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Application of genetic algorithm to numerical experiment in robust parameter design for signal multi-response problem

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Abstract. The conventional approach by Dr. Taguchi has been known as an off-line quality control to improve the performance of products or processes at low cost. Most previous Taguchi method applications have dealt only with static single-response problems. But in the recent years, the design has more complicated requirements; not only have more than one quality characteristic, but also deal in dynamic system. Therefore, several approaches dealing with multi-response problems have been increasingly reported. However, they have focused on the static system; the multi-response problems in dynamic system still have received only limited attention. This research proposes an approach using the genetic algorithm to find the best setting of the controllable factors, and outer orthogonal array to consider noises. The objective is to minimize the total average quality loss for the dynamic multi-response numerical experiment. In addition, to enhance the capability of the proposed approach, identifying the adjustment factor according to the two-step method by Dr. Taguchi is applied for the case of changing products or processes' requirements in the future. The effectiveness of the proposed approach will be demonstrated by an example of a temperature control circuit.

Keywords: robust parameter design, genetic algorithm, quality engineering, numerical experiment, Taguchi method, Multi-response problem, dynamic system

1 Introduction

Dr. Taguchi's method is a highly effective method of improving product or process quality at low cost. Despite its widespread industrial applications, Dr. Taguchi's parameter design methodology can only be used for optimizing single-response problems. While, in light of the increasing complexity of modern product design studies has shown that the optimal factor settings for one performance characteristic are not compatible with those for several performance characteristics. Therefore, recently industry has increasingly emphasized developing procedures capable of optimizing the multi-response problems to determine the optimal settings of factors which simultaneously optimize several responses.

Several approaches dealing with multi-response problems have been increasingly reported. For example, Pignatiello (1993)[17] proposed strategies for robust multi-response quality engineering by using multivariate loss as performance measure. Messac A. (2002)[10] used physical programming to solve multi-objective design, but not concerned with any noises. Some researchers [Chao-Ton Su (1997)[20], Jiju Antony (2000)[1], Chin-Ping Fung (2005)[4] proposed using principle component analysis for multi-response optimization. However, some researchers argued that there are other approaches more suitable. Such as; Corinna Auer et al. (2004)[2] proposed multi-response optimization using desirability function rather than principle component analysis and multivariate loss, Kai Xu et al.(2004)[24] proposed using a goal attainment approach comparing with generalized distance, desirability function, and fuzzy approach. In parallel, the new approaches are gradually developed such as VIKOR (Lee-Ing Tong, et al., 2007)[23], weighted principal component (Hung-Chang

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Liao, 2006)[9], process capability ratio, new quality loss ((Young-Hyun Ko. et al., 2005))[6], genetic algorithm (Ortiz, 2004)[13], TOPSIS (Hung-Chang Liao, 2003)[8], etc. However, they did not consider the effects of noises which are the important part of the philosophy of robust design.

Genetic Algorithm (GA) is a heuristic search approach that uses the historical information from previously examined solutions in selecting new search points where improved performances. GA has been gradually used as an alternative method for robust design with multi-objectives. For example, T. S. Li et al. (2003)[7] proposed using a novel neural and genetic algorithm to solve multi-response problems. Main L. (2005)[11] proposed using GA by new Robust Multi-Objective Genetic Algorithm (RMOGA) that optimizes two objectives: a fitness value and a robustness index to be least sensitive to the parameter variations. In addition, Forouraghi (2000)[3] expanded using GA in multi-objective robust design for tolerance design. Even under known or assumed uncertainties in the parameters of the variability optimization problems, GA is one of the efficient proposed methods for robust design to find the required global minimum Lagrangian form, which is the performance measure, as shown in article by Parkinson D. B. (1997 and 2000)[14, 15].

Unfortunately, those past studies have focused only on the static system, the multi- response problems in dynamic system still have received only limited attention and some have not considered the effects of noises. In addition, Dr. Taguchi focused on information of both sensibility and variance of a quality characteristic using the signal to noise (SN) ratio according to the two-step method, a major philosophy of robust design. Although, this philosophy is one of the remarkable features in robust parameter design, it has seldom been applied in the simple application of robust parameter design by GA. Therefore, in order to rectify those problems, this study based on dynamic system will present an alternative approach using the genetic algorithm to find the best setting of the controllable factors on the basis of the quality loss, and outer orthogonal array to consider noises. By using the summation of variance and sensibility, tracing the search process of GA and applying the regression analysis, the identifying not only the dispersion factors, but also the adjustment factors, and consequently the two-step method can be incorporated. Finally, the optimal setting of the controllable factors can be determined to simultaneously reduce the quality variation and optimize several responses in dynamic system. The temperature control circuit indicates that the proposed procedure yields a satisfactory result.

2 Basic theory

2.1 Framework of parameter design (Taguchi, G. 1992 and 2000)[21, 22]

Robust design is an engineering methodology that provides a product or process insensitivity to the effects of variability. This methodology is applied during the research and development stage to ensure that products can be produced with high quality and at low cost. The Taguchi method incorporates two principal tools, namely, SN ratio to measure the quality of the design and orthogonal array to design the experiment.

Fig. 1 shows the parameter diagram of a dynamic product or process system. First we identify the signal (input) factors and the response (output) factors.Next we consider the parameters that are beyond the control of the designer. Those factors are called noise factors for example; the errors in resistors. It should be realized that the most important strategy is taking noise factors into account during the design stage. At last, parameters that can be specified by the designer, controllable factors are set to provide the best performance and the least sensitivity to noises. The ideal relationship between signal and response should be a straight line for all

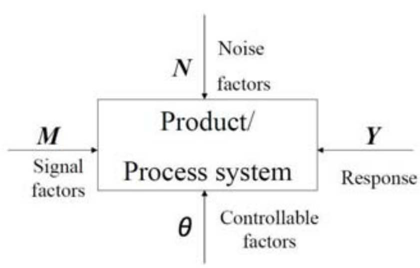

Fig. 1. Parameter diagram of a dynamic product or process system

operating conditions. We suppose the target function is

$$E(Y) = \beta M. \tag{1}$$

where β is the target slope, M is regarded as the signal factor and Y is considered to be the response factor. However, the noise factors cause the relationship to deviate from the ideal. The job of the designer is to select appropriate controllable factors so that the deviation from the ideal is minimized at low cost. Such a design is called dynamic robust design which provides minimum sensitivity.

Dynamic SN ratios:

Suppose y_{ij} represent the jth observed response at the i^{th} signal leve (M_i). Now consider the least squares fit to the model

$$E(Y_{ij}) = \beta M_i. \tag{2}$$

$\hat{\beta}$ represents the least squares estimate of β, and s^2 represents the estimated mean square error, MSE, by

$$s^2 = (n-1)^{-1} \sum_i \sum_j (y_{ij} - \hat{\beta} M_i)^2$$

The signal-to-noise ratio for dynamic system by Dr. Taguchi has been defined as

$$SN = \log(\hat{\beta}^2 / s^2)$$

Minimizing MSE is an effective method to maximize SN ratio, because it reduces the variance induced by external noises. However, increasing the value of $\hat{\beta}$ can lead to the undesirable result enhancing the system sensitivity. A larger $\hat{\beta}$ can give a wider range of the response Y, which may be outside the specification limits of the target. (Miller and Wu, 1996)[12].

2.2 Average loss function

Loss functions play a fundamental role in every quality engineering method to posses some interesting properties and lead to theoretical results that cannot be handled with other loss functions.

Average loss function:

$$R(\theta) = E_I L(y, t) \tag{3}$$

where θ is a setting of controllable factors, E is the expectation, I is a number of signal levels, L is a loss function, y is a response quality characteristic, and t is the target value.

$$L(y, t) = \sum_{k=1}^{K} \sum_{j=1}^{J} (y_{jk} - t_k)^2 \tag{4}$$

where y_{jk} represents the k^{th} response in the j^{th} experimental number of noise factors in the outer array. And t_k is the target value of the k^{th} response.

2.3 The two-step method

Dr. Taguchi focused on the information of the sensibility and variance of a quality characteristic according to the two-step method, a major philosophy of robust design.

1. Maximize the SN ratio by using the dispersion factor that influences the process variation and interacts with the noises. This is the step of variance reduction.
2. Adjust the mean to the target by using the adjustment factor that affects the mean, but not the variance. This is the step of adjusting the mean to the target and also adjusting the mean to compensate for process variation during manufacturing.

This two-step method by Dr. Taguchi has the advantage that certain changes to product specifications or process requirements can be accommodated by changing only the setting of the adjustment factors. The remaining factors are still same as the initial setting. It is beneficial for multi-product or small quantity production.

2.4 Genetic algorithm method

Genetic algorithm (GA) is a term used for a search technique that incorporates the concepts of natural selection in its iterative steps. GA uses historical information from previously examined solutions to select new search points which improved performances are expected. GA differs from conventional optimization algorithm in that it examines a population of points at each iteration rather than one point and uses the objective function rather than the derivative or gradient directly in the search.

The unique features of GA are that GA does not need many mathematical requirements for optimization problems. It can handle any kind of objective functions and constraints, linear or nonlinear, defined on discrete, continuous, or mixed search spaces. Moreover, it is effective at performing global search, while some traditional approaches perform local search. GA also provides great flexibility to hybridize with domain dependent heuristics to make an efficient implementation for a specific problem. Therefore, a problem that is highly nonlinear and heavily constrained can benefit from GA.

General structure of GA starts with an initial set of random solutions called population. Each individual in the population is called chromosome, representing a solution to the problem. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated, using some measures of fitness (objective value). To create the next generation, new chromosome, called offspring, is formed by either merging two chromosomes from current generation using crossover or modifying a chromosome using mutation. A new generation is formed by selecting some of the parents and offspring, according to the fitness values, and also rejecting others to keep the population size constant. After several generations, the algorithm converges to the best chromosome (Gen, Cheng, 1997)[5].

3 Proposed procedure

In this section, the step of proposed approach which searches for the best setting of controllable factors by GA and also considers noise factors will be shown.

Step 1. Set the setting of controllable and noise factors GA with continuous random search for the best setting of controllable factors is used replacing of the inner orthogonal array which can consider only two or three levels of controllable factors. But the outer orthogonal array is still used to take noise factors into account.

Therefore, the first step is setting the boundaries of controllable factors $R1, R2, \cdots$ for GA search and setting the levels of noise factors $R1', R2', \cdots$ for the outer orthogonal array

-Boundaries of

$$\begin{aligned} R1 : &\quad R1_l, \quad R1_u \\ R2 : &\quad R2_l, \quad R2_u \end{aligned}$$

where l is the lower boundary and u is the upper boundary of factor.

-Levels of noises

$$\begin{aligned} R1 : &\quad R1'_1, \quad R1'_2, \quad R1'_3 \\ R2 : &\quad R2'_1, \quad R2'_2, \quad R2'_3 \end{aligned}$$

where 1, 2, 3 are the levels of noise factors.

Step 2. Select the suitable performance measure, set the objective and GA parameter setting. The traditional OA use SN ratio as the performance measure, but Ramon (1987)[18] argued that maximizing SN ratio does not always minimize the expected loss. Therefore, robust parameter design by GA will use average loss which directly answers to objective of all design as the performance measure.

Hence, the objective of robust parameter design with GA is to minimize average loss caused by deviations of the output from target.

And then set the parameters of GA.

Step 3. Perform automatic continuous search process by GA to find the near optimum result. While parameter design by OA has to maximize SN ratio first and then adjust the mean to the target, parameter design by GA can get the best setting of controllable factors within one step with minimizing average loss.

4 The example of robust parameter design: temperature control circuit

Phadke (1989)[16] proposed a numerical example of temperature control circuit as shown in Fig. 2. For a special target temperature, the circuit must turn a heater ON or OFF to control the heat input. The thermistor resistance, R_T, decreases upon increasing the temperature. When the temperature rises above a certain value, the resistance R_T drops below a threshold value (denoted R_{T-OFF}) so that the difference in the voltages between terminals 1 and 2 of the amplifier becomes sufficiently large and negative. The relay is then actuated to turn OFF the heater. Similarly, when the temperature falls below a certain value, the resistance R_T rises above the threshold value (denoted R_{T-ON}) so that the difference in voltage between terminals 1 and 2 of the amplifier becomes sufficiently large and positive. The relay is then actuated to turn ON the heater.

Therefore, the threshold resistance, R_{T-ON}, at which the heater turns ON, and the threshold resistance, R_{T-OFF} can be expressed as:

$$R_{T-ON} = \frac{R3R2(EzR4 + E0R1)}{R1(EzR2 + EzR4 - E0R2)} \tag{5}$$

$$R_{T-OFF} = \frac{R3R2R4}{R1(R2 + R4)} \tag{6}$$

where $R1, R2, R3, R4$ is the resistance, $E0$ is power supply voltage and Ez is nominal voltage.

The variation of R_{T-ON} and R_{T-OFF} as a function of $R3$ generated the dynamic problems. In the temperature control circuit, there are four control factors ($R1, R2, R4,$ and Ez); and one signal factor ($R3$).

There are five noise factors ($R1, R2, R4, E0$ and Ez); each noise factor has three alternate levels. Level 2 is the mean value, and levels 1 and 3 are displaced from level 2 as shown in Tab. 1.

The ideal relationship of R_{T-ON} and R_{T-OFF} with linear $R3$ passes through the origin. Therefore, the relationship of R_{T-ON} and R_{T-OFF} on $R3$ can be expressed as:

$$R_{T-ON} = \beta_1 R3 + e_1 \tag{7}$$

$$R_{T-OFF} = \beta_2 R3 + e_2 \tag{8}$$

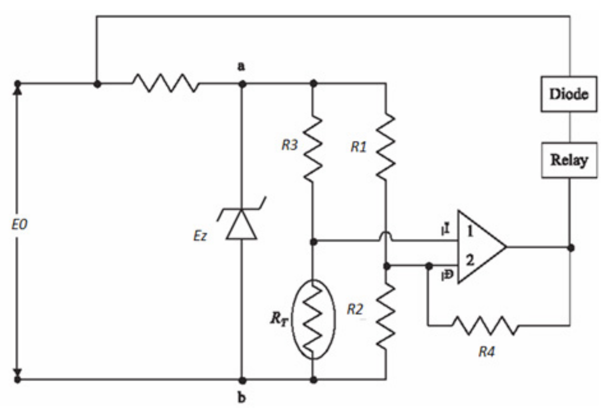

Fig. 2. Temperature control circuit

Table 1. Noise factors level

Levels	$R1'(\%)$	$R2'(\%)$	$R4'(\%)$	$E0'(\%)$	$Ez'(\%)$
1	+2.04	+2.04	+2.04	+2.04	+2.04
2	0	0	0	0	0
3	−2.04	−2.04	−2.04	−2.04	−2.04

Robust parameter design by GA

GA with continuous random search is used for finding the best setting of controllable factors, while the outer orthogonal array is still used to take noise factors into account as shown in Tab. 3 The detail of robust parameter design by GA

-Controllable factors' boundaries:

$2.67 <= R1 <= 6.00, 5.33 <= R2 <= 12.00, 26.67 <= R4 <= 60.00, 4.8 <= Ez <= 7.2.$

-Noise factors' levels: Each noise has three levels as shown in Tab. 1. And L18 is used to be the outer array. The 18 different noise conditions will be assigned.

Objective: Minimize $R(\theta)$, average loss caused by deviations of the output from the targe R_T.

For example, if $R1 = 6, R2 = 5.33, R3 = 0.5, R4 = 60, E0 = 10, Ez = 7.2$ according to Tab. 3, target R_{T-ON} is obtained from Eq. (5) while all factors are at the normal level.

$$\text{Target}_{R_{T-ON}} = \frac{0.5 \times 5.33 \times (7.2 \times 60 + 10 \times 6)}{6 \times (7.2 \times 5.33 + 7.2 \times 60 - 10 \times 5.33)} = 0.524$$

$\text{Target}_{R_{T-OFF}}$ is obtained from Eq.(6) while all factors are at the normal level.

$$Target_{R_{T-OFF}} = \frac{0.5 \times 5.33 \times 60}{6 \times (5.33 + 60)} = 0.408$$

$$Loss_{R_{T-ON|R3=0.5}} = (0.524 - 0.524)^2 + (0.515 - 0.524)^2 + \cdots + (0.525 - 0.524)^2 = 2.8 \times 10^{-3}$$

$$Loss_{R_{T-OFF|R3=0.5}} = (0.408 - 0.408)^2 + (0.400 - 0.408)^2 + \cdots + (0.409 - 0.408)^2 = 1.5 \times 10^{-3}$$

$$L(Y, t) = 2.8 \times 10^{-3} + 1.5 \times 10^{-3} = 4.3 \times 10^{-3}$$

$$R(\theta) = \frac{(4.3 \times 10^{-3} + 17.20 \times 10^{-3} + 38.8 \times 10^{-3})}{3} = 2.01 \times 10^{-2}$$

-Population Size: 50 chromosomes (appropriate setting by Ortiz, JR., 2004 [13])

-Mutation rate: 0.1

-Crossover rate: 0.5

-Stopping constraint: Fitness changes less than 0.01% in 5000 trials. This is the most popular stopping condition, because it gives the effective way to stop GA after the improvement rate is slowing down, and GA does not seem to find any better solutions. Let GA run until the improvement levels off. The GA parameter setting has been studied from the previous researches. And in order to validate it, GA parameter test is conducted by changing the crossover and mutation rate as the previous studies recommended, with the stopping criteria that the average loss changes less than 0.01% in last 5000 trials, the test result is shown in Tab. 2.

Table 2. The result of GA parameter test

Crossover	Mutation	R1	R2	R4	E0	Ez	S/N	ave. loss	No. trials	Time	trials/sec.
50%	1%	6.0	5.37	59.8	10	7.17	6.37	$2.07E-02$	16155	0.50	32310
50%	10%	6.0	5.33	60.0	10	7.20	6.38	$2.01E-02$	17376	1.10	15971
50%	40%	6.0	5.33	60.0	10	7.20	6.38	$2.01E-02$	19593	1.54	13067
85%	40%	6.0	5.33	60.0	10	7.20	6.38	$2.01E-02$	16640	1.54	10667
85%	10%	6.0	5.33	60.0	10	7.20	6.38	$2.01E-02$	11607	0.94	12656
85%	1%	6.0	5.34	59.9	10	7.19	6.38	$2.03E-02$	14366	0.45	31924

It is noticed that there is no significant difference in the setting of controllable factors and their results of average loss. However, the average loss is best at the crossover rate 50% and mutation rate 10%. The speed of searching time is quite different in trends that smaller mutation rate provides faster search process. But the very small mutation rate, 1%, performed poor search result. Therefore, in this temperature control circuit example we decided to use crossover at 50% and mutation at 10%.

Results

After let GA run for searching the best setting of controllable factors with minimum average loss, the result is shown in Tab. 3. The best setting is $R1 = 6, R2 = 5.33, R4 = 60, Ez = 7.2$, with average loss 2.01×10^{-2} (Number of trial generations $= 20, 389$ trial generations by using a personal computer pentium4)

Table 3. The result of average loss by GA

					$R3$ (signal)	0.5	0.5	0.5	1	1	1	1.5	1.5	1.5			
					Ez'	1	2	2	1	2	2	1	2	2			
					$E0'$	1	2	1	1	2	1	1	2	1			
					$R4'$	1	2	2	1	2	2	1	2	2			
					$R2'$	1	2	3	1	2	3	1	2	3			
					$R1'$	1	1	3	1	1	3	1	1	3			
$R1$	$R2$	$R4$	$E0$	Ez	Noise	1	2	18	1	2	18	1	2	18	**Ave. loss**	β	**MSE**
6.0	**5.33**	**60.0**	**10**	**7.2**	R_{T-ON}	0.524	0.515	0.525	1.049	1.030	1.050	1.573	1.545	1.576	2.01E-02	1.049 0.817	7.5E-04 4.1E-04
					R_{T-OFF}	0.408	0.400	0.409	0.816	0.800	0.818	1.225	1.200	1.227			
					Target R_{T-ON}	0.524	0.524	0.524	1.049	1.049	1.049	1.573	1.573	1.573			
					Target R_{T-OFF}	0.408	0.408	0.408	0.816	0.816	0.816	1.225	1.225	1.225			
					Loss R_{T-ON}	1.2E-32	8.5E-05	8.7E-07	4.9E-32	3.4E-04	3.5E-06	4.9E-32	7.6E-04	7.8E-06			
					Loss R_{T-OFF}	3.1E-33	6.7E-05	4.6E-07	1.2E-32	2.7E-04	1.9E-06	0	6.0E-04	4.2E-06			

Comparison

In quantitative comparison, the design by GA performs better than by OA not only in results of SN ratio, but also in average loss as shown in Tab. 4. This better result is obtained by the continuous random search of GA, and using average loss as the performance measure.

Table 4. Comparison the results by the different methods

	R1	R2	R4	E0	E_z	Ave.loss	β	*MSE*	*SN*	*Sum SN*
Starting	4.0	8.00	40.0	10	6.0	$1.5E-01$	2.694	$6.8E-03$	3.03	6.27
							1.667	$1.6E-03$	3.24	
Taguchi OA	2.7	5.33	60.0	10	7.2	$9.4E-02$	2.200	$3.3E-03$	3.16	6.37
							1.837	$2.1E-03$	3.21	
Phadke[16]	4.0	5.33	60.0	10	7.2	$4.3E-02$	1.510	$1.6E-03$	3.16	6.37
							1.225	$9.3E-04$	3.21	
Proposed	6.0	5.33	60.0	10	7.2	$2.0E-02$	1.049	$7.5E-04$	3.17	6.38
method							0.817	$4.1E-04$	3.21	

Top: parameter of R_{T-ON} Bottom: parameter of R_{T-OFF}

In qualitative comparison, there are some of advantages of robust parameter design by GA. Firstly, comparing in terms of speed to find the result, GA search was run on computer, so it can operate faster than OA experiment. Next, comparing in terms of flexibility, it is noticed that by OA it is difficult to change the levels of the controllable factors to find the best setting because of the interaction among each factors. This will cause troubles, if the problem is more complicated or contain many of controllable and noise factors. With GA, it is more flexible to change setting of controllable factors or add more constraints. In addition, GA could search automatically in continuous numerals, not limited in two or three levels of each factors like OA does. Consequently, the final result from GA is better than the one from OA. Moreover, it is necessary for OA to have some specific knowledge, for example; size of OA according to number of factors, how to assign each factor in each column of OA, etc. But in case of GA, it is easier, because it needs only the objective, constraints, boundaries of factors, GA parameter setting, and stopping constraint. Finally, GA can perform even in case of no idea what the range of solution could be, but for OA the designer has to know roughly what the solution could be in order to set the levels of factors.

On the other hand, there are some limitations in GA. The main one is that it can be applied with only the known input-output relationship, or numerical experiment. A numerical equation is needed to search the best result, while with OA it could be done by the real experiment. However, we can find a numerical equation by doing experiments and using regression analysis or using the advantages of CAE (Computer Aided Engineering). In addition, Parkinson D.B (2000)[15] supported that a viable alternative to costly prototype testing is the study of a mathematical model (analytic model or defined numerical computation) which describes the best setting of controllable factors and which permits variability minimization. The computer experiment allows the virtually cost free including a large number of noise and controllable factors, which is a particularly attractive feature when considering the cost incurred due to the unjustified neglect of troublesome variables. And in some cases it is too expensive or dangerous to conduct the real experiment or difficult to control noise factors. Furthermore, A. Messac (2002)[10] mentioned that although Dr. Taguchi's method was effective at improving quality, the statisticians pointed to inefficiencies in the method for highly nonlinear problems, the results were often less than satisfactory. Therefore, mathematical model is the one of the alternatives for robust design.

The other limitation is that normally GA could not do factor analysis to determine the dispersion and the adjustment factors according to the remarkable philosophy, two-step method, by Dr. Taguchi. It was argued that if there are some changes in product specifications or process requirements, we have to find all new setting of controllable factors, while with OA it can be accommodated by changing only the setting of the adjustment factors.

In spite of those improvements achieved by this proposed approach, some disadvantages remain. To overcome the limitations of dynamic robust design by GA, the two-step method with GA is also applied in section5.

5 Two-step method with genetic algorithm

As the main limitation in the parameter design by GA is mentioned above, by using the summation of variance and sensibility, tracing the search process of GA in particular and applying the regression analysis, the two-step method to identify the adjustment factor which affects only the mean, but not the variance can be incorporated to overcome this limitation.
(1) Find the dispersion factor according to the two-step method by reducing the process variation. It has to find the dispersion factors by using regression analysis of Sum SN ratio. Firstly, the data is obtained from the part of observations by GA as shown in Tab. 5. Ordinary, they are not shown explicitly. Each observation came from best answer of every 300 iterations.

Sum SN ratio $= SN$ of $R_{T-ON} + SN$ of R_{T-OFF}

Sum $\beta = \beta$ of $R_{T-ON} + \beta$ of R_{T-OFF}

Then, the regression analysis of Sum SN ratio is used as shown in Tab. 6. The result shows that factors R2 and R4 are sensitive to variance. This regression analysis of variance can also take the place of the graph of factors' effect by OA, because it can imply the significant factors that affect variance.
(2) The next step of the two-step method is to identify the adjustment factor which affects the slope $\hat{\beta}$ without affecting the variance by using the regression analysis of Sum $\hat{\beta}$. The result of regression analysis of Sum $\hat{\beta}$ is shown in Tab. 7 that shown factors $R1$ and $R2$ sensitive to Sum $\hat{\beta}$. But $R2$ affects both slope $\hat{\beta}$ and variance, so only $R1$ is considered as the adjustment factor in this example.

This regression analysis of Sum $\hat{\beta}$ can also imply the significant factors that affect sensitivity.

Finally, in the case of changing product specifications or process requirements in the future, it can be done by changing only the setting of the adjustment factor R1.

Table 5. The part of observations

R1	R2	R4	E0	Ez	Ave.loss	Sum SN	Sum β
2.7	12.0	26.7	10	4.8	$9.8E+00$	5.59	13.726
2.7	12.0	26.7	10	4.8	$9.8E+00$	5.59	13.726
2.7	12.0	59.9	10	5.0	$8.7E-01$	6.19	9.883
2.7	12.0	60.0	10	5.4	$7.5E-01$	6.23	9.618
4.0	8.0	40.0	10	6.0	$1.5E-01$	6.27	4.361
4.4	8.1	43.0	10	6.1	$1.2E-01$	6.29	4.003
4.0	6.7	39.2	10	5.9	$9.8E-02$	6.29	3.685
4.6	8.0	48.3	10	6.2	$9.6E-02$	6.31	3.739
2.7	5.3	60.0	10	7.2	$9.4E-02$	6.37	4.037
4.3	6.7	58.7	10	6.1	$6.8E-02$	6.34	3.314
4.0	5.4	51.8	10	5.3	$5.7E-02$	6.32	2.973
4.0	5.3	60.0	10	7.2	$4.3E-02$	6.37	2.734
6.0	7.2	54.2	10	7.0	$3.9E-02$	6.36	2.541
5.8	5.7	45.5	10	5.1	$3.7E-02$	6.28	2.256
6.0	5.3	26.7	10	6.4	$3.5E-02$	6.27	2.096
5.9	5.6	48.3	10	5.4	$3.1E-02$	6.31	2.156
6.0	5.3	26.7	10	6.9	$3.1E-02$	6.30	2.032
5.9	5.6	48.3	10	6.4	$2.6E-02$	6.35	2.042
5.9	5.6	52.3	10	6.4	$2.5E-02$	6.36	2.028
5.8	5.7	59.2	10	6.9	$2.5E-02$	6.37	2.053

Table 6. Regression analysis of Sum SN ratio

Regression Statistics					
Multiple R	87%				
R Square	76%				
Adjusted R Square	71%				
Standard Error	0.089				
Observations	40				
ANOVA					
	df	SS	MS	F	Significance F
Regression	5	0.893	0.179	28.446	$3.08E-11$
Residual	35	0.275	0.008		
Total	40	1.167			
	Coefficients	Std.Error	t Stat	P-value	
Intercept	6.196	0.260	23.843	$3.2E-23$	
R1	0.005	0.020	0.250	$8.0E-01$	
R2	-0.049	0.013	*-3.807*	$5.4E-04$	
R4	0.007	0.002	*4.435*	$8.7E-05$	
Ez	0.003	0.030	0.093	$9.3E-01$	

6 Conclusions

The approach is motivated by the universal recognition of robustness as a key reliability and quality characteristic in today's products and processes, where increased sensitivity to operating conditions would result in increased performance fluctuations and costly time consuming efforts to meet design targets. However, in practical applications of modern complex product designs most of designs are multi-responses, but the robust design problem frequently focused on only one response. Even in recent years multi-responses have been increasingly emphasized developing procedures capableof simultaneously optimizing the several quality characteristics, but only in the static system without any signal factors. This paper shows that the multi-response robust design in dynamic system by GA can be successfully applied to reduce variation and bring the mean to the target, resulting in improved quality at low cost.

The proposed approach successfully provides the best setting of controllable factors at which a certain model outcome is best in performance and is less sensitive to variations in noises. This paper combines Dr.

Table 7. Regression analysis of Sum $\hat{\beta}$

Regression Statistics					
Multiple R	96%				
R Square	93%				
Adjusted R Square	89%				
Standard Error	0.857				
Observations	40				
ANOVA					
	df	SS	MS	F	Significance F
Regression	5	327.604	65.521	111.560	$4.36E-20$
Residual	35	25.695	0.734		
Total	40	353.299			
	Coefficients	Std.Error	t Stat	P-value	
Intercept	0.334	2.514	0.133	$9.0E-01$	
R1	-0.560	0.192	*-2.912*	$6.2E-03$	
R2	1.098	0.125	*8.820*	$2.0E-10$	
R4	-0.034	0.016	-2.172	$3.7E-02$	
Ez	0.099	0.291	0.341	$7.4E-01$	

Taguchi's robust design with the consideration of noises and the two-step method to incorporate robustness into the GA search. The proposed approach has compensated for the various shortcomings of Dr. Taguchi's experimental design with OA such as limited information about interactions, insufficient two or three-level design when the factors are continuous, etc. by using the effective GA search. In addition, it includes the use of quality loss function to replace the S/N ratio, and enhances with the study of the dispersion and adjustment factors for dynamic multi-response problems. In case of changing product specifications or process requirements in the future, it can be done by changing only the setting of the adjustment factor.

The result of this paper supports Sanchez et al (1996)'s[19] statement that the larger the range of parameter settings, the greater the potential for identifying good designs, whereas conducting experiments with fixed parameter levels impacts the quality of the solution obtained. Dynamic robust design by GA with continuous searching in a wide range of parameter settings shows high potential for identifying better results than by OA with two or three levels of parameters.

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