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ORIGINAL ARTICLE

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Applying grey model to prioritise technical measures in quality function deployment

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Abstract The traditional approach to prioritise the technical measures in quality function deployment is to view an entire process as a decision-making problem and to use a one-to-one relationship, a standard series versus a compared series, instead of using a systematic viewpoint to determine the importance of technical measures by assuming the technical measures are independent. In this study, grey model, both GM(1,N) and GM(0,N) models, is applied to determine the priority of technical measures by evaluating the impact of each technical measure in the system. The technical measure with the highest impact in the system is considered to be the most important technical measure. Therefore, technical measures can be prioritised by their respective impacts in the system.

Keywords Grey model · House of quality · Impact · Quality function deployment · Technical measure

1 Introduction

Quality function deployment (QFD) is one of the very effective and practical quality systems commonly used to fulfil customer requirements and improve customer satisfaction in many industries [1]. QFD defined by Akao [2] is "a method for developing a design quality aimed at satisfying the customer and then translating the customer's demand into design targets and major quality assurance points to be used throughout the production phase." QFD, on the other hand, defined by Hauser and Clausing [3] is as follows: "quality function deployment focuses and coordinates skills within an organization, first to design, then to manufacture and market goods that customers want to purchase and will continue to purchase." The most commonly seen QFD model in literature is a four-phase model, depicted in Fig. 1, including product planning (also known as house of quality (HOQ)), parts deployment, process planning, and production planning.

The HOQ, as shown in Fig. 2, has six major steps [4]: (1) customer needs (WHATs), (2) planning matrix, (3) technical measures (HOWs), (4) relationship matrix between WHATs and HOWs, (5) technical correlation matrix and (6) technical matrix. The first step is to collect customer requirements and then to prioritise these customer requirements. Later, when customer requirements are identified and prioritised, customers are asked to evaluate the company's product along with its main competitors' similar products in terms of the products' performance in the planning matrix. The third step is to translate customer requirements into technical measures by corporate language.

The fourth step is to evaluate the relationship between WHATs and HOWs. When the relationship matrix is check, the correlation matrix is to evaluate how technical measures are interrelated together with their respective importance. Finally, the technical matrix is to assess the performance between the company's product and its competitor's similar products from the viewpoints of the technical measures. When the HOQ matrix is completed, parts deployment begins if necessary. For further information about QFD and HOQ, please refer to references [1–4].

Chan and Wu [4] have stated that completing the relationship between WHATs and HOWs is a vital step in the QFD matrix since the final analysis relies heavily on this relationship matrix. When the importance of technical measures is identified in the final step of HOQ, the more important HOWs can be chosen to enter into the next phase of QFD for further analysis and development. To identify and prioritise the importance of HOWs, Chan and Wu [5] and Wu [6, 7] have applied several different decision-making approaches and have considered the entire process as a decision-making problem. Thus, the importance of HOWs can be prioritised.

Burke, Kloeber and Deckro [8], however, have said that the column weights computed during the development of QFD matrix should not be used to determine the priority

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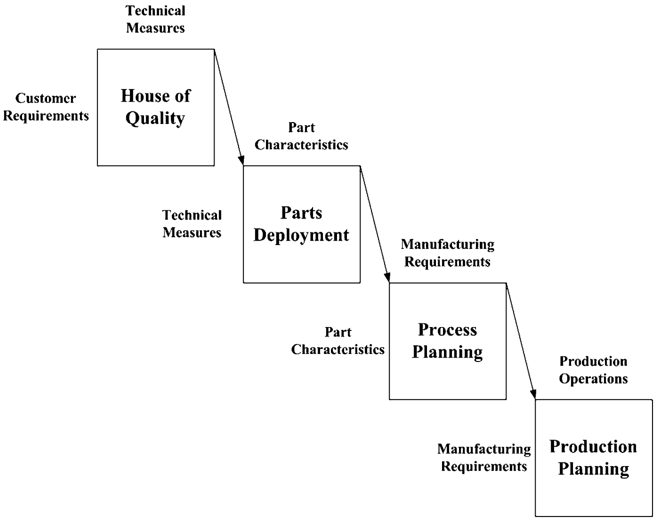

Fig. 1 A four-phase quality function deployment

but are simply a recommendation without appropriate assumptions. The traditional decision-making approaches, such as technique for order preference by similarity to ideal solution (TOPSIS) and grey relational analysis (GRA), consider the entire decision-making process as a one-to-one relationship, i.e. the standard or referential series versus a compared series, but do not provide a systematic viewpoint in determining the priority of HOWs. The underlying assumptions of the traditional approaches are to assume that each technical measure is independent and that they have no relationship with one another. Since the HOQ matrix is a system, it is better to evaluate the impact of each technical measure in this system instead of using a one-to-one relationship to prioritise the importance of HOWs.

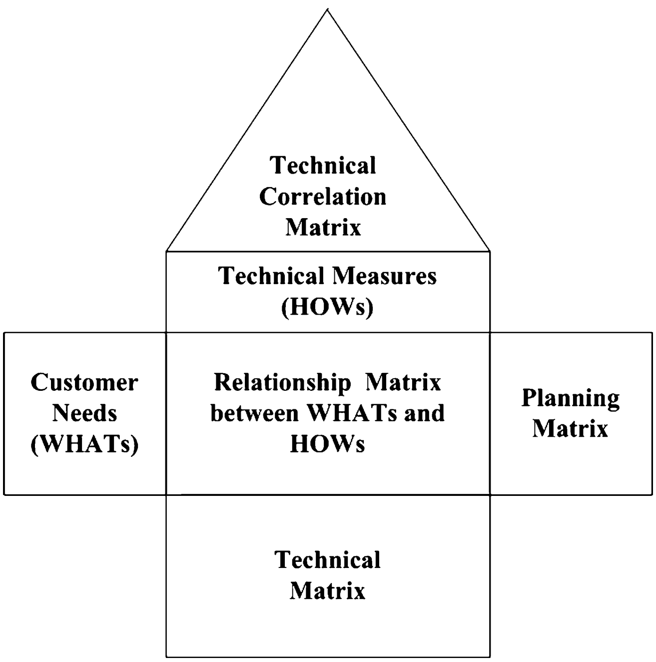

Fig. 2 The structure of house of quality

In this study, grey model is introduced and implemented into this HOQ matrix to determine the importance of technical measures from a systematic viewpoint. Each technical measure is evaluated based upon the impact in the system. That is, the higher impact a technical measure has, the more important technical measure it is. This paper is organised as follows: Grey model is reviewed in Sect. 2. An example of applying grey model to prioritise the importance of HOWs systematically is illustrated in Sect. 3. Finally, conclusions are provided in Sect. 4.

2 Grey model

Grey theory, originally developed by Deng, is to avoid the inherent defects of conventional, statistical methods, and the advantage is to use a limited amount of data to estimate the behaviour of an uncertain system when the data are discrete and the information is incomplete [9, 10]. The areas covered and applied by grey theory include systems analysis, data processing, modelling, prediction, decision-making and control [6, 7, 11–15]. Wen [16] has pointed out that three types of grey model are commonly seen in literature, including GM(1,1) model, GM(1,N) model and GM(0,N) model. These models use dummy concepts to translate different equations into differential equations.

GM(1,1) model is typically applied to grey forecasting, while GM(1,N) and GM(0,N) models are to carry out the calculation of measurement among the discrete sequences and to compensate the disadvantages of the traditional methods [16]. The definition of GM(1,N) model is as follows:

$$x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{j=2}^{N} b_j x_j^{(1)}(k), \tag{1}$$

where k=1,2,3,…,n, $z_1^{(1)}(k)=0.5x_1^{(1)}(k)+0.5x_1^{(1)}(k-1)$ for $k\geq 2$, and a and b_j are coefficients. To compute the results, the first step is to set up the original or observed series, which is $x_1^{(0)}(k)=(x_1^{(0)}(1), x_1^{(0)}(2),\ldots, x_1^{(0)}(k),\ldots, x_1^{(0)}(n))$. Then the next step is to set up accumulative generating operation (AGO) series of $x^{(0)}$, where $x^{(0)} = x^{(1)} = \sum_{m=1}^{k} x^{(0)}(m)$. By integrating the AGO series of $x^{(0)}$ into Eq. 1, Eq. 1 can be further expressed as a matrix format:

$$\begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ -z_1^{(1)}(n) & x_2^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{bmatrix} \begin{bmatrix} a \\ b_2 \\ \vdots \\ b_N \end{bmatrix}. \tag{2}$$

Therefore, the absolute values of b_2, b_3,..., and b_N can be solved from Eq. 2, and the relationship between the major and influencing series can be found. Any factor which has higher absolute value of b_N is considered to have higher impact in the system.

GM(0,N) model is a special case of GM(1,N) and is to investigate the cardinal relationship during the *N*th variable [16]. In addition, GM(0,N) model is based on the statistical state, whereas GM(1,N) model is based on the dynamic state. The definition of GM(0,N) model is

$$az_1^{(1)}(k) = \sum_{j=2}^{N} b_j x_j^{(1)}(k), \tag{3}$$

where $z_1^{(1)}(k)=0.5x_1^{(1)}(k)+0.5x_1^{(1)}(k-1)$ for $k\geq 2$, and a and b_j are coefficients. The computational steps are quite similar to those of GM(1,N) model discussed earlier. Thus, Eq. 3 can be further expanded as a matrix format similar to Eq. 2:

$$\begin{bmatrix} 0.5x_1^{(1)}(1) + 0.5x_1^{(1)}(2) \\ 0.5x_1^{(1)}(2) + 0.5x_1^{(1)}(3) \\ \vdots \\ 0.5x_1^{(1)}(n-1) + 0.5x_1^{(1)}(n) \end{bmatrix} = \begin{bmatrix} x_2^{(1)}(2) & x_3^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ x_2^{(1)}(3) & x_3^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ x_2^{(1)}(n) & x_3^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{bmatrix} \begin{bmatrix} \frac{b_2}{a} \\ \frac{b_3}{a} \\ \vdots \\ \frac{b_N}{a} \end{bmatrix}. \tag{4}$$

If we assume $b_N/a = \hat{b}_m$, where m=2, 3, 4,…,N, then, Eq. 4 is simplified as follows:

$$\begin{bmatrix} 0.5x_1^{(1)}(1) + 0.5x_1^{(1)}(2) \\ 0.5x_1^{(1)}(2) + 0.5x_1^{(1)}(3) \\ \vdots \\ 0.5x_1^{(1)}(n-1) + 0.5x_1^{(1)}(n) \end{bmatrix} = \begin{bmatrix} x_2^{(1)}(2) & x_3^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ x_2^{(1)}(3) & x_3^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ x_2^{(1)}(n) & x_3^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{bmatrix} \begin{bmatrix} \hat{b}_2 \\ \hat{b}_3 \\ \vdots \\ \hat{b}_N \end{bmatrix}. \tag{5}$$

Based upon Eq. 5, the absolute values of $\hat{b}_2$, $\hat{b}_3$,..., and $\hat{b}_N$ can be solved, and the relationship between the major and the influencing series can be analysed.

3 An example

Suppose there is a HOQ matrix, provided in Table 1, with eight customer requirements, denoted as CR, along with their respective weights where the blank means no relationship with zero in importance and six technical measures, denoted as TM. If the simple additive method is used, TM 4 is the most important technical measure, whereas TM 2 is the least important technical measure. The traditional decision-making techniques, such as TOPSIS and GRA, are to use a one-to-one relationship in determining the importance of technical measures without considering the impact of each technical measure in the system. Typically, the assumption is that each technical measure is independent, and there is not any kind of relationship among technical measures.

It is essentially important to evaluate if the assumption holds if the traditional decision-making approaches are to be used. However, GM(1,N) and GM(0,N) models provide different viewpoints even if the assumption is

Table 1 The assumed HOQ matrix with the simple additive method

	Weight	TM 1	TM 2	TM 3	TM 4	TM 5	TM 6
CR 1	6.03			1	1		
CR 2	4.14			9	9	9	1
CR 3	5.01	3	3			9	
CR 4	4.06	9	1	3	9		9
CR 5	4.32		3			9	9
CR 6	6.44		3	3	1		
CR 7	6.32			1	3		
CR 8	4.33			9	9		9
Total weight		51.57	51.37	120.08	144.20	121.23	118.53

Table 2 The relationship between WHATs and HOWs

	TM 1	TM 2	TM 3	TM 4	TM 5	TM 6
CR 1	0	0	6.03	6.03	0	0
CR 2	0	0	37.26	37.26	37.26	4.14
CR 3	15.03	15.03	0	0	45.09	0
CR 4	36.54	4.06	12.18	36.54	0	36.54
CR 5	0	12.96	0	0	38.88	38.88
CR 6	0	19.32	19.32	6.44	0	0
CR 7	0	0	6.32	18.96	0	0
CR 8	0	0	38.97	38.97	0	38.97

violated. The priority of technical measures is determined by the impact of each technical measure in the HOQ matrix. Before using the GM(1,N) and GM(0,N) models in the HOQ matrix, we can set up a table, as shown in Table 2, to document the quantitative relationship between WHATs and HOWs by multiplying their respective weights. For instance, the relationship between CR 3 and TM 1 is 5.01×3=15.03. In fact, different quantitative values for the relationship can be viewed as different impacts in this system.

If GM(1,N) model is to be used to prioritise technical measures, the procedure is as follows: The first step of GM(1,N) model is to set up the original series. In this case, $x_1^{(0)}(k)$=(1, 2, 3, 4, 5, 6, 7, 8), where k=1, 2, 3,..., 8, because there are eight customer requirements in this matrix. The next step is to set up AGO series of $x^{(0)}$:

$$
\begin{aligned}
x_1^{(1)} &= (1, 3, 6, 10, 15, 21, 28, 36),\\
x_2^{(1)} &= (0, 0, 15.03, 51.57, 51.57, 51.57, 51.57, 51.57),\\
x_3^{(1)} &= (0, 0, 15.03, 19.09, 32.05, 51.37, 51.37, 51.37),\\
x_4^{(1)} &= (6.03, 43.29, 43.29, 55.47, 55.47, 74.79, 81.11, 120.08),\\
x_5^{(1)} &= (6.03, 43.29, 43.29, 79.83, 79.83, 86.27, 105.23, 144.20),\\
x_6^{(1)} &= (0, 37.26, 82.35, 82.35, 121.23, 121.23, 121.23, 121.23),
\end{aligned}
$$

and

$$x_7^{(1)} = (0, 4.14, 4.14, 40.68, 79.56, 79.56, 79.56, 118.53),$$

where x_2, x_3, x_4, x_5, x_6, and x_7 represent TM 1, TM 2, TM 3, TM 4, TM 5, and TM 6, respectively. On the other hand, $z_1^{(1)}$=((1+3)/2, (3+6)/2, (6+10)/2, (10+15)/2, (15+21)/2, (21+28)/2, (28+36)/2)=(2, 4.5, 8, 12.5, 18, 24.5, 32). Now, by integrating the AGO series of $x^{(0)}$ into Eq. 2, Eq. 2 becomes

$$
\begin{bmatrix} 2\\3\\4\\5\\6\\7\\8 \end{bmatrix} =
\begin{bmatrix}
-2 & 0 & 0 & 43.29 & 43.29 & 37.26 & 4.14\\
-4.5 & 15.03 & 15.03 & 43.29 & 43.29 & 82.35 & 4.14\\
-8 & 51.57 & 19.09 & 55.47 & 79.83 & 82.35 & 40.68\\
-12.5 & 51.57 & 32.05 & 55.47 & 79.83 & 121.23 & 79.56\\
-18 & 51.57 & 51.37 & 74.79 & 86.27 & 121.23 & 79.56\\
-24.5 & 51.57 & 51.37 & 81.11 & 105.23 & 121.23 & 79.56\\
-32 & 51.57 & 51.37 & 120.08 & 144.20 & 121.23 & 118.53
\end{bmatrix}
\begin{bmatrix} a\\b_2\\b_3\\b_4\\b_5\\b_6\\b_7 \end{bmatrix}.
$$

To solve the values of b_2, b_3, b_4, b_5, b_6, and b_7, Let

$$
A = \begin{bmatrix}
-2 & 0 & 0 & 43.29 & 43.29 & 37.26 & 4.14\\
-4.5 & 15.03 & 15.03 & 43.29 & 43.29 & 82.35 & 4.14\\
-0 & 51.57 & 19.09 & 55.47 & 79.83 & 82.35 & 40.68\\
-12.5 & 51.57 & 32.05 & 55.47 & 79.83 & 121.23 & 79.56\\
-18 & 51.57 & 51.37 & 74.79 & 86.27 & 121.23 & 79.56\\
-24.5 & 51.57 & 51.37 & 81.11 & 105.23 & 121.23 & 79.56\\
-32 & 51.57 & 51.37 & 120.08 & 144.20 & 121.23 & 118.53
\end{bmatrix}, \quad
B = \begin{bmatrix} 2\\3\\4\\5\\6\\7\\8 \end{bmatrix}, \quad
and\ C = \begin{bmatrix} a\\b_2\\b_3\\b_4\\b_5\\b_6\\b_7 \end{bmatrix}.
$$

The matrix C can be computed numerically by $C=(A^TA)^{-1}A^TB$, and the numerical results are

$$C=\begin{bmatrix} a \\ b_2 \\ b_3 \\ b_4 \\ b_5 \\ b_6 \\ b_7 \end{bmatrix}=\begin{bmatrix} 0.0353 \\ -0.0361 \\ 0.0749 \\ -0.0391 \\ 0.0779 \\ 0.0112 \\ -0.0064 \end{bmatrix}.$$

Taking the absolute values of b_2, b_3, b_4, b_5, b_6, and b_7, then $|b_2|=0.0361$, $|b_3|=0.0749$, $|b_4|=0.0391$, $|b_5|=0.0779$, $|b_6|=0.0112$, and $|b_7|=0.0064$. Clearly, $|b_5| > |b_3| > |b_4| > |b_2| > |b_6| > |b_7|$, and TM 4 > TM 2 > TM 3 > TM 1 > TM 5 > TM 6. Therefore, TM 4 has the highest impact in this system, while TM 6 has the lowest impact.

If GM(0,N) model is applied, the procedure is as follows: The original series of $x_1^{(0)}$ is $x_1^{(0)}(k)=(1, 2, 3, 4, 5, 6, 7, 8)$, where $k=1, 2, 3,..., 8$. The AGO series of $x^{(0)}$ are

$$x_1^{(1)}=(1, 3, 6, 10, 15, 21, 28, 36),$$
$$x_2^{(1)}=(0, 0, 15.03, 51.57, 51.57, 51.57, 51.57, 51.57),$$
$$x_3^{(1)}=(0, 0, 15.03, 19.09, 32.05, 51.37, 51.37, 51.37),$$
$$x_4^{(1)}=(6.03, 43.29, 43.29, 55.47, 55.47, 74.79, 81.11, 120.08),$$
$$x_5^{(1)}=(6.03, 43.29, 43.29, 79.83, 79.83, 86.27, 105.23, 144.20),$$
$$x_6^{(1)}=(0, 37.26, 82.35, 82.35, 121.23, 121.23, 121.23, 121.23),$$

and

$$x_7^{(1)}=(0, 4.14, 4.14, 40.68, 79.56, 79.56, 79.56, 118.53),$$

where x_2, x_3, x_4, x_5, x_6, and x_7 represent TM 1, TM 2, TM 3, TM 4, TM 5, and TM 6, respectively. $z_1^{(1)}=((1+3)/2, (3+6)/2, (6+10)/2, (10+15)/2, (15+21)/2, (21+28)/2, (28+36)/2)=(2, 4.5, 8, 12.5, 18, 24.5, 32)$. Now, by integrating the AGO series of $x^{(0)}$ into Eq. 5, Eq. 5 becomes

$$\begin{bmatrix} 2 \\ 4.5 \\ 8 \\ 12.5 \\ 18 \\ 24.5 \\ 32 \end{bmatrix}=\begin{bmatrix} 0 & 0 & 43.29 & 43.29 & 37.26 & 4.14 \\ 15.03 & 15.03 & 43.29 & 43.29 & 82.35 & 4.14 \\ 51.57 & 19.09 & 55.47 & 79.83 & 82.35 & 40.68 \\ 51.57 & 32.05 & 55.47 & 79.83 & 121.23 & 79.56 \\ 51.57 & 51.37 & 74.79 & 86.27 & 121.23 & 79.56 \\ 51.57 & 51.37 & 81.11 & 105.23 & 121.23 & 79.56 \\ 51.57 & 51.37 & 120.08 & 144.20 & 121.23 & 118.53 \end{bmatrix}\begin{bmatrix} \hat{b}_2 \\ \hat{b}_3 \\ \hat{b}_4 \\ \hat{b}_5 \\ \hat{b}_6 \\ \hat{b}_7 \end{bmatrix}.$$

To solve the values of $\hat{b}_2, \hat{b}_3, \hat{b}_4, \hat{b}_5, \hat{b}_6$, and $\hat{b}_7$, Let

$$A=\begin{bmatrix} 0 & 0 & 43.29 & 43.29 & 37.26 & 4.14 \\ 15.03 & 15.03 & 43.29 & 43.29 & 82.35 & 4.14 \\ 51.57 & 19.09 & 55.47 & 79.83 & 82.35 & 40.68 \\ 51.57 & 32.05 & 55.47 & 79.83 & 121.23 & 79.56 \\ 51.57 & 51.37 & 74.79 & 86.27 & 121.23 & 79.56 \\ 51.57 & 51.37 & 81.11 & 105.23 & 121.23 & 79.56 \\ 51.57 & 51.37 & 120.08 & 144.20 & 121.23 & 118.53 \end{bmatrix}, \quad B=\begin{bmatrix} 2 \\ 4.5 \\ 8 \\ 12.5 \\ 18 \\ 24.5 \\ 32 \end{bmatrix}, \quad and\, C=\begin{bmatrix} \hat{b}_2 \\ \hat{b}_3 \\ \hat{b}_4 \\ \hat{b}_5 \\ \hat{b}_6 \\ \hat{b}_7 \end{bmatrix}.$$

The matrix C can be computed numerically as follows by $C=(A^TA)^{-1}A^TB$:

$$C=\begin{bmatrix}\hat{b}_2\\ \hat{b}_3\\ \hat{b}_4\\ \hat{b}_5\\ \hat{b}_6\\ \hat{b}_7\end{bmatrix}=\begin{bmatrix}-0.2863\\ 0.4687\\ -0.3010\\ 0.4317\\ -0.0634\\ 0.0289\end{bmatrix}.$$

Taking the absolute values of $\hat{b}_2, \hat{b}_3, \hat{b}_4, \hat{b}_5, \hat{b}_6,$ and $\hat{b}_7$, $\left|\hat{b}_2\right|=0.2863$, $\left|\hat{b}_3\right|=0.4687$, $\left|\hat{b}_4\right|=0.3010$, $\left|\hat{b}_5\right|=0.4317$, $\left|\hat{b}_6\right|=0.0634$, and $\left|\hat{b}_7\right|=0.0289$. The priority is $\left|\hat{b}_3\right|>\left|\hat{b}_5\right|>\left|\hat{b}_4\right|>\left|\hat{b}_2\right|>\left|\hat{b}_6\right|>\left|\hat{b}_7\right|$, i.e. TM 2 > TM 4 > TM 3 > TM 1 > TM 5 > TM 6. Therefore, TM 2 has the highest impact in the system, whereas TM 6 has the lowest impact.

If the results generated by both GM(1,N) and GM(0,N) models are compared, the priorities of technical measures are almost the same, except for TM 2 and TM 4. If GM(1, N) model is used, TM 4 has higher impact than TM 2. On the contrary, if GM(0,N) model is applied, TM 2 is more important than TM 4 from a systematic viewpoint. If the importance of each technical measure is evaluated and prioritised by its impact in the QFD matrix, TM 2 and TM 4 are the two most important technical measures. Obviously, the results could be significantly different when the priority of technical measures is viewed as a decision-making process without verifying whether or not the assumption that the technical measures are independent.

4 Conclusions

This study uses both GM(1,N) and GM(0,N) models to prioritise the technical measures in the QFD matrix from a systematic viewpoint instead of considering the entire process as a decision-making problem. Instead of using a one-to-one relationship to determine the importance of technical measures, both GM(1,N) and GM(0,N) models use the impact of each technical measure in the system to prioritise the technical measures. Thus, the higher impact a technical measure has, the more important technical measure it is in the system. Unless a decision maker is able to ensure all of the technical measures are independent and there is not any kind of relationship among the technical measures, both GM(1,N) and GM(0,N) models might be more appropriate than the traditional decision-making approaches to apply in the QFD matrix.

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