A Hybrid Mining and Predicting System Based on Quadratic Exponential Smoothing Model and Grey Relational Analysis for Green Supply Chain

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Abstract: - Green product design is a proactive approach to minimize the product's environmental impact in green supply chain. Environmental concern about the green product gradually becomes driving force in business activity. Though the effect of this concern on the market is still invisible, the potential is continuously growing so that an environmentally friendly green product takes a higher position on the market. This study proposed a hybrid mining and predicting system to use quadratic exponential smoothing model and grey relational analysis in quality function deployment (QFD) for mining and predicting dynamic trends for life cycle assessment-oriented green supply chain. By applying the proposed system, the dynamic trends of customer requirements and technical requirements of green product can be found from a large database to enhance green competitiveness. Owing to an empirical example is provided to demonstrate the applicability of the proposed approach, the proposed system to mine and predict dynamic trends is advantageous because it can (1) find the future trends of customer requirements and technical requirements; (2) allocate limited company resources in advance; (3) provide the designers and manufacturers with well reference points to satisfy customer requirements in advance. The results of this study can provide an effective and systematic procedure of mining and predicting the dynamic trends of customer requirements and technical requirements for life cycle assessment-oriented green supply chain.

Key-Words: - Life cycle assessment, Green supply chain, Hybrid mining and predicting system, Quadratic exponential smoothing model, Grey relational analysis.

1 Introduction

Adequate reuse of subassemblies and recycling of materials can deeply reduce waste generation on the environment, and then increase green product competitiveness in the marketplaces [37]. From the past until now, designers and manufacturers have usually focused on the cost and quality of a product. The environmental issues in a company have been regarded only as a traditional end-of-pipe treatment to comply with the environmental regulation. However, environmental concern about a product gradually becomes another driving force in business decisions. Though the effect of this concern on the market is still invisible, the potential is continuously growing so that an environmentally friendly green product takes a higher position on the market [24].

Green products can reduce the environmental burden during raw materials, product manufacture, logistics, transportation/distribution, marketing, usage, and final disposition. Green product design refers to green technical design. The aim of green technical design is to develop an understanding of how design decisions impact on a product environmental compatibility. As opposed to the traditional end-of-pipe treatment for pollution control, green product design is a proactive approach to minimize the product's environmental impact in green supply chain, and thus to increase the product competitiveness [7, 13]. Furthermore, the activities at International Organization for Standardization (ISO) have driven industries in the world to pay more attention to the environmental burden of a product. For these reasons, many industries have researched the ways to develop an environmentally friendly green product.

Zust and Wagner [35] clarified four steps of the product life cycle: (1) product definition, (2) product development, (3) product manufacturing, and (4) product usage. Some researchers also had five phases of the product life cycle, including the last phase of the product EOL (End-of-Life) [40]. For evaluating the environmental profile of a green product, the life cycle assessment (LCA) is the most approved methodology [15]. The early application of LCA can serve as an effective decision making tool to guide the deployment of the final product [38]. The execution of LCA is a first step to developing an environmentally friendly green product. The LCA has been expanded to other products design in many fields, because 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 and long-term improvable goals [23]. LCA was also an important tool in a green product design, which provided information on the environmental aspects of the product system - from the raw materials, product manufacture, logistics, transportation/distribution, marketing, usage, and to final disposition [42].

By performing the LCA framework, many green products are evaluated and created based life cycle. Within the LCA framework, the greatest challenge is the assessment of the impacts associated with environmental releases during the raw materials, product manufacture, logistics, transportation /distribution, marketing, usage, and final disposition of products. Therefore, designers and manufacturers should listen to the customer voices for improving customer satisfaction when considering green product design [36, 41].

In addition, quality function deployment (QFD) has been a successful appliance to develop new product systematically and assist the product design in translating customer requirements into the technical requirements to be met in many product design fields [18, 29]. First conceptualized in 1966 as a concept for new product development under the umbrella of Total Quality Control, quality deployment was developed by Dr. Shigeru Mizuno and Yoji Akao. They detailed methods of quality deployment in 1972. QFD is used to translate customer requirements to technical requirements. It is a link between customers - designers - manufacturers - competitors. It provides an insight into the whole design and manufacturing operation from concept to manufacture and it can dramatically improve the efficiency as production problems are resolved early in the design phase [18, 29].

QFD has been widely applied to fulfil customer requirements 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 customer requirement into one or more technical requirements in the first stage of QFD. The main goal of HOQ is to identify customer requirements and weights for the product (WHATs) and then to convert these requirements into technical requirements (HOWs). It has a great benefit that combining the customer requirements and technical requirements for the designers and manufacturers could help companies provide better products, enhance their competitiveness in marketplace, increase customer satisfaction [21, 29]. The components of HOQ are shown in Figure 1.

The six sections of the HOQ were identified and described as follow [21]:

(1). Customer requirements (CRs)**:**
The CRs are on the left side of the HOQ matrix. This section documents the voice of customer. The CRs represent the "what's" of the HOQ system and use questionnaires to elicit the information of customer for understanding the customer requirements.

(2). Technical requirements (TRs):
The TRs are on the top of the HOQ matrix. This section lists how the designers and manufacturers will meet the CRs. This is the "HOWS" of the HOQ. The TRs represent the voice of company. The QFD design team collected information, such as product requirements, product capabilities or features, top-level solution-independent metrics.

(3). Interrelationship Matrix:
It is located on the middle of the HOQ which is the largest portion. It uses the prioritization matrix. It shows how well CRs are addressed by TRs.

(4). Rank and importance of TRs:
This the final section of the HOQ matrix. It summarizes the rank and importance of TRs. It includes three parts, such as relative priorities and importance of each TR, engineering target values to be met by the new product design, competitive benchmarks.

(5). Planning Matrix:
It is on the right side of the HOQ matrix. It provides customers views that represent the

customer competitive assessment for the similar products.

(6). Roof:
Roof is the correlation matrix that focuses on design improvement. It focuses on relationships for TRs in the design.

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 design and development [1, 2].

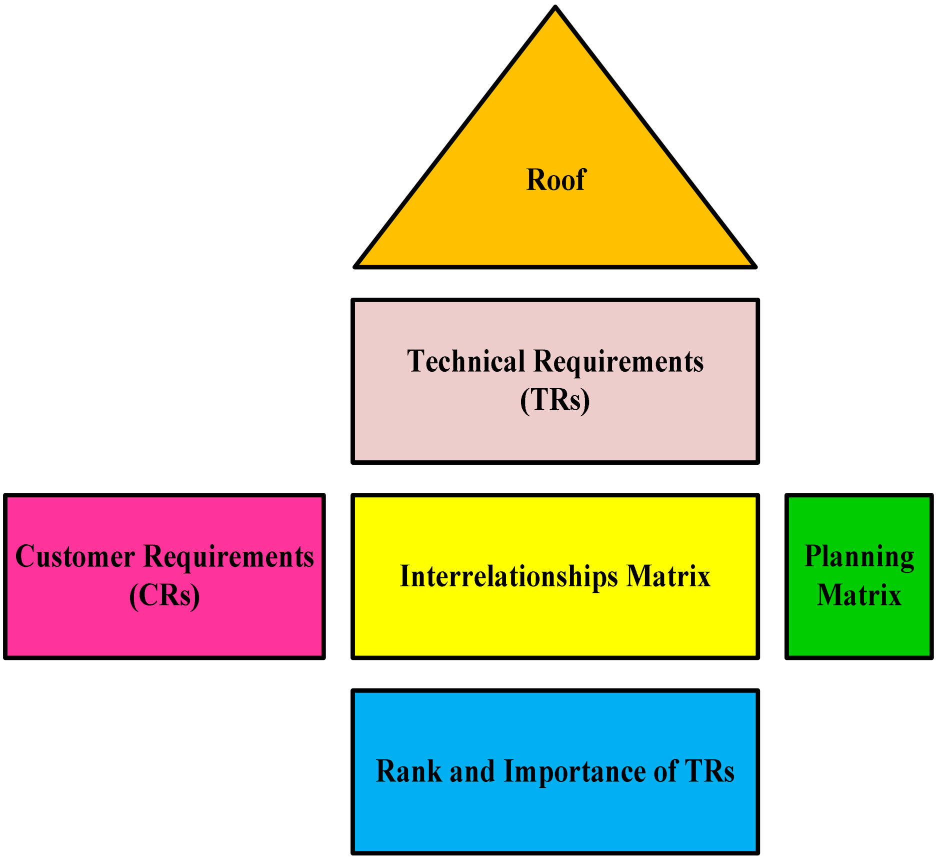

Figure 1. The six sections of HOQ matrix.

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 [12, 31]. The application domain of data mining is very wide in semiconductor manufacturing [4], surface roughness prediction [11], production schedule [14], human resource management [22], risk management [25], marketing [26], biomedical technology [32] , business process management [33], business logistics [5] and others [6, 8, 9, 30]. However, little research has established a hybrid mining and predicting system for life cycle assessment-oriented green supply chain in the QFD of mining and predicting the dynamic trends of CRs and TRs using quadratic exponential smoothing model and grey relational analysis.

This study proposed a hybrid system to use quadratic exponential smoothing model and grey relational analysis in QFD for mining and predicting dynamic trends for life cycle assessment-oriented green supply chain. By applying the proposed system, the dynamic trends of CRs and TRs 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.

2 Quadratic Exponential Smoothing Model and Grey Relational Analysis

One of the most important data mining techniques is time series analysis. Time series data often appear when tracking corporate business trends [16, 17, 39]. Forecasting can do for just that - if a time series has behaved a certain way in the past, the future trend and behaviour can be predicted within certain confidence limits by building models [3, 19].

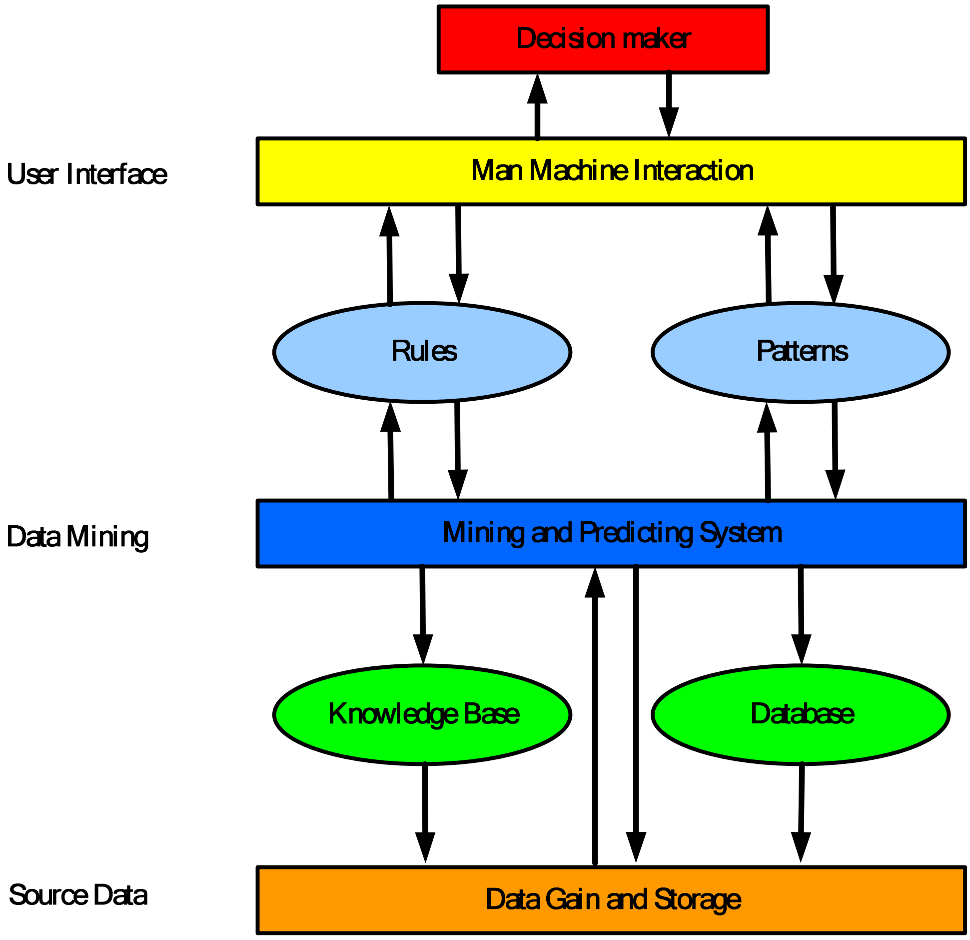

Figure 2. The hybrid mining and predicting system.

The quadratic exponential smoothing is the most important trend forecasting technique for time series analysis. Quadratic exponential smoothing is a refinement of the popular simple exponential smoothing model but adds another component which takes into account any trend in the data. Simple exponential smoothing models work best with data where there are no trend or seasonality components to the data. When the data exhibits either an increasing or decreasing trend over time, simple exponential smoothing forecasts tend to lag behind observations. Furthermore, quadratic exponential smoothing is designed to address this type of data series by taking into account any trend in the data. There are three equations associated with quadratic exponential smoothing that showed as follow.

$$Y_{t+1} = S_t + T_t \tag{1}$$

where

S_t = smoothed forecast,

T_t = current trend estimate,

And

$$S_t = y_t + \alpha(d_t - y_t) \tag{2}$$

$$T_t = T_{t-1} + \beta(y_t - y_{t-1} - T_{t-1}) \tag{3}$$

where α and β are smoothing constants, $0 \le \alpha \le 1$ and $0 \le \beta \le 1$.

The output of the algorithm is written as Y_{t+1}, an estimate of the value of Y at time $t+1$, thus further values can be evaluated [19, 20, 34].

In addition, grey relational analysis is also one of the most important data mining techniques. Let the original reference sequence and comparability sequences be represented as $x_0^{(O)}(k)$ and $x_i^{(O)}(k)$, *i = 1, 2, . . .,m; k = 1, 2, . . ., n*, respectively.

Data pre-processing is normally required since the range and unit in one data sequence may differ from the others. Data pre-processing is also necessary when the sequence scatter range is too large, or when the directions of the target in the sequences are different. Data pre-processing 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 pre-processing available for the grey relational analysis [27].

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 [27, 28]:

$$x_i^*(k) = \frac{x_i^{(O)}(k) - \min x_i^{(O)}(k)}{\max x_i^{(O)}(k) - \min x_i^{(O)}(k)} \tag{4}$$

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

$$x_i^*(k) = \frac{\max x_i^{(O)}(k) - x_i^{(O)}(k)}{\max x_i^{(O)}(k) - \min x_i^{(O)}(k)} \tag{5}$$

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

$$x_i^*(k) = 1 - \frac{|x_i^{(O)}(k) - \mathrm{OB}|}{\max\{\max x_i^{(O)}(k) - \mathrm{OB}, \mathrm{OB} - \min x_i^{(O)}(k)\}} \tag{6}$$

OB：chosen value in $x_i^{(O)}(k)$

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:

$$x_i^*(k) = \frac{x_i^{(O)}(k)}{x_i^{(O)}(1)} \tag{7}$$

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:

$$\gamma(x_0^*(k), x_i^*(k)) = \frac{\Delta_{\min} + \zeta\,\Delta_{\max}}{\Delta_{0i}(k) + \zeta\,\Delta_{\max}},$$
$$0 < \gamma(x_0^*(k), x_i^*(k)) \leq 1 \tag{8}$$

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

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

$$\Delta_{0i}(k) = |x_0^*(k) - x_i^*(k)|,$$
$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} |x_0^*(k) - x_j^*(k)|,$$
$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} |x_0^*(k) - x_j^*(k)| \tag{9}$$

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

The grey relational grade is a weighting-sum of the grey relational coefficient. It is defined as follows:

$$\gamma(x_0^*, x_i^*) = \sum_{k=1}^{n} \beta_k \gamma(x_0^*(k), x_i^*(k)), \quad \sum_{k=1}^{n} \beta_k = 1 \tag{10}$$

Here, the grey relational grade $\gamma(x_0^*, x_i^*)$ represents the level of correlation between the reference sequence and the comparability sequence [10, 28, 37].

Thus, this study proposed a hybrid system to use quadratic exponential smoothing model and grey relational analysis in QFD, in order to mine and predict the dynamic trends of CRs and TRs for life cycle assessment-oriented green supply chain.

3 An Empirical Case

This study uses a hybrid mining and predicting system using quadratic exponential smoothing model and grey relational analysis with each respective step closely involved. The hybrid mining and predicting system involves a series of activities, from defining the problem to evaluating and applying the results. The previous steps can be served as the baseline reference for the next step, and the steps for the dynamic and future trends of life cycle assessment-oriented green supply chain are described as follow.

3.1 Defining the problem for data mining

Because unknown weights for future CRs, a professional computer manufacturer create a large marketing database, 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 mine a huge amount of data, by employing a hybrid mining and predicting system, so as to identify the weights within customer questionnaires in each period. The dynamic trend of future CRs and TRs may be discovered for the computer life cycle assessment-oriented green supply chain based on these weights of CRs, so the discoveries and results 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 [12]. Also, there are ten TRs and seven CRs for each customer questionnaire as shown in Table 1 and Table 2. The QFD matrix for the computer interrelationship is shown in Figure 3. It showed how well CRs were addressed by TRs according to the judgements of designers and manufacturers.

Table 1. Definitions of technical requirements (TRs)

	Phases	Voice of company	Technical requirements
Life cycle assessment-oriented green supply chain	Raw materials extraction/processing	TR1	Material reduction
		TR2	Safety material
	Product manufacture	TR3	Clean production
		TR4	Modularization
	Logistics transportation/distribution	TR5	Delivery saving
		TR6	Energy saving
	Marketing	TR7	Modify advertising
	Usage	TR8	Electricity consumption
		TR9	Easily maintenance
	Final disposition	TR10	Recycle

Table 2. 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	Cost & price
CR7	Recyclable

		Life cycle assessment-oriented green supply chain									
		Raw materials extraction /processing		Product manufacture		Logistics transportation /distribution		Marketing	Usage		Final disposition
	Weights	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10
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
Rank and importance of TR											

Figure 3. The QFD interrelationship matrix.

3.3 Data mining and predication

For the designers and manufacturers, it is essential to reflect CRs by corporate language and then fulfil those TRs to satisfy CRs. When CRs are translated by HOWs, the designers and manufacturers have to check the interrelationship between WHATs and HOWs. The weights of five 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 represents 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 [29]. Taking period 1 as an example, the interrelationship matrix between CRs and TRs according to the judgements of designers and manufacturers is shown in Table 4.

Through checking the interrelationship between WHATs and HOWs, the interrelationship matrix between CRs and TRs were determined. Subsequently, data mining was undertaken, using a hybrid mining and predicting system, to mine and predict the weights and determine the trend of each CR for the next period.

3.3.1 Data mining by quadratic exponential smoothing model

According to the data mining, the predicted weights of CRs in the next period (period 6) would be estimated as shown in Table 5. As shown, the predicted weight of CR1 in the period 6 is 6.2; thus, these predicted weights of the CRs were chosen for the next stage of processing.

Table 3. The weights of five periods for CRs

	Period 1	Period 2	Period 3	Period 4	Period 5
CR1	5.3	5.7	6.4	5.7	5.6
CR2	6.9	7.1	7.5	8.4	8.5
CR3	8.1	8.3	8.5	8.8	8.7
CR4	7.5	7.7	8.4	9.1	8.8
CR5	5.6	5.8	4.5	6.4	6.5
CR6	6.6	6.7	5.8	4.3	6.1

CR7	6.4	5.3	7.6	8.7	8.3

Table 4. The interrelationship matrix of period 1 HOQ

	Weights	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10
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
Rank and importance of TR											

Table 5. Predicted weights in the period 6 for the CRs

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6 prediction
CR1	5.3	5.7	6.4	5.7	5.6	6.2
CR2	6.9	7.1	7.5	8.4	8.5	8.1
CR3	8.1	8.3	8.5	8.8	8.7	8.6
CR4	7.5	7.7	8.4	9.1	8.8	8.7
CR5	5.6	5.8	4.5	6.4	6.5	6.9
CR6	6.6	6.7	5.8	4.3	6.1	7.2
CR7	6.4	5.3	7.6	8.7	8.3	9.3

3.3.2 Data mining by grey relational analysis

Through determining the future weights of CRs, the HOQ between TRs and future weights of CRs were shown in Table 6.

Generate the referential series, which are the target value for each CR. In this case, the referential series of x_0 =(10,10,10,10,10,10,10,10,10,10). On the other hand, the compared series are the CRs, i.e., x_1, x_2, x_3, x_4, x_5, x_6, x_7 represent CR 1, 2, 3, 4, 6, and 7, respectively. The data sets of x_1, x_2, x_3, x_4, x_5, x_6, x_7 are normalized. Obviously, each CR belongs to larger-is-better, and Eq. (4) is used to transform the data. Furthermore, the original sequence would be normalized as shown in Table 7.

Table 6. The HOQ between CRs and TRs for the period 6 prediction

	Weights	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10
CR1	6.2	1	3		9	1	3	1		9	3
CR2	8.1	3	1	3	9	1		1		9	3
CR3	8.6	9	3	9	9	9	9	9	9	3	3
CR4	8.7		9	9	1	1	3	1		3	9
CR5	6.9		9	3	3		1	1	3	3	1

CR6	7.2	3	3	3	3	9	9	3	9	3	1
CR7	9.3	3	3	9	9		3	1		9	9

After data preprocessing was carried out, the distance would be calculated with the preprocessed sequences. Compute the distance of $\Delta_{0i}(k)$ as shown in Table 8, the absolute value of difference.

Apply grey relational equation to compute grey relational coefficient $r(x_0^*(k), x_i^*(k))$, and the results are summarized in Table 9.

Furthermore, the sequence of grey relational grade for the future rank and importance of TRs was shown in Table 10.

Table 7. The normalization of original sequence for the period 6 prediction

	Weights	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10
CR1	6.2	0.11	0.33	0	1	0.11	0.33	0.11	0	1	0.33
CR2	8.1	0.33	0.11	0.33	1	0.11	0	0.11	0	1	0.33
CR3	8.6	1	0.33	1	1	1	1	1	1	0.33	0.33
CR4	8.7	0	1	1	0.11	0.11	0.67	0.11	0	0.3	1
CR5	6.9	0	1	0.33	0.33	0	0.11	0.11	0.33	0.33	0.11
CR6	7.2	0.33	0.33	0.33	0.33	1	1	0.33	1	0.33	0.11
CR7	9.3	0.33	0.33	1	1	0	0.33	0.11	0	1	1

Table 8. The distance of $\Delta_{0i}(k)$ for the period 6 prediction

	Weights	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10
CR1	6.2	0.89	0.67	1	0	0.89	0.67	0.89	1	0	0.67
CR2	8.1	0.67	0.89	0.67	0	0.89	1	0.89	1	0	0.67
CR3	8.6	0	0.67	0	0	0	0	0	0	0.67	0.67
CR4	8.7	1	0	0	0.89	0.89	0.67	0.89	1	0.67	0
CR5	6.9	1	0	0.67	0.67	1	0.89	0.89	0.67	0.67	0.89
CR6	7.2	0.67	0.67	0.67	0.67	0	0	0.67	0	0.67	0.89
CR7	9.3	0.67	0.67	0	0	1	0.67	0.89	1	0	0

Table 9. The grey relational coefficient for the period 6 prediction

	Weights	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10
CR1	6.2	0.53	0.6	0.5	1	0.53	0.6	0.53	0.5	1	0.6
CR2	8.1	0.6	0.53	0.6	1	0.53	0.5	0.53	0.5	1	0.6
CR3	8.6	1	0.6	1	1	1	1	1	1	0.6	0.6
CR4	8.7	0.5	1	1	0.53	0.53	0.6	0.53	0.5	0.6	1
CR5	6.9	0.5	1	0.6	0.6	0.5	0.53	0.53	0.6	0.6	0.53
CR6	7.2	0.6	0.6	0.6	0.6	1	1	0.6	1	0.6	0.53
CR7	9.3	0.6	0.6	1	1	0.5	0.6	0.53	0.5	1	1

Table 10. The TR rank and importance of the period 6 prediction

	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10
	0.6263	0.7032	0.7822	0.8231	0.6562	0.6914	0.6127	0.6552	0.7712	0.7712
Rank and Importance	9	5	2	1	7	6	10	8	3	4

3.4 Evaluation and Application of Results

This study proposed a hybrid mining and predicting system to use quadratic exponential smoothing model and grey relational analysis in QFD for mining and predicting dynamic trends for life cycle assessment-oriented green supply chain.

The mean squared error (MSE) and control charts of forecast were applied to monitor the accuracy of forecast in this study owing to the entire forecast methods have forecast errors. The MSE is the average of the squared forecast errors. Forecast error is defined as the squared difference between actual value and the forecast, i.e.,

$$e_t = d_t - y_t \tag{11}$$

The MSE equation is shown as follow.

$$MSE = \sum_{i=1}^{n} e_t^{\,2} \Big/ n-1 \tag{12}$$

Taking the CR1 as an example, the MSE is 0.4. Furthermore, the study calculated the double control limit according to the principles of control charts. We decided on an upper limit and a lower limit to track and control the forecast errors over time. Now let's add the double control limit, and let fix the upper limit at 1.26 and the lower limit at -1.26: We can notice that all of the forecast errors of CR1 is not going out of boundaries at the end, meaning that these forecast errors were under the double control limit. The forecast errors in other CRs are less than the double control limit. Thus, the quadratic exponential smoothing analysis is clearly quite accurate.

To gain a better insight into the predicted weights among the seven CRs resulting from the hybrid mining and predicting system, a line chart was drawn for the weights of the CRs. As can be shown in Figure 4, the weights of CRs bear marked differences for each period. The CR dynamic trend for the period 6 can be understood and controlled by the designers and manufacturers with the well information. The designers and manufacturers can design green products and arrange resources to satisfy with future CRs in advance.

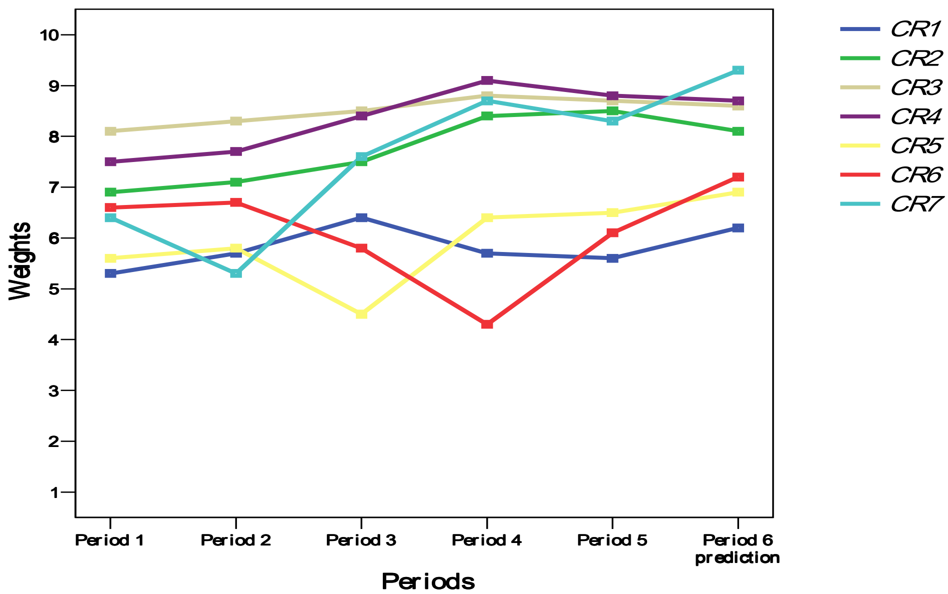

Figure 4. Dynamic trend prediction of the CRs.

The future rank decision of each TR to satisfy CRs was analysed in Table 10. According to the TR sequence of grey relational grade of the period 6 prediction, TR4, TR3 and TR9 should be closely noticed since they have front sequence and could become the most important technical requirements to satisfy CRs in the future. By contrast, TR7 has a back sequence and could become the least important technical requirement in the future. For designers and manufacturers, different sequence of TRs should be considered differently for green product design for life cycle assessment-oriented green supply chain.

In addition, the hybrid mining and predicting system emphasizes the dataset information by repeating interaction activities. Since CRs can change rapidly, the database of CRs must be updated continually; therefore, the quadratic exponential smoothing model and grey relational analysis for mining and predicting dynamic trends, proposed in this study, will continually update the database and continually identify the dynamic CRs and TRs trends for the designers and manufacturers. These revised TRs will exactly satisfy with CRs, allowing the designers and manufacturers to the latest CRs, thus facilitating advanced green product design for life cycle assessment-oriented green supply chain.

4 Conclusions

Green products can reduce the environmental burden during raw materials, product manufacture, logistics, transportation/distribution, marketing, usage, and final disposition. The LCA is the most approved technique to evaluate the environmental profile of a green product design. Furthermore, the satisfaction of customer requirements is crucial issue for the designers and manufacturers in company, because product design is a high risk and value-added challenges.

In addition, data mining has also been successfully applied in many fields. However, little research has been established a hybrid mining and predicting system for life cycle assessment-oriented green supply chain in the QFD of mining the dynamic trends of CRs and TRs. This study proposed a hybrid system to use quadratic exponential smoothing model and grey relational analysis for mining and predicting dynamic trends for life cycle assessment-oriented green supply chain. By applying the proposed system, the dynamic trends of CRs and TRs of green product in green supply chain can be found from a large database.

The proposed system to mine and predict dynamic trends is advantageous because it can (1) find the future trends of CRs and TRs; (2) arrange limited company resources with well information in advance; (3) provide the designers and manufacturers with TRs reference points to satisfy CRs in advance. Since CRs can change rapidly, the database of CRs must be updated continually; therefore, the proposed system in this study will continually mine the database and predict the dynamic trends for the designers and manufacturers. The results of this study can provide an effective and systematic procedure of mining and predicting the dynamic trends of CRs and TRs for life cycle assessment-oriented green supply chain to enhance green competitiveness in the global marketplace.

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