

DEALING WITH KANO MODEL DYNAMICS: STRENGTHENING THE QUALITY FUNCTION DEPLOYMENT AS A DESIGN FOR SIX SIGMA TOOL

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ABSTRACT

Six Sigma has been known to be a breakthrough business strategy to achieve customer satisfaction through defect reduction and cost optimization. A flawless product or service would, however, be of little value if it does not sell. Thus, it is of considerable importance to begin with the customer. Quality Function Deployment (QFD), as a customer-driven tool in Design for Six Sigma (DFSS) toolset, can be regarded as one of the most powerful tools to serve this purpose. The success of QFD use relies heavily on the accuracy of the primary input, that is, the Voice of the Customer (VOC). To better identify and obtain more accurate VOC, the use of Kano Model in QFD has been incorporated in the literature. Unfortunately, the dynamics of Kano Model, such as the fact that what now delights the customer will become an expected need in the future is often oversimplified and has not been adequately addressed. The aim of this paper is to shed some light on Kano Model dynamics modeling by providing a quantitative technique which is based on compositional data analysis. It is expected that a timely update of customer needs data may serve as a useful indicator to monitor the progress of how well a company satisfies its customer over time, and at the same time provide a ground for formulating the next strategies as to enable the company to respond differently and continuously over time of its operations. To give some practical insights, an illustrative example is provided.

Keywords: six sigma, kano model dynamics, compositional data, QFD.

1. INTRODUCTION

In recent years, the speed of change in technology and innovation has been increasing significantly. The quest to provide better, cheaper and faster product/service in order to achieve customer satisfaction has been greatly intensified. For almost two decades, Six Sigma, which was introduced at and popularized by Motorola in 1980s (Harry and Schroeder, 2000), has been known to be a breakthrough business strategy to achieve customer satisfaction through defect reduction and cost optimization. It has fundamentally changed the paradigm of how statistics is applied in business and industry, and thus a precursor to the way statisticians will be working in the future (Hahn et al., 1999). Although the novelty issue of Six Sigma has been argued (Catherwood, 2002; Bisgaard and De Mast, 2006), the trend of its increased use has been remarkable. This is indicated by the increasing academic interest (Hoerl, 2001; Brady and Allen, 2006) and the exponentially growing number of books published in the market (Goh, 2002).

More recently, the Six Sigma strategy has been criticized mainly in the sense that it is of little value if a company is producing flawless product/service that does not sell (Lee, 2001). Therefore, Six Sigma should begin with the customer. In view of this, a later reformulation of Six Sigma, which is termed as 'Design for Six Sigma' (DFSS), is proposed to properly address the need to conform to the customer requirement by providing accurate fundamental design in early design phase so that the company may obtain Six Sigma products and services from the very beginning

(Antony and Banuelas, 2002; Tenant, 2002; Banuelas and Antony, 2004; Kwak and Anbari, 2006). As noted by Antony and Banuelas (2002) "If an error in design is detected during the manufacturing stage, it costs a hundred times more to repair than the same error that is detected and repaired in the design stage".

One of the most prominent tools in the DFSS is the Quality Function Deployment (QFD) (Breyfogle, 2003; Creveling et al., 2003; Rahardjo et al., 2003). It has become a widely accepted methodology for new or improved product/service design (Chan and Wu, 2002; Xie et al., 2003). The most critical determinant of QFD success lies in the accuracy of the primary input, that is, the Voice of the Customer (VOC) (Cristiano et al., 2001). In other words, the cost of not having accurate VOC would be substantially huge since it determines all the subsequent downstream processes. Thus, it is of great importance to obtain the VOC as accurately as possible.

With respect to obtaining accurate VOC, one of the most important techniques is to incorporate the Kano's classification (Kano et al. 1984) in the VOC. Kano Model, in general, provides a unique way of distinguishing the impact of different customer needs (VOC) on total customer satisfaction in the early stage of product/service development. This will substantially lead to a much higher degree of effectiveness and efficiency in the subsequent processes. Some examples that showed the importance of incorporating Kano Model in QFD can be found in Shen, et al. (2000), Tan and Shen, (2000) or Tan and Pawitra (2001).

Essentially, Kano model categorizes the customer's needs into three major groups, namely, must-be (M), one-dimensional (O), and attractive attribute (A). A brief explanation of each of these attributes is provided in Section 2. It is worth highlighting that as the passage of time, what now excites the customer (A) will become an expected requirement (O/M) in the future since it will have been a common thing ($A \rightarrow O$ or $A \rightarrow M$). Hence, in order to provide competitive product/service which at the same time addresses the future needs of the customer, this fact should not be overlooked.

Nevertheless, very little attention has been paid in investigating Kano Model dynamics. One example is an empirical study done by Witell and Fundin's (2005), which showed the dynamics of customer attributes in e-service. However, they did not provide a formal methodology to account for the attributes' change over time. Therefore, to fill in this niche, this paper proposes the use of the compositional data analysis, based on the exponential smoothing technique, to shed some light in dealing with Kano Model dynamics. Specifically, the proposed method attempts to quantitatively model the limited historical data, which are derived from Kano questionnaires' results, in order to forecast the future Kano's category for each of the quality attributes or customer requirements (VOC).

This paper is organized as follows. Section 2 provides a brief review on the Kano Model and the importance of considering its dynamics. Afterwards, a short review of the fundamental theory in compositional data analysis, which is used in this paper, is given in Section 3. The key contribution of this paper, namely, the compositional exponential smoothing method for dealing with the Kano Model dynamics, will be elaborated in Section 4. How the results of the Kano's categories forecast strengthen and fit into the QFD context will be described in Section 5. An illustrative example of the proposed model will be given to provide some practical insights (Section 6). Lastly, Section 7 will provide a discussion and some directions for future work.

2. THE KANO MODEL AND ITS DYNAMICS

This section provides a brief review on Kano model and some explanations on why change of category takes place. As mentioned previously, Kano model basically categorizes customer attributes into three different types, namely, Must-be, One-dimensional, and Attractive.

A must-be (M) attribute is associated with those needs that are not mentioned explicitly or taken for granted by the customer, the non-existence will cause a great deal of dissatisfaction while the existence does not bring a significant satisfaction. A one-dimensional (O) attribute reflects the spoken needs of the customer, the more it is fulfilled, the more the customer becomes satisfied in proportional way to the degree of fulfillment. While, the attractive attribute (A) is known as the delighters, which means a little improvement on the product/service performance will make a significant increase in the level of customer satisfaction. Kano believes that the VOC, either it is spoken or unspoken, can be exploited through a questionnaire (CQC, 1993; Matzler and Hinterhuber, 1998; Widiawan and Irianty, 2004).

Recently, Witell and Fundin's (2005) gave an empirical study to show the dynamics of customer attributes in e-service. They pointed out that at different time, the category of the customer attributes changed accordingly. With respect to the Kano Model, what now excites the customer (A) will be an expected requirement (O/M) in the future because it will have become a common thing ($A \rightarrow O$ or $A \rightarrow M$). On the other hand, what is now taken for granted (M) will possibly be a required attribute (O) or attractive attribute (A) as the customer begins to realize the importance of that particular attribute in the future ($M \rightarrow O$ or $M \rightarrow A$), although this case is rather rare.

It is worth noting that customers usually do not know or yet realize the attractive attribute (A), thus, it can be a surprise or delighter to them. However, this attractive attribute serves as the largest determinant of the customer satisfaction degree, and is particularly useful for providing innovative products/services. In other words, there must be a breakthrough or innovation from the existing attributes to be an attractive attribute. Another possible factor that makes a product/service attribute becomes an attractive one is the external condition influence, which makes the customer begin to realize the importance of that particular attribute.

3. COMPOSITIONAL DATA FUNDAMENTALS

This section describes the necessary fundamentals of compositional data analysis that is used in this paper. Readers who are familiar with the concept may just skip this section and proceed to Section 4.

3.1 Simplex Sample Space

The sample space of the compositional data is called the Simplex space (Aitchison, 1982; 1986). Specifically, the D -part simplex space can be expressed as in (1). Note that, in the context of the Kano questionnaires results, the value of k is equal to 1.

$$S^D = \left\{ X = [x_1, x_2, \dots, x_D]; x_i > 0; \sum_{i=1}^D x_i = k \right\}, \text{ where } k \text{ is a constant.} \quad (1)$$

3.2 Operations in the Simplex

There are four important terminologies in terms of the operations in the simplex space, namely, the closure operator, the perturbation operation, the power transformation, and the inner product. For any vector $Z = [z_1, \dots, z_d] \in \mathfrak{R}_+^d$, the closure operator $C[\cdot]$ is obtained by dividing each component by the sum of all the components and multiplying the result by the constant k , which is described in the definition of the simplex space (1):

$$C[Z] = \left(\frac{kz_1}{\sum_{i=1}^d z_i}, \frac{kz_2}{\sum_{i=1}^d z_i}, \dots, \frac{kz_d}{\sum_{i=1}^d z_i} \right) \quad (2)$$

Let $X = [x_1, \dots, x_D]$ and $Y = [y_1, \dots, y_D]$, where $X, Y \in S^D$, then the main two operations in the simplex, namely, the perturbation and the power transformation, can be written as in (3) and (4), respectively:

$$X \oplus Y = C[x_1y_1, x_2y_2, \dots, x_Dy_D] \quad (3)$$

$$k \otimes X = C[x_1^k, x_2^k, \dots, x_D^k], \text{ where } k \in \mathfrak{R}_+ \quad (4)$$

whereas the other operation such as difference (\ominus) may easily derived from the above equations, for example:

$$X \ominus Y = X \oplus (-1 \otimes Y) \quad (5)$$

The inner product of two vectors composition (X, Y) can be written as follows:

$$\langle X, Y \rangle_a = \sum_{i=1}^D \ln \frac{x_i}{g(X)} \ln \frac{y_i}{g(Y)} \quad (6)$$

$$\text{where } g(X) = \sqrt[D]{\prod_{i=1}^D x_i}, \quad g(Y) = \sqrt[D]{\prod_{i=1}^D y_i}$$

For a brief mathematical review of the compositional data basics with simple examples, interested readers may refer to Tolosana-Delgado et al. (2005).

2. MODELING KANO DYNAMICS

2.1 The Input

The main input of the proposed model is the Kano's questionnaires results, which are in compositional data form. Generally, it describes the percentage of the attractive, one-dimensional, must-be, and other categories for each of the customer attributes (CQM, 1993; Matzler and Hinterhuber, 1998). The focus is to model the change pattern of the percentage data for each category over time. The forecasted data will later be used in QFD analysis to prioritize efforts to meet the future needs of the customer. In other words, the QFD team may make use of this information to design a product/service that will meet the future VOC (Xie et al., 2003).

Since the Kano questionnaire results are in percentage form (summed to unity), then they can be regarded as a compositional data problem. The proper sample space of the compositional data, as explained in Aitchison (1982), is the simplex space (S^D), rather than the real sample space (\mathfrak{R}). Therefore, a novel approach, by staying in the simplex space, is proposed to deal with the Kano category's percentage change over time using the idea of the exponential smoothing approach.

2.2 Proposed Method

The proposed approach, which will be described in the next subsections, can be applied using a simple forecasting framework (see Hanke and Wichern, 2005). Basically, one needs to collect the necessary historical data, that is, the Kano questionnaire results. Afterwards, to obtain a visual view of the past data change behavior, a time series plot can be drawn using the Cartesian

coordinate system or a ternary diagram for three-dimensional data (von Eynatten et al., 2002). When using the proposed approach, one may select the best coefficient of the model based on which that gives the lowest value of fitting error. Finally, using the optimal model coefficient, the fitting and the forecasting process can be carried out accordingly. The difference between the original data and the fitted values serves as the measure of forecast error, which will be explained in Section 4.3.

2.2.1 Compositional Single Exponential Smoothing (CSES)

Let $Y_t = [y_{t1}, y_{t2}, \dots, y_{tD}]$, where $y_{ti} \in \mathfrak{R}_+$, denote a vector of an observation of D -part compositional data at time point t which is also subject to the sum constraint $\sum_{i=1}^D y_{ti} = 1$, then Y_t

can be regarded as a vector in the simplex sample space S^D at time point t . Following the widely known single exponential smoothing formula (Hanke and Wichern, 2005), the Compositional Single Exponential Smoothing (CSES) formula can be analogously expressed as in (7).

$$\hat{Y}_t = \alpha \otimes Y_{t-1} \oplus (1 - \alpha) \otimes \hat{Y}_{t-1}, \text{ where } 0 \leq \alpha \leq 1 \quad (7)$$

Interestingly, the real space single exponential smoothing shares some similarities with the CSES. When $\alpha=0$, then \hat{Y}_t would be equal to \hat{Y}_{t-1} , which can be easily shown as follows:

$$\begin{aligned} \hat{Y}_t &= 0 \otimes Y_{t-1} \oplus 1 \otimes \hat{Y}_{t-1} \\ \hat{Y}_t &= C[y_{1(t-1)}^0, y_{2(t-1)}^0, \dots, y_{D(t-1)}^0] \oplus C[\hat{y}_{1(t-1)}^1, \hat{y}_{2(t-1)}^1, \dots, \hat{y}_{D(t-1)}^1] \\ &= C[1, 1, \dots, 1] \oplus \hat{Y}_{t-1} = \hat{Y}_{t-1} \end{aligned} \quad (8)$$

Note that $C[1, 1, \dots, 1]$ is the identity vector in the simplex space. By the same token, when $\alpha=1$, then \hat{Y}_t would be reduced to Y_{t-1} . This fact is exactly the same case as that of in the real space (\mathfrak{R}). Therefore, when α ranges between 0 and 1, it is hoped that it can perform equally well and give time-efficient forecasts as in the real space.

2.2.2 Compositional Double Exponential Smoothing (CDES)

The Brown's double exponential smoothing (Brown and Meyer, 1961) technique is generally useful for modeling trend in the data. The model may analogously be adopted into the simplex space as in the CSES case. The Compositional Double Exponential Smoothing (CDES) formula, where $0 \leq \alpha \leq 1$ and $p \in \mathfrak{R}_+$, is given as follows:

$$S_t = \alpha \otimes Y_t \oplus (1 - \alpha) \otimes S_{t-1} \quad (9)$$

$$S'_t = \alpha \otimes S_t \oplus (1 - \alpha) \otimes S'_{t-1} \quad (10)$$

$$A_t = 2 \otimes S_t \ominus S'_t \quad (11)$$

$$B_t = \frac{\alpha}{1 - \alpha} \otimes (S_t \ominus S'_t) \quad (12)$$

$$\hat{Y}_t = A_t \oplus B_t \otimes p \quad (13)$$

This CDES method, which is generally more superior to the CSES method, particularly when there is a data trend, is suggested to be used in this paper.

2.3 Fitting Error Measurement

The distance between compositional vector X and vector Y in the simplex space, which indicates the goodness of fit, is called the Aitchison distance, of which expression is shown in (14). This distance, which is a scalar quantity, is used as the primary yardstick to judge the goodness of fit of the model proposed. In general, the smaller the value of the distance, it implies that the better the model is. The Aitchison distance can be considered as a more superior distance measure than the Euclidean distance since it has all the necessary properties of scale invariance, permutation invariance, perturbation invariance and subcompositional dominance (Aitchison, 1986, 1992; Pawlowsky-Glahn and Egozcue, 2002).

$$d_a(X, Y) = \sqrt{\sum_{i=1}^D \left(\ln \frac{x_i}{g(X)} - \ln \frac{y_i}{g(Y)} \right)^2}, \text{ where } g(X) = \sqrt[D]{\prod_{i=1}^D x_i}, g(Y) = \sqrt[D]{\prod_{i=1}^D y_i} \quad (14)$$

3. INTEGRATING KANO MODEL DYNAMICS INTO QFD

To have an effective and accurate prioritization in the VOC, the QFD users should first categorize the customer needs properly. In view of this, Kano Model has been suggested to be used to distinguish those attributes that have stronger impact to customer satisfaction from those that have less. Some examples can be found in Shen et al. (2000), Tan and Shen (2000), or Tan and Pawitra (2001). Basically, the differentiation of a customer attribute from the others, with respect to its impact towards customer satisfaction, is done by assigning different values of multiplier to the VOC importance rating.

The forecasted results for each of the customer attributes can be dovetailed with the QFD optimization framework which is aimed to meet the future needs of the customer. An example of a QFD prioritization framework, with respect to meeting future VOC, can be found in Raharjo et al. (2006). With respect to the prioritization framework, the forecast variability, which is a measure of future uncertainty of a customer attribute, can be derived from the variance of the Aitchison distances. By understanding the future category, it is hoped that the QFD users may satisfy or even exceed the future needs of the customers.

4. AN ILLUSTRATIVE EXAMPLE

An illustrative example in the field of computer technology, which is adopted from Lai et al. (2007), would be described in this section to demonstrate the applicability of the proposed method. Let suppose DQ_1 , DQ_2 , DQ_3 , and DQ_4 , which are the Demanded Qualities (DQ) or customer attributes/requirements, are 'Smaller Size', 'Business Performance', 'Good Appearance', and 'Wireless LAN function', respectively. The Kano questionnaire results, which have been collected for 10 months for each DQ, are shown in Table 1. The proposed framework using the compositional exponential smoothing technique, as explained in Section 4, can be applied to fit the historical data and eventually obtain the forecasted values. Some realistic descriptions of the customer attributes are given as follows.

Let assume that 'Smaller Size' (DQ_1) was initially 'attractive' to the customer in the first few months, but it gradually becomes a 'must-be' attribute as more and more companies produce small

size personal computers. Therefore, the company should be ready to innovate as the market has no longer regarded this attribute as delighter. Some modification of the old one or other attribute innovation should be considered. This change is shown in the percentage numbers in Table 1 (column DQ₁). ‘Business Performance’ (DQ₂) appeared to be rather stable as a ‘one-dimensional’ attribute over time, and it very slowly becomes ‘must-be’ attribute. This situation is intuitively justifiable as it is quite natural. With respect to DQ₂, the company may not have to allocate too much effort to innovate compared to that of DQ₁. Likewise, the change is shown in Table 1 (column DQ₂).

‘Good Appearance’ (DQ₃) turns out to have the fastest change of category over time, only after several months, it has become a ‘must-be’ for computer buyer. In view of this, the company should react responsively to improve the existing attribute in order to stay competitive. ‘Wireless LAN function’ (DQ₄) was regarded as ‘indifferent’ attribute as the beginning since most of the customer did not realize the function. As the passage of time, more and more customer realizes the function, and as a result, they become delighted of the existence of the attribute. However, in the last few months, there is also a little indication that this attribute may slowly become ‘one-dimensional’. The changes of DQ₃ and DQ₄ are as well represented in Table 1 (column DQ₃ and DQ₄).

Table 1. Initial Historical Data

t	DQ ₁				DQ ₂				DQ ₃				DQ ₄			
	A	O	M	I	A	O	M	I	A	O	M	I	A	O	M	I
1	0.75	0.12	0.07	0.06	0.04	0.77	0.18	0.01	0.72	0.20	0.06	0.02	0.08	0.12	0.05	0.75
2	0.68	0.19	0.08	0.05	0.05	0.72	0.22	0.01	0.62	0.28	0.09	0.01	0.15	0.10	0.06	0.69
3	0.57	0.26	0.10	0.07	0.06	0.68	0.25	0.01	0.40	0.35	0.20	0.05	0.22	0.08	0.07	0.63
4	0.45	0.40	0.13	0.02	0.05	0.65	0.28	0.02	0.31	0.38	0.28	0.03	0.45	0.07	0.09	0.39
5	0.29	0.55	0.15	0.01	0.05	0.62	0.31	0.02	0.25	0.30	0.43	0.02	0.64	0.13	0.11	0.12
6	0.19	0.60	0.18	0.03	0.04	0.58	0.35	0.03	0.15	0.27	0.51	0.07	0.58	0.20	0.12	0.10
7	0.15	0.52	0.31	0.02	0.05	0.54	0.39	0.02	0.14	0.22	0.52	0.12	0.44	0.28	0.19	0.09
8	0.13	0.48	0.35	0.04	0.04	0.48	0.47	0.01	0.11	0.21	0.55	0.13	0.32	0.33	0.28	0.07
9	0.10	0.40	0.42	0.08	0.06	0.41	0.52	0.01	0.09	0.16	0.61	0.14	0.29	0.38	0.31	0.02
10	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?

Using the CDES method, the fitting and forecasting process were carried out, and the results are shown in Table 2 – Table 5, for DQ₁, DQ₂, DQ₃, and DQ₄, respectively. Note that the fitted data are denoted by DQ’, while the fitting error values are in the column denoted by ‘Ad’ which stands for Aitchison distance.

Table 2. Fitting, Forecast, and Fitting Error Data for DQ₁

t	DQ ₁				DQ’ ₁				Ad
	A	O	M	I	A’	O’	M’	I’	
1	0.75	0.12	0.07	0.06	0.672	0.184	0.084	0.060	-
2	0.68	0.19	0.08	0.05	0.672	0.184	0.084	0.060	0.172
3	0.57	0.26	0.10	0.07	0.683	0.193	0.078	0.046	0.453
4	0.45	0.40	0.13	0.02	0.521	0.297	0.107	0.075	1.289
5	0.29	0.55	0.15	0.01	0.352	0.494	0.143	0.011	0.250
6	0.19	0.60	0.18	0.03	0.185	0.656	0.154	0.004	1.649
7	0.15	0.52	0.31	0.02	0.116	0.665	0.190	0.029	0.707
8	0.13	0.48	0.35	0.04	0.098	0.491	0.393	0.018	0.702
9	0.10	0.40	0.42	0.08	0.096	0.429	0.427	0.049	0.447
10	?	?	?	?	0.072	0.311	0.469	0.149	0.709*

*) Mean of Ad using $\alpha = 0.72$

Table 3. Fitting, Forecast, and Fitting Error Data for DQ₂

t	DQ ₂				DQ' ₂				Ad
	A	O	M	I	A'	O'	M'	I'	
1	0.04	0.77	0.18	0.01	0.050	0.725	0.215	0.010	-
2	0.05	0.72	0.22	0.01	0.050	0.725	0.215	0.010	0.022
3	0.06	0.68	0.25	0.01	0.050	0.719	0.221	0.010	0.190
4	0.05	0.65	0.28	0.02	0.061	0.673	0.255	0.010	0.679
5	0.05	0.62	0.31	0.02	0.052	0.632	0.295	0.022	0.091
6	0.04	0.58	0.35	0.03	0.049	0.594	0.333	0.024	0.297
7	0.05	0.54	0.39	0.02	0.038	0.547	0.378	0.037	0.649
8	0.04	0.48	0.47	0.01	0.047	0.504	0.425	0.024	0.733
9	0.06	0.41	0.52	0.01	0.038	0.438	0.514	0.009	0.399
10	?	?	?	?	0.087	0.342	0.562	0.010	0.382*

*) Mean of Ad using $\alpha = 0.56$

Table 4. Fitting, Forecast, and Fitting Error Data for DQ₃

t	DQ ₃				DQ' ₃				Ad
	A	O	M	I	A'	O'	M'	I'	
1	0.72	0.20	0.06	0.02	0.588	0.282	0.107	0.023	-
2	0.62	0.28	0.09	0.01	0.588	0.282	0.107	0.023	0.6862
3	0.40	0.35	0.20	0.05	0.618	0.280	0.091	0.011	1.455
4	0.31	0.38	0.28	0.03	0.427	0.350	0.185	0.038	0.581
5	0.25	0.30	0.43	0.02	0.284	0.383	0.298	0.035	0.657
6	0.15	0.27	0.51	0.07	0.201	0.300	0.478	0.021	1.150
7	0.14	0.22	0.52	0.12	0.112	0.240	0.593	0.055	0.729
8	0.11	0.21	0.55	0.13	0.091	0.185	0.603	0.121	0.206
9	0.09	0.16	0.61	0.14	0.074	0.166	0.602	0.159	0.241
10	?	?	?	?	0.072	0.120	0.661	0.147	0.713*

*) Mean of Ad using $\alpha = 0.46$

Table 5. Fitting, Forecast, and Fitting Error Data for DQ₄

t	DQ ₄				DQ' ₄				Ad
	A	O	M	I	A'	O'	M'	I'	
1	0.08	0.12	0.05	0.75	0.140	0.100	0.060	0.699	-
2	0.15	0.10	0.06	0.69	0.140	0.100	0.060	0.699	0.064
3	0.22	0.08	0.07	0.63	0.160	0.100	0.060	0.681	0.417
4	0.45	0.07	0.09	0.39	0.308	0.062	0.078	0.553	0.529
5	0.64	0.13	0.11	0.12	0.685	0.046	0.087	0.182	1.080
6	0.58	0.20	0.12	0.10	0.691	0.179	0.101	0.028	1.097
7	0.44	0.28	0.19	0.09	0.504	0.293	0.125	0.078	0.427
8	0.32	0.33	0.28	0.07	0.303	0.355	0.270	0.073	0.107
9	0.29	0.38	0.31	0.02	0.214	0.358	0.379	0.050	0.915
10	?	?	?	?	0.249	0.417	0.329	0.006	0.580*

*) Mean of Ad using $\alpha = 0.99$

An example of a visual graph to demonstrate the fitting process as well as the forecasted data, for the case of DQ₂, can be seen in Figure 1. The final results, namely, the forecasted data for each

category of the corresponding DQ, which are shown in bolded figures of Table 2- Table 5, may later serve as an important input for the QFD optimization framework.

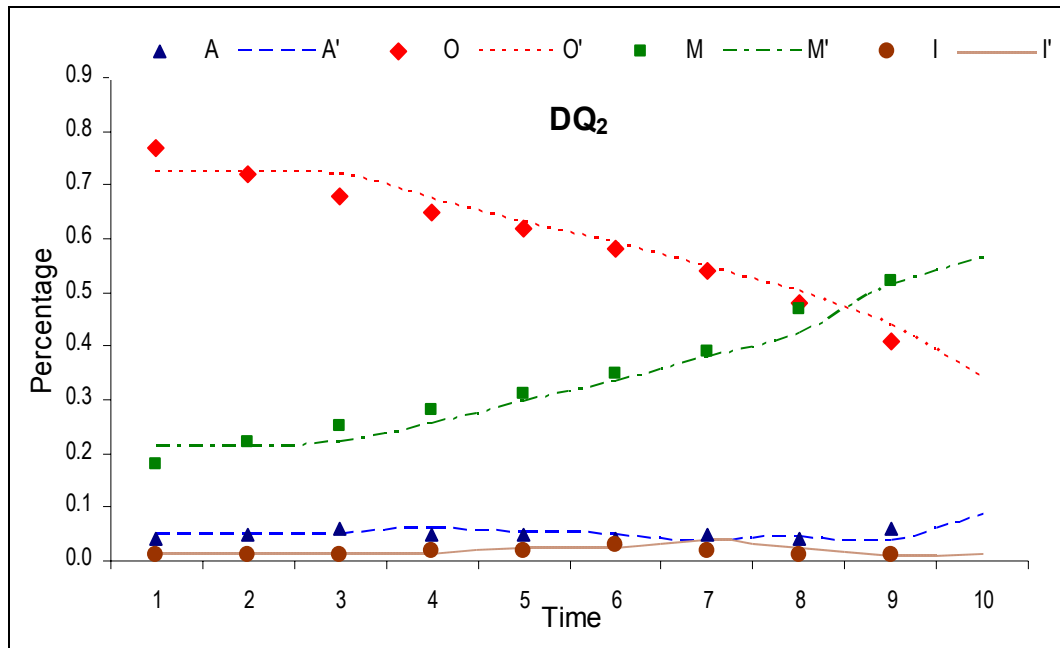


Figure 1. Graph of Fitting and Forecasting Process for DQ₂

5. DISCUSSION

The purpose of this paper was to shed some light in dealing with Kano Model dynamics. The proposed compositional exponential smoothing method may serve two main functions. First, it is to investigate the pattern of Kano's category change over time so as to enable the system to continuously respond differently over time of its operation. This is particularly useful with respect to the constantly changing market. Second, it is to know when a particular quality attribute or customer requirement, which is considered as one particular attribute, such as an attractive attribute (A), will become another attribute, such as a one-dimensional (O) or a must-be (M) attribute. Not only this strengthens the QFD input, but also is useful for providing a ground for customer-driven innovation (Byrne et al., 2007). At least, it gives an indication for the company to decide when they have to innovate or provide necessary changes to their products/services in order to stay competitive.

On top of that, this paper aims to strengthen the Six Sigma as it moves beyond the traditional manufacturing and engineering applications into transactional and service industries (Montgomery, 2007) by providing a better analysis on Kano Model, which is a prerequisite in the 'Measure' phase in the Define-Measure-Analyze-Improve-Control (DMAIC) stage (Tang et al., 2007).

Another alternative way to deal with this type of situation is to use the multivariate time series analysis, which requires more involved computational steps, for example, see Quintana and West (1988), Grunwald et al. (1993), or Brunson and Smith (1998). At the expense of model complexity, using the multivariate time series approach will possibly give lower values of fitting

error. Nevertheless, to deal with limited number of data, which is exactly the case for early stage product/service development, the proposed approach can be considered adequate to serve the purpose of modeling the Kano Model dynamics. On the other hand, this also shows another advantage of the proposed method, that is, it is relatively simple and time-efficient compared to that of multivariate time series approach.

From a theoretical point of view, a further investigation of the proposed model when the dimension of the composition or the number of data gets larger may become a future issue to be addressed. While from a practical point of view, a real-world case study to showcase the effectiveness of the proposed method would be a significant contribution.

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