Applying Data Mining and Grey QFD to Mine the Dynamic Trends for Computer Life Cycle-oriented Green Supply

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Abstract: - Green products can reduce the environmental burden during design and disposal. The most approved technique to evaluate the environmental profile of a green product is the life cycle assessment. Data mining has also been successfully applied in many fields. However, little research has been done in the quality function deployment of mining the dynamic trends of customer requirements and engineering characteristics, using data mining and grey theory. This study proposed an approach to use data mining and grey theory in quality unction deployment for mining dynamic trends of the computer life cycle-oriented green supply. An Empirical example is provided to demonstrate the applicability of the proposed approach. Certain advantages may be observed when the dynamic and future requirements trends were identified, using the proposed approach. Since CRs can change rapidly, the database of CRs must be updated continually; therefore, the proposed approach in this study, will continually mine the database and identify the dynamic trends for the designers and manufacturers. The results of this study can provide an effective procedure of mining the dynamic trends of CRs and ECs for improving customer satisfaction and green competitiveness in the marketplace.

Key-Words: - Data mining, Grey theory, Quality function deployment, Dynamic trends, Life cycle, Green supply.

1 Introduction

Green products can reduce environmental pollution during design and disposal. Recycling of materials, and adequate reuse of subassemblies can deeply reduce waste generation, thus increasing green product competitiveness in the marketplaces [27]. Manufacturing has usually focused on the quality of a product and the cost. The environmental issues in a company have been regarded only as an 'End-of-Pipe' treatment to comply with the environmental regulation. However, environmental concern about a product gradually becomes another driving force in business activity, i.e. as extended designer and manufacturer responsibility and environmental labeling. Though the effect of this concern on the market is still invisible, the potential is continuously growing so that an environmentally friendly product takes a higher position on the market [15]. Furthermore, the International Organization for Standardization (ISO) has been working on standardizing environmental management systems since 1993. The activities at ISO have driven industries in many countries to pay more attention to the environmental performance of a product. For these reasons, many industries have explored ways to develop an environmentally friendly product. The most approved methodology to evaluate the environmental profile of a green product is the life cycle assessment (LCA) [8]. LCA was an evaluation tool, which provided information on the environmental aspects of the product system - from the raw material extraction through material, manufacturing, Transportation, use, marketing, and to the waste management, and this holistic information was also very important in a green product design [30]. The LCA has been expanded to other products in many fields. The implementation of LCA is a first step to developing an environmentally friendly product. The outputs of a LCA study can give the product designers and manufacturers guidance to improve the environmental performance of a product, and to help a decision-maker establish short-term goals as well as long-term goals for the improvement [14]. Zust and Wagner [25] clarified four stages of the product life cycle: (1) product definition, (2) product development, (3) product manufacturing, and (4) product usage. Many green products based life cycle are evaluated and created by performing the LCA framework. Within the LCA framework, the greatest challenge is the assessment of the impacts associated with environmental releases during the materials, manufacturing, transportation, marketing, use and disposal of products. Therefore, when considering green design, designers and manufacturers should listen the customer voices for improving customer satisfaction [26, 29].

Quality Function Deployment (QFD) has been a successful appliance to develop new product systematically and assist the product design in translating customer requirements (CRs) into the engineering characteristics (ECs) to be met in many product design fields [10, 20]. After the concept of QFD was introduced in the US through parts suppliers and car manufacturers, many US companies, such as AT&T, Digital Equipment, Ford, GM, Hewlett-Packard, Procter & Gamble, and Raychem, applied QFD to improve product development [1, 2, 21]. QFD has been widely applied to fulfil CRs and improve customer satisfaction in many industries, because it is a cross-functional planning technique which is used to ensure that the customer voices are deployed throughout the product planning and design stages. Because the customer voice is necessary, the House of Quality (HOQ) converts each CR into one or more ECs in the first stage of QFD. The main goal of HOQ is to identify CRs and weights for the product (WHATs) and then to convert these requirements into ECs (HOWs). It has a great benefit that combining the CRs and ECs for the designers and manufacturers could help companies provide better products, enhance their competitiveness in marketplace, increase customer satisfaction [61, 62]. The components of HOQ are shown in Figure 1.

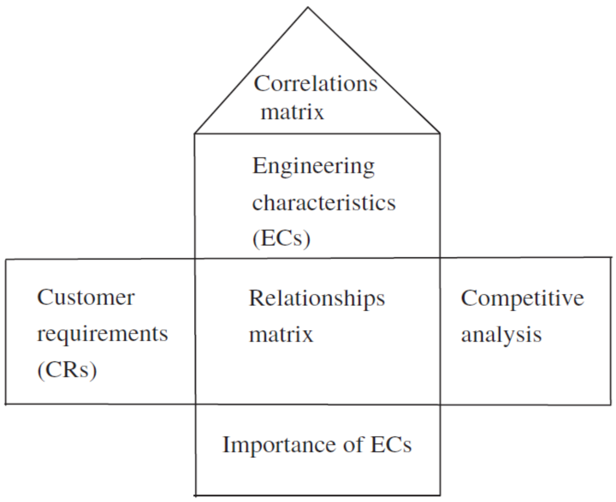

Figure 1. Components of HOQ.

On the other hand, the application domain of data mining is quite broad and plausible in surface roughness prediction [6], biomedical technology [23], risk prediction [16], human resource management [13], semiconductor manufacturing [4], production schedule [9], marketing [17, 29] and others [7, 22]. However, little research has been done in the QFD of mining the dynamic trends of customer requirements and engineering characteristics, using data mining and grey theory. This study proposed an approach to use data mining and grey theory in QFD for mining dynamic trends for the computer life cycle-oriented green supply. By applying the proposed approach, the dynamic trends of CRs and ECs of green product can be found from a large database to enhance green competitiveness in the global marketplace.

The data mining system of this study has three layers, including source data layer, data mining layer, and user interface layer. Source data layer is composed of database and knowledge base. Data mining layer is composed of data mining system. Man machine interaction system is included in user interface layer. The structure is shown as Figure 2.

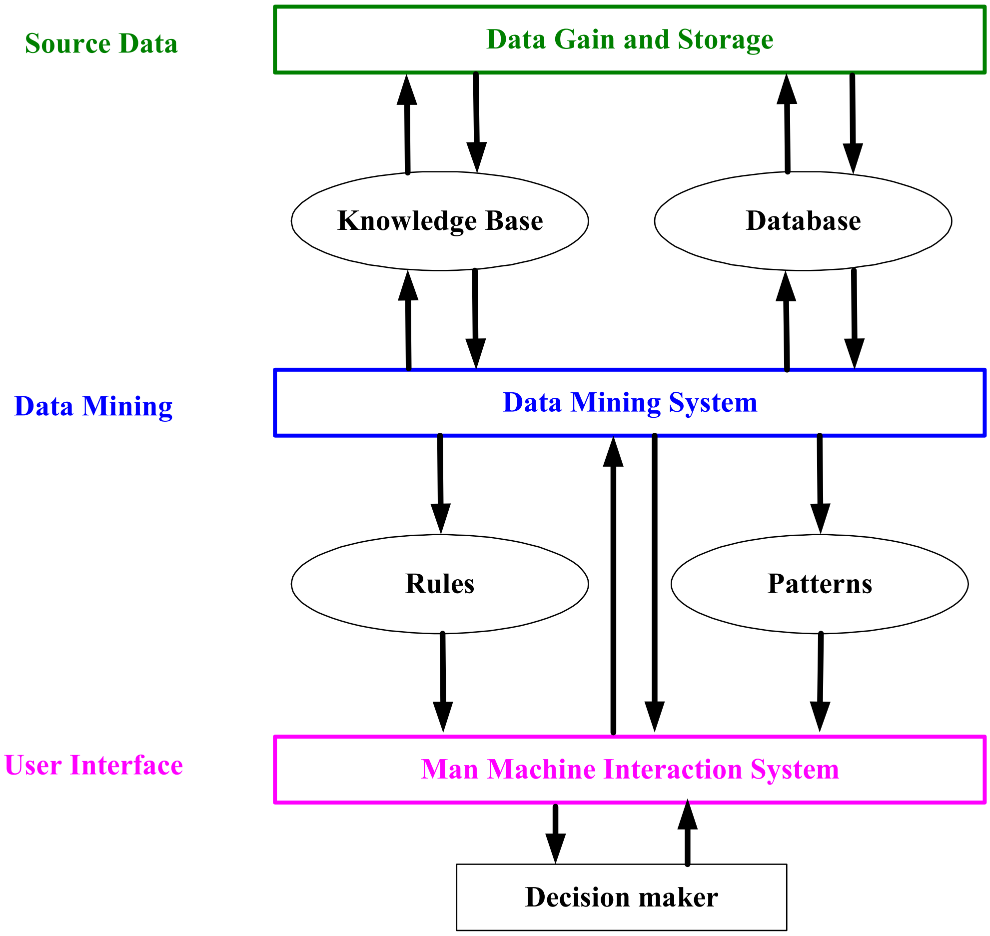

Figure 2. The structure of data mining system.

2 Data Mining and Grey Relational Analysis

Berry and Linoff defined data mining as the analysis of huge amounts of data by automatic or semi-automatic means, in order to identify significant rules or patterns [7, 22]. One of the most important data mining techniques is time series analysis. Time series data often arise when monitoring industrial processes or tracking corporate business trends [28]. Forecasting can do for just that - if a time series has behaved a certain way in the past, the future behavior can be predicted within certain confidence limits by building models [3, 11]. Forecasts generated with this method are a weighted average of the past values of the variable. The forecast for period *t+1* calculated in period *t* is called *Ft+1*. Therefore, *Ft* is the forecast for period *t* calculated in period *t-1*. The forecast for period *t+1* is,

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t \qquad (1)$$

which represents a weighted average of the actual value (*At*) and the forecast (*Ft*) of the actual value (calculated at *t-1*). The higher the value of alpha the more weight is given to current values [12].

On the other hand, one of the most important grey theory techniques is grey relational analysis. Let the original reference sequence and comparability sequences be represented as $x_0^{(0)}(k)$

and $x_i^{(O)}(k)$, $i = 1, 2, \ldots, m$; $k = 1, 2, \ldots, n$, respectively.

Data preprocessing is normally required since the range and unit in one data sequence may differ from the others. Data preprocessing is also necessary when the sequence scatter range is too large, or when the directions of the target in the sequences are different. Data preprocessing is a process of transferring the original sequence to a comparable sequence. Depending on the characteristics of data sequence, there are various methodologies of data preprocessing [18] available for the grey relational analysis.

If the target value of original sequence is infinite, then it has a characteristic of "the-larger-the-better". The original sequence can be normalized as follows:

$$x_i^*(k) = \frac{x_i^{(O)}(k) - \min x_i^{(O)}(k)}{\max x_i^{(O)}(k) - \min x_i^{(O)}(k)} \tag{2}$$

when the-smaller-the-better is a characteristic of the original sequence, then the original sequence should be normalized as follows:

$$x_i^*(k) = \frac{\max x_i^{(O)}(k) - x_i^{(O)}(k)}{\max x_i^{(O)}(k) - \min x_i^{(O)}(k)} \tag{3}$$

However, if there is a definite target value to be achieved, then the original sequence will be normalized in the form:

$$x_i^*(k) = 1 - \frac{|x_i^{(0)}(k) - \mathrm{OB}|}{\max\{\max x_i^{(0)}(k) - \mathrm{OB}, \mathrm{OB} - \min x_i^{(0)}(k)\}} \tag{4}$$

Or, the original sequence can be simply normalized by the most basic methodology, i.e. let the values of original sequence are divided by the first value of the sequence:

$$x_i^*(k) = \frac{x_i^{(O)}(k)}{x_i^{(O)}(1)} \tag{4}$$

where $x_i^{(O)}(k)$ is the original sequence, $x_i^*(k)$ the sequence after the data preprocessing, max $x_i^{(O)}(k)$ the largest value of $x_i^{(O)}(k)$ and min $x_i^{(O)}(k)$ the smallest value of $x_i^{(O)}(k)$.

After data preprocessing is carried out, a grey relational coefficient can be calculated with the preprocessed sequences. The grey relational coefficient is defined as follows [18]:

$$\gamma(x_0^*(k), x_i^*(k)) = \frac{\Delta_{\min} + \zeta\,\Delta_{\max}}{\Delta_{0i}(k) + \zeta\,\Delta_{\max}}, \quad 0 < \gamma(x_0^*(k), x_i^*(k)) \le 1 \tag{5}$$

where $\Delta_{0i}(k)$ is the deviation sequence of the reference sequence $x_0^*(k)$ and the comparability sequence.

$x_i^*(k)$, i.e.

$$\begin{aligned} \Delta_{0i}(k) &= |x_0^*(k) - x_i^*(k)|, \\ \Delta_{\max} &= \max_{\forall j \in i} \max_{\forall k} |x_0^*(k) - x_j^*(k)|, \\ \Delta_{\min} &= \min_{\forall j \in i} \min_{\forall k} |x_0^*(k) - x_j^*(k)| \end{aligned} \tag{6}$$

ζ: distinguishing coefficient, $\zeta \in [0, 1]$.

The grey relational grade is a weighting-sum of the grey relational coefficient [5, 19]. It is defined as follows:

$$\gamma(x_0^*, x_i^*) = \sum_{k=1}^{n} \beta_k \gamma(x_0^*(k), x_i^*(k)), \quad \sum_{k=1}^{n} \beta_k = 1 \tag{7}$$

Here, the grey relational grade $\gamma(x_0^*, x_i^*)$ represents the level of correlation between the reference sequence and the comparability sequence.

Thus, this study proposed a time series-based data mining cycle and grey relational analysis, in order to mine dynamic trends for the computer life cycle-oriented green supply in QFD for satisfying customer needs.

3 An Empirical Example

This study uses data mining cycle and grey QFD to mine dynamic trends of CRs and ERs with each respective step closely involved. The data mining cycle involves a series of activities, from defining the problem to evaluating and applying the results [7, 22]. The previous steps can be served as the baseline reference for the next step, and the steps for the dynamic and future trends of computer life cycle-oriented green supply are described as follow.

3.1 Defining the problem for data mining

Owing to unknown weights for future CRs, a professional notebook computer manufacturer create a large marketing database in Taiwan, based on many customer questionnaires on website, this resulted in a huge amount of data continuously. The goal of this study was to explore and analyze a huge amount of data, by employing a time series-based data mining cycle in grey QFD, so as to identify the weights within customer questionnaires in each period. The dynamic trend of future CRs and ECs may be discovered for the computer life cycle of green product based on these the weights of CRs, so the results and discoveries can be encouraged and beneficial the computer designers and manufacturers.

3.2 Data preparation for data mining

In order to enhance the efficiency and ensure the accuracy of the results, the data was processed. It had to be checked and processed before mining the data, with all abnormal or missing data being separated out [7]. As a result, of the 16,000 questionnaires, 286, which had missing or abnormal data, were deleted. Also, there are seven CRs for each customer questionnaire and ten ECs for the computer life cycle-oriented green supply as shown in Table 1 and Table 2. The QFD matrix for the notebook computer is shown in Figure 3.

Table 1. Definitions of customer requirements (CRs)

Voice of Customer	Customer Requirements
CR1	Easily disassembly
CR2	Easily maintenance
CR3	Energy saving
CR4	No toxical material released
CR5	Operating quality
CR6	Price or cost
CR7	Recyclable

Table 2. Definitions of engineering characteristics (ECs)

	Phases	Voice of Engineering	Engineering Characteristics
Life cycle-based green supply	Raw materials extraction/processing	EC1	Material reduction
		EC2	Safety material
	Product manufacture	EC3	Clean production
		EC4	Modularization
	Transportation /distribution	EC5	Delivery saving
		EC6	Energy saving
	Marketing	EC7	Modify advertising
	Usage	EC8	Electricity consumption
		EC9	Easily maintenance
	Final disposition	EC10	Recycle

		Life cycle-based green supply									
		Raw materials extraction /processing		Product manufacture		Transportation /distribution		Marketing	Usage		Final disposition
	Weights	EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10
CR1		1	3		9	1	3	1		9	3
CR2		3	1	3	9	1		1		9	3
CR3		9	3	9	9	9	9	9	9	3	3
CR4			9	9	1	1	3	1		3	9
CR5			9	3	3		1	1	3	3	1
CR6		3	3	3	3	9	9	3	9	3	1
CR7		3	3	9	9		3	1		9	9
Importance of EC											

Figure 2. The QFD matrix for the notebook computer.

3.3 Data mining by time series analysis

For the designers and manufacturers, it is essential to reflect CRs by corporate language and then fulfil those ECs to satisfy CRs. When CRs are translated by HOWs, the designers and manufacturers have to check the relationship between WHATs and HOWs. The weights of four periods for each CR are periodically mined in Table 3. The weight for each CR is evaluated by a 1–10 scale, where a CR with a lower weight is not more important.

QFD represent the respective strong (with a weight of 9), moderate (with a weight of 3), and weak relationship (with a weight of 1), while the blank is zero [20, 21]. Taking period 1 as an example, the matrix relationship between CRs and ECs is shown in Table 4.

Through checking the relationship between WHATs and HOWs, the matrix relationship between CRs and ECs were determined. Subsequently, data mining was undertaken, using a time series-based data mining cycle, to mine the weights and determine the trend of each CR for the next period.

According to the data mining cycle, the predicted weights of CRs in the next period (period 5) would be estimated as shown in Table 5. As shown, the predicted weight of CR1 in the period 5 is 5.9; thus, these predicted weights of the CRs were chosen for the next stage of processing.

Table 3. The weights of four periods for CRs

	Period 1	Period 2	Period 3	Period 4
CR1	5.3	5.7	6.4	5.7
CR2	6.9	7.1	7.5	8.4
CR3	8.1	8.3	8.5	8.8
CR4	7.5	7.7	8.4	9.1
CR5	5.6	5.8	4.5	6.4
CR6	6.6	6.7	5.8	4.3
CR7	6.4	5.3	7.6	8.7

Table 4. The HOQ of period 1

	Weights	EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10
CR1	5.3	1	3		9	1	3	1		9	3
CR2	6.9	3	1	3	9	1		1		9	3
CR3	8.1	9	3	9	9	9	9	9	9	3	3
CR4	7.5		9	9	1	1	3	1		3	9
CR5	5.6		9	3	3		1	1	3	3	1
CR6	6.6	3	3	3	3	9	9	3	9	3	1
CR7	6.4	3	3	9	9		3	1		9	9
Importance of EC											

Table 5. Predicted weights for the CRs in the period 5

	Period 1	Period 2	Period 3	Period 4	Period 5 predicted
CR1	5.3	5.7	6.4	5.7	5.9
CR2	6.9	7.1	7.5	8.4	7.9
CR3	8.1	8.3	8.5	8.8	8.6
CR4	7.5	7.7	8.4	9.1	8.6
CR5	5.6	5.8	4.5	6.4	5.8
CR6	6.6	6.7	5.8	4.3	5.3
CR7	6.4	5.3	7.6	8.7	7.8

3.4 Evaluation and Application of Results

This study uses data mining cycle in grey QFD to mine the weights and determine the dynamic trend of each CR and ER. Owing to the entire forecast techniques have forecast errors, the mean squared error (MSE) and control charts of forecast were applied to monitor the accuracy of forecast in this study. The MSE is the average of squared forecast errors. Forecast error is defined as the difference between the actual value and the forecast value. Taking the CR1 as an example, the mean squared error is 0.33. Furthermore, the study calculated the double control limit for the control charts of forecast. Because the upper control limit is 0.66 and lower control limit is -0.66, all of the forecast errors of CR1 were under the double control limit. The forecast errors in other CRs are less than the double control limit. Thus, the exponential smoothing analysis is clearly quite accurate.

To gain a better insight into the predicted weights among the seven CRs resulting from the time series-based data mining cycle, a bar chart was drawn for the weights of the CRs. As can be seen in Figure 4, the weights of CRs bear marked differences for each period. The dynamic trend for each CR can be understood and controlled by the designers and manufacturers with the well information. The weight trend of each CR can be considered to know future CR trend. The designers and manufacturers can design and plan green computer to satisfy with future CRs in advance.

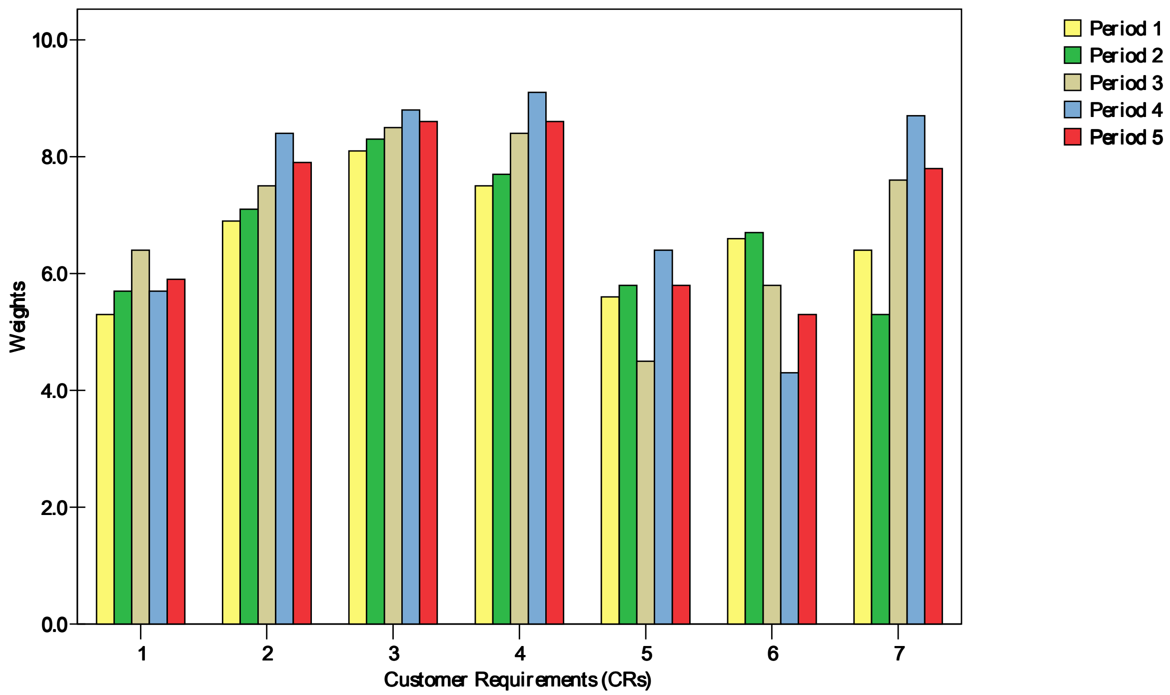

Figure 4. Dynamic trend forecasting of the seven CRs.

The future trends and ranks of ECs to satisfy future CRs can be analysed in Table 6. According to the future trend and rank of each EC, some ECs should be closely noticed since its importance has increased and could become the most important ECs to satisfy CRs in the future. On the other hand, the dynamic and future ranks of ECs to satisfy future CRs can be analysed in Figure 5. According to the future rank of each EC, EC10 should be closely noticed since its importance has increased and EC6 important could become has decreased. Different ECs should be considered differently for the computer designers and manufacturers with the more information. The dynamic trend of future CRs and ECs may be discovered, so the results and discoveries can be encouraged and beneficial the computer designers and manufacturers for improving customer satisfaction and green competitiveness in the marketplace.

Table 6. Dynamic trend forecasting of the ten ECs

	EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10
Period 1	0.6335	0.7024	0.7781	0.8373	0.7315	0.7035	0.622	0.679	0.7602	0.7013
Period 1 rank	9	6	2	1	4	5	10	8	3	7
Period 2	0.6336	0.7053	0.7706	0.8338	0.7365	0.7048	0.6239	0.6822	0.7554	0.6928
Period 2 rank	9	5	2	1	4	6	10	8	3	7
Period 3	0.6341	0.6952	0.7881	0.8491	0.7067	0.6956	0.6204	0.6624	0.7766	0.7167
Period 3 rank	9	7	2	1	5	6	10	8	3	4
Period 4	0.6307	0.7091	0.7959	0.8481	0.7032	0.6769	0.6163	0.6485	0.7774	0.7239
Period 4 rank	9	5	2	1	6	7	10	8	3	4
Period 5 predicted	0.6318	0.7042	0.7884	0.8455	0.7108	0.6874	0.6183	0.6591	0.773	0.7158
Period 5 rank	9	6	2	1	5	7	10	8	3	4

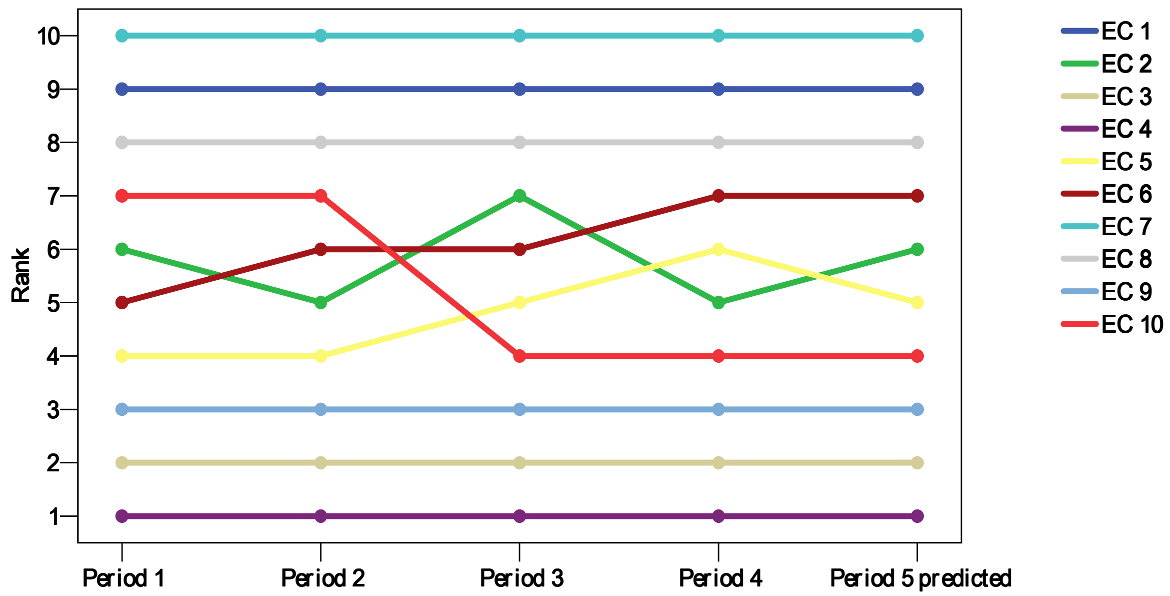

Figure 5. Dynamic trend of the ten ECs.

The data mining cycle emphasizes the dataset information by repeating interaction activities. Since CRs can change rapidly, the database of CRs must be updated continually; therefore, the time series-based data mining cycle and grey QFD, proposed in this study, will continually update the database and continually identify the dynamic CRs and ECs trends for the designers and manufacturers. These revised ECs will exactly satisfy with CRs, allowing the computer designers and manufacturers to the latest CRs, thus facilitating advanced design for the green computers.

4 Conclusions.

Green products can reduce the environmental burden during design and disposal. The most approved technique to evaluate the environmental profile of a green product design is the LCA. The satisfaction of customer requirements is critical issue for the designers and manufacturers, because product design is a high risk and value-added technology. Data mining has also been successfully applied in many fields. However, little research has been done in the QFD of mining the dynamic trends of customer requirements and engineering characteristics, using data mining and grey theory. This study proposed an approach of using data mining and exponential smoothing method in grey QFD to mine dynamic CRs and ECs trends for the life cycle-based green supply of green product. The proposed approach to mine the dynamic trends is advantageous because it can (1) find the future trends of CRs and ERs; (2) provide the designers and manufacturers with ERs reference points to satisfy CRs in advance. Since CRs can change rapidly, the database of CRs must be updated continually; therefore, the proposed approach in this study, will continually mine the database and identify the dynamic trends for the designers and manufacturers. The results of this study can provide an effective procedure of mining the dynamic trends of CRs and ECs for improving customer satisfaction and enhancing green competitiveness in the marketplace.

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