Industrial Engineering
& Management Systems
Vol 15, No 4, December 2016, pp.318-323
ISSN 1598-7248 | EISSN 2234-6473 |
https://doi.org/10.7232/iems.2016.15.4.318

Determining the Optimum Brands Diversity of Cheese Using PSO (Case Study: Mashhad)

Amir Dadrasmoghadam, Mohammad Ghorbani*, Alireza Karbasi, Mohammad Reza Kohansal
Department of Agricultural Economics, Ferdowsi University of Mashhad, Mashhad, Iran

(Received: November 15, 2016 / Revised: November 22, 2016 / Accepted: November 25, 2016)

ABSTRACT

In the current study, factors affecting cheese brands products in grocery stores were evaluated with an emphasis on diversity. The sample data were collected from Noushad and Pegah Milk Industry in 2015 and data were extracted, reviewed, and analyzed from 435 grocery stores in Mashhad using seemingly unrelated regression model and particle swarm optimization algorithm. Results showed that optimum amount of Kalleh product diversity is higher than other competitors in the market, and Kalleh UF diversity is 100 to 250 grams, and Kalleh UF diversity with weight of 300 to 500 grams is more than other modes of diversity, and Kalleh brand must remove tin cheese from the market. Sabah Brand also should eliminate its glass and creamy diversity from market, UF diversity is mostly welcomed in market.

Keywords: Brand Diversity, Share Brand, PSO Algorithms, Seemingly Unrelated Regression

* Corresponding Author, E-mail: ghorbani@um.ac.ir

1. INTRODUCTION

Nowadays, commercial companies increase the profitability with respect to the competitive environment issues, globalization of markets, and shortening of product life cycles, and rapid technological development should have become a pioneer of diversity.In such circumstances, new product development is considered with respect to companies' important achievements in the field of high technology because of efforts to respond to consumer preferences and new markets. A brand must continuously introduce new products or redesign them. To minimize risk, managers try to succeed in the field of new product marketing research. However, optimal product line design is problematic (Papadimitriou and Steiglitz, 1983). A number of marketing studies have been done applying optimization algorithms with dynamic programming (Kohli and Sukumar, 1990), the beam search (Nair *et al*., 1995), genetic algorithms (Balakrishnan *et al*., 2004), and Lagrangian method (Camm *et al*., 2006). Almost in all optimization methods which solve design problem, a production line has been used for global optimal solution. Reasonable achievements in the field of operation research seem to solve product design issues complexity since expertise in marketing and engineering is requires. In this context, to gain optimal solution for customer preferences is very important for a brand. Diversity may cause too heavy costs for modern technologies and production (Balakrishnan *et al*., 2004). The fact is that optimization is to increase market share and profit in which design lines can take place. Consumer preferences are important for managers and especially for brands that many products have in the market share. To solve such problems, best solutions should be used. It is possible for producers and builders to lead a specific product line. It is, therefore, very important for managers to give a true picture of the wide range of consumers replacing suitable diversity. Inappropriate production line design may not change the expected share from that brand. Thus, taking into consideration various factors to diversity may lead to the optimal solution of market share. This can be done by two methods: using a population-based optimization algorithm or running the algorithm many times with different values for the tuning parameters. The second method is deceitful because constraints should be entered continuously. In addition, all optimization methods of the

production line assume that the market is static. And the current companies do not want to introduce one or more new products (Alexouda and Paparrizos, 2001; Steiner and Hruschka, 2003; Tsafarakis *et al*., 2011).

In the area of diversity optimal level of trade markers, we can refer studies conducted by Michalek *et al*. (2011), which they considered production lines design useful for many of new products by using optimization methods. Results indicated that optimal level of products in the production line increase profitability. Yang (2011) used hybrid systems for designing new mobile product and optimization of system. In this study, support vector regression (SVR) and Multi Objective Genetic Algorithm (MOGA) were integrated and the results showed that customer needs should be considered in the design of new products.

Using combined method of particle swarm algorithm and leaping algorithm to optimize industrial production lines in both discrete and continuous modes, Stelios et al suggested that using the artificial intelligence would provide better yield for companies in relation to concepts of customer relationship and strategic management of production. Chen *et al*. (2012) used Bayesian Nash equilibrium and particle swarm optimization (PSO) to maximize the diversity of quality. Foster. and Ferguson (2013) designed a car production line using multi-objective optimization genetic algorithm in a study and they showed that this approach improved the car production. Foster *et al*. (2014) used discrete genetic algorithm optimization technique to maximize the diversity of their production. The advantages of this method resulted in saving in calculations and increased brand share in the market. Wang and Yeh (2014) used modified particle swarm algorithm (MPSO) to design the production line. In this paper, they compared the MPSO performance with standard PSO (SPSO), and Genetic Algorithm (GA). The results showed that MPSO is better than SPSO and GA in terms of reliability and rate of convergence. Wu and Chen (2014) designed production lines and pricing for smart phones in a competitive market (with high product diversity). In the study, discrete choice model and genetic algorithms were used to optimize the prices of smart phones. Saridakis *et al*. (2015) introduced new vehicle models in production lines tailored to customer needs in their study. In this study, swarm intelligence mechanism was used to optimize the degree of product differentiation in vehicle models. Sampling was performed among 1,164 passenger car consumers and the results showed that the diversity in models of car production lines led to increased customer satisfaction.

In summary, it can be said that each brand's product diversity has an important role in the final selection of the brand consumers. The main purpose of the current study was to investigate factors affecting brands share of Kalleh, Pegah, and Sabah according to diversity. The results offer profitable information for cheese product brands (Kalleh, Pegah, and Sabah) on market share and guide their decisions in determining the optimum diversity of the product from every brand. Firstly, the relationship between diversity of every brand and share of every brand in Mashhad market is estimated by seemingly unrelated regression equations. Secondly, the optimal value of every brand's diversity is obtained using particle swarm optimization algorithm (PSO).

2. MATERIALS AND METHODS

2.1 The Optimum Diversity of Three Brands (Kalleh, Pegah, and Sabah)

To obtain the optimal value, five modes of diversity (glass, tin, cream, UF 100 to 250 grams, and UF 300 to 500 grams) for three brands (Kalleh, Pegah, and Sabah) were obtained by total of brands' shares from seemingly unrelated regression model. n_{11}, n_{12}, n_{13}, n_{14}, n_{15}, n_{21}, n_{22}, n_{23}, n_{24}, n_{25}, n_{31}, n_{32}, n_{33}, n_{34}, and n_{35} are 15 states of Kalleh, Pegah, and Sabah diversity and include glass, tin, cream, UF100 to 250 grams and UF 300 to 500 grams for three brands of grocery store. Applying seemingly unrelated regression approach and Stata software were used for factors affecting brand share.

$$S_{1i}^{*} = S_1^{*}(n_{11}, n_{12}, n_{13}, n_{14}, n_{15}, n_{21}, n_{22}, n_{23}, n_{24}, n_{25}, n_{31}, n_{32}, n_{33}, n_{34}, n_{35}) + u_{1i} \quad (1)$$

$$S_{2i}^{*} = S_2^{*}(n_{11}, n_{12}, n_{13}, n_{14}, n_{15}, n_{21}, n_{22}, n_{23}, n_{24}, n_{25}, n_{31}, n_{32}, n_{33}, n_{34}, n_{35}) + u_{2i} \quad (2)$$

$$S_{3i}^{*} = S_3^{*}(n_{11}, n_{12}, n_{13}, n_{14}, n_{15}, n_{21}, n_{22}, n_{23}, n_{24}, n_{25}, n_{31}, n_{32}, n_{33}, n_{34}, n_{35}) + u_{3i} \quad (3)$$

The objective function is the sum of the market shares (Kalleh, Pegah, and Sabah) which is a function of the five modes of diversity of three selected brands, maximized considering the following formula:

$$\max \sum_{i=1}^{435} (S_{1i}^{*} + S_{2i}^{*} + S_{3i}^{*}) \quad (4)$$

Also, restrictions of the sum of the shares in the market according to formula (5) are calculated as (Kohli and Sukumar, 1990; Tsafarakisetal, 2011; Tsafarakis *et al*., 2013):

$$\sum_{i=1}^{435} (S_{1i}^{*} + S_{2i}^{*} + S_{3i}^{*}) = 1 \quad (5)$$

Applying PSO algorithm, optimized amount of diversity (Kalleh, Pegah, and Sabah) is obtained, and PSO algorithm is executed using MATLAB software. PSO algorithm was used regarding the brands' diversity.

The implementation of PSO algorithm for this search is following figure:

```
1. Procedure Particle Swarm
2. Begin
3. For each particle
4. Initialize particle
5. For each particle
6. Calculate share
7. If the share is better than the best share (pbest) in history
8. Set current value as the new pbest
9. Choose particle with best share of all the particles as
   gbest
10. Update particle position
11. While maximum iterations or optimum result
12. End
```

Figure 1. Particle swarm algorithm.

2.2 Particle Swarm Optimization

PSO is a meta-heuristic technique. The basic idea was introduced by Eberhart, a computer scientist, and Kennedy, an expert in the field of social psychology in 1995 (Kennedy and Eberhart, 1995). PSO algorithm is based on the production of a random population inspired by social behavior of animals such as bird flocking or fish schooling. The population is called a swarm, and each population member is called a particle (Kennedy and Eberhart, 1995; Eberhart and Kennedy, 1995; He, 2004). The basic idea of PSO is that each particle is moved in search space to find the optimum point and the best situation that is the best individual position of the particle, stored in various stages; this value is called ($P_{best,i}$) at each search step. Particles exchange information about the situation to help each other to find the optimal situation. Each particle uses a particle, having the best match (i.e., the best global situation of the community (P_{best}) to adjust its pace). After finding the two best values, the particle updates its velocity and positions according to the following formula (Kennedy and Eberhart, 1995; Eberhart and Kennedy, 1995):

$$V_{i,j}^{t} = \omega V_{i,j}^{t-1} + c_1 r_1 \left(P_{best,ij}^{t-1} - X_{ij}^{t-1} \right) + c_2 r_2 \left(G_{best,ij}^{t-1} - X_{ij}^{t-1} \right) \quad (6)$$

$$X_{ij}^{t} = X_{ij}^{t-1} + V_{ij}^{t} \qquad j = 1, 2, \cdots, d \;\; i = 1, 2, \cdots, n \quad (7)$$

V_{id}^{t-1}, V_{id}^{t}, and X_{id}^{t} are the velocity vector in the previous cycle, the velocity vector in the current cycle, and the position vector of particle i in the current cycle along the dth dimension, respectively. $P_{best,t}^{t}$ is the best position in the history of particle i along the dth dimension in cycle t. G_{best}^{t} is the best position in the history of all the particles along the dth dimension in cycle t. c_1 and c_2 are acceleration coefficients. r_1 and r_2 are two independent random numbers distributed uniformly in the range of [0, 1]. ω is the inertia weight factor.

2.3 Data

The sample of project data of Noushad and Pegah Milk Industry in 2014was extracted from 435 grocery stores in Mashhad. Selected brands were Kalleh, Pegah, and Sabah, the major shares of cheese products of Mashhad market. In terms of cheese variety including glass, tin, cream, UF 100 to 250 grams, and UF 300 to 500 grams for three brands of Kalleh, Pegah, and Sabah, five main features were considered for a diversity of brands.

3. RESULTS AND DISCUSSION

3.1 Estimating SUR system

Before estimating equations system with SUR method, simultaneous correlation between the residuals should be tested. Therefore, the Brush Pagan LM test statistic was used. In the following table, statistic Brush Pagan is significant at 0.01. The null hypothesis is rejected, and the correlation between the residuals is not rejected. Therefore, equations must be estimated by seemingly unrelated regression.

The results are provided for three brand shares (Kalleh, Pegah, and Sabah) along with interpretation. Based on the findings (Table 2), factors affecting Kalleh brand share were Kalleh glass diversity, Kalleh cream diversity, Kalleh UF 100 to 250 grams , and Kalleh UF 300 to 500 grams with coefficients of 0.527, 0.110, 0.123, and 0.238, respectively, which were positively significant, and only Kalleh tin diversity was not significant regarding Kalleh brand share. Pegah glass diversity, Pegah cream diversity, Pegah UF 100 to 250 grams diversity had significant and negative relationship with Kalleh brand share.

Pegah tin diversity had not significant effect on Kalleh brand share, and only Pegah UF 100 to 250 grams diversity had positive and significant relationship with Kalleh brand share. Also, Sabah diversity coefficients had not significant relationship with Kalleh brand share.

Table 1. Significant test using equations system

statistic	First equation system	Second equation system	Third equation system
Significant System	2088.71***	1678.09***	1321.97***
Fitness of good coefficient	0.82**	0.78***	0.74***
Brush Pagan (Total system)	40.764***		

* Significant at 10% level, ** significant at the 5% level, *** significant at 1% Source: Research Findings.

Table 2. Estimating cheese producers' brands shares with SUR structure

Variables	Sabah brand share		Pegah brand share		Kalleh brand share	
	Z Statistic	coefficient	Z Statistic	coefficient	Z Statistic	coefficient
glass diversity Kalleh	-0.72	-0.058	0.17	0.022	4.48	0.527***
tin diversity Kalleh	-0.06	-0.006	-0.52	-0.078	0.145	0.224
cream diversity Kalleh	-2.68	-0.031***	-2.96	-0.057***	6.54	0.11***
Kalleh UF 100 to 250 grams	-3.11	-0.033***	-2.69	-0.047***	8.07	0.123***
Kalleh UF 300 to 500 grams	-0.18	-0.001	-2.14	-0.027**	21.25	0.238***
glass diversity Pegah	-0.69	-0.021	1.64	0.084*	-2.21	-0.098**
tin diversity Pegah	-1.90	-0.061*	1/11	0.059	-0.98	-0.045
cream diversity Pegah	-1.64	-0.023*	8.80	0.209***	-2/17	-0.044***
Pegah UF 100 to 250 grams	-1.36	-0.020	5.9	0.142***	2.4	-0.051*
Pegah UF 300 to 500 grams	0.83	0.009	21.6	0.392***	3.3	0.048***
glass diversity Sabah	1.41	0.145	-0. 92	-0.156	0.19	0.028
tin diversity Sabah	-0.27	-0.019	-0.54	-0.063	-0.10	-0.0097
cream diversity Sabah	0.28	0.011	-0.62	-0.043	0.31	0.018
Sabah UF 100 to 250 grams	0.42	0.018	-0.15	-0.011	-1.25	-0.079
Sabah UF 300 to 500 grams	31.14	0.291***	-1.38	-0.021	0.39	0.005

* Significant at 10% level, ** significant at the 5% level, *** significant at 1% Source: Research Findings.

Considering factors affecting Pegah brand share, Kalleh cream diversity, Kalleh UF 100 to 250 grams, and Kalleh UF 300 to 500 grams with coefficients of -0.057, -0.047, and -0.027 were, respectively, negative and significant, and Kalleh tin and glass diversity was not affective on Pegah brand share. Coefficients obtained from Pegah glass diversity, Pegah cream diversity, Pegah UF 100 to 250 grams diversity, and Pegah UF 300 to 500 grams diversity were 0.084, 0.209, -0.142, and 0.392 respectively, and only Pegah tin diversity coefficient was not significantly correlated with Pegah brand share. Also, Sabah diversity coefficient had negative and non-significant relationship with Pegah brand share. Assuming factors affecting Sabah brand share, coefficient of Kalleh diversity was negative, but only Kalleh cream diversity and Kalleh UF 100 to 250 grams were 0.031 and -0.033 significant. Pegah cream and tine diversity had negative significant relationship with Sabah brand share. Among factors affecting Sabah brand share, coefficient of Sabah UF 100 to 250 grams was positively significant.

This study is compatible with previous studies which have evaluated the effect of product diversity on increasing the share of each brand in the market leads, but increasing diversity of its competitors reduces their share in the market (Bayus and Putsis, 1999; Horrace *et al*., 2009; Edward *et al*., 2014).

3.2 Optimizing Diversity of Brands Cheese Products

According to the results of PSO algorithm, the optimum diversity values of brands are presented in Table 3. The optimum amount of brands of cheese product diversity included Kalleh glass diversity, Kalleh cream diversity, Kalleh tin diversity, Kalleh UF diversity 100 to 250 grams, and Kalleh UF diversity 100 to 250 gram-sobtained, respectively, 1, 0, 1, 2, and 2, showing that some diversity of cheese are optimal product diversity and Kalleh UF diversity 300 to 500 grams, and Kalleh UF which are more than the other modes of diversity, and the optimal value for tin diversity is 0.

The optimum amount of brands of cheese product diversity included Pegah glass diversity, Pegah cream diversity, Pegah tin diversity, Pegah UF diversity 100 to 250 grams, and Pegah UF diversity 300 to 500 grams obtained, respectively, 1, 1, 1, 1, and 1 showing that the diversity scenarios for Pegah brand are one type of diversity with optimum value. For Sabah brand, optimum amount of Sabah glass diversity, Sabah cream diversity, Sabah tin diversity, Sabah UF diversity 100 to 250 grams, and Sabah UF diversity 300 to 500 grams were obtained 0, 1, 0 1, and 1,respectively. In other words, the optimal value is zero for Sabah glass, and cream and optimum value for other diversity scenarios is one.

Maximum diversity for optimum value of diversity between different states is related to Kalleh UF diversity 100 to 250 grams and Kalleh UF diversity 300 to 500 grams.

Also, Kalleh tin diversity could be removed from the consumer market according to optimum amount and required amount. In sum, based on the findings, Kalleh brand should remove tin cheese from the market, and Sabah brand should remove tin diversity and cream diversity from Mashhad markets, and UF diversity should have the most sales.

Table 3. Optimizing diversity of brands cheese products

Component		Amount
optimum value of Kalleh diversity		
	Glass diversity	1
	Tin diversity	0
	Cream diversity	1
	UF diversity 100 to 250 grams	2
	UF diversity 300 to 500 grams	2
optimum value of Pegah diversity		
	Glass diversity	1
	Tin diversity	1
	Cream diversity	1
	UF diversity 100 to 250 grams	1
	UF diversity 300 to 500 grams	1
optimum value of Sabah diversity		
	Glass diversity	0
	Tin diversity	1
	Cream diversity	0
	UF diversity 100 to 250 grams	1
	UF diversity 300 to 500 grams	1

Source: Research Findings.

4. CONCLUSION

In conclusion, cheese brands (Kalleh, Pegah, and Sabah) should pay special attention to diversity in the cheese production in order to increase their shares. Results showed that factors affecting Kalleh brand share were Kalleh glass diversity, Kallehcream diversity, Kalleh UF diversity100 to 250 grams, and Kalleh UF diversity 300 to 500 grams, and only Kalleh tin diversity was not significantly effective on Kalleh brand share. Pegah glass diversity, Pegah cream diversity, Pegah UF diversity100 to 250 grams, and Pegahdiversity had significant and negative relationship with Kalleh brand share. Factors negatively and significantly affecting Pegah brand share were Kallehcream diversity, KallehUF diversity 100 to 250 grams, and Kalleh UFdiversity300 to 500 grams, and Kalleh tin and glass diversity was not significantly effective on Pegah brand share. Pegah glass diversity, Pegah cream diversity, and Pegah UF diversity 300 to 500 grams were positively and significantly related; only Pegah tin diversity coefficient was not significantly correlated with Pegah brand share. Also, Sabah diversity coefficient was negative, but not significant regarding Pegah brand share. Kalleh diversity was negatively correlated with factors affecting Sabah brand share; however, only Kalleh cream diversity and Kalleh UF 100 to 250 grams were significantly negative. Pegah cream and tin diversity had negative significant relationship with Sabah brand share. One of the factors having positive and significant effect on Sabah brand share was Sabah UF 100 to 250 grams. The optimum amount of Kalleh product diversity is higher than other competitors in the market. One of the main reasons is that Kallehbrand has a special share in Mashhad market in term of diversity. This study showed that Kalleh UF diversity 100 to 250 grams and Kalleh UF diversity 300 to 500 grams are more than other modes of diversity, and Kalleh brand must remove tin cheese from the market. Pegah's optimum diversity value for each type of diversity is 1, and Sabah brand should remove tin diversity and cream diversity from Mashhad market, and Uf diversity should have most sales.

REFERENCES

Alexouda, G. and Paparrizos, K. (2001), A Genetic Algorithm approach to the product line design problem using the Seller's Return criterion: An exhaustive comparative computational study, *European Journal of Operational Research*, **134**(1), 165-178.

Balakrishnan, P., Gupta, R., and Jacob, V. (2004), Development of hybrid genetic algorithms for product line designs, *IEEE Transactions on Systems, Man, and Cybernetics*, **34**(1), 468-483.

Balakrishnan, P. and Jacob, V. (1996). Genetic algorithms for product design, *Management Science*, **42** (8), 1105-1117.

Bayus, B. L. and Putsis, J. W. (1999), Product proliferation: An empirical analysis of product line determinants and market outcome, *Marketing Science*, **18**

(2): 137-153.

Camm, J. D., Cochran, J. J., Curry, D. J., and Kannan, S. (2006), Conjoint optimization: An exact branch-and-bound algorithm for the share-of-choice problem, *Management Science*, **52**(3), 435-447.

Chen, C., Gao, X., Pei, Q., and Li, X. (2012), BNE-based concurrent transmission considering channel quality and its PSO searching strategy in Ad Hoc networks, *Journal of Systems Engineering and Electronics*, **23**(5), 649-660.

Eberhart, R. and Kennedy J. (1995), *New optimizer using particle swarm theory*, In: Proceedings of the sixth international symposium on micro machine and human science, Japan: Nagoya, 39-73.

Edward, F., Laura, N., and John, S. (2014), *A dynamic model of shopping and consumption*, Southern Methodist University.

Foster, G. and Ferguson, S. (2013), *Enhanced Targeted Initial Populations for Multi objective Product Line Optimization*, In ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers.

Foster, G., Turner, C., Ferguson, S., and Donndelinger, J. (2014), Creating targeted initial populations for genetic product searches in heterogeneous markets, *Engineering Optimization*, **46**(12), 1729-1747.

Green, W. H. (2002), *Econometric analysis* (5th ed), prentice Hall.

He, S., QH, W., Wen, J. Y., Saunders, J. R., and Paton, R. C. (2004), A particle swarm optimizer with passive congregation, *Bio Systems*, **78**, 135-147.

Horrace, R. H., William, C., and Jeffrey, M. P. (2009), *Variety: Consumer choice and optimal diversity. Food Marketing Policy*, Center Research Report, **115**.

Kennedy, J. and Eberhard, R. C. (2001), *Swarm intelligence*, San Francisco: Morgan Kaufmann Publishers.

Kennedy, J. and Eberhart, R. C. (1995), *Particle swarm optimization*, Proceedings of the IEEE International Conference on Neural Networks, Piscataway, NJ, USA: IEEE Press, 1942-1948.

Kohli, R. and Sukumar, R. (1990), Heuristics for product line design using conjoint analysis, *Management Science*, **36**(12), 1464-1478.

Michalek, J. J., Ebbes, P., Adigüzel, F., Feinberg, F. M., and Papalambros, P. Y. (2011), Enhancing marketing with engineering: Optimal product line design for heterogeneous markets, *International Journal of Research in Marketing*, **28**(1), 1-12.

Nair, S. K., Thakur, L. S., and Wen, K. (1995), Near optimal solutions for product line design and selection: Beam Search heuristics, *Management Science*, **41**(5), 767-785.

Papadimitriou, C. H. and Steiglitz, K. (1983), *Combinatorial optimization-Algorithms and complexity*, Upper Saddle River, NJ: Prentice-Hall.

Poli, R., Kennedy, J., and Blackwell, T. (2007), Particle swarm optimization, An overview, *Swarm Intelligence*, **1**, 33-57.

Saridakis, C., Tsafarakis, S., Delias, P., Baltas, G., and Matsatsinis, N. (2015), Optimizing differentiation and commonality levels among models in car lineups: An empirical application of a nature-inspired heuristic mechanism, *Expert Systems with Applications*, **42**(5), 2323-2335.

Steiner, W. and Hruschka, H. (2003), Generic Algorithms for product design: How well do they really work?, *International Journal of Market Research*, **45**(2), 229-240.

Stelios, T., Yannis, M., and Nikolaos, M. (2011), Particle swarm optimization for optimal product line design, *International Journal of Research in Marketing*, **28**, 13-22.

Stelios, T., Charalampos, S., George, B., and Nikolaos, M. (2013), Hybrid particle swarm optimization with mutation for optimizing industrial product lines: An application to a mixed solution space considering both discrete and continuous design variables, *Industrial Marketing Management*, **42**, 496-506.

Tsafarakis, S., Marinakis, Y., and Matsatsinis, N. (2011), Particle swarm optimization for optimal product line design, *International Journal of Research in Marketing*, **28**(1), 13-22.

Tsafarakis, S., Saridakis, C., Baltas, G., and Matsatsinis, N. (2013), Hybrid particle swarm optimization with mutation for optimizing industrial product lines: An application to a mixed solution space considering both discrete and continuous design variables, *Industrial Marketing Management*, **42**(4), 496-506.

Wang, S. C. and Yeh, M. F. (2014), A modified particle swarm optimization for aggregate production planning, *Expert Systems with Applications*, **41**(6), 3069-3077.

Wu, S. and Chen, S. (2014), *A Bi-level algorithm for product line design and pricing*, In 2014 IEEE International Conference on Industrial Engineering and Engineering Management, 14-18.

Yang, C. C. (2011), Constructing a hybrid Kansei engineering system based on multiple affective responses: Application to product form design, *Computers and Industrial Engineering*, **60**(4), 760-768.

Zellner, A. (1962), An efficient method of estimating seemingly unrelated regression and tests of regression bias, *Journal of American Statistical Assocation*, **57**, 500-509.