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SIMULATION-BASED DECISION MODEL TO CONTROL DYNAMIC MANUFACTURING REQUIREMENTS: APPLICATION OF GREY FORECASTING - DQFD

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Manufacturing systems have to adapt to changing requirements of their internal and external customers. In fact, new requirements may appear unexpectedly and may change multiple times. Change is a straightforward reality of production, and the engineer has to deal with the dynamic work environment. In this perspective, this paper proposes a decision model in order to fit actual and future processes' needs. The proposed model is based on the dynamic quality function deployment (DQFD), grey forecasting model GM (1,1) and the technique for order preference by similarity to ideal solution (TOPSIS). The cascading QFD-based model is used to show the applicability of the proposed methodology. The simulation results illustrate the effect of the manufacturing needs changes on the strategic, operational and technical improvements.

Keywords: Dynamic Quality Function Deployment, Grey Forecasting, AHP, TOPSIS, Decision-Making.

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1. INTRODUCTION

One of the most important factors that enable manufacturing firms to succeed is their ability to adapt to a dynamic environment and to react quickly to a changing market and customer requirements (Li *et al.*, 2019). Companies facing this issue should expect changes in future market and customer requirements and incorporate these needs earlier in the design process. Analyzing "future" customer needs is very critical to an organization's long-term competitiveness since customer needs are dynamic and may vary drastically from time to time (Shen *et al.*, 2001; Shieh and Wu, 2009). Besides, predicting future customer requirements early on could help organizations provide better products and, eventually, increase customer satisfaction (Wu *et al.*, 2005).

In the studies of dynamic customer requirements (Chong and Chen, 2010; Goh *et al.*, 2003; Horan, 2022; Wu and Shieh, 2006), the intentions were, in general, to counter the uncertainties that the variable contributes to new product development (NPD). To meet this imminent need, dynamic quality function deployment (DQFD) has been widely applied to fulfill dynamic customer requirements and improve customer satisfaction (Chan and Wu, 2002).

Given the above background, these different studies have certain limitations, two of them are stated as follows:

- Researchers have deployed the DQFD for NPD. However, any changes in the characteristics of existing products or any new needs coming from the market require rapid changes in the production process. So far, to the best of our knowledge, no study on DQFD has been done to model changes in process needs (*PNs*) toward production process improvement.
- These various studies were limited to the study of the first house of quality (HoQ) (Bostaki and Roghanian, 2014; Raharjo *et al.*, 2011). There is a lack of research using cascading DQFD to study the propagation of data from the first dynamic HoQ to other houses of quality.

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Referring to these two observations, one could say that there is a need to develop a proactive method that can predict changes in process requirements for a manufacturing process improvement over time. In this perspective, the objective of this study consists in proposing a proactive method to deal with dynamic manufacturing processes needs in quality function deployment (QFD). Herein the term 'Dynamics' to QFD is interpreted as the change of process needs' importance weights over time (Bostaki and Roghanian, 2014; Raharjo *et al*., 2006; Raharjo *et al*., 2011).

The model based on cascading DQFD is associated with a decision support system to study the anticipation of a future need of the production process. The internal and external needs generally come from the dynamic market, a new need of the customer or a need to adapt the production system to any internal demands. These needs belong a priori to five classes, namely cost, quality, lead-time, flexibility and manpower.

This paper is organized as follows. First, we briefly review the changes in manufacturing systems, the main QFD models, and dynamics in QFD. Section 3 provides the proposed methodology, where we apply the analytic hierarchy process (AHP) to compute the importance rating (I_i). The grey forecasting cycle is used to predict future importance ratings and determine future technical characteristics. The grey forecasting model would serve as a useful model to deal with the problem of limited information and reduce the risks associated with decision-making. The multi-criteria decision-making is considered as an alternative, which may be combined with DQFD to prioritize engineering requirements (ERs). A case study is presented in Section 4 to demonstrate the effectiveness and practicality of the proposed approach. In this perspective, the integrated model is used as a discrete event simulation model to analyze the effect of changing needs on the decision of selecting manufacturing improvements. Finally, the conclusion, limitations and further research are discussed in Section 5.

2. LITERATURE REVIEW

2.1 Changes in manufacturing systems

In recent years, the factors driving changes in manufacturing enterprises have been extensively studied. In the United States, the planning and re-planning of public services have cost more than $250 billion (Tompkins *et al*., 2010). In this context, Ah Kioon *et al*. (2009) proposed a cellular manufacturing model that incorporates multiple manufacturing attributes, which consider multi-period planning, reconfiguration and production planning. ElMaraghy, (2009) pointed out different drivers of change, such as different new products, markets or manufacturing technologies. These drivers of change are seen as static effects, but in fact, most of them show dynamic behavior over time (Zäh *et al*., 2010).

Qiao *et al*. (2003) developed a simulation model for adjusting manufacturing capacity and manufacturing processes, re-layout, and reallocating resources in response to changes in demand. Ebadian *et al*. (2009) performed a simulation experiment to test the effectiveness of a hierarchical production planning structure for make-to-order company. Lu *et al*. (2012) used simulation experiments and multi-criteria decision-making to find the optimal junction point of push and pull production control policies to maximize productivity and minimize inventory levels. Negahban *et al*. (2014) developed a simulation model that can predict future demand, adjust production levels, and evaluate the performance of alternative production at different levels of production, flexibility, and market dynamics.

2.2 QFD and manufacturing requirements

A series of HoQs are commonly used to develop products, services and business processes. 'Four matrices' and 'Thirty-matrix' Revelle *et al*. (1996) are the two well-known models. In business process design activity, Revelle *et al*. (1996) proposed five matrices model that are successively deployed to identify work instructions. They started the model by mapping the total quality management outputs to the major paragraphs and items in one-quality system requirements. Barad and Gien (2001) developed an approach for determining improvement priorities. The propagation of the improvement needs from a strategic to an operational one is realized by two QFD-oriented matrices. In this perspective, (Nimmons *et al*., 1994) proposed two cascading QFD matrices to design cellular manufacturing systems. Lazreg and Gien (2009) proposed five-cascading QFD-based Six Sigma model to implement the DMAIC process (define, measure, analyze, improve, control) in a manufacturing system.

2.3 Dynamic QFD

The main goal of HoQ is to identify PNs (WHATs) and weights for the process and then to convert these requirements into ERs (HOWs). Given the changing of PNs, ERs may not satisfy the requested specifications. In practice, a company may not be able to keep pace with PNs without considering the time dimension. In this regard, some researchers have integrated temporal measures into HoQ using predictive methods such as fuzzy trend analysis (Shen *et al*., 2001), grey theory (Wu *et al*., 2005), double exponential smoothing (Gardner, 2006) and Markov chain analysis (Wu and Shieh, 2006). These studies have stated analyzing "future" customer needs, which are dynamic and can change dramatically from time to time. Herein, the concept of DQFD is treated as an extension of the standard QFD since it takes into account changes over time.

(Horan, 2022) used dynamic quality function deployment for sustainability to model changes in customer requirements for sustainable design over time. In the literature, three approaches have been used to model dynamics in QFD:

- *Customer needs changing*: this approach relates to the result of changes in customer needs (Adiano and Roth, 1994). The enterprise must adapt new needs to the technical characteristics to continue to respond effectively to the needs of its customers. This adaptation translates customer needs into relevant product and process parameters.
- *Importance weight changing*: (Shen *et al*., 2001) have used fuzzy trend analysis in QFD to study future customer needs by monitoring the important trend for each customer requirement. (Raharjo *et al*., 2011) modeled the dynamic priorities in the HoQ. (Lu *et al*., 2011) recommended that engineers apply AHP to determine the importance degrees of customer requirements. The proposed model is used to monitor the importance of each customer requirement and change it from time to time, and evaluate the relative weight of each technical characteristic to meet the dynamic and future customer needs.
- *Combined process*: In a recent study, (Parameswaranpillai and Al-Khazraji, 2022) proposed to collect data with the help of smart devices to provide an interface for the users to input product feature rating or innovative requirements to the company involved in making the product. The QFD interface uses modern algorithms to act as a dynamic deployment platform.

3. DYNAMIC QFD-BASED DECISION MODEL

In the QFD literature, most of the studies dealing with the DQFD use only the top-level house of quality. (Mehrjerdi, 2010) reported that most enterprises claiming to use QFD are only working with the first HoQ, and there has been almost no study dealing with such process needs propagation and their impact on decision-making.

DQFD seems to be the most appropriate method dealing with changing process needs over time and supporting decision-making. To cope with changing customer requirements over time, QFD analysis is based on the forecasted process needs (Bostaki and Roghanian, 2014) to form DQFD.

To capture this thinking, the dynamics in QFD are referred to the importance of weight changing. The basic DQFD model for m PNs and n ERs is detailed in Figure 1.

	ER1	ER2	…	ERn	Importance (t=1)	Importance (t=2)	…	Importance (t=K)	Forecasted Importance (t=1)	…	Forecasted Importance (t=K+1)
PN1	R_{11}	R_{12}	...	R_{1n}	I_1	I_1	...	I_1	$\hat{I}_1$	...	$\hat{I}_1$
PN2	R_{21}	...	...		I_2	I_2	...	I_2	$\hat{I}_2$	...	$\hat{I}_2$
…	...	...	...	...	...	...	...	...	...	...	...
PNm	R_{m1}		...	R_{mn}	I_m	I_m	...	I_m	$\hat{I}_m$		$\hat{I}_m$
Weight	w_1	w_2	...	w_n							
Weight of forecasted ER	$\hat{w}_1$	$\hat{w}_2$	...	$\hat{w}_n$							

Figure 1. Basic dynamic QFD

In this paper, we propose a DQFD-based decision model to adjust the production process in response to demand changes. The operational needs are weighted with the objective to maximize the throughput and minimize the re-planning or the system reconfiguration. The new idea lies in finding a balance between operational needs and the decision to adjust the manufacturing system.

Although there exist many cascading QFD models (Revelle *et al*., 1996; Barad and Gien, 2001), which can be used as a platform to integrate dynamics, forecasting and decision-making, we have used the QFD-based model as an application tool to meet the changing needs of the internal functioning of the manufacturing process.

3.1 Methodology

The proposed methodology has three main stages. The details are presented as follows (Figure 2):

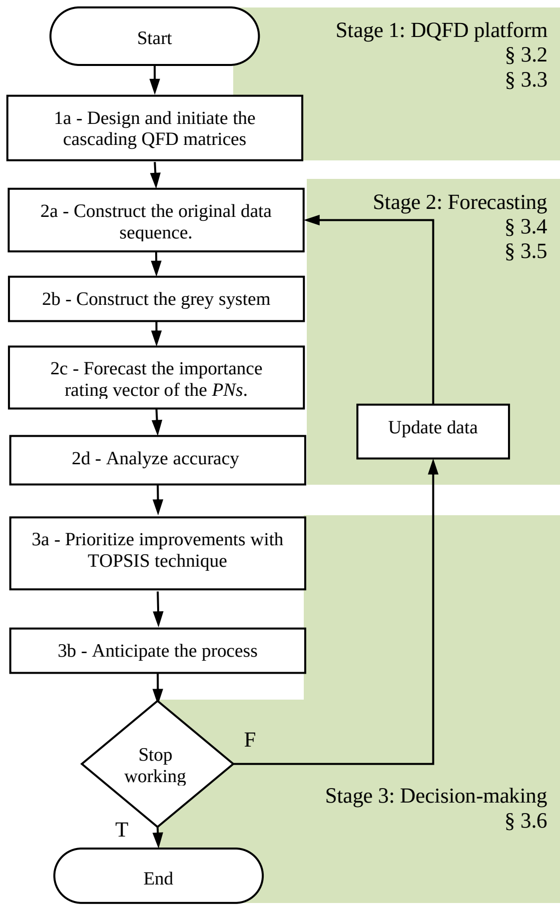

Figure 2. Process of the proposed DQFD-based decision model.

Stage 1: In a traditional QFD, the HoQ is aimed at converting the customer requirements into engineering characteristics. In this first step, the designer has to understand the process demands and fill up PNs, ERs and values of the relationship matrix in each HoQ of the cascading QFD. Once the components of the cascading QFD model are achieved and the feedback from the manufacturing process is available, the designer adjusts the production objectives by prioritizing PNs. In this perspective, the AHP approach is used to compute the importance rating values for 4 periods, that is, I_{t+1}, I_{t+2}, I_{t+3} and I_{t+4}. These weights are assigned to PNs of the first HoQ. By using the principle of transformation of the ERs of one matrix to the PNs of the following matrix, the QFD model becomes ready to apply the forecasting module.

Stage 2: The GM(1, 1) model begins by converting the original data series (I_{t+1}, I_{t+2}, I_{t+3}, I_{t+4}) into a monotonically increasing data series by a preliminary transformation called accumulated generating operation (AGO). The first-order grey differential equation is built to model the data series from AGO and forecast the future importance rating (I_{t+5}) for each PN in the first HoQ. Knowing that accuracy is one of the most important criteria for the forecasting model, the designer examines its validity.

Stage 3: The TOPSIS technique offers a greater level of refinement in ranking and prioritizing the forecasted ERs. The implementation of the selected improvement leads to anticipate the performance gap of the manufacturing system.

Finally, the process ends by applying three tasks: IF: the condition is not satisfied, THEN: the raw data is updated to construct the new grey system, ELSE: the algorithm ends.

3.2 Mathematical model

Referring to Figure 1 and Figure 2, the detailed mathematical computing procedure in QFD is as follows:

Step 1: The normalized transformation on the relationship values contained in the relationship matrix (R_{ij}) is described by the following equation (Wasserman, 1993):

$$R_{ij}^{norm} = \frac{R_{ij}}{\sum_{j=1}^{n} R_{ij}} \ , \tag{1}$$

where
R_{ij}^{norm} stands for the normalized relationship value between the i^{th} PN and j^{th} ER;
R_{ik} stands for the quantified relationship between the i^{th} PN and k^{th} ER;

Step 2: The weight ($\hat{w}_j$) of the forecasted ER in the DQFD model is computed as follows:

$$\hat{w}_j = \sum_{i=1}^{m} R_{ij}^{norm} \,.\, \hat{I}_i, \quad i = 1,2,\ldots,m \ ; \ j = 1,2,\ldots,n \ \ , \tag{2}$$

where
$\hat{w}_j$ stands for the j^{th} weight of the forecasted ER_j;
$\hat{I}_i$ stands for forecasted importance rating of the PN_i;

3.3 Importance rate computation

The AHP method is used to determine the importance weights of customer requirements. This method is a structured *technique*, and it uses pairwise comparison questions to weight the importance degrees of attributes (Saaty, 1980). The AHP method has the advantages of providing more accurate results and confirming the consistency of judgments. A five-step implementation technique is evolved to evaluate the relationships between customer requirements and design characteristics.

The AHP technique takes the following steps (Yadav and Gangele, 2017):

Step 1: The development of a pairwise comparison matrix is performed using a scale of relative importance. The values assigned to a_{ij} according to the Saaty Scale, are generally range from 1 to 9 (Table 1).

Table 1. Pair-wise comparison scale for AHP preferences

Numerical rating	Verbal judgments of preferences
1	Equally important
3	Slightly more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2, 4, 6, 8	Intermediate values

Given *n* attributes, the pairwise comparison of attribute i with attribute j yields a square matrix A_{nxn} where a_{ij} denotes the comparative importance of attribute i with respect to attribute j. In the matrix, $a_{ij} = 1$ when $i = j$ and $a_{ji} = 1/a_{ij}$ for i, j = 1,2, . . ., n.

$$A_{nxn} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ . & . & & . \\ . & . & \dots & . \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \tag{3}$$

Step 2: The normalized geometric mean (NGM) method is used to determine the importance degrees of customer requirements. Let I_i denote the importance degree for the i^{th} customer requirement:

$$I_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}} \quad i, j = 1, 2, \dots, n\ . \tag{4}$$

Step 3: Consistency checks are performed to ensure that the pairwise comparison matrix evaluation is meaningful and acceptable.

Let *C* be an n-dimensional column vector representing the sum of the weighted values of the importance rating of customer requirements, then

$$C = [c_i]_{nx1} = A\ .\ I \quad i = 1, 2, \dots, n\ , \tag{5}$$

where

$$A_{nxn}.I = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ . & . & & . \\ . & . & \dots & . \\ a_{n1} & a_{n2} & \dots & 1 \end{bmatrix} . \begin{bmatrix} I_1 \\ I_2 \\ . \\ . \\ I_n \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ . \\ . \\ c_n \end{bmatrix} . \tag{6}$$

The consistency values for the cluster of customer requirements can be represented by the vector $CV = [cv_i]_{1xn}$ with a typical element cv_i defined as:

$$cv_i = \frac{c_i}{I_i} \quad i = 1, 2, \dots n\ . \tag{7}$$

Step 4: However, to avoid inconsistencies when using different measurement scales in the evaluation process, it is proposed to use the largest eigenvalue λ_{max} to evaluate the validity of the measurement. The largest eigenvalue λ_{max} can be determined by:

$$\lambda_{max} = \frac{\sum_{i=1}^{n} cv_i}{n} \quad i = 1, 2, \dots, n\ . \tag{8}$$

Step 5: With the maximal eigenvalue λ_{max}, a consistency index CI can then be determined by:

$$CI = \frac{\lambda_{max} - n}{n - 1}\ . \tag{9}$$

Generally, a consistency ratio CR can be used for guidance to check for consistency with the appropriate value in Table 2 below.

$$CR = \frac{CI}{RI}\ . \tag{10}$$

where RI denotes the average random index.

Table 2. Average random index (RI) for corresponding matrix size (n)

n	3	4	5	6	7	8	9	10
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

A totally consistent matrix A_{nxn} has a CR equal to 0. It is considered acceptable if the CR does not exceed 0.1. If the CR is large, the rating matrix is inconsistent. Judgments need to be checked and improved to get a consistent matrix. Moreover, when $CI/RI < 0.10$, then the match is good, and the relatively significant column vector C is computed.

3.4 Grey forecasting

The most traditional methods of dealing with forecasting problems include time series analysis, autoregression, linear regression and multivariate regression, etc. These models have the advantage of accurately describing long-term trend phenomena but have the limitation of requiring a large number of observations to build the model (Ma *et al*., 2011). On the other hand, due to the requirements of flexible manufacturing systems and the need of rapid response to changing of process parameters, usually, only a few observations can be made over a short period to anticipate future improvements to meet customer specifications. Moreover, the grey system theory can generate satisfactory results using a relatively small number of data or with large variability in factors since it can increase the regularity of the data with an appropriate data treatment (Wu *et al*., 2013; Li *et al*., 2021; Manickam and Rathinasamy, 2022). Besides, the newest data is considered more important than the old historic data (Acherjee *et al*., 2011).

In grey systems theory, $GM(n, m)$ denotes a grey model, where n is the order of the differential equation, and m is the number of variables. Although various kinds of grey models can be mentioned, most of the previous research has focused on models in forecasting due to their computational efficiency (Kayacan and Kaynak, 2011).

$GM(1,1)$ grey model is the most widely used in the literature and is pronounced 'grey model first order one variable'. This model is a time series forecasting model. It contains a set of differential equations, which vary with time rather than being general difference equations.

We don't have to build the $GM(1,1)$ model with all the data from the original series; we need at least four values from the series. Additionally, the data should be recorded in an evenly spaced and consecutive order without bypassing the data (Deng, 1989). Different studies have used grey forecasting in QFD (Chen and Wang, 2008; Z. Li and Wang, 2011; Wu and Shieh, 2006). Using the proposed model, the importance of each customer requirement is monitored and analyzed, and the importance of each technical measure is assessed to meet dynamic and future customer needs. (Haijiang *et al*., 2016).

The $GM(1,1)$ model constructing process is described below:

Consider a system with single input and a single output. The time sequence $X^{(0)}$, which represents the outputs of the system is defined as follows (Figure 2-2a):

$$X^{(0)} = \left(X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(n)\right) \quad n \geq 4, \tag{11}$$

where n is the sample size.

Referring to Figure 2-2b, the first-order accumulated generating operation (AGO) is made to provide an intermediate message for model construction and derandomize the original series. Here $X^{(1)}$ is defined as the first-order AGO series of $X^{(0)}$, that is

$$X^{(1)} = \left(X^{(1)}(1), X^{(1)}(2), \cdots, X^{(1)}(n)\right), \tag{12}$$

where

$$X^{(1)}(1) = X^{(0)}(1) \text{ and } X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i) \quad k = 1,2, \cdots, n \ . \tag{13}$$

The $GM(1,1)$ model can be constructed by setting the first-order differential equation for $X^{(1)}(k)$ as:

$$\frac{dX^{(1)}(k)}{dk} + aX^{(1)}(k) = b \ , \tag{14}$$

where k denotes the system independent variable; a represents the development coefficient, b is the grey control variable.

Therefore, the solution of Eq. (14) is expressed by using the least square method. That is,

$$\hat{X}^{(1)}(k+1) = (X^{(0)}(1) - \frac{\hat{b}}{\hat{a}})e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}} \ , \tag{15}$$

where

$$[\hat{a}, \hat{b}]^T = (B^T B)^{-1} B^T X_n \,. \tag{16}$$

The accumulated matrix B is:

$$B = \begin{bmatrix} -0.5(X^{(1)}(2) + X^{(1)}(1)) & 1 \\ -0.5(X^{(1)}(3) + X^{(1)}(2)) & 1 \\ \vdots & \vdots \\ -0.5(X^{(1)}(n) + X^{(1)}(n-1)) & 1 \end{bmatrix} = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix}. \tag{17}$$

and the constant term vector X_n is:

$$X_n = \left[X^{(0)}(2), X^{(0)}(3), \cdots, X^{(0)}(n)\right]^T \,. \tag{18}$$

We obtained the restored series value $\widehat{X}^{(1)}$ from Eq. (15).
Let $\hat{X}^{(0)}$ the fitted and predicted series:

$$\hat{X}^{(0)} = \left(\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \cdots, \hat{X}^{(0)}(n)\right), \tag{19}$$

where

$$\hat{X}^{(1)}(1) = \hat{X}^{(0)}(1) \,.$$

As indicated in Figure 2-2c, the third step consists of applying the inverse AGO. We then have:

$$\hat{X}^{(0)}(k+1) = \left[X^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right] e^{-\hat{a}k}(1 - e^{\hat{a}}) \quad k = 1,2,\cdots,n\,, \tag{20}$$

where $\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \cdots, \hat{X}^{(0)}(n)$ are called the GM(1,1) fitted sequence, while $\hat{X}^{(0)}(n+1), \hat{X}^{(0)}(n+2), \cdots, \hat{X}^{(0)}(n+m)$ are called the $GM(1,1)$ forecast values, and m is the expected forecast number.

In general, the smaller the value m, the more accurate the result. Note that if the results of grey modeling are sufficiently accurate, the prediction process can be applied. In fact, model error analysis is used instead of model validation.

3.5 Forecasting accuracy

The grey system looks at discrete data series with limited data, so the model cannot be rigorously validated. The results of the model should not be unique, and different pre-processing of the data will give different results. There has been some discussion about accuracy analysis (Hyndman and Koehler, 2006; Davydenko and Fildes, 2013; Koutsandreas *et al*., 2022). In this study, as shown in Figure 2-2d, we adopt three grades accuracy (Chiou *et al*., 2004; Huang and Lee, 2011; Jasni *et al*., 2022; Mehdiyev *et al*., 2016) to evaluate the forecasting performance and examine the validity of the used forecasting model (Armstrong, 1978).

- Root mean square error (RMSE) is evaluated by the following equation:

$$\zeta = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(\hat{X}^{(0)}(k) - X^{(0)}(k))^2} \,. \tag{21}$$

The closer the RMSE is to 0, the more accurate the model is. The RMSE does not have a general rule for what is considered "good" value. The quality of the metric's value can only be evaluated within the dataset context it is working on. In a discussion on the ResearchGate website, Saeedi (2020) noted that RMSE values between 0.2 and 0.5 show that the model can predict the data accurately. In our context, these two values are taken into account to create the accuracy intervals (Table 3).

- The parameter of post-error ratio C is expressed as follows:

$$C = \frac{S_1}{S_2}. \tag{22}$$

The mean and the root mean square error of the estimated data are defined as $\bar{\varepsilon}$ and S_1:

$$\bar{\varepsilon} = \frac{\sum_{k=1}^{n} \varepsilon^{(0)}(k)}{n} \tag{23}$$

$$S_1 = \sqrt{\frac{\sum_{k=1}^{n} \left(\varepsilon^{(0)}(k) - \bar{\varepsilon}\right)^2}{n}}. \tag{24}$$

The mean and the root mean square error of the observed data are defined as $\bar{X}$ and S_2:

$$\bar{X} = \frac{\sum_{k=1}^{n} X^{(0)}(k)}{n} \tag{25}$$

$$S_2 = \sqrt{\frac{\sum_{k=1}^{n} \left(X^{(0)}(k) - \bar{X}\right)^2}{n}}. \tag{26}$$

Herein, the lower value of the post-error ratio implies a better model.

- The small error probability P

$$P = P\left\{\frac{|\varepsilon(k) - \bar{\varepsilon}|}{S_1} < 0.6745\right\}. \tag{27}$$

The higher the P value, the higher the model's accuracy. In general, the P value should be greater than 0.95. This indicator of forecasting accuracy shows the probability that the relative bias of the forecasting error is less than 0.6745.

The combination of the above indexes (ζ, C, P) results in three grades of evaluating model accuracy is presented in Table 3 (Chiou *et al*., 2004).

Table 3: The three grades of forecasting accuracy

Grade	ζ	C	P
Grade 1: very good	<0.01	<0.35	>0.95
Grade 2: good	<0.2	<0.50	>0.80
Grade 3: qualified	<0.5	<0.65	>0.70
Grade 4: unqualified	≥0.5	≥0.65	≤0.70

3.6 Decision making

Given a set of goals or criteria, numerous decision-making models and methodologies have been developed to evaluate and select the best alternative. This approach is called the Multiple Attribute Decision Making (MADM) approach. It was explored as a means of evaluating advanced propulsion concepts against a variety of criteria. Various types of methods have been developed based on the MADM approach. Among these methods are TOPSIS, Lexicographic, SMART, PROMETHEE, Goal programming, ELECTRE, weighted sum, and more. The TOPSIS technique is adopted in the decision-making stage of the proposed DQFD-based decision model (Figure 2). The choice of this technique is motivated mainly by the fact that it is more efficient when dealing with tangible attributes and the number of alternatives to be assessed (Bhangale *et al*., 2004; Olson, 2004; Yadav and Gangele, 2017).

The TOPSIS technique takes the following steps (Yadav and Gangele, 2017):

Step 1: Construction of the normalized decision matrix. One way is to divide the result of each criterion by the norm of the entire result vector, also called the Euclidean length of the vector.

The element $\bar{r}_{ij}$ of the normalized decision matrix R is expressed as follows:

$$\bar{r}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \tag{28}$$

where x_{ij}, the relation between the attribute *i* and the technical characteristics *j* and, $\bar{r}_{ij}$ is the normalized preference measure of the i^{th} customer requirement in terms of the j^{th} technical characteristics.

Now, all attributes have the same vector unit length.

Step 2: Construction of the weighted normalized decision matrix with the set of weights $W = (w_1, w_2, \ldots, w_n)^T$.

Step 3: The weighted normalized matrix V can be generated as follows:

$$V = RW = \begin{bmatrix} w_1\bar{r}_{11} & w_2\bar{r}_{12} & . & . & . & w_n\bar{r}_{1n} \\ w_1\bar{r}_{21} & w_2\bar{r}_{22} & . & . & . & w_n\bar{r}_{2n} \\ . & . & & & & \\ . & . & & & & \\ w_1\bar{r}_{m1} & w_2\bar{r}_{m2} & . & . & . & w_n\bar{r}_{mn} \end{bmatrix}, \tag{29}$$

where *m* is the number of alternatives and *n* is the number of criteria.

Step 4: Determination of the positive-ideal solution (Y^+) and the negative-ideal solution (Y^-):

$$Y^+ = \left\{ \begin{matrix} \left(max(v_{ij})_j / i \in I_1\right), & \left(min(v_{ij})_j / i \in I_2\right) \\ \left(min(v_{ij})_j / i \in I_3\right), & \left(min(v_{ij})_j / i \in I_4\right) \end{matrix} \right\} \; with\; j = 1,2, \ldots, m \tag{30}$$

$$Y^- = \left\{ \begin{matrix} \left(min(v_{ij})_j / i \in I_1\right), & \left(max(v_{ij})_j / i \in I_2\right) \\ \left(max(v_{ij})_j / i \in I_3\right), & \left(max(v_{ij})_j / i \in I_4\right) \end{matrix} \right\} \; with\; j = 1,2, \ldots, m \tag{31}$$

$$Y^{+/-} = \left\{v_1^{+/-}, v_2^{+/-}, v_3^{+/-}, \ldots, v_m^{+/-}\right\}. \tag{32}$$

Step 5: Calculation of the distance of each alternative from the positive-ideal solution S_j^+ and the negative-ideal solution S_j^- is defined as follows:

$$S_j^{+/-} = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_j^{+/-}\right)^2} \;\; for\; j = 1,2, \ldots, m. \tag{33}$$

Step 6: Calculation of relative proximity to the ideal solution. This is given by:

$$\chi_j = \frac{S_j^-}{S_j^+ + S_j^-} \;\; where\; 0 < \chi_j < 1 \; and\; j = 1,2, \ldots, m. \tag{34}$$

Step 7: Ranking the preference order according to the ascending order of χ_j. The best alternative is the one with the highest χ_j value.

4. APPLICATION

As an illustrative case study, we introduce the QFD-based model, which will serve as a platform to integrate forecasting and decision-making. Next, we discuss the detailed steps and computational results of the simulation.

4.1 The DQFD-based model

Towards a better understanding of the DQFD based-decision model, this section introduces its main modules and their mutual interactions.

The QFD phases are a guide through the redesign process from the *strategic* to the *technical level*. As shown in Figure 3. This phase includes three cascading matrices. The relationship between these different matrices is similar to the traditional QFD model.

The matrix R_1 is the initial stage of developing an action plan. It has two main inputs. The first includes PNs, which are necessary for a competitive process functioning. The second input corresponds to the strategic requirements (*SRs*) at the strategic level.

The second matrix R_2 captures the *SRs* from the first matrix. It is described as the PNs in matrix rows and aligns these to the operational requirements (*ORs*) in matrix columns. The 'relationship matrix' section of the R_2 matrix measures the relationships between strategic requirements and operational requirements. The matrix R_3 deploys these *ORs* in matrix columns and aligns these to the selected technical requirements (*TRs*) in the matrix rows.

For more details on the *PNs, SRs, ORs* and *TRs* of this model, the reader can refer to the *Appendix*.

The relationship between the manufacturing process and the integrated model is performed by the timely update of process information that enables the designer to react differently and continuously over time to formulate improvements to meet the changing needs of the process. Herein, the level of successful forecasts depends on how the engineer obtains and interprets the relevant information.

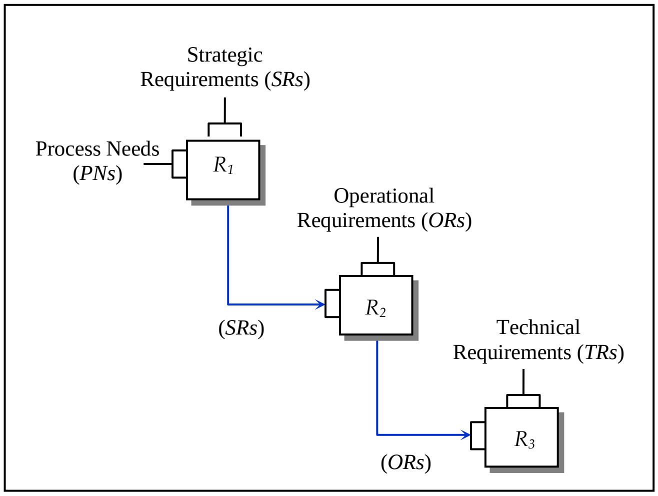

Figure 3. QFD-based model

The importance weights of the PNs in the R_1 matrix are the inputs to the proposed model, whereas the outputs are issued from each matrix of the three successive matrices. In practice, these outputs are prioritized periodically to maintain a competitive product. In each period, the decider can focus on one or several needs from the set of the PNs by assigning them the highest importance value. Herein, prioritizing PNs is based on monitoring process requirements, which provide the required information in a timely manner. On the other side, predicting future process needs is another way to enhance the ability to maintain quality in production (Kahraman *et al*., 2010).

4.2 Simulation

The simulation aims at determining which improvements will have the desired positive effect on the end result before the producer actually puts forth the time and effort in the real process. Figure 3 shows the configuration of this simulation framework developed in this paper, which is built following a methodology of three stages detailed below in nine steps. The current simulation focuses on analyzing the effect of prioritizing the PNs of the *strategic matrix* on the *TRs* from the *technical matrix*.

Stage 1: DQFD platform

Step 1**:** Fill in the QFD-based model

Observing and studying the manufacturing system enabled to understand the process in terms of work content, sequence of operations and dysfunctions on each workstation. This analysis provides the designer with the necessary data to fill the different components of the QFD-based model.

Step 2: Record the AHP-based importance rating values

For each period (t_i), the importance vector is determined by using the AHP method.

Step 3: Prioritize ‘process needs’ in each period.

The identification of the *PNs* in each period is based on the current and future desired state of the process and helps the designer determine a set of actions to close the gap. From the first period to the fourth one, the designer identified different *PNs*, as shown in Figure 4. The ‘Respect delivery time’ internal need has the top importance rating (I_1 = 0,457) in the first period. Whereas in period 2 (I_2 = 0,229), *PN* changed and moved towards the ‘Reduce the time for raw material’. In the third period of time (I_3 = 0,232), the need was to ‘React quickly to the variations of the demand’. However, in the last period (I_4 = 0,374), the objective focused on the ‘Improve production quality’ process need.

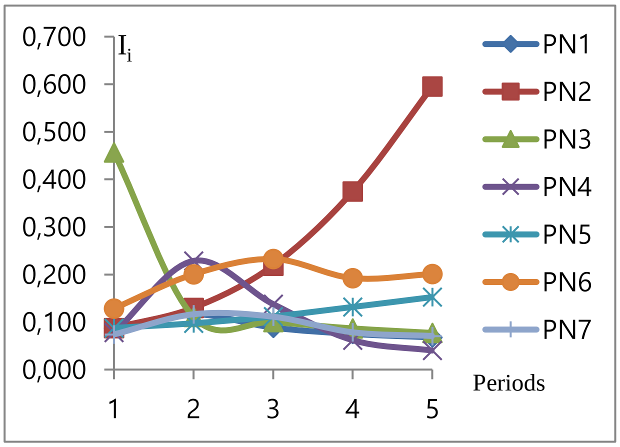

Figure 4. *Strategic level* – Prioritising of *PNs*

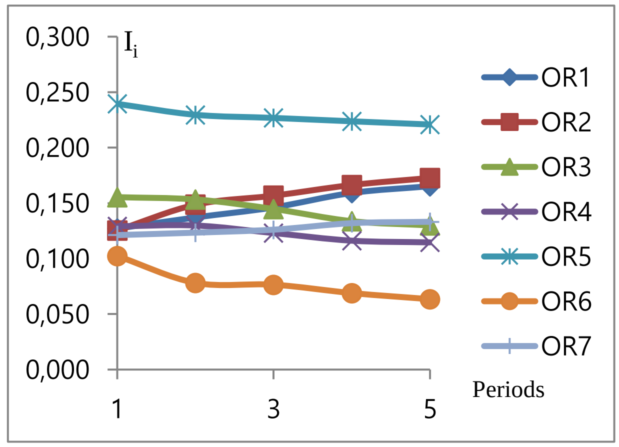

Figure 6. *Operational level* - Importances of *ORs*

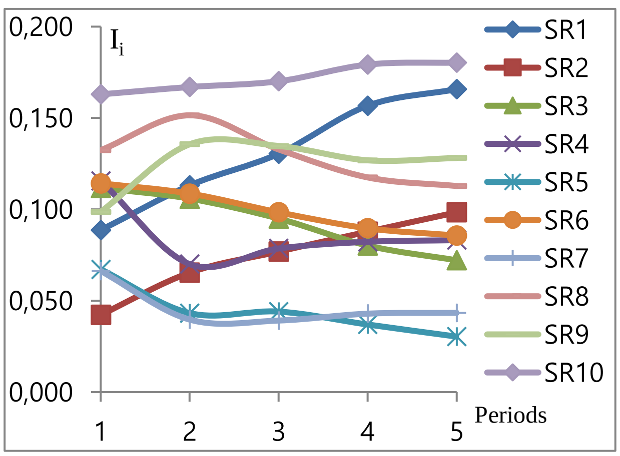

Figure 5. *Strategic level*– Importances of *SRs*

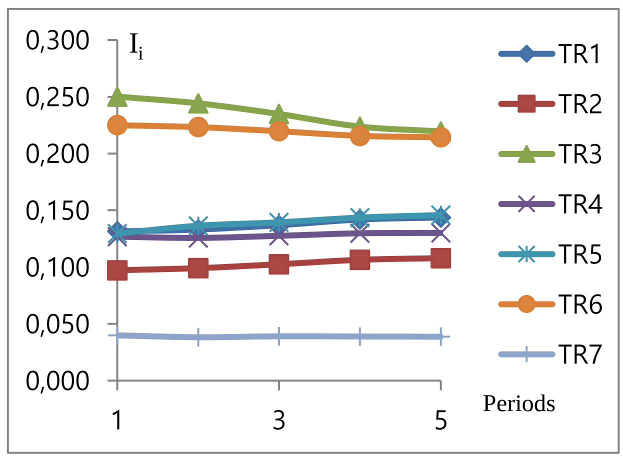

Figure 7. *Technical level* - Importances of *TRs*

Step 4: Compute and prioritize *ERs* in each matrix of the QFD-three matrices process.

Based on the *PNs*, Figure 5 shows the importance rating of the engineering requirements in each period of the strategic level. Indeed, to link the *strategic matrix* to the *operational matrix*, the weights of the *strategic matrix* ‘Hows’ are transferred to the right side of the *operational matrix*. These inputs are used to prioritize *ERs* in each period. This process of transition from one matrix to another is performed through the model. The importance weights of the *strategic*, *operational* and *technical matrices* are shown successively in Figures 5-7.

Stage 2: **Forecasting**

Step 1: Forecast importance weights in the Strategic matrix.

The grey prediction model is employed to forecast the important requirement in the strategic level of the process. As shown in Table 4, importance weights are computed directly from the QFD model using equations (11-20).

Step 2: Examine the accuracy of the forecasted importance.

Accurate forecasts are essential for risk reduction and crucial for successful manufacturing. They can lead to considerable savings when implemented efficiently. For each importance weight, we consider the lowest attribute from the four grades. The forecasting power, as shown in Table 5, is considered "Very Good" for I_3, I_4, I_5 and I_7 and "Good" for the first and second importance weights, whereas it is "Qualified" for the 6^{th} importance weight. As a result, the forecasting power of the proposed grey forecasting model is 'Qualified'.

Step 3: Compute the weight of forecasted ERs' priorities.

Once the importance weights of the PNs are available at the first matrix, the model uses them to compute the weights of the *ERs* in the first matrix as well as in the other matrices of the model. Herein, these weights are computed by using the TOPSIS technique presented above in Section 3.6.

Table 4. Actual and forecasted importance weights

t_i	t_1		t_2		t_3		t_4		t_5
	$X^{(0)}(k)$	$\hat{X}^{(0)}(k+1)$	$X^{(0)}(k)$	$\hat{X}^{(0)}(k+1)$	$X^{(0)}(k)$	$\hat{X}^{(0)}(k+1)$	$X^{(0)}(k)$	$\hat{X}^{(0)}(k+1)$	$\hat{X}^{(0)}(k+1)$
I1	0,088	0,088	0,116	0,108	0,088	0,093	0,075	0,079	0,068
I2	0,088	0,088	0,130	0,125	0,219	0,211	0,374	0,354	0,595
I3	0,457	0,457	0,111	0,111	0,100	0,098	0,087	0,087	0,077
I4	0,078	0,078	0,229	0,227	0,432	0,127	0,062	0,071	0,040
I5	0,088	0,088	0,097	0,097	0,112	0,112	0,132	0,131	0,152
I6	0,129	0,129	0,200	0,212	0,232	0,208	0,192	0,205	0,201
I7	0,074	0,074	0,116	0,120	0,111	0,101	0,078	0,084	0,071
CR	2,93%		7,83%		7,89%		8,68%		

Table 5. Summary of evaluation indexes of GM(1,1) accuracy in the *Strategic* level

Ii	Root mean square error (ζ)		Post-error ratio (C)		Small error probability (P)		Forecasting power
I1	0,0016	Very good	0,1146	Good	1	Very good	Good
I2	0,0116	Good	0,0594	Very good	1	Very good	Good
I3	0,0014	Very good	0,0096	Very good	1	Very good	Very good
I4	0,0043	Very good	0,0694	Very good	1	Very good	Very good
I5	0,0048	Very good	0,4629	Very good	1	Very good	Very Good
I6	0,0215	Qualified	0,4524	Good	1	Very good	Qualified
I7	0,0065	Very good	0,4060	Good	1	Very good	Very Good

Table 6: Ranking of TR_i in the *Technical* matrix

	TRi						
Rank	TR_1	TR_2	TR_3	TR_4	TR_5	TR_6	TR_7
Forecast: t=5	3	6	2	5	4	1	7
t=4	4	6	1	3	5	2	7
t=3	3	6	2	5	4	1	7
t=2	5	6	2	4	3	1	7
t=1	4	6	1	3	5	2	7

Table 7. Actual (t_1-t_4) and forecasted (t_5) improvement actions

t_i	Process needs	1^{st} Improvement action related to the technical matrix
t_1	Respect delivery time	Adjust the stock level
t_2	Reduce the time for raw material reception	Set up and update visual performance indicators
t_3	React quickly to the variations of the demand	Set up and update visual performance indicators
t_4	Improve production quality	Adjust the stock level
t_5	Improve production quality	Set up and update visual performance indicators

Stage 3: Decision making

Step 1: Rank improvements

The relative score of each improvement action obtained from the TOPSIS technique makes the final ranking of each action a simple task. The major outputs of the analysis are the results shown in Table 6 for technical requirements (*TRs*) ranking. The calculations performed to rank the improvement actions are important to highlight the selected action.

Step 2: Plan improvements

Once priorities are established, attention is paid to work plans, cost reviews, planning schedules, and related resources. All of these items are taken into account to ensure that the project reorganization is performed, including setting up the work.

Here, it is recommended that the designer makes a conscious effort to focus on the first improvement action that aligns with the operational needs and that should, therefore, be actually deliverable.

4.3 Discussion

The main results of the simulation are shown in Figures 4-7, and a brief summary is given as follows:

- When designing the pairwise comparison matrix in the AHP method and the correlation matrix in the HoQ, we generate different assessment results, complete and incomplete, precise and imprecise, leading to (I_i) and ($\hat{I}_i$) with great uncertainty. Herein, the decision maker has to take great care when assigning weights in these matrices.
- Comparing growth curves in Figure 6 with respect to the preceding Figures 4-5, we notice a slight oscillation of most of the curves, which are increasingly straightened. Herein, we can talk about the beginning of the dynamic QFD model saturation.
- Coordinates of the importance rating vector $I(x_1,x_2,..., x_n)$ should have at least one element (x_i) different from the others $\{x_j\}$. Otherwise, the value of the consistency ratio in the AHP method becomes null. The case where $x_i = x_j = x_n$ may be used to initiate the model before starting the simulation.
- From the set of importance rating vectors $\{I_1, I_2, I_3, I_4, I_5\}$ of the model, at least one vector of importance rating I_i should be different from the others. Otherwise, there will be a non-determination of I_5.

5. CONCLUSION

This paper proposed a new dynamic QFD-based decision model, which aims at controlling dynamic manufacturing requirements. The proposed framework may serve two main functions. First, it studies the operational and technical requirements change over time to continuously respond to changing customer/process needs. Second, it predicts new parameters of the QFD-three phases process when the priorities of process demands are considered.

An interesting trend in the application of changes in manufacturing systems is the use of simulation to study the behavior of each phase of the QFD-three phases process. Indeed, this work showed that simulation could be a powerful tool to identify the most suitable decisions to respond to changing manufacturing requirements and, thereby, improve the performance of manufacturing systems.

The model we developed has three limitations. The first concerns the short list of improvement actions at the level of the technical matrix. An in-depth study of industrial needs is necessary to complete this list. The second is the QFD model, which is limited to continuous process improvements. The reconfiguration of the production system has not been considered in this paper.

From a methodological standpoint, there are four areas which might be worth investigating for future work. First, it would be interesting to investigate on how one may deal with the condition where there is a new process need or exclusion of an old one. Second, in the present work, the uncertainty relative to the input information of QFD, AHP and TOPSIS has been neglected. The neutrosophic set (NS), which is a generalization of fuzzy sets, is introduced to solve problems with inconsistent, incomplete, and indeterminate information. The aim of this future study is to improve uncertain decision-making by incorporating the advantages of the NS and fuzzy sets with the QFD, AHP and TOPSIS to construct a ranking model for process improvement. The third point focuses on the robustness of the model. The final priorities of the alternatives are dependent on parameters attached to AHP, QFD, grey forecasting and TOPSIS technique. Changes in these parameters can therefore cause changes of the final ranking. Since such parameters are quantitative and others are highly subjective judgments, the stability of the ranking under varying parameters must be tested. For this purpose, sensitivity analysis for the proposed model should be performed for each technic and parameter class. Finally, a more realistic application of the proposed methodology would be of great help in emphasizing the usefulness of dynamic QFD in practice.

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APPENDIX

Strategic matrix: process needs

1. Reduce cost
2. Improve production quality
3. Respect delivery time
4. Reduce the time for raw material reception
5. Support the versatility
6. React quickly to the variations of the demand
7. Improve human security

Strategic matrix: strategic requirements

1. Train the operators
2. Improve working conditions
3. Reduce breackdowns
4. Reduce work in progress (WIP)
5. Avoid manufacturing bottleneck
6. Improve the supply of machinery
7. Reduce tool change times
8. Improve scheduling
9. Increase the use of information technology
10. Improve information flow

Operational matrix: operational requirements

1. Train operators by increasing their capacity and autonomy
2. Simplify operations to be carried out by operators
3. Optimize the batch size
4. Adapt the type of inventory management to products
5. Refer to sales forecasts
6. Change the thinking from reactive to proactive
7. Have the control carried out by the operators

Technical matrix: technical requirements

1. Train operators in first level maintenance
2. Involve operators in daily maintenance
3. Adjust the stock level

4. Providing employees access to the necessary information their job requires
5. Create visual controls to rapidly identify variation
6. Set up and update visual performance indicators
7. Simplify the shop floor communication.