	1.22			

Table 2 (Contd….)

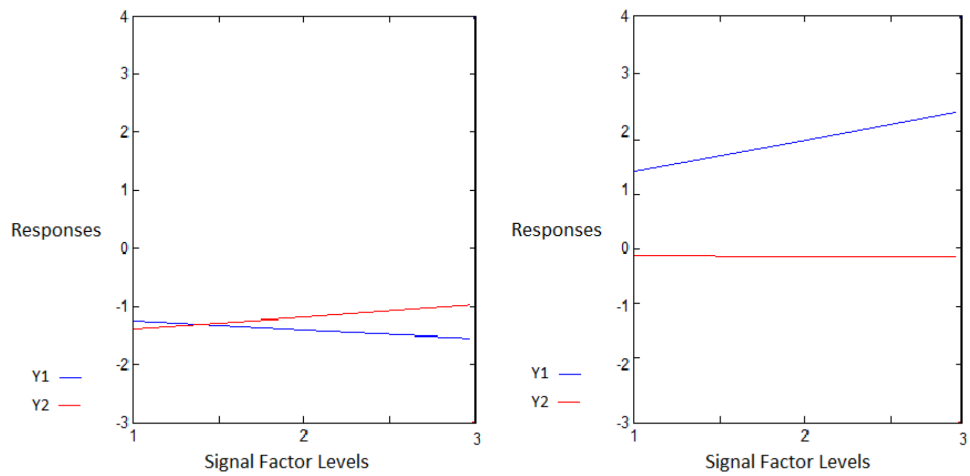
No.	M1=0.1				M2=0.2				M3=0.3				M1=0.1	M2=0.2	M3=0.3
	Mean (Y1)	Mean (Y2)	Var.-Cov. Matrix		Mean (Y1)	Mean (Y2)	Var.-Cov. Matrix		Mean (Y1)	Mean (Y2)	Var.-Cov. Matrix				
24	9.63	5.10	0.99	0.19	10.74	5.16	0.84	0.26	11.05	4.37	0.65	0.23	0.17	0.22	0.37
			0.19	1.21			0.26	0.51			0.23	0.91			
25	4.78	2.25	1.56	-0.08	4.32	2.20	0.32	-0.04	3.70	2.13	1.59	1.02	0.36	0.12	0.28
			-0.08	0.66			-0.04	0.42			1.02	1.59			
26	-6.64	-0.33	0.33	0.01	-7.77	-0.39	1.32	-0.28	-8.56	0.00	0.65	-0.09	0.47	0.68	0.79
			0.01	0.83			-0.28	1.13			-0.09	0.43			
27	-0.78	-5.48	1.12	-0.23	-0.06	-5.39	1.93	0.09	0.58	-5.03	1.04	-0.02	0.97	0.93	0.91
			-0.23	0.82			0.09	1.13			-0.02	1.73			
28	-10.03	-6.39	0.63	0.24	-10.53	-7.75	0.69	0.12	-10.77	-7.70	1.90	0.05	0.16	0.18	0.12
			0.24	1.05			0.12	0.43			0.05	2.08			
29	-2.06	-1.63	0.77	0.50	-1.89	-1.58	0.79	-0.09	-2.28	-1.30	0.59	0.41	0.14	0.16	0.29
			0.50	2.00			-0.09	0.33			0.41	1.54			
30	1.72	4.05	1.22	0.56	2.29	3.68	0.81	0.53	2.77	3.42	0.83	0.95	0.56	0.42	0.34
			0.56	0.60			0.53	1.98			0.95	3.14			
31	-3.76	-4.96	0.50	-0.16	-3.87	-5.01	0.15	0.18	-4.83	-5.00	2.30	0.48	0.89	0.95	0.88
			-0.16	0.85			0.18	0.64			0.48	1.14			
32	9.19	3.22	1.22	-0.03	9.28	3.44	0.87	0.46	10.44	3.31	1.00	-0.04	0.34	0.53	0.19
			-0.03	0.95			0.46	1.71			-0.04	1.16			

To select best treatment, a single measurement (*GI*) is calculated for each treatment. Table 3 shows results of obtained *GI* for each treatment. Note that *GI* is geometric mean of calculated DEA in signal factor levels.

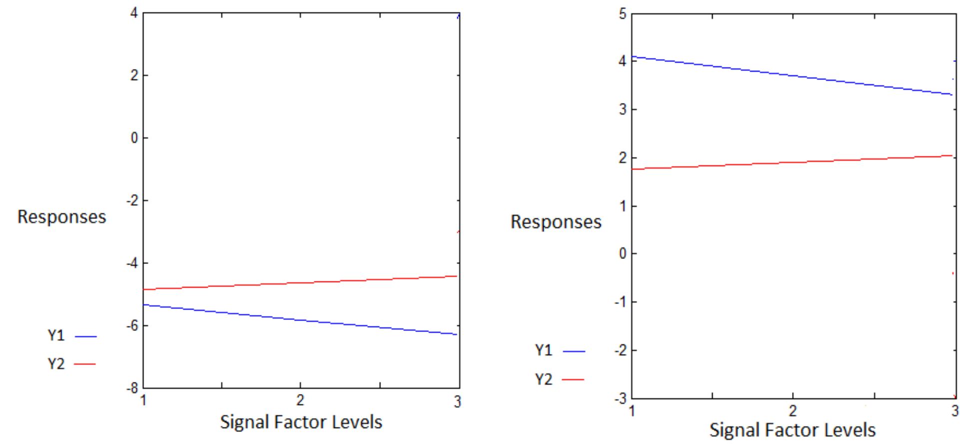
Table 3:
Computed general index for each treatment in the numerical example

Treatment	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
GI	0.207	0.445	0.25	0.293	0.153	0.502	0.903	0.185
Treatment	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
GI	0.170	0.298	0.791	0.403	0.233	0.252	0.933	0.166
Treatment	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*
GI	0.309	0.808	0.836	0.160	0.642	0.450	0.542	0.240
Treatment	*25*	*26*	*27*	*28*	*29*	*30*	*31*	*32*
GI	0.227	0.632	0.936	0.151	0.187	0.431	0.906	0.325

According to the proposed *GI*, treatment 27 with maximum value of *GI* (0.936) and 31 with 0.906 value of *GI* are selected as proper treatments for experiment. Figure 2 displays responses Y_1 and Y_2 according to the signal factor.



(a-1) (a-2)



(a-3) (a-4)

Fig.2: Shape of responses
(a-1) Treatment 31, (a-2) Treatment 27
(a-3) Treatment 5, (a-4) Treatment 22

Figure 2 depicted treatments 31 and 27 as proposed treatment versus treatments 5 and 22 as random treatments from the designed experiment. As Figure 2 (a-1) and (a-2) shows, proposed setting for control factors make responses robust and there is less variation in the responses in levels of the signal factor. In contrast, responses for treatments 5 and 22 (see Figure 2 (a-3) and (a-4)) have large variation and there is a large distance between responses and their targets.

4. CONCLUSION

In this paper, a method based on Data Envelopment Analysis (DEA) is proposed to consider multivariate signal-response systems. By using DEA, location and dispersion of responses can be considered with a single measurement (GI) in each level of the signal factor. Finally, proper control factor levels are obtained by considering GI in each level of the signal factor. The simulated result shows efficiency of the proposed method. To find the optimal value of controllable factors in a continuous space, modeling of GI according to the control factors as general linear model is recommended as a future research.

REFERENCES

1. Chang, H.H. (2008). A data mining approach to dynamic multiple responses in Taguchi experimental design. *Expert Systems with Applications,* 35, 1095-1103.
2. Charnes, A., Cooper, W.W. and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research,* 2, 429-444.
3. Dasgupta T., Miller A. and Wu, C.F.J. (2010). Robust design of measurement systems, *Technometrics,* 52(1), 338-346.

4. Derringer, G. and Suich, R. (1980). Simultaneous optimization of several response variables. *Journal of quality technology*, 12(4), 214-219.
5. Dyson, R.G., Thanassoulis, E. and Boussofiane, A. (1990). Data envelopment analysis. In L.C. Hendry and R.W. Eglese (Eds.) Tutorial papers in operational research. UK: Operational Research Society.
6. Elsayed, E.A. and Chen, A. (1993). Optimal levels of process parameters for products with multiple characteristics. *Int. J. Prod. Res.,* 31(5), 1117-1132.
7. Gupta, S., Kulahci, M., Montgomery, D.C. and Borror, C.M. (2010). Analysis of Signal-Response Systems Using Generalized Linear Mixed Models. *Quality and Rel. Engg. Int.,* 26, 375-385.
8. Khattree, R. (1996). Robust parameter design: A response surface approach. *J. Quality Tech.,* 28(2), 187-198.
9. Khuri, A.I. and Conlon, M. (1981). Simultaneous optimization of multiple responses represented by polynomial regression functions. *Technometrics,* 23(4), 363-375.
10. Lesperance, M.L. and Park, S.M. (2003). GLMs for the analysis of robust design with dynamic characteristics. *J. Quality Tech.,* 35(3), 253-263.
11. Lin, C.L., Lin, J.L. and Ko, T.C. (2002). Optimisation of the EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method. *Int. J. Adv. Manufacturing Tech.,* 19(4), 271-277.
12. Logothetis, N. and Haigh, A. (1988). Characterizing and optimizing multi-response processes by Taguchi method. *Quality and Rel. Engg. Int.,* 4(2), 159-169.
13. Lu, D. and Antony, J. (2002). Optimization of multiple responses using a fuzzy-rule based inference system. *Int. J. Prod. Res.,* 40(7), 1613-1625.
14. Lunani, M., Nair, V.N. and Wasserman, G.S. (1997). Graphical methods for robust design with dynamic characteristics. *Journal of Quality Technology,* 29, 327-338.
15. McCaskey, S.D. and Tsui, K.L. (1997). Analysis of dynamic design experiments. *Int. J. Prod. Res.,* 35(6), 1561-1574.
16. Miller, A. and Wu, C.F.J. (1996). Commentary on Taguchi's parameter design with dynamic characteristics. *Quality and Rel. Engg. Int.,* 12(2), 75-78.
17. Miller, A. and Wu, C.F.J. (1996). Parameter design for signal-response systems: a different look at Taguchi's dynamic parameter design. *Statistical Science,* 11(2), 122-136.
18. Miller, A. (2002). Analysis of parameter design experiments for signal-response systems. *Journal of Quality Technology,* 34(2), 139-151.
19. Roshan, J. and Wu, C.F.J. (2002). Performance Measures in Dynamic Parameter Design. *J. Jap. Quality Engg. Soc.,* 10, 82-86.
20. Roshan, J. and Wu, C.F.J. (2002). Robust parameter design of multiple target systems. *Technometrics,* 44(4), 338-346.
21. Shoemaker, A.C., Tsui, K.L. and Wu, C.F.J. (1991). Economical experimentation method for robust design. *Technometrics,* 33, 415-427.
22. Su, C.T. and Hsieh, K.L. (1998). Appling neural network approach to achieve robust design for dynamic quality characteristics. *Int. J. Quality and Rel. Mngt.,* 15(5), 509-519.
23. Su, C.T. and Tong, L.I. (1997). Multi-response robust design by principal component analysis. *Total Quality Management,* 8(6), 409-416.
24. Taguchi, G. (1987). *System of experimental design*. Unipub/Kraus Int, White Plains, NY.

25. Tong, L.I., Su, C-T. and Wang, C-H. (1997). The optimization of multiresponse problems in the Taguchi method. *Int. J. Quality and Rel. Mngt.,* 14(4), 367-380.
26. Tsui, K.L. (1999). Robust design optimization for multiple characteristic problems. *Int. J. Prod. Res.,* 37(2), 433-445.
27. Tsui, K.L. (1999). Modeling and analysis of dynamic robust design experiments. *IIE Transaction,* 31(12), 1113-1122.
28. Vining, G.G. (1998). A compromise approach to multiresponse optimization. *J. Quality Tech.,* 30(4), 309-313.
29. Wasserman, G.S. (1996). Parameter design with dynamic characteristics: a regression perspective. *Quality and Rel. Engg. Int.,* 12, 113-117.
30. Welch, W.J., Yu, T.K., Kang, S.M. and Sacks, J. (1990). Computer experiments for quality control by parameter design. *J. Quality Tech,.* 22, 15-22.
31. Wu, C.F.J. and Hamada, M. (2000). *Experiments: Planning, analysis, and parameter design optimization*. John Wiley & Sons Inc.
32. Wu, F.C. (2002). Optimisation of multiple quality characteristics based on percentage reduction of Taguchi's quality loss. *Int. J. Adv. Manufacturing Tech.,* 20(10), 749-753.
33. Wu, F.C. and Yeh, C.H. (2005). Robust design of multiple dynamic quality characteristics, *Int. J. Adv. Manufacturing Tech.,* 25, 579-588.
34. Zhiyu, Z., Zhen, H. and Xiangfen, K. (2006). New desirability function method for multi-response robust parameter design. *International Technology and Innovation Conference*.