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Nonlinear Multi Attribute Satisfaction Analysis (N-MUSA): Preference Disaggregation Approach to Satisfaction

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Abstract

Nonlinear MUSA is an extension of MUSA, which employs a derived approach to analyze customer satisfaction and its determinants. It is a preference disaggregation approach, widely welcomed by scholars since 2002, following the principles of ordinal regression analysis. N-MUSA as a goal programing model, evaluates the level of satisfaction among some groups including customers, employees, etcetera according to their values and expressed preferences. Using simple satisfaction survey data, N-MUSA aggregates the different preferences in a unique satisfaction function. The main advantage of this approach is to consider and convert the qualitative form of customer judgments and preferences in an ordinal scale based on a simple questionnaire to an interval scale, in the first place, and to develop various fruitful analytical indices in order to get more knowledge of customers in the second place. In spite of the abovementioned strengths, this paper tackles some computational shortcomings within MUSA and leads to the development of nonlinear form (N-MUSA), which is more effective and efficient in practice. This paper takes MUSA and its drawbacks into account, to introduce N-MUSA as a more efficient alternative, then, deploys it in numerical examples and a real case for more insights.

Keywords

multiple criteria analysis, goal programming, satisfaction analysis, N-MUSA.

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Introduction

A good understanding of customer satisfaction is an essential, yet challenging pursuit for both scholars and practitioners. According to Huang and Sarigöllü (2008), providing the feedback for customers with regard to management for improving performance and gaining competitive advantage can result in higher profitability. Customer satisfaction is one of the most important issues concerning business organizations of all types, which is justified by the customer-orientation philosophy and the main principles of continuous improvement of modern enterprises. For this reason, customer satisfaction should be measured and interpreted into a number of measurable parameters. Customer satisfaction measurement may be perceived as the most reliable feedback system, with regard to this idea that it can provide an effective, direct, meaningful and objective way of the clients' preferences and expectations. In this regard, as Gerson (1993) pointed out, customer satisfaction is a baseline standard of performance and a possible standard of excellence for any business organization.

As customers are the heart of any industry (Senthikumar et al., 2011), planning for customer satisfaction is critical for the survival of any business (Hirata, 2009). Further, as Fečikovà (2004) contends, success is largely about the retention of customers, relying on the customer satisfaction. Hence, it can be regarded as one of the fastest growing segments of the marketing field (Matsatsinis et al., 1999). Finally, customer satisfaction can result in enhancing the customer loyalty, reducing price sensitivity, and increasing cross-buying and positive word of mouth (Deng et al., 2008).

Accordingly, focusing on customer satisfaction is a primary goal within various industries. According to Arbore and Busacca (2009), a comprehensive understanding of customer satisfaction antecedents has therefore, become a critical issue for both researchers and practitioners. On the other hand, Mihelis et al. (2001) believe that customer satisfaction is an abstract and intangible notion, which needs to be quantified in a number of factors people can be influenced by.

Through decades, fully considering the qualitative form of customers' judgments is tackled by several approaches like fuzzy theory (Ahmadi & Ranjbary, 2013). Regarding that, Multi Attribute Satisfaction Analysis (MUSA) is one of the most familiar ones. Since it was first developed, scholars and practitioners broadly welcomed it as a means of customer satisfaction analysis. Different industries have utilized MUSA, which its fruitful indices led to a deep analysis of satisfaction and its determinants, regarding the ordinal data collected among the customers. The main advantage of this method is to cope with the ordinal data, gathered from customer satisfaction surveys to establish the functions of the customers' preferences, instead of pre-assuming the interval scale within the data, which is not necessarily true. MUSA can be found as a technique of derived importance analysis through which the importance of attributes can be defined indirectly (Dolinsky, 1991; Huang & Sarigöllü, 2008). According to Huang and Sarigöllü (2008), a derived approach refers to the relationship between attributes rating (predictors) and overall rating (criterion) which is figured according to correlation and regression analysis. In this approach, MUSA takes the qualitative form of customer judgment into consideration, distinguishing it from other common derived-approach methods such as various developed regression methods. Although some models of ordinal regression analysis are being developed (Arbore & Busaca, 2009; Al-Eisa & Alhemound, 2008), MUSA is implementing the advantages of mathematical programming which can facilitate the modeling process and manipulation. In addition to the advantages of using MUSA in dealing with the customer satisfaction analysis, MUSA can be modified to be more practical in real case studies. This paper aims to introduce N-MUSA model as an extension to MUSA which includes all above mentioned advantages while it overcomes its practical pitfalls. For this purpose, after a short review of the MUSA methodology and its applications, N-MUSA is elaborated and well defined. Ultimately, two numerical examples are presented to ensure the N-MUSA applicability in comparison with MUSA. This comparison ends up with a real case application of both models in an

Iranian private bank.

Literature

MUSA

The MUSA method is a multi-criteria preference disaggregation approach providing quantitative measures of satisfaction analysis, considering the qualitative form of individuals' judgments. The main objective of the MUSA method is the aggregation of individuals' judgments into a collective value function, assuming that client's global satisfaction depends on a set of criteria or variables representing service characteristics dimensions (Grigoroudis et al., 2008). The method infers an additive collective value function $Y^*$and a set of partial satisfaction functions X_i, given customer's global satisfaction Y and partial satisfaction X_i according to the criterion i (ordinal scaling). The main objective of the method is to achieve the maximum consistency between the value function Y^* and the customers' judgments Y. Based on the model of preference disaggregation approach, the ordinal regression equation is as follows:

$$\begin{aligned} Y^* &= \sum_{i=1}^{n} b_i X_i^* \\ \sum_{i=1}^{n} b_i &= 1 \end{aligned} \qquad (1)$$

Where the global and partial value functions (Y^* ,X_i^*) are normalized between [0-100]. In other words, for $i = 1,2, \dots, n$ it can be concluded that $Y^{*1} = X_i^{*1} = 0$ and $Y^{*\alpha} = X_i^{*\alpha_i} = 100$. The number of satisfaction criteria in the analysis is denoted by n whereas b_i denotes the weight of criterion i. We can rewrite the above regression model (Equation 1) as Equation 2.

$$\widetilde{Y}^* = \sum_{i=1}^{n} b_i X_i^* - \delta^+ + \delta^- \qquad (2)$$

In Equation 2, δ^+, δ^- denote error variables. According to this model, the customers' satisfaction evaluation problem can be formulated as a linear program in which the goal is to minimize the sum of errors by introducing the following transformation variables (Equation 3):

$$z_m = y^{*m+1} - y^{*m} \quad for \ m = 1,2, \dots, \alpha - 1 \qquad (3)$$

$$w_{ik} = b_i x_i^{*k+1} - b_i x_i^{*k} \qquad for\ \ k = 1,2,\dots,\alpha_i - 1\ and\ i = 1,2,\dots,n$$

Ultimately, the LP model, considering the transformation variables, is presented as a MUSA in Equation 4. As it is clear from the above equation, MUSA is a linear goal-programming model, which was developed to fit the clients' global satisfaction to their partial satisfaction in the most efficient way.

$$\begin{aligned}
&[min]F = \sum\nolimits_{j=1}^{M} \delta_j^+ + \delta_j^- \\
&\quad Subject\ to \qquad\qquad\qquad\qquad\qquad (4) \\
&\sum_{i=1}^{n} \sum_{k=1}^{x_i^j - 1} w_{ik} - \sum_{m=1}^{y^j - 1} z_m - \delta_j^+ + \delta_j^- = 0\ \ for\ \ j = 1,2,\dots,M \\
&\sum_{m=1}^{\alpha-1} z_m = 100 \\
&\sum_{i=1}^{n} \sum_{k=1}^{\alpha_i - 1} w_{ik} = 100 \\
&z_m \geq 0, w_{ik} \geq 0 \quad \forall m,i,j,k \\
&\quad \delta_j^+ \geq 0\ , \delta_j^- \geq 0 \quad for\ j = 1,2 \dots M
\end{aligned}$$

According to the transformation variable, the primal model variable can be retrieved by Equation 5.

$$\begin{aligned}
&y^{*m} = \sum_{t=1}^{m-1} z_t \quad for\ m = 2,3,\dots,\alpha \qquad\qquad (5) \\
&x_i^{*k} = 100 \sum_{t=1}^{k-1} w_{it} \Big/ \sum_{t=1}^{\alpha_i - 1} w_{it} \qquad i = 1,2,\dots,n\ and\ k = 2,3,\dots,\alpha_i
\end{aligned}$$

Considering the result of above-mentioned LGP, MUSA methodology has developed some fruitful indices resulting in deep analysis of satisfaction. In this case, the weights of determinants (satisfaction criteria) based on the LGP result, can be computed using EQUATION 6.

$$b_i = \sum_{t=1}^{\alpha_i - 1} w_{it} \Big/ 100 \quad for\ i = 1,2,\dots,n \qquad\qquad (6)$$

In addition, the satisfaction level of each criterion (S_i) as well as the global satisfaction (S) is computed through Equation (7).

$$S = \frac{1}{\sum_{m=1}^{\alpha} p^m} \sum_{m=1}^{\alpha} p^m y^{*m}, \ \sum\nolimits_{m=1}^{\alpha} p^m = M \text{, where } M \text{ is the total number of customers} \qquad (7)$$

$$S_i = \frac{1}{\sum_{k=1}^{\alpha_i} p_i^k} \sum_{k=1}^{\alpha_i} p_i^k x_i^{*k}, \qquad \sum\nolimits_{k=1}^{\alpha_i} p_i^k = M, \qquad for\ i = 1,2,\dots,n$$

Some other efficacious indices of MUSA methodology include value function, demanding index, improvement index and action diagram, which Grigoroudis and Siskos (2002) elaborate in details. Added value curve and demanding index are designed to identify the demanding level of the customers. According to Senthikumar et al. (2011), the perception of the customers has undergone a sea change and customers are more demanding nowadays. Therefore, demanding index is so valuable for developing marketing plans.

Regarding that the MUSA method is based on a linear programming modeling, it should be noted that in several cases, particularly in large-scale LPs, it could raise the problem of multiple or near optimal solutions. MUSA is utilizing a post optimality analysis in this case in order to have more consistent results, which can be done through Equation 8.

$$[max]\ \acute{F} = \sum_{k=1}^{\alpha_i - 1} w_{ik} \qquad for\ \ i = 1,2,\dots,n \qquad (8)$$

$under\ constrains$:

$F \leq F^* + \varepsilon$

$all\ the\ constrains\ of\ original\ LP$

It is worth mentioning that the average of the optimal solutions given by the *n* LPs may be considered as the final solution of the problem, which is a stability analysis within MUSA methodology (Grigoroudis & Siskos, 2002). MUSA is also embedded with reliability analysis, in terms of AFI and ASI, as it is clear from Equation 9.

$$AFI = 1 - \frac{F^*}{100.M} \quad , \ ASI = 1 - \frac{1}{n} \sum_{i=1}^{n} \frac{\sqrt{n \sum_{j=1}^{n} \left(b_i^j\right)^2 - \left(\sum_{j=1}^{n} b_i^j\right)^2}}{\sqrt{n-1}} \qquad (9)$$

AFI is an index to demonstrate the fitness of the model results to the clients' value system and ASI indicates the stability of the model in post optimality analysis. The more the results of LPs are similar, the more ASI indicates the stability of the model. These indices vary between [0-1] which in both, 1 demonstrates the highest efficiency of the model.

MUSA in Practice

Since its development, MUSA was applied in several satisfaction studies. For example, Grigoroudis et al. (2002) employed MUSA for customer satisfaction analysis within two branches of banking organization in Cyprus. Mihelis et al. (2001) applied MUSA to customer satisfaction analysis in Commercial bank of Greece. Furthermore, Grigoroudis and Siskos (2004) used MUSA for analyzing the customers' satisfaction even at national level within transportation-communications sector. Politis and Siskos deployed this powerful technique as a multi criteria methodology for the evaluation of a Greek engineering department in 2004. Grigoroudis et al. (2008) used the MUSA methodology as a satisfaction benchmarking approach for the assessment of user perceived web quality. Grigoroudis et al. (2007) implemented the MUSA for tracking changes of e-customer preferences during the period 2004-2005. In addition, it was utilized within the satisfaction analysis of a post office, a university department as well as the mobile phone service provider, a case of an airline company and a fast food company, which were explained in more details in Siskos and Grigoroudis's (2002). Matsatsinis et al. (1999) made use of MUSA in combination with data mining techniques for deep customer satisfaction evaluation. It is also employed as a tool for a national park satisfaction analysis to find out the critical points for improvement actions (Arabatzis & Grigourdis, 2010). Grigoroudis and Spyridaki (2003) employed this method as a means of comparing the derived and stated approaches in customer satisfaction analysis. Moreover, Grigourdis and Politis (2015) extended MUSA method ultimately through robust modeling with the aim of reaching results that are more justifiable. In addition, Aouadni and Rebai (2016) developed a fuzzy approach for MUSA in order to cope with the uncertainty and vagueness of the gathered data.

Fuzzification of MCDM techniques such as MUSA is debated and recommended by scholars in the recent literature (Celik et. al., 2015).

Methodology

This paper aims to develop a mathematical model on customer satisfaction analysis and its determinants in order to overcome the prior models pitfalls. Therefore, it is an applied research based on mathematical modeling and testing. Model validation is also considered according to its feasibility and two developed indices; AFI and ASI.

N-MUSA

Although MUSA is a powerful methodology for a deep analysis of the clients' satisfaction based on a simple survey, estimating the results of variables in LGP model is not as simple as it appears. There are many modifications proposed by Grigoroudis and Siskos (2002) in terms of its post optimality analysis extended through MUSA I to MUSA IV. However, according to Grigoroudis and Siskos (2002), the problem of multiple or near optimal solutions with large scale LPs is not vanquished effectively. In some practical cases, the MUSA is not useful because of inconsistent results and in some cases, it needs a large computational effort through post optimality analysis. It means modeling and solving several LPs, at least equal to the number of satisfaction attributes weaken the applicability of MUSA in real world problems. In this regard, the N-MUSA can be developed by a little computational effort without considering the necessity of post optimal analysis. N-MUSA model is the MUSA model with quadratic objective function trying to minimize the power two of the error variables depicted in Equation 10.

$$[min]NF = \sum_{j=1}^{M} {\delta_j^{+}}^2 + {\delta_j^{-}}^2$$

$$Subject\ to \qquad (10)$$

$$\sum_{i=1}^{n} \sum_{k=1}^{x_i^j-1} w_{ik} - \sum_{m=1}^{y^j-1} z_m - \delta_j^{+} + \delta_j^{-} = 0 \ \ for\ j = 1,2,\ldots,M$$

$$\sum_{m=1}^{\alpha-1} z_m = 100$$
$$\sum_{i=1}^{n} \sum_{k=1}^{\alpha_i-1} w_{ik} = 100$$
$$z_m \geq 0, w_{ik} \geq 0 \quad \forall m, i, j, k$$
$$\delta_j^+ \geq 0\,, \delta_j^- \geq 0 \quad \text{For} \quad j=1, 2\ldots M$$

N-MUSA model is a Nonlinear Goal Programing (NLGP) with a convex objective function, which ensures the global optimality of the derived optimal solution. Although the nonlinear model solvers are not as common as linear models, scholars and practitioners can treat quadratic nonlinear models like N-MUSA efficiently nowadays in a very simple way. Since that deploying N-MUSA needs to solve one model instead of several models to find the optimal solution, it ensures the efficiency of the proposed model in real case problems. Computational efficiency is a critical feature of MCDM techniques, which is underlined by scholars in recent studies (Zamani-Sabzi et al., 2016).

N-MUSA optimal solution can be applied for satisfaction engineering through developing several fruitful indices as well as customer demanding level, determinants weights and improvement strategies in addition to figure out the satisfaction level based on a simple questionnaire. It should be noted that, quadratic objective function leads to a more effective weight distribution of all satisfaction criteria. It is done by precluding the allocation of the values to only a small number of variables within the model. Using N-MUSA, all the satisfaction indices can be computed according to the aforementioned formulas, except the Average Fitness Index (AFI), which should be computed through Equation 11. In this equation, the nominator of the equation is the same as F^* in MUSA. Therefore, AFI can be compared in both models.

$$AFI = 1 - \frac{\sum_{j=1}^{M} \delta_j^+ + \delta_j^-}{100.M} \qquad (11)$$

In the following section, some comparisons of N-MUSA and basic MUSA are detailed in two numerical examples and one real case. Results demonstrate valuable findings of N-MUSA, which overcomes MUSA in practice and ensures its effectiveness.

Findings

In this section, N-MUSA is delineated by two numerical examples and a real case study in comparison with MUSA. By comparing the results, the applicability of both models considering their efficiency and effectiveness will be scrutinized. The first numerical example is the one provided by Grigoroudis and Siskos (2002) for MUSA development and the case study is the real data gathered from an Iranian commercial bank in the time of 2015 in Tehran. Comparing both models, results can be so elaborating in case of the model's effectiveness and efficiency.

Numerical Example 1

As mentioned before, the first data set was provided by Grigoroudis and Siskos (2002) for introducing MUSA. Three attributes were piloted in this data set by considering the results of global satisfaction for 20 clients. Each client could choose from three levels of satisfaction for each criterion including dissatisfied, satisfied and completely satisfied. The summary of the data set is presented in Table 1. As an example, the first line in Table 1 indicated that 6 clients were dissatisfied, 8 satisfied, and other clients were completely satisfied with the given firm.

Table 1. Summary of Data Set 1, (Adapted From Grigoroudis And Siskos, 2002)

Criteria	*dissatisfied*	*satisfied*	*Completely satisfied*	*Total*
Global satisfaction	6[1]	8	6	20
Attribute 1	5	5	10	20
Attribute 2	9	3	8	20
Attribute 3	9	5	6	20

1. Number of customers

After employing MUSA and N-MUSA for Data Set 1, findings of both models are presented in Table 2. Employing MUSA and N-MUSA in the above-mentioned example leads to similar results. It is fruitful to declare that the N-MUSA results are the same as MUSA where ε is chosen as a small percentage of the F^* in MUSA post optimality analysis which is recommended by the MUSA methodology. It is worth mentioning that, in Grigoroudis and Siskos's

(2002) paper, the methodology is violated since F^* is equal to 0 and ε is assumed equal to 10. This leads to a different result between the present study and the Grigoroudis and Siskos's (2002) paper.

Considering the results of Table 2, AFI and ASI indices are the same for MUSA and N-MUSA. Although post optimality with N-MUSA is not necessary, it was done in this study according to MUSA methodology for better clarification.

Table 2. Numerical Example 1, MUSA and N-MUSA Satisfaction Indices

Criteria	Average satisfaction index(S_i)	Weight (%)	Average demanding index(D_i)	Average improvement index(b_i)
Global satisfaction	50.00[1] (50.00)[2]	---	0.00 (0.00)	---
Attribute 1	50.00 (50.00)	25.00 (25.00)	1.00 (1.00)	0.12 (0.12)
Attribute 2	47.50 (47.50)	50.00 (50.00)	0.00 (0.00)	0.26 (0.26)
Attribute 3	55.00 (55.00)	25.00 (25.00)	-1.00 (-1.00)	0.11 (0.11)
AFI	1.00 (1.00)	ASI	1.00 (1.00)	

1. MUSA 2. N-MUSA

In the first numerical example, the results of both models are the same indicating the same effectiveness of both models, but as far as efficiency is concerned, MUSA needs employing 4 LPs to reach the results, which can be provided just by a simple quadratic programing in N-MUSA. Therefore, although both models are effective, N-MUSA is more efficient according to this case.

Numerical Example 2

Table 3. Numerical Example 2, Data Set 2

Customers	Attribute 1	Attribute 2	Attribute 3	Global satisfaction
Customer 1	very satisfied	very satisfied	very satisfied	very satisfied
Customer 2	satisfied	very satisfied	very satisfied	very satisfied
Customer 3	very satisfied	very satisfied	very satisfied	very satisfied
Customer 4	very satisfied	very satisfied	satisfied	very satisfied
Customer 5	very satisfied	very satisfied	very satisfied	satisfied
Customer 6	dissatisfied	Dissatisfied	very satisfied	very satisfied
Customer 7	dissatisfied	Satisfied	dissatisfied	satisfied

The second data set includes three satisfaction attributes as well as global satisfaction gathered from seven customers. Each attribute has 3 levels similar to Data Set 1. Table 3 depicts Data Set 2.

Both MUSA and N-MUSA initial optimal solutions are presented in Table 4. It is clear that, based on the initial results of MUSA, only the second attribute can be analyzed through the methodology. Based on initial MUSA optimal solution, the other variables have no effect on the global satisfaction according to the value system of the customers. Therefore, the methodology failed even to produce the satisfaction level related to Attributes 1 and 3. N-MUSA provided more reliable results. The objective function (NF^*) of N-MUSA is about 3333.33, but it should be mentioned that it is the sum of the power of the two deviations from customers' points of view ($NF = \sum_{j=1}^{M} \delta_j^{+2} + \delta_j^{-2}$). Therefore, the sum of the deviations is about 99.99 in N-MUSA, which is almost the same as the sum in MUSA objective function. N-MUSA approved Attributes 2 and 3 as determinants of the global satisfaction function.

It should be pointed out that MUSA methodology is not based on the solution of initial LP. Therefore, the post optimality analysis is done as follows. Table 5 indicates the results.

Table 4. Optimal Solution of Initial MUSA and N-MUSA for Data Set 2

Model	Attribute 1		Attribute 2		Attribute 3		Global satisfaction		F^*,NF^*
	W_{11}	W_{12}	W_{21}	W_{22}	W_{31}	W_{32}	Z_1	Z_2	
MUSA	0	0	100	0	0	0	100	0	100
N-MUSA	0	0	33.33	0	66.66	0	66.66	33.33	3333.33

Table 5 presents the ultimate MUSA results of Data Set 2. The global satisfaction is 100% although Customers 5 and 7 are not very satisfied with the organization. The ASI is about 0.33, which determines the instability of the model, and the weight of Attribute 2 is twice more than Attribute 3. Analysis of Attribute 1 cannot be pondered because the LPs solutions for this attribute are zero. Deploying the N-MUSA for this data set provides some differences. According to Table 6, the global satisfaction of the firm is about

90.47% and the attribute satisfactions are the same as the results in MUSA.

Table 5. MUSA Results for Data Set 2

Criteria	Average satisfaction index(S_i)	Weight (%)	Average demanding index(D_i)	Average improvement index(b_i)
Global satisfaction	100	---	-1	---
Attribute 1	NC[1]	0.00	NC	NC
Attribute 2	86.00	66.66	-1	0.09
Attribute 3	86.00	33.33	-1	0.04
AFI: 0.857			ASI: 0.33	

1. Failed to be computed based on the LPs results (NC: Not Computable)

As it is elaborated in Table 6, the weights of the attributes are opposite to each other. Attribute 3 is twice more important than Attribute 2, while the stability of the model according to ASI, is equal to 1 if we use the post optimality analysis for N-MUSA, although it is not necessary.

Table 6. N-MUSA Results for Data Set 2

Criteria	Average satisfaction index(S_i)	Weight (%)	Average demanding index(D_i)	Average improvement index(b_i)
Global satisfaction	90.47	---	-0.33	---
Attribute 1	NC[1]	0.00	NC	NC
Attribute 2	86.00	33.33	-1	0.04
Attribute 3	86.00	66.66	-1	0.09
	AFI: 0.857	ASI[2]: 1.00		

1. Failed to be computed based on the NLP result (NC: Not Computable)
2. It can be computed by deploying the MUSA post optimality analysis method

Therefore, instability in MUSA leads to incorrect results. The global satisfaction is equal to 100% and all the demanding indices are equal to 1, according to the results obtained from MUSA, which mean that all the customers are not satisfied based on the attributes and global satisfaction. It is worth declaring that by arbitrary quantification of the collected information, the global satisfaction is about 90%[1] and A_1, A_2 and A_3 satisfaction levels are 76%, 85% and 85%, respectively. It is clear that N-MUSA results are more acceptable than MUSA results even after post optimality analysis.

In comparison, it should be also pointed out that the initial results of MUSA are not appropriate because it allocates the whole value of 100 only to z_1 and w_{21}. Based on post optimality analysis, this shortcoming is modified but the lack of stability within the LPs may mislead the decision makers. The nature of data set and the lack of stability within MUSA results prove that N-MUSA result is more acceptable and compatible with the collected data, on one hand, and it is more valid, on the other hand. Although the data provided here are not enough for satisfaction analysis, the results indicated that N-MUSA is more effective and efficient than MUSA at providing the final results.

Case Study

Table 7. Summary of Data Set 3 (Central Branch of Iranian Commercial Bank)

Criteria	Completely dissatisfied	Dissatisfied	Slightly satisfied	Satisfied	Completely satisfied	Total
Global satisfaction	1*	7	3	49	32	92
Cost	3	8	32	36	13	92
Accessibility	3	6	18	28	37	92
Bank Brand	4	1	7	23	57	92
Employee	1	5	9	44	33	92
Products	2	10	22	38	20	92
Other services	1	6	5	58	22	92

* Number of customers

As a case study, a sample of customers was selected from the biggest Iranian commercial private bank. The survey was randomly administered by using a sample of 135 customers referred to central branch in Tehran. The response rate was about 68% and ultimately 92 responses were analyzed as Table 7 indicates the results. Each customer was expected to declare his or her satisfaction with 6 critical

1. $\frac{5\times3+2\times2}{7\times3}\times 100 = 90\%$

bank performance attributes according to Grigoroudis et al.(2002) and the global satisfaction on the five Likert-scale including completely dissatisfied to completely satisfied. The collected data were analyzed by means of MUSA and N-MUSA, as shown in Table 8. Findings ensure that N-MUSA out-performs MUSA in real world problems.

Then, the MUSA and its post optimality analysis were utilized for Data Set 3. As it is clear from Table 8, results proved the ineptness of the MUSA for satisfaction analysis within the provided data. In comparison to MUSA, N-MUSA provided appropriate results with favorable fitness index. Sum of the error variables is 266 based on N-MUSA results resulting in average fitness index of 97.1%.

Table 8. Optimal Solution of MUSA and N-MUSA for the Case of Iranian Bank

Attributes	Model Variables	MUSA Initial solution	Post Optimality Analysis Average	N-MUSA
Cost	W_{11}	0.00	0.00	0.00
	W_{12}	0.00	0.00	0.00
	W_{13}	0.00	0.00	0.00
	W_{14}	0.00	0.00	0.612
Accessibility	W_{21}	0.00	0.00	0.00
	W_{22}	0.00	0.00	4.754
	W_{23}	0.00	0.00	0.00
	W_{24}	0.00	0.00	0.00
Bank Brand	W_{31}	0.00	0.00	0.00
	W_{32}	0.00	0.00	0.00
	W_{33}	0.00	0.00	0.00
	W_{34}	0.00	0.00	0.00
Employee	W_{41}	0.00	0.00	0.00
	W_{42}	0.00	0.00	13.31
	W_{43}	0.00	0.00	0
	W_{44}	0.00	0.00	0.07
Products	W_{51}	0.00	0.00	13.02
	W_{52}	0.00	0.00	0.00
	W_{53}	0.00	0.00	0.00
	W_{54}	0.00	0.00	0.79

Attributes	Model Variables	MUSA Initial solution	Post Optimality Analysis Average	N-MUSA
Other services	W_{61}	100	100	62.16
	W_{62}	0.00	0.00	5.07
	W_{63}	0.00	0.00	0.09
	W_{64}	0.00	0.00	0.12
Global satisfaction	Z_1	100	100	70.9
	Z_2	0.00	0.00	24.64
	Z_3	0.00	0.00	2.10
	Z_4	0.00	0.00	2.29
	F^*	100	---	3987.79

According to the above results in Table 9, it is evident that based on MUSA method, no meaningful analysis can be done to the provided data even after post optimality analysis. The results indicated that the other attributes could not have an effect on the global satisfaction except “Products”. Therefore, the satisfaction indices, based on MUSA methodology, cannot be computed for the other attributes. The stability of the model and average fitness index are 1 and 0.989, respectively meaning that the model fits well with a high stability but the results cannot be confirmed. For instance, the average global satisfaction, based on MUSA results, is about 98.91% whereas 12% of the sampled customers chose slightly satisfied or less. Employing the N-MUSA led to results that are more appropriate. Although the AFI is a little lower (0.971) in N-MUSA, the distribution of the weights within attributes and average satisfaction within the attributes were more acceptable and were approved by the experts of the studied case as well. The global satisfaction is about 91.78%, which is more satisfying.

Catching up to 98.91% level of global satisfaction because of 97.82% satisfaction in products, which is resulted by MUSA, is not acceptable by the studied case experts. They believe that the N-MUSA results are more suited for the existing case study. According to N-MUSA results, “Products” is the most important attribute, but it is not the only determinant as it was proposed by MUSA. N-MUSA results were more appropriate according to the bank decision makers' standpoints, which may increase the applicability of N-MUSA. It is worth mentioning that ASI cannot be considered for N-MUSA, since post optimality analysis is not necessary for N-MUSA.

Table 9. MUSA and N-MUSA Satisfaction Indices, the Case of Iranian Bank

Criteria	Average satisfaction index(%)	Weights (%)	Average demanding index(D_i)	Average improvement index(b_i)
Global satisfaction	98.91[1] (91.78)[2]	---	-1.00(-0.76)	---
Cost	NC[3](14.13)	0.00 (0.006)	NC (0.999)	NC (0.005)
Accessibility	NC (88.04)	0.00 (0.048)	NC (-0.33)	NC (0.005)
Bank Brand	NC (NC)	0.00 (0.00)	NC (NC)	NC (NC)
Employee	NC (87.67)	0.00 (0.134)	NC (-0.33)	NC (0.016)
Products	97.82(95.88)	1.00 (0.674)	-1.00(-0.88)	0.022 (0.027)
Other services	NC (92.01)	0.00 (0.138)	NC (-0.94)	NC (0.011)
AFI	0.989 (0.971)	ASI	1.00 (Not considered)	

1. MUSA 2. N-MUSA 3. Failed to be computed (NC: Not Computable)

Conclusion

This paper reviewed the MUSA method with its preference on disaggregation approach to deep customer satisfaction analysis, which is based on the ordinal data obtained from satisfaction surveys. This is the main advantage of MUSA comparing to other quantification methods of customer satisfaction. MUSA as a linear goal programming technique proved its applicability in several studies. In addition to its prevalent application, MUSA in some data sets needs more consideration. In this case, N-MUSA is developed using nonlinear goal programing approach with a convex objective function in a quadratic form. This model can perform the analysis in a more efficient way without the necessity of post optimality analysis, which needs solving several LPs in MUSA, and it can be regarded as a more effective and robust aproach within various data sets in reaching the optimal solution. For better understanding, both techniques were investigated through two numerical examples and a real case of banking firm in Iran.

In dealing with the first numerical example, although the results of both models are the same, N-MUSA can deliver the results more efficiently. It means that employing the N-MUSA, the same results are derived without the necessity of post optimality analysis. In addition to the efficiency, it is worth mentioning that, according to Grigoroudis and Siskos (2002), the average of post optimality analysis in MUSA may be able to present the final solution; it needs more consideration in practice. In addition, it should be clarified that in MUSA post optimality analysis, the value of ε is so critical in reaching the results. Grigoroudis and Siskos (2002) debated that ε should be a small percentage of the objective function of the initial model. However, this rule is violated in their numerical example, reproduced in this paper as Example 1. Since the objective function of their initial model was zero, ε should have not been more than zero, but they assumed ε equal to 10 in their post optimality analysis. That is why there is difference between the MUSA results in the first numerical example of this paper and its origin in Grigoroudis and Siskos (2002). Implementing both models to numerical Example 2, we can conclude that MUSA cannot be performed like N-MUSA in determining the satisfaction and the other indices. AFI and ASI indicate weaker performance of the MUSA in comparison with N-MUSA. Global satisfaction is estimated about 100% according to MUSA results, which is not acceptable in case that Customer 5 and Customer 7 are not completely satisfied with the assumed firm. N-MUSA provided 90.47% of global satisfaction that is more acceptable in common sense. Accordingly, the results obtained from Iranian banking firm showed the strengths of N-MUSA in analyzing the customers' satisfaction. As the results indicated, although MUSA has got 0.98 fit to data set (AFI=0.98), the findings only verified one attribute as a determinant of customer satisfaction which is not confirmed by the studied bank experts. On the contrary, N-MUSA chose that attribute as the most important, but not the only determinant of the global satisfaction. The average satisfaction level can be considered as a drawback in the case under study, which is solved by N-MUSA.

Finally, we can conclude that employing both techniques in two numerical examples and one real case study lead to proving the effectiveness of N-MUSA as well as its lower computational effort. The result highlighted that, in addition to being more efficient, N-MUSA can perform better in dealing with various data sets. Findings of the models indicated that N-MUSA solutions are more acceptable to experts in common sense, playing a vital role in the evaluation of the model results as emphasized by Hooley and Hussey's (1994) study in which they debated that common sense should be considered in the evaluation of quantitative analysis. Therefore, N-MUSA is recommended to scholars and practitioners for better understanding of customers.

Ultimately, it should be emphasized that N-MUSA is a precise tool to grasp the customers' view, while developing interval scale from the customers' ordinal responses to questions. It can develop several indicating indices, which can be used to develop the firm's performance aligned with the customers' needs, and in the end, it can determine the demanding level of the customers which is critical in quality planning of the firms.

Although yet some shortcomings exist with the N-MUSA such as non-basic variables in the optimal solution leading to non-computable indices such as "Bank Brand" in Case Study 3, they can be amended by scholars. As an instance, the non-basic variables are avoidable through the methodology of strictly increasing value functions proposed by Grigoroudis and Siskos (2002).

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