Comparative Study on Robust Design Optimization Models for Multiple Chemical Responses

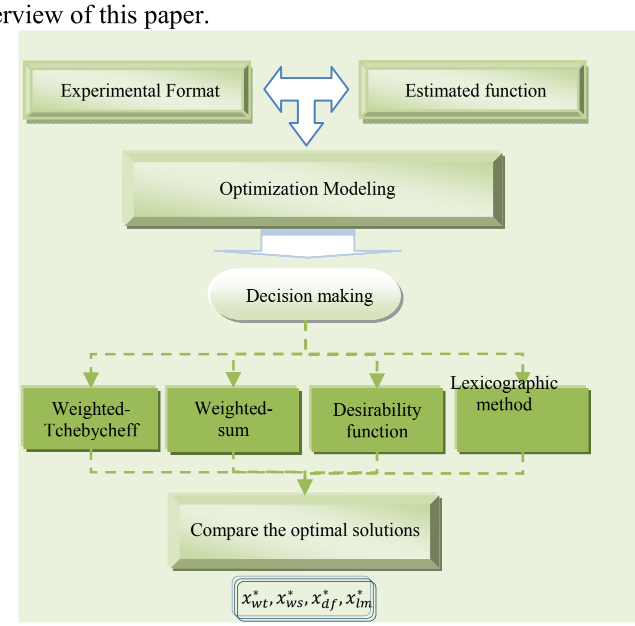
Vo Thanh Nha, Sangmun Shin, Woo-Sik Jeong, Chul-Soo Kim, Hwa-il Kim, and Seong Hoon Jeong

Abstract—**Improving the quality of products is one of significant research issues in many industrial situations. In order to address these issues, many researchers and practitioners have considered that robust design (RD) is one of the most effective methodologies to find the optimal factor settings on many chemical formulation problems. To these problems, a robust optimization method for a number of multiple responses is often required. The primary objective of this paper is to investigate existing multi-objective RD methods and to conduct their associated comparative study. In addition, a fitted function for each response is obtained by using response surface methodology (RSM). In order to perform a comparative study in terms of optimization aspects, a number of existing multi-objective optimization models and criteria are utilized. Final, a chemical chase study is performed for verification purposes.**

Index Terms—**Robust design, comparative study, multi-objective optimization, Response Surface Methodology (RSM).**

I. Introduction

Robust design (RD) is one of the most effective methodologies which can improve the quality of a product. A number of researches have been developed RD and its applications to many industrial problems for more than twenty years. RD was introduced by Taguchi in 1979. Based on the Taguchi's RD philology, Vining and Myers [1] introduced a dual-response approach based on response surface methodology (RSM) as an alternative for modeling process relationships by separately estimating the response functions of the process mean and variance in order to achieve the primary goal of RD by minimizing the process variance while adjusting the process mean at the target. Del Castillo and Montgomery [2] and Copeland and Nelson [3] showed that the optimization technique proposed by Vining and Myers [1] might not always guarantee the optimal RD solutions, and proposed standard non-linear programming techniques, such as the generalized reduced gradient and the Nelder–Mead simplex methods, which can provide better RD solutions. Modified dual-response approaches using fuzzy theory were further developed by Kim and Lin [4]. However, Lin and Tu [5] pointed out that the RD solutions obtained from the dual-response model may not necessarily be optimal since this model forces the process mean to be located at the target value, and proposed the mean squares error (MSE) model, relaxing the zero-bias assumption. Because the MSE approach provide a small process bias with process variance is less than mostly equal to the variance obtained from the Vining and Myers' model. Thus, the MSE model may provide better (or equal, at least) RD solutions unless the zero-bias assumption must be met. Further modifications to the MSE model have been discussed by Kim and Cho [6], Shin and Cho [7]. However, most of those identified RD models were considered as a single response problem, even though a number of real-world problems are often related to multi-response optimization problems. In order to address these multi-response problems using the RD principle, a number of multi-objective RD models have been proposed by Kovach and Cho [8] and Shin and Cho [9]. To this end, a robust optimization method for a number of multiple responses is often required. The primary objective of this paper is to investigate existing multi-objective RD methods (i.e., weighted sum (WS), weighted-Tchebycheff (WT), lexicographic method (LM) and desirability function (DF) approach) and to conduct their associated comparative study. In addition, a fitted function for each response is obtained by using response surface methodology (RSM). In order to perform a comparative study in terms of optimization aspects, a number of existing multi-objective optimization models and criteria are utilized. Final, a chemical chase study is performed for verification purposes. Figure 1 illustrates an overview of this paper.



II. Model Development

A. Experiment Format

Assuming that a number of responses $(y_1, y_2, \ldots y_n)$ is

Manuscript received May 16, 2012; revised June 20, 2012.
V. T. Nha, S. Shin, W-S Jeong, and C-S Kim are with the Inje University, Gimhae, 621-749, South Korea (e-mail: vothanha@gmail.com; sshin@inje.ac.kr; jeongws@inje.ac.kr; charles@inje.ac.kr).
H-i Kim is with the Department of Industrial Health, Catholic University of Pusan, Busan 609-757, Korea (e-mail: hikim@cup.ac.kr).
S. H. Jeong is with the College of Pharmacy, Dongguk University, Goyang, Gyeonggi 410-820, South Korea (e-mail: shjeong@dongguk.edu).

influenced by a number of control factors ($x_1,x_2,\ldots,x_N$). And the number of replication was observed at each response y_i which is q replications. Based on the observation value, the mean and variance for each response can be found. Table 1 represents a standard experiment format for this study.

TABLE I: THE GENERAL EXPERIMENTAL FORMAT FOR MULTIPLE CHARACTERISTICS

runs	X	y1		
		Replications	$\bar{y}_1$	s_1^2
1	Control factor settings	y111 y112….y11q	$\bar{y}_{11}$	s_{11}^2
…		…		
k		y1k1 y1k2….y1kq	$\bar{y}_{1k}$	s_{1k}^2
runs	X	y2		
		Replications	$\bar{y}_2$	s_2^2
1	Control factor settings	y211 y212….y21q	$\bar{y}_{21}$	s_{21}^2
…		…		
k		y2k1 y2k2….y2kq	$\bar{y}_{2k}$	s_{2k}^2
…				
runs	X	yn		
		Replications	$\bar{y}_n$	s_n^2
1	Control factor settings	yn11 yn12….yn1q	$\bar{y}_{n1}$	s_{n1}^2
…		…		
k		ynk1 ynk2….ynkq	$\bar{y}_{nk}$	s_{nk}^2

B. Response Surface Methodology (RSM)

Based on the proposed experimental framework, an estimation method must then be developed for obtaining functional relationships between input factors and their associated output responses. It is known that response surface methodology (RSM) is one of popular estimation methods. RSM is a collection of mathematical and statistical techniques that is useful for modeling and analyzing these problems when the response of interest is influenced by several factors. Its objective is to optimize (either minimize or maximize) the optimal function of output responses. RSM is typically used to optimize the optimal function by estimating input-output functional forms when the exact functional relationships are not known or very complicated [14]. As a comprehensive presentation of RSM, Myers and Montgomery [14] provided insightful comments on the current status and future direction of RSM. Using the output responses (i.e., mean responses y_i and variance responses s_i^2), the second-ordered estimated response functions of the process mean and variance are given as

$$\hat{\mu}(x) = \hat{\alpha}_0 + \mathbf{x}^T\mathbf{a} + \mathbf{x}^T\mathbf{A}\mathbf{x} \quad (1)$$

where

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}, \mathbf{a} = \begin{bmatrix} \widehat{\alpha_1} \\ \widehat{\alpha_2} \\ \vdots \\ \widehat{\alpha_N} \end{bmatrix} \text{ and}$$

$$\mathbf{A} = \begin{bmatrix} \widehat{\alpha_{11}} & \widehat{\alpha_{12}}/2 & \cdots & \widehat{\alpha_{1N}}/2 \\ \widehat{\alpha_{12}}/2 & \widehat{\alpha_{22}} & \cdots & \widehat{\alpha_{2N}}/2 \\ \vdots & \vdots & \ddots & \cdots \\ \widehat{\alpha_{1N}}/2 & \widehat{\alpha_{2N}}/2 & \cdots & \widehat{\alpha_{NN}} \end{bmatrix}$$

and

$$\widehat{\sigma^2}(x) = \hat{\beta}_0 + \mathbf{x}^T b + \mathbf{x}^T\mathbf{B}\mathbf{x} \quad (2)$$

where

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}, \mathbf{b} = \begin{bmatrix} \widehat{\beta_1} \\ \widehat{\beta_2} \\ \vdots \\ \widehat{\beta_N} \end{bmatrix} \text{ and}$$

$$\mathbf{B} = \begin{bmatrix} \widehat{\beta_{11}} & \widehat{\beta_{12}}/2 & \cdots & \widehat{\beta_{1N}}/2 \\ \widehat{\beta_{12}}/2 & \widehat{\beta_{22}} & \cdots & \widehat{\beta_{2N}}/2 \\ \vdots & \vdots & \ddots & \cdots \\ \widehat{\beta_{1N}}/2 & \widehat{\beta_{2N}}/2 & \cdots & \widehat{\beta_{NN}} \end{bmatrix}$$

and where vector a and matrix A denote the estimated regression coefficients for the process mean; and vector b and matrix B represent the estimated regression coefficients for the process variance, respectively.

C. Optimization Models

By using RSM as discussed in the previous section, the fitted functions of the process mean and variance (i.e., $\widehat{\mu_i}(\mathbf{x})$ and $\widehat{\sigma_i^2}(\mathbf{x})$) are obtained at each response y_i. After obtaining the estimated functions, the next step is to find the optimal factor settings (i.e., the optimal chemical formulation). By using the MSE concept, the objective function for each response y_i can be expressed as $\mathrm{MSE_i}(\mathbf{x}) = \widehat{\mu_i}(\mathbf{x}) + \widehat{\sigma_i^2}(\mathbf{x})$. Based on this formulation, the general optimization model can be identified as follows:

Minimize $\{\mathrm{MSE_1}(\mathbf{x}), \mathrm{MSE_2}(\mathbf{x}), \ldots, \mathrm{MSE_i}(\mathbf{x}), \ldots, \mathrm{MSE_n}(\mathbf{x})\}$

Subject to: $\mathbf{x} \in \boldsymbol{\Omega}$ (3)

Where $\mathrm{MSE_i}(\mathbf{x}) = \widehat{\mu_i}(\mathbf{x}) + \widehat{\sigma_i^2}(\mathbf{x})$

In order to address this multi-objective optimization, we use a number of methods (i.e.,WS, WT, LM and DF) for handing the multi-responses as shown in Table II.

III. PILOT STUDY

In this paper, a chemical case study is conducted for multiple responses reported in the chemical engineering literature (Jauregi et al., 1997) is employed to demonstrate the use of the existing multi-response optimization approaches. When surfactant solutions are mixed at high speeds, micro bubbles (10–100 μm in diameter) are formed. It is postulated that these bubbles, called colloidal gas aphrons (CGAs), are composed of a gaseous inner core surrounded by a thin soapy film. The properties of the CGAs are measured by two responses, such as stability (y_1) and temperature (y_2). The purpose of this experiment is to determine the effects of concentration of surfactant (x_1), concentration of salt (x_2), and time of stirring (x_3) on the CGA properties. The experimental data is displayed in Table 3. By using Equations (1) and (2), the fitted response function of each response can be obtained as

$$\begin{aligned} y_{1\mu}(x) = {} & 4.9778 + 0.8170x_1 - 0.4480x_2 + 0.0390x_3 \\ & -0.1113x_1x_2 + 0.0688x_1x_3 - 0.0613x_2x_3 \\ & -0.1372x_1^2 + 0.2878x_2^2 - 0.0672x_3^2 \end{aligned}$$

$$y_{1\sigma}(x) = -0.0180 - 0.0208x_1 + 0.0632x_2 + 0.0476x_3$$

$$-0.0146x_1x_2 - 0.0561x_1x_3 + 0.0522x_2x_3 + 0.0495x_1^2 + 0.0379x_2^2 + 0.0489x_3^2$$

$$y_{2\mu}(x) = 28.9202 - 1.4800x_1 - 0.0900x_2 + 2.3300x_3 - 0.0875x_1x_2 - 0.7125x_1x_3 + 0.4000x_2x_3 - 0.6078x_1^2 - 1.0078x_2^2 - 0.6078x_3^2$$

$$y_{2\sigma}(x) = 34.8412 - 29.0930x_1 + 8.0802x_2 + 78.6949x_3 - 8.9552x_1x_2 - 25.2268x_1x_3 + 0.2055x_2x_3 + 11.6216x_1^2 + 41.3620x_2^2 + 11.0680x_3^2$$

TABLE II: THE OPTIMIZATION MODELS FOR MULTI-RESPONSES

Weighted-sum	*Minimize* $\sum_{i=1}^{n} \omega_i \mathrm{MSE}_i(\mathbf{x})$ *Subject to* $\sum_{i=1}^{n} \omega_i = 1, i = \overline{1,n}$, $\mathbf{x} \in \Omega$, *where* $\mathrm{MSE}_i(\mathbf{x}) = \widehat{\mu_i}(\mathbf{x}) + \widehat{\sigma_i^2}(\mathbf{x})$	(4)
Desirability function	*Minimize* $\prod_{i=1}^{n} d_i(\mathbf{x})$ *Subject to* $\mathbf{x} \in \Omega$ *Where* $d_i(\mathbf{x}) = \begin{cases} 0 & \text{if } \mathrm{MSE}_i(\mathbf{x}) < MSE_i^{\min} \\ \frac{\mathrm{MSE}_i(\mathbf{x}) - MSE_i^{\min}}{MSE_i^{\max} - MSE_i^{\min}} & \text{if } MSE_i^{\min} \le \mathrm{MSE}_i(\mathbf{x}) \le MSE_i^{\max} \\ 1 & \text{if } \mathrm{MSE}_i(\mathbf{x}) > MSE_i^{\max} \end{cases}$, $MSE_i^{\min} = minimize\{\mathrm{MSE}_i(\mathbf{x}) \mid \mathbf{x} \in \Omega\}$ $MSE_i^{\max} = maximize\{\mathrm{MSE}_i(\mathbf{x}) \mid \mathbf{x} \in \Omega\}$ $\mathrm{MSE}_i(\mathbf{x}) = \widehat{\mu_i}(\mathbf{x}) + \widehat{\sigma_i^2}(\mathbf{x})$	(5)
Weighted-Tchebycheff method	*Minimize* $\{\varepsilon, e^T(\mathbf{MSE} - \mathbf{U}^*)\}$ *Subject to* $\omega_i[\mathrm{MSE}_i(\mathbf{x}) - U_i^*] - \varepsilon \le 0, i = \overline{1,n}$, $\sum_{i=1}^{n} \omega_i = 1$, $\mathbf{x} \in \Omega$, *Where* $\mathrm{MSE}_i(\mathbf{x}) = \widehat{\mu_i}(\mathbf{x}) + \widehat{\sigma_i^2}(\mathbf{x})$, $U_i^* = \min\{\mathrm{MSE}_i(\mathbf{x}) \mid \mathbf{x} \in \Omega\}$, $\mathbf{MSE} = \begin{bmatrix} \mathrm{MSE}_1(\mathbf{x}) \\ \vdots \\ \mathrm{MSE}_n(\mathbf{x}) \end{bmatrix}, \mathbf{U}^* = \begin{bmatrix} U_1 \\ \vdots \\ U_n \end{bmatrix}$	(6)
Lexicographic method	First step *Minimize* $\mathrm{MSE}_1(\mathbf{x})$ *Subject to* $\mathbf{x} \in \Omega$ *Where* $\mathrm{MSE}_1(\mathbf{x}) = \widehat{\mu_1}(\mathbf{x}) + \widehat{\sigma_1^2}(\mathbf{x})$, Generalized priority optimization model for second step *Minimize* $\mathrm{MSE}_i(\mathbf{x})$ *Subject to* $\mathrm{MSE}_j(\mathbf{x}) = \mathrm{MSE}_j^*, j = \overline{1, \imath - 1}$, $\mathbf{x} \in \Omega$, *Where* $\mathrm{MSE}_j^* = \mathrm{MSE}_j(\mathbf{x}_j^*)$, $\mathrm{MSE}_i(\mathbf{x}) = \widehat{\mu_i}(\mathbf{x}) + \widehat{\sigma_i^2}(\mathbf{x})$	(7)

After obtaining the estimated functions of the process mean and variance for responses y_1 and y_2, the optimization models which are given in Table 2 is applied in order to find the optimal factor settings. By setting the target values for both responses y_1 and y_2 as 7 and 30, respectively, the optimal solutions by using four models, such as WS, WT, LG and DF, are obtained as follows: $x_{ws}^*(0.7269; 0.0842; -0.3592)$, $x_{wt}^*(-1.0000; -0.0289; -0.7890)$, $x_{lm}^*(0.1688; 0.1306; 0.2609)$, and $x_{df}^*(1.0000; -1.0000; -0.0020)$, respectively, as shown in Table IV.

TABLE III: THE CAG STUDY

runs	x1	x2	x3	rep	y1	y2	$\bar{y}_1$	$\bar{y}_2$	s_1^2	s_2^2
1	−1	−1	−1	1	4.5	29	4.5	26	0	4.24
	−1	−1	−1	2	4.5	23				
2	1	−1	−1	1	6.04	23	6.22	24.2	0.25	1.7
	1	−1	−1	2	6.39	25.4				
3	−1	1	−1	1	3.81	22	3.95	24.5	0.2	3.54
	−1	1	−1	2	4.09	27				
4	1	1	−1	1	5.67	25.5	5.43	23.25	0.34	3.18
	1	1	−1	2	5.19	21				
5	−1	−1	1	1	4.67	20	4.45	30.5	0.32	14.85
	−1	−1	1	2	4.22	41				
6	1	−1	1	1	6.73	35.5	6.65	26.75	0.11	12.37
	1	−1	1	2	6.57	18				
7	−1	1	1	1	3.4	43	3.86	31.5	0.65	16.26
	−1	1	1	2	4.32	20				
8	1	1	1	1	5.72	19	5.41	26.5	0.45	10.61
	1	1	1	2	5.09	34				
9	−1	0	0	1	4.09	36	4.24	30	0.21	8.49
	−1	0	0	2	4.38	24				
10	1	0	0	1	5.52	30	5.46	27	0.09	4.24
	1	0	0	2	5.39	24				
11	0	−1	0	1	5.92	32	5.93	27.7	0.01	6.08
	0	−1	0	2	5.93	23.4				
12	0	1	0	1	4.74	36	4.62	28.5	0.17	10.61
	0	1	0	2	4.5	21				
13	0	0	−1	1	5.01	27	4.86	25.5	0.22	2.12
	0	0	−1	2	4.7	24				
14	0	0	1	1	4.94	38	4.98	31.5	0.05	9.19
	0	0	1	2	5.01	25				
15	0	0	0	1	4.85	34	4.94	28.17	0.06	6.37
	0	0	0	2	4.94	34				
	0	0	0	3	4.98	33				
	0	0	0	4	4.89	24				
	0	0	0	5	4.94	19				
	0	0	0	6	5.01	25				

In addition, Figure 2 insulates the criterion space of y_1 and y_2 and the optimal factor settings. Based on these results, we obtained four different solutions and each set of the optimal solutions has different criteria (i.e., weight and priority).

IV. CONCLUSION

The primary goal of this paper is to make a comparison between methodologies which were used in the RD optimization step. We utilized a combination of the estimated function of the process mean and variance at each response into one objective function. A chemical case study was conducted in order to demonstrate how the proposed methodology can provide solutions. Based on the case study results, there are two main criteria in the decision making process of the optimization model which are weight and priority. In effect, these criteria depend on the purpose of each problem associated with importance of quality characteristics. This comparative study can provide a guide line to select a suitable optimization model for a given situation. In this paper, a comparative study was performed based on only RD optimization methodologies while considering the estimation method by using RSM. For further study, a number of different estimation methodologies can be considered and compared.

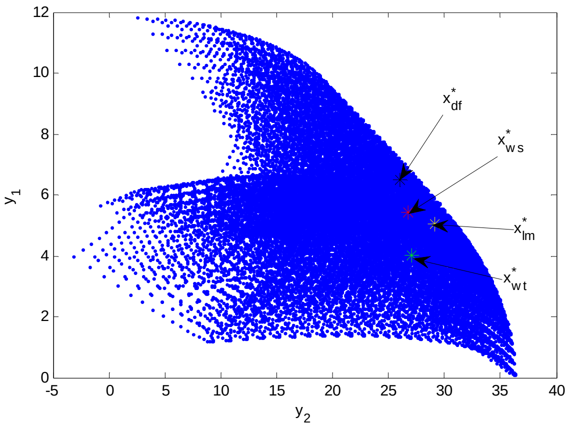


Fig. 2. The criterion space of y_1 and y_2.

TABLE IV: THE OPTIMAL SETTINGS FOR MULTI-RESPONSES BASED ON THE FOUR MODELS: WEIGHTED-SUM, WEIGHTED-TCHEBYCHEFF, LEXICOGRAPHICAL METHOD AND DESIRABILITY FUNCTION

Models	Optimal value(x*)			$\bar{y_1}$	s_1^2	T1	$\bar{y_2}$	s_2^2	T2
	x1	x2	x3						
WS	0.73	0.08	-0.36	5.42	0.00		26.76	0.00	
WT	-1.00	-0.03	-0.79	4.01	0.00	7	27.02	0.00	30
LM	0.17	0.13	0.26	5.06	0.00		29.17	52.00	
DF	1.00	-1.00	0.00	6.50	0.00		26.00	59.50	

ACKNOWLEDGMENT

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (20120463).

REFERENCES

[1] G. G. Vining and R. H. Myers, “Combining taguchi and response surface philosophies: A dual response approach,” *Journal of Quality Technology*, vol. 22, no. 1, pp 38-45, 1990.

[2] E. D. Castillo and D. C. Montgomery, “A nonlinear programming solution to the dual response problem,” *Journal of Quality Technology*, vol. 25, no. 3, pp. 199-204, 1993.

[3] K. A. F. Copeland and P. R. Nelson, “Dual response optimization via direct function minimization,” *Journal of Quality Technology*, vol. 28, no. 3, pp. 331-336, 1996.

[4] K. J. Kim and D. K. J. Lin, “Dual response surface optimization: A fuzzy modeling approach,” *Journal of Quality Technology*, vol. 30, no. 1, pp. 1-10, 1998.

[5] D. K. J. Lin and W. Tu, “Dual response surface optimization,” *Journal of Quality Technology*, vol. 27, no. 1, pp. 34-39, 1995.

[6] B. R. Cho, Y. J. Kim, D. L. Kimber, and M. D. Phillips, “An integrated joint optimization procedure for robust and tolerance design,” *International Journal of Production Research*, vol. 38, no. 10, pp. 2309-2325, 2000.

[7] S. Shin and B. R. Cho, “Bias-specified robust design optimization and an analytical solutions,” *Computers and Industrial Engineering*, vol. 48, no. 1, pp. 129-148, 2005.

[8] J. Kovach and B. R. Cho, “Development of a multidisciplinary -multiresponse robust design optimization model,” *Engineering Optimization*, vol. 40, no. 9, pp. 805-819, 2008.

[9] S. Shin and B. R. Cho, "Studies on a bi-objective robust design optimization problem," *IIE Transactions*, vol. 41, no. 11, pp. 957-968, 2009

[10] S. Shin and B. R. Cho, "Development of a sequential optimization procedure for robust design and tolerance design within a bi-objective paradigm," *Engineering Optimization*, vol. 40, no. 11, pp. 989-1009, 2008.

[11] K. J. Kim and D. K. J. Lin., “Optimization of multiple response considering both location and dispersion effects,” *European Journal of Operational Research*, vol. 169, no. 1, pp. 133-145, 2004.

[12] S. Shin, D. H. Choi, N. K. V. Truong, N. A. Kim, K. R. Chu, and S. H. Jeong, "Time-oriented experimental design method to optimize hydrophilic matrix formulations with gelation kinetics and drug release profiles," *International Journal of Pharmaceutics*, vol. 407, no. 8, pp.53-62, 2011.

[13] G. Taguchi, *Introduction to Quality Engineering: Designing Quality into Products and Processes,* Tokyo: Asian Productivity Association, 1986.

[14] R. H. Myers and D. C. Montgomery, *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*, New York: Wiley, 1995.

Vo Thanh Nha is currently a PhD candidate at Inje University, South Korea. He holds a bachelor’s degree in Mathematics and Computer Science from Ho Chi Minh City University of Science Vietnam and a master of System Management Engineering from Inje University, South Korea. His research interests include robust design, tolerance design, pharmaceutical quality by design (QbD), and muli-objective optimization methods and applications.

Sangmun Shin is an Associate Professor at the Department of Systems Management and Engineering and the Director of the Quality Design Laboratory at the Inje University, South Korea. He received his MS and PhD in Industrial Engineering from the Clemson University, USA. His research interests include quality engineering, robust and tolerance designs, multi-objective optimization and pharmaceutical process design. He received his Career Development Research Award from the Korea Research Foundation. He currently serves on the editorial board of both International Journal of Quality Engineering and Technology and International Journal of Experimental Design and Process Optimization. He is a member of IIE and Alpha Pi Mu.

Woo-Sik Jeong is an Associate Professor in the Department of Food and Life Sciences at Inje University, South Korea. He received his PhD in Food Science at Rutgers University, USA. After he worked in the College of Pharmacy at Rutgers University as a Postdoctoral Associate, he joined Inje University as an Assistant Professor. His research interests include molecular mechanisms of natural chemopreventive agents and their interaction with pharmaceutical drugs. He currently serves as an Editorial Board member of the Korean Journal of Cancer Prevention and the Preventive Nutrition and Food Science. He is the vice chair of Industry-University Cooperation Foundation and the director of Business Incubation Center at Inje University.

Chul-Soo Kim is a professor in the School of Computer Engineering at Inje University, South Korea. He received Ph.D. from the Pusan National University, South Korea and worked for ETRI (Electronics and Telecommunication research Institute) from 1985 - 2000 as a senior researcher for developing TDX exchange. Aside from the involvement in various domestic and international projects, his primary research interests include network protocols, traffic management, OAM issue, and NGN charging. He is a member of ITU-T SG3, SG11, SG13 and a Rapporteur of ATM Lite from 1998 to 2002, and CEO in WIZNET from 2000 to 2001. He was the chairperson of BcN Reference Model in South Korea, and a Rapporteur of ITU-T SG3 NGN Charging. From 2008 to 2010, he worked for Ministry of Knowledge and Economics in South Korea as BcN Program Director.

Hwail Kim is a professor in the Department of Industrial Health at Catholic University of Pusan, South Korea. He received his PhD in Human Environment Engineering from the Kyushu University, Japan. He is interested in environmental engineering, especially work environment at various types of business. His focused further research is associated with integration of work environment and quality control to small enterprises.

Seong Hoon Jeong is an Assistant Professor at the College of Pharmacy, Dongguk University, South Korea. He received his PhD in Industrial & Physical Pharmacy from Purdue University, USA. After he worked for Pfizer Global R&D Center (previously Wyeth Research) as a Senior Research Scientist, he joined the College of Pharmacy, Pusan National University as an Assistant Professor. His research interests include design of experiment regarding the pharmaceutical development, preformulation and formulation development, and analytical method development. He currently serves on the editorial board of the Journal of Pharmaceutical Investigation. He is the member of Rho Chi Societh.