# 다중반응표면최적화 : 현황 및 향후 연구방향

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# Multiresponse Optimization: A Literature Review and Research Opportunities

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Key Words : Response Surface Methodology, Multiple Responses, Optimization, Review, Future Research Direction

**Abstract**

A common problem encountered in product or process design is the selection of optimal parameter levels which involves simultaneous consideration of multiple response variables. This is called a multiresponse problem. A multiresponse problem is solved through three major stages: data collection, model building, and optimization. Up to date, various methods have been proposed for the optimization, including the desirability function approach and loss function approach. In this paper, the existing studies in multiresponse optimization are reviewed and a future research direction is then proposed.

## 1. Introduction

Response surface methodology (RSM) consists of a group of techniques used in empirical study of the relationship between a response and a number of input variables. Consequently, the experimenter attempts to find the optimal setting for the input variables that maximizes (or minimizes) the response 「Box and Draper, 1987; Khuri and Cornell, 1996; Myers and Montgomery, 2002」.

In product or process development, it is quite common that several response variables are of interest. In this case, determination of optimum conditions on the input variables would require simultaneous consideration of all the responses. This is called a multiresponse problem 「Khuri, 1996」.

A multiresponse problem is solved through three stages: data collection (by the experimental design), model building, and optimization. In the optimization stage, two questions must be addressed: "what-to-optimize"(optimization goal) and "how-to-optimize-it"(solution technique). This paper focuses on the "what-to-optimize" aspect, assuming that the data have been collected and the response models have been fitted reasonably well. A multiresponse optimization (MRO) problem is formally defined as:

$$\begin{aligned} Optimize \quad & [\hat{y}_1(\boldsymbol{x}), \hat{y}_2(\boldsymbol{x}), \cdots, \hat{y}_k(\boldsymbol{x})] \\ s.t. \quad & \boldsymbol{x} \in \boldsymbol{\Omega}, \end{aligned} \tag{1}$$

where $\hat{y}_i(\boldsymbol{x})$ denotes the estimated $i$th response ($i$ = 1, ⋯, $k$), $\boldsymbol{x}$ is an input variable vector, and $\boldsymbol{\Omega}$ is the experimental region.

Up to date, various methods have been proposed

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for MRO, including the desirability function 「Harrin gton, 1965; Derringer and Suich, 1980; Derringer, 1994」 and loss function approaches 「Pignatiello, 1993; Vining, 1998; Ko et al., 2005」. MRO problems often involve incommensurate and conflicting criteria in multiple responses. To obtain a satisfactory compromise in such a case, a decision maker (DM)'s preference information on the trade-offs among the responses should be incorporated into the problem. Recently, a few studies have pro posed new methods to effectively extract the DM's preference information in MRO such as, for example, the interactive desirability function methods 「Jeong and Kim, 2003; Jeong and Kim, 2005; Jeong and Kim, 2009」 and posterior preference articulation methods 「Lee et al., 2010; Lee et al., 2011a」.

This paper aims at reviewing the existing studies in MRO and then proposing a future research direction. Specifically, it first reviews the numerous papers in the six MRO approaches each (Se ction 2), and then evaluates them via two aspects: statistics and preference information (Section 3). Finally, a promising research direction in MRO is presented (Section 4).

## 2. Review of the Existing Studies in MRO

The existing studies in MRO can be categorized into six approaches: graphical, priority-based, desirability function, loss function, process capability, and probability-based approaches. The last five approaches can be grouped into an analytical appr oach. They take a common strategy that reduces a multidimensional problem in Equation (1) into a one-dimensional problem and then solves it. Each approach is reviewed below.

### 2.1 Graphical approach

The graphical approach superimposes the response contour plots and determines an optimal solution by a visual inspection 「Lind et al., 1960」. It had been widely used before analytical methods were developed 「Hill and Hunter, 1966」. This approach has a shortcoming that its usefulness is severely limited by the number of input variables and/or responses. Nevertheless, it has been utilized until recently due to its simplicity and intuitiveness 「Gupta et al., 2001; Hamed and Sakr, 2001; Theppaya and Prasertsan, 2004; Huang et al., 2004; Huang et al., 2005」.

### 2.2. Priority-based approach

The priority-based approach selects the most important response among a number of ones and then uses it as the objective function. The other responses are employed as constraints:

$$\begin{aligned} & Optimize\ \ \hat{y}_p(\boldsymbol{x}) \\ & \quad s.t.\ \ \hat{y}_s(\boldsymbol{x}) \in \boldsymbol{R}_s,\ s=1,\cdots,k\,(s \neq p), \\ & \quad\quad\ \ \boldsymbol{x} \in \boldsymbol{\Omega}, \end{aligned} \tag{2}$$

where $\hat{y}_p(\boldsymbol{x})$ and $\hat{y}_s(\boldsymbol{x})$ denote the estimated primary and secondary responses, respectively, and $\boldsymbol{R}_s$ is a set of requirements for $\hat{y}_s(\boldsymbol{x})$.

Assuming there are only two responses of interest, Myers and Carter (1973) proposed an optimization formulation that maximizes (or minimizes) the primary response with an equality constraint on the other response. Biles (1975) extended this idea by allowing not only more than two responses, but also inequality constraints on the secondary responses. Del Castillo (1996) proposed an optimization formulation that treats the confidence regions for the stationary points of responses as constraints. More specifically, it first finds a stationary point of each response and then computes the confidence regions for the stationary points of responses. These confidence regions are used as constraints in Equation (2).

The priority-based approach has an advantage that it utilizes the typical formulation style in the optimization field as it is. However, it does not fulfill the philosophy of MRO that simultaneously cons iders the multiple responses 「Kim et al., 2002」.

## 2.3. Desirability function approach

The desirability function approach transforms an estimated response (e.g., the $i$th estimated response $\hat{y}_i$) into a scale-free value, called a desirability (denoted as $d_i$ for $\hat{y}_i$). It is a value between 0 and 1, and increases as the corresponding response value becomes more desirable. The overall desirability $D$, another value between 0 and 1, is defined by combining the individual desirability values (i.e., $d_i$'s). Then, the optimal setting is determined by optimizing $D$.

Harrington (1965) first proposed a simple form of a desirability function. Derringer and Suich (1980) extended Harrington's approach by suggesting a more systematic transformation scheme from $\hat{y}_i$ to $d_i$. As an example, in the case of a nominal-the-best (NTB)-type, the desirability function is given as:

$$d_i(\hat{y}_i(\boldsymbol{x})) = \begin{cases} 0 & \text{if } \hat{y}_i(\boldsymbol{x}) \le Y_i^{\min} \text{ or } \hat{y}_i(\boldsymbol{x}) > Y_i^{\max}, \\ \left[\dfrac{\hat{y}_i(\boldsymbol{x}) - Y_i^{\min}}{T_i^{\min} - Y_i^{\min}}\right]^{s_i} & \text{if } Y_i^{\min} < \hat{y}_i(\boldsymbol{x}) \le T_i^{\min}, \\ \left[\dfrac{Y_i^{\max} - \hat{y}_i(\boldsymbol{x})}{Y_i^{\max} - T_i^{\max}}\right]^{t_i} & \text{if } T_i^{\max} < \hat{y}_i(\boldsymbol{x}) \le Y_i^{\max}, \\ 1 & \text{if } T_i^{\min} < \hat{y}_i(\boldsymbol{x}) \le T_i^{\max}, \end{cases} \tag{3}$$

where $d_i(\hat{y}_i(\boldsymbol{x}))$ is the desirability function of $\hat{y}_i(\boldsymbol{x})$, $Y_i^{\min}$ and $Y_i^{\max}$ are, respectively, the lower and upper bounds on the response, $T_i^{\min}$ and $T_i^{\max}$ ($T_i^{\min} \le T_i^{\max}$) are, respectively, the lower and upper targets of the response, and $s_i$ and $t_i$ are the parameters that determine the shape of $d_i(\hat{y}_i(\boldsymbol{x}))$: if $s_i$ (or $t_i$) = 1, the shape is linear; if $s_i$ (or $t_i$) > 1, convex; and if 0 < $s_i$ (or $t_i$) < 1, concave. It should be noted that, if $T_i^{\min}$ = $T_i^{\max}$, the trapezoidal desirability function in Equation (3) reduces to a triangular one. For a definition on the desirability functions of larger-the-better (LTB)- and smaller-the-better (STB)-type responses, see Derringer and Suich (1980).

The desirability function proposed by Derringer and Suich (1980) contains non-differentiable points as shown in Equation (3). Del Castillo et al. (1996) proposed modified desirability functions that are everywhere differentiable so that an efficient gradient-based optimization method, which requires a differentiability assumption, can be used.

The overall desirability can be obtained by aggregating the individual desirability functions using the geometric mean:

$$D = (d_1 \times d_2 \times \cdots \times d_k)^{1/k}. \tag{4}$$

Later, different forms of aggregation have been proposed. For example, Derringer (1994) proposed the use of a weighted geometric mean. Kim and Lin (2000) suggested maximizing the lowest $d_i$, which is equivalent to maximizing the overall degree of satisfaction of all the responses.

Most of the studies in the desirability function approach have been focused mainly on the location effects (i.e., means) of responses. However, as the Taguchi's robust design concept became more pop ular, the desirability function approach tried to consider the dispersion effects (i.e., variances) as well as the location effects 「Tong et al., 2001; Rib ardo and Allen, 2003; Wu, 2005; Kwon et al., 2005; Kim and Lin, 2006」.

The most important advantage of the desirability function approach is easy to use in practice. Moreo ver, it incorporates the DM's preference inform ation through various channels. However, the acquisition of such information may be quite difficult because he/she provides the information assumptively without recognizing the tradeoffs among the multiple conflicting responses. To overcome this lim itation, Jeong and Kim (2003, 2005, 2009) proposed interactive desirability function methods to incorp orate the DM's preference information well. The methods adjust the shape, bound, and, target of a desirability function using the preference inform ation extracted from the DM in an interactive manner.

## 2.4. Loss function approach

The loss function approach aims to find the optimal parameter setting by minimizing the expected loss function. Pignatiello (1993) first proposed the use of a squared error loss function in MRO:

$$L(\boldsymbol{y}(\boldsymbol{x})) = (\boldsymbol{y}(\boldsymbol{x}) - \boldsymbol{\theta})' \boldsymbol{C} (\boldsymbol{y}(\boldsymbol{x}) - \boldsymbol{\theta}), \tag{5}$$

where $\boldsymbol{y}(\boldsymbol{x})$ is a vector of response variables, $\boldsymbol{\theta}$ is the target vector of responses, and $\boldsymbol{C}$ is the cost matrix representing the relative importance of each response. Then, the expected loss, which is to be minimized, can be derived as:

$$E[L(\boldsymbol{y}(\boldsymbol{x}))] = (E(\boldsymbol{y}(\boldsymbol{x})) - \boldsymbol{\theta})' \boldsymbol{C} (E(\boldsymbol{y}(\boldsymbol{x})) - \boldsymbol{\theta}) + trace[\boldsymbol{C}\boldsymbol{\Sigma}_{\boldsymbol{y}}(\boldsymbol{x})], \tag{6}$$

where $\boldsymbol{\Sigma}_{\boldsymbol{y}}(\boldsymbol{x})$ is the variance-covariance matrix of the responses. Tsui (1999) extended the Pignatiello's model, which was developed only for an NTB-type response, to the cases for LTB-and STB-type responses.

Vining (1998) proposed a modification to the Pignatiello's model by employing a vector of the estimated responses $\hat{\boldsymbol{y}}(\boldsymbol{x})$ in loss function, instead of $\boldsymbol{y}(\boldsymbol{x})$. Consequently, the expected loss can be expressed as:

$$E[L(\hat{\boldsymbol{y}}(\boldsymbol{x}))] = (E(\hat{\boldsymbol{y}}(\boldsymbol{x})) - \boldsymbol{\theta})' \boldsymbol{C} (E(\hat{\boldsymbol{y}}(\boldsymbol{x})) - \boldsymbol{\theta}) + trace[\boldsymbol{C}\boldsymbol{\Sigma}_{\hat{\boldsymbol{y}}}(\boldsymbol{x})], \tag{7}$$

where the $\boldsymbol{\Sigma}_{\hat{\boldsymbol{y}}}(\boldsymbol{x})$ is the variance-covariance matrix of the predicted responses. The Vining's approach includes Khuri and Conlon (1981)'s method using the generalized distance concept as a special case.

Ko et al. (2005) proposed an improvement over the Pignatiello's and Vining's models. They employ a vector of the newly estimated responses $\hat{\boldsymbol{y}}_{\boldsymbol{n}}(\boldsymbol{x})$ in the loss function, as opposed to $\boldsymbol{y}(\boldsymbol{x})$ in the Pignatiello's or $\hat{\boldsymbol{y}}(\boldsymbol{x})$ in Vining's model. Then, the expected loss is expressed as:

$$E[L(\hat{\boldsymbol{y}}_{\boldsymbol{n}}(\boldsymbol{x}))] = (E(\hat{\boldsymbol{y}}(\boldsymbol{x})) - \boldsymbol{\theta})' \boldsymbol{C} (E(\hat{\boldsymbol{y}}(\boldsymbol{x})) - \boldsymbol{\theta}) + trace[\boldsymbol{C}\boldsymbol{\Sigma}_{\hat{\boldsymbol{y}}}(\boldsymbol{x})] + trace[\boldsymbol{C}\boldsymbol{\Sigma}_{\boldsymbol{y}}(\boldsymbol{x})], \tag{8}$$

The expected loss in Equation (8) includes both the variance of the estimated and the variance of the estimated responses. Thus, the Ko et al.'s model is a more generalized model and includes both the Pignatiello's and Vining's models as special cases.

The loss function approach originates from the Taguchi's robust design concept. Therefore, it nec essarily considers the dispersion effects of responses (i.e., $\boldsymbol{\Sigma}_{\boldsymbol{y}}(\boldsymbol{x})$ in Equations (6) and (8)). The loss function approach is statistically good, but it requires strong statistical assumptions as a conse quence.

## 2.5. Process capability approach

The process capability approach derives a process capability index using the estimated mean and standard deviation of a response. The overall capability index is obtained by combining the individual process capability indices. Then, the optimal setting is determined by maximizing the overall capability index.

Barton and Tsui (1991) proposed a performance centering as a process capability index:

$$PC_i = \min\left\{ \frac{\hat{\mu}_i(\boldsymbol{x}) - Y_i^{\min}}{\hat{\sigma}_i(\boldsymbol{x})}, \frac{Y_i^{\max} - \hat{\mu}_i(\boldsymbol{x})}{\hat{\sigma}_i(\boldsymbol{x})} \right\}, \tag{9}$$

where $PC_i$, $\hat{\mu}_i(\boldsymbol{x})$, and $\hat{\sigma}_i(\boldsymbol{x})$ are the performance centering measure, the estimated mean, and the estimated standard deviation of the $i$th response variable, respectively. Then, they suggest ed maximizing the minimum of $PC_i$'s. Plante (1999) extended the Barton and Tsui's approach by developing several multicriteria models based on the performance centering. Plante (2001) proposed the use of two typical process capability indices, *Cpk* and *Cpm*:

$$Cpk_i = \min\left\{ \frac{\hat{\mu}_i(\boldsymbol{x}) - Y_i^{\min}}{3\hat{\sigma}_i(\boldsymbol{x})}, \frac{Y_i^{\max} - \hat{\mu}_i(\boldsymbol{x})}{3\hat{\sigma}_i(\boldsymbol{x})} \right\}, \tag{10}$$

$$Cpm_i = \frac{Y_i^{\max} - Y_i^{\min}}{6\sqrt{(\hat{\sigma}_i(\boldsymbol{x}))^2 + (\hat{\mu}_i(\boldsymbol{x}) - \theta_i)^2}}, \quad (11)$$

where $\theta_i$ is the target of the $i$th response variable. As shown in Equations (9) and (10), $PC_i$ and $Cpk_i$ are fundamentally the same index. Then, he suggested maximizing the (weighted) geometric mean of $Cpk_i$'s (or $Cpm_i$'s). Ch'ng et al. (2005) proposed to maximize the weighted sum of $Cpm_i$'s. Köksalan and Plante (2003) proposed an interactive optimization method to incorporate the DM's preference information in their proposed method.

The major advantage of the process capability approach is that its objective function, namely, $Cpk$ and $Cpm$, are familiar to quality practitioners and it considers the dispersion effects of responses via the variance term (i.e., $\hat{\sigma}_i(\boldsymbol{x})$ in Equations (9)-(11)).

## 2.6. Probability-based approach

The probability-based approach assumes a multivariate probability distribution of a multivariate response $\boldsymbol{Y}$. It first models the distributional parameters in terms of input variables and then finds the optimal setting which maximizes the probability that all responses simultaneously meet their specifications.

Chiao and Hamada (2001) assumed the multivariate normal distribution with mean $\boldsymbol{\mu} = (\mu_1, \mu_2, \cdots, \mu_k)'$ and variance-covariance matrix $\boldsymbol{\Sigma}$ (the diagonal elements of which are the variances $\sigma_1^2, \sigma_2^2, \cdots, \sigma_k^2$ and the off-diagonal elements of which are the covariances $\rho_{ij}\sigma_i\sigma_j$ $(1 \le i < j \le k)$, where $\rho_{ij}$ is the correlation between the $i$th and $j$th responses). The joint probability density function, $f(\boldsymbol{Y}; \boldsymbol{\mu}, \boldsymbol{\Sigma})$, is given as:

$$f(\boldsymbol{Y}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{(k/2)}|\boldsymbol{\Sigma}|^{1/2}} e^{-(1/2)(\boldsymbol{Y}-\boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\boldsymbol{Y}-\boldsymbol{\mu})}. \quad (12)$$

The distributional parameters are modeled as a function of $\boldsymbol{x}$: $\hat{\mu}_i(\boldsymbol{x})$, $\hat{\sigma}_i(\boldsymbol{x})$, and $\hat{\rho}_{ij}(\boldsymbol{x})$. Then, they suggested maximizing the proportion of conformance, $P(\boldsymbol{Y} \in \boldsymbol{S} | \boldsymbol{x})$, where $\boldsymbol{S}$ is a set of specifications for the responses. Peterson (2004) and Miró-Quesada et al. (2004) estimated the distributional parameters in the multivariate $t$ distribution using a Bayesian approach.

The major advantage of this approach is that it stands on the solid statistical basis. However, it has some shortcomings that it makes a strong statistical assumption and allows no interaction with the DM.

## 2.7. Other approaches

There are a few studies that are not directly included in, but closely related to the desirability function approach. Kumar and Goel (2002) and Lai and Chang (2004) proposed a fuzzy modeling approach, which can be viewed as the desirability function approach. Peterson (2000) proposed a combined approach of the desirability function and probability-based approaches.

Several variants of the loss function approach have also appeared in the literature. Ribeiro et al. (2000), Teeravaraprug and Cho (2002), and Savage and Seshadri (2003) added a "cost-of-loss" concept to the loss function approach. Tong and Su (1997), Su and Tong (1997), Antony (2000), Yang and Chou (2005), Wang and Tong (2005), and Liao (2006) considered a new variable called "quality loss" as a response. Chen (1997), Lu and Antony (2002), Maghsoodloo and Chang (2001), Wu (2002), and Tong et al. (2004a, 2004b) considered the "signal-to-noise" ratio as a response. Romano et al. (2004) proposed a loss function method integrating both robust parameter design and tolerance design. Logothetis and Haigh (1988), Artiles-Leon (1996), Tong et al. (1997), and Jayaram and Ibrahim (1997) also modified the conventional loss function approach or introduced a new concept into it.

Reddy et al. (1997) and Xu et al. (2004) proposed a goal programming approach. Kumar et al. (2000)

proposed to apply a utility concept to the Taguchi method.

# 3. Evaluation of the Existing Studies

In this section, the existing studies in MRO are evaluated in two aspects: statistics and preference information. The statistics-based evaluation identifies whether an existing study considers the important statistical properties (which will be described in detail in Subsection 3.1) for MRO and how many. The preference information-based eval uation finds how many channels an existing approach holds in order to represent the DM's preference information and at which timing, namely, before, during, or after solving the problem, the preference information are specified.

The evaluation results will show the limitations of the existing studies and present some insights on a further research direction in MRO. It should be noted that the papers in the analytical approach in Section 2 are used in the evaluation. Therefore, the graphical approach is excluded for evaluation. It should be also noted that the framework of this evaluation refers to Kim et al. (2002).

## 3.1. Statistics-based evaluation

In this subsection, the existing studies in MRO are evaluated depending on whether or not it considers the following three statistical properties: (i) correlation structure among responses, (ii) robustness of response, and (iii) quality of response models.

### 3.1.1. Correlation structure among responses

The correlation structure means the strength of relationships among responses. The first column of Table 1 shows the evaluation results on the correlation structure. All the studies in the priority-based and process capability approaches do not consider the correlation structure at all. Few studies in the desirability function approach consider the correlation structure among responses. Wu (2005) is the only study considering the correlation structure in this approach.

On the other hand, nearly half the studies in the loss function approach and all the studies in the probability-based approach consider the correlation structure through variance-covariance matrix. In the loss function approach, Elsayed and Chen (1993), Ribeiro and Elsayed (1995), Ames et al. (1997), and Lamghabbar et al. (2004) did not consider the correlation structure.

### 3.1.2. Robustness of response

The robustness refers to the low sensitivity of the response to other factors, that is, the small dispersion effects. Two types of sensitivity have been addressed: robustness to uncontrollable (noise) factors and robustness to parameter fluctuation. The robustness to uncontrollable factors means how large the variance of a response is at specific setting of input variables. On the other hand, the robustness to parameter fluctuation means how large the variance of a response is amplified by the parameter fluctuation of input variables.

The second column of Table 1 shows the results of evaluation on the robustness of response. All the studies in the priority-based approach and most of the studies in the desirability function and probability-based approaches do not consider the robu stness. But, several papers in the desirability func tion approach consider the robustness. Tong et al. (2001), Ribardo and Allen (2003), Wu (2005), and Kim and Lin (2006) considered the robustness to uncontrollable factors, while Kwon (2005) considered both the robustness to uncontrollable factors and the robustness to parameter fluctuation.

On the other hand, all the studies in the process capability approach and most of the studies in the loss function approach, including Wu and Chyu (2004), consider the robustness. This is because the loss function approach originates from the Taguchi's robust design concept and the process capability approach uses the indices involving the estimated standard deviation of a response.

3.1.3. Quality of response models

The quality of response models refers to how reliable the estimated response models are. Two approaches have been proposed in this regard: quality of description and quality of prediction. The quality of description measures how well the estimated response models explain data. The $R^2$, adjusted $R^2$, or mean squared error can be employed as measures of the quality of description. On the other hand, the quality of prediction measures how large the variance of a model itself is at specific setting of input variables.

The last column of Table 1 shows the results of evaluation on the quality of response models. Most of the studies in all the approaches do not consider the quality of response models. But, a couple of papers in the desirability function, loss function, and probability-based approaches each consider the quality of response models. Kim and Lin (2000, 2006) in the desirability function approach proposed a method to adjust the desirability function shape by incorporating the levels of the quality of description. Vining (1998) and Ko et al. (2005) in the loss function approach considered the quality of prediction by employing the variance-covariance matrix of the predicted responses (i.e., $\boldsymbol{\Sigma}_{\hat{y}}(\boldsymbol{x})$ in Equations (7) and (8), respectively). Peter son (2004) and Miró-Quesada et al. (2004) in the probability-based approach also employed the vari ance-covariance matrix of the predicted responses.

3.1.4. Summary

Table 1 shows that the robustness is the most considered property by the existing studies in MRO, while the quality of response models is not much considered. Many studies in the loss function and probability-based approaches seem to consider two properties. The ratios of papers considering two properties amount to 56% in the loss function approach and 67% in the probability-based approach, respectively. All the studies in the process capability approach and most of the studies in the desirability function approach consider only the robustness. The only paper considering all the properties is Ko et al. (2005). In the future, a newly conducted study in MRO needs to consider all the three statistical properties.

## 3.2. Preference information-based evaluation

Most of the MRO approaches require the DM's preference information on the tradeoffs among mu ltiple responses. The preference information is rep resented through preference parameters. The shape, bound, and target of a desirability function or the cost matrix of a loss function are examples of such preference parameters. The preference information can be extracted at one of the following timings: before, during, and after solving the problem. In this subsection, the existing MRO approaches are evaluated in terms of: (i) the number of preference parameters and (ii) the timing of extracting the DM's preference information.

3.2.1. Number of preference parameters

In general, the preference parameters in MRO include the target (of a response), specifications (of a response), and relative weights (among respon ses). The priority-based approach considers the target and specifications. The desirability function approach considers not only all those parameters, but also the pattern or curve of the desirability (of a response). The loss function approach considers the target and relative weights. The process capability approach considers all the parameters, but it does not consider any additional parameter unlike the desirability function approach. The probability-based approach considers only the specifications.

As of now, the desirability function approach con siders the most preference parameters among the MRO approaches. This means that the desirability function approach enables the DM to have flexible options to provide his/her preference information in various ways. Therefore, this approach is ex-

<Table 1> The results of evaluation based on statistical properties

| Approach | Existing Studies | Correlation | Robustness | Quality |
|---|---|---|---|---|
| Priority-based approach | Myers and Carter (1973) | | | |
| | Biles (1975) | | | |
| | Del Castillo (1996) | | | |
| Desirability function approach | Derringer and Suich (1980) | | | |
| | Derringer (1994) | | | |
| | Del Castillo et al. (1996) | | | |
| | Kim and Lin (2000) | | | ● |
| | Tong et al. (2001) | | ○ | |
| | Jeong and Kim (2003) | | | |
| | Ribardo and Allen (2003) | | ○ | |
| | Wu (2005) | ○ | ○ | |
| | Kwon et al. (2005) | | ◎ | |
| | Jeong and Kim (2005) | | | |
| | Kim and Lin (2006) | | ○ | ● |
| Loss function approach | Pignatiello (1993) | ○ | ○ | |
| | Elsayed and Chen (1993) | | ○ | |
| | Ribeiro and Elsayed (1995) | | ◎ | |
| | Ames et al. (1997) | | | |
| | Vining (1998) | ○ | | ○ |
| | Tsui (1999) | ○ | ○ | |
| | Lamghabbar et al. (2004) | | ○ | |
| | Wu and Chyu (2004) | ○ | ○ | |
| | Ko et al. (2005) | ○ | ○ | ○ |
| Process capability approach | Barton and Tsui (1991) | | ○ | |
| | Plante (1999) | | ○ | |
| | Plante (2001) | | ○ | |
| | Köksalan and Plante (2003) | | ○ | |
| | Ch'ng et al. (2005) | | ○ | |
| Probability-based approach | Chiao and Hamada (2001) | ○ | ○ | |
| | Peterson (2004) | ○ | | ○ |
| | Miró-Quesada et al. (2004) | ○ | | ○ |

In the Robustness column, the symbol ◎ represents that the corresponding paper considers both the robustness to uncontrollable factors and the robustness to parameter fluctuation, while the symbol ○ only the robustness to uncontrollable factors.
In the Quality column, the symbol ● represents that the corresponding paper considers only the quality of description, while the symbol ○ only the quality of prediction.

pected to have a good potential to effectively extract the DM preference information.

3.2.2. Timing of extracting the DM's preference information

Existing MRO methods can be categorized through the multiobjective optimization (MOO) classification system. Generally, the MOO literature classifies various optimization methods into three categories by the timing of the DM's preference information into a model: prior, progressive, and posterior preference articulation methods 「Hwang et al., 1979; Zeleny, 1982; Steuer, 1986; Miettinen, 1999; Collette and Siarry, 2003; Figueira et al., 2005」.

The prior method requires that all the preference information of the DM be extracted prior to solving the problem. The progressive method, often referred to as the interactive method, requires that the DM input his/her preference information into a model during the problem solving process. The posterior method first finds all (or most) of the efficient solutions without any substantial articulation of the DM's preference information. The DM then chooses the best one from the set of efficient solutions a posteriori.

Most of the studies in the MRO approaches are categorized into the prior method in terms of MOO 「Park et al., 2000; Park and Kim, 2005」. However, a few studies, for example, Montgomery and Bettencourt (1977), Mollaghasemi and Evans (1994), Boyle and Shin (1996), Köksalan and Plante (2003), Jeong and Kim (2003, 2005, 2009), Park and Kim (2005), proposed an interactive method to MRO problems.

Montgomery and Bettencourt (1977) and Park and Kim (2005) applied the GDF algorithm 「Geoffrion et al., 1972」 to a battle tank crew-training problem and a polymer design problem, respectively. Mollaghasemi and Evans (1994) applied a modified version of STEM 「Benayoun et al., 1971」 to a job shop simulation problem. Köksalan and Plante (2003) proposed to use the parametric Achievement-Scalarizing Program 「Korhonen and Laakso, 1986」 to solve an MRO problem.

The studies employing the posterior method in solving MRO problems have scarcely been found. Recently, Lee et al. (2010) and Lee et al. (2011a) proposed a posterior method to MRO. Both studies adopt the ε-constraint method 「Haimes et al., 1971」 to generate a good number of efficient solutions. However, they proposed a different method in selecting the best solution. Lee et al. (2010) proposed a "graphically"nteractive selection method focusing on the two-response case. Lee et al. (2011a) proposed to use the Köksalan and Sagala (1995)'s interactive selection method for the multi-response case.

The prior method is conceptually easy to understand, but the DM may have difficulties in specifying all the required preference information in advance. The posterior method requires minimal cognitive efforts of the DM in the beginning, but it is impractical to generate a good representative set of efficient solutions. Moreover, it may require an excessive cognitive effort of the DM after all in selecting the best solution, especially when the solution space is represented with a large number of solutions 「Lee et al., 2011b」. The interactive method is more realistic in that it requires the DM's preference information progressively rather than requiring all preference information in advance, although the DM has only to provide his/her preference information by a local level due to the "one-solution-at-a-time" scheme. This method would be highly effective and efficient in searching the DM's preference structure for a satisfactory compromise as stated in Steuer (1986).

# 4. Conclusions and a Future Research Direction

This paper has reviewed the existing studies in MRO under the categories of the graphical, priority-based, desirability function, loss function, process capability, and probability-based approaches. Then, it has evaluated them in two aspects: statistics and preference information.

In the future, a new study is required to consider the following two points. First, it should consider all the three important statistical properties for MRO : correlation structure among responses, robustness of response, and quality of response mod els. Second, it should try to effectively extract the DM's preference information on the multiple conflicting responses.

The second requirement can be well resolved by a combination of the desirability function approach and the interactive method. As mentioned in Subs ection 3.2.1, the desirability function approach has the most preference parameters, namely, the target, specifications, shape, and relative weights. Such a good number of preference parameters allow the DM to have flexible options to provide his/her preference information in various ways. As mentioned in Subsection 3.2.2, an interactive method is the most realistic alternative in effectively searching the DM's preference structure for a satisfactory compromise. Therefore, the combined approach is certainly believed to be a very promising alternative for MRO.

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2011년 6월 2일 접수, 2011년 9월 7일 수정, 2011년 9월 16일 채택