An Empirical Study of Constructing a Dynamic Mining and Forecasting System for the Life Cycle Assessment-based Green Supply Chain

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Abstract: - Green products – products that can reduce the load on the environment during design and disposal – have additional marketing appeal. The most approved technique to evaluate the environmental profile of a green product is the life cycle assessment. An approach of using double exponential smoothing-based data mining in quality function deployment was proposed to forecast dynamic and future customer requirements and engineering characteristics for the life cycle assessment-based green supply chain. With the use of the proposed approach, the importance and the trend of every future customer requirement and engineering characteristic are monitored and evaluated in order to meet dynamic and future customer needs. An empirical example is provided to demonstrate the applicability of the proposed approach. Doing so would allow the designers and manufacturers to plan customer requirements and engineering characteristics in advance, fulfil their needs, and most significantly improve customer satisfaction and enhance green competitiveness in the global marketplace.

Key-Words: - Dynamic forecasting system, Life cycle assessment, Green supply chain, Double exponential smoothing-based data mining.

1 Introduction

Green products that can reduce environment pollution during design and disposal have additional marketing competitiveness. Recycling of materials, and enough reuse of subassemblies can greatly reduce waste generation, thus increasing product green compatibility in the global marketplace. However, most green products are not valuable in the market as expected since those products are focused entirely on environmental impact analysis without regarding to the customer requirements (CRs), so the environmental impact analysis of green products is also a critical issue for the designers and manufacturers [7, 33, 34].

Many product designers and manufacturers may face many uncertainties, conflicting objectives and cost effectives, because changing design procedures are particularly difficult. Rarely in one product greener in every dimension than other products; there are usually tradeoffs among features [34]. Therefore, when considering green design, designers and manufacturers should incorporate the voices from the customers because they are the driving force.

Zust and Wagner [29] defined four phases 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).

Past researches have been studied in disassembly sequences analysis, recycling analysis and disassembling planning [12, 31, 34]. Also, the most approved methodology to evaluate the environmental profile for green product is the life cycle assessment (LCA) but other AI techniques, such as agent based modeling, may be used like in [13]. Many green products are produced and evaluated according to the LCA evaluation. However, those green products are focused totally on environmental impact analysis without regarding to the customer requirements, so most green products are not valuable in the market as expected. Even though they understand buying the green products could reduce the environmental impacts, these customers might be not interesting to buy those green products [33].

Many green products based product life cycle are evaluated and produced by performing the LCA framework. Within the LCA framework, the greatest challenge is the assessment of the impacts associated with environmental releases during the manufacturing, transportation, use and disposal of products. Therefore, when considering green design, designers and manufacturers should incorporate the voices from the customers [3, 30, 36].

On the other hand, 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 patterns or rules [10, 25]. The application domain of data mining is quite broad and plausible in semiconductor manufacturing [8], surface roughness prediction [9], production schedule [11], human resource management [18], risk prediction [22], marketing [23], domain ontologies [26], biomedical technology [29], health insurance [35], customer lifetime value [4] and others [10, 13, 25, 27]. However, little research has been applied to forecast dynamic and future customer requirements for the life cycle assessment-based green supply chain of green product using data mining.

This study applied a proposed approach of using double exponential smoothing-based data mining in QFD to forecast dynamic and future customer requirements and engineering characteristics (ECs). By applying the proposed approach, the future trends of customer requirements and engineering characteristics of green products can be found from a large marketing database to enhance green competitiveness.

This proposed approach helps designers and manufacturers reduce the use of material, energy, money, work force, etc., and the greatest impact is to drastically shorten the cycle time of product design and production. In the early phases, the voices from the customers are actually listened and responded by the best alternative in the drawing board such that green compatibility can be considered.

2 Related Research

2.1 Quality function deployment

Quality Function Deployment (QFD) was first introduced by Akao in 1972 at Mitsubishi's Kobe shipyard site, and then Toyota and its suppliers developed it further for a rust prevention study [15]. QFD is a Japanese development and design technology [20]. After the concept of QFD was introduced in the US through car manufacturers and parts suppliers [24], many US companies, such as Raychem, Procter & Gamble, Hewlett-Packard, Ford, GM, Digital Equipment and AT&T, applied QFD to improve communication, product design and development [1, 2].

Some companies have claimed great success with QFD. Proponents assert that QFD has helped them reduce production costs, design time and cost; increase product quality and customer satisfaction [2, 32]. QFD has been widely applied to achieve customer requirements and improve customer satisfaction in many fields [21]. Some researchers defined QFD as follows: "This technology focuses and coordinates skills within an organization, first to design, then to manufacture and market products that customers want to purchase and will continue to purchase" [10].

QFD is a cross-functional planning tool which is used to ensure that the voice of the customer is deployed throughout the product planning and design stages. QFD is used to encourage breakthrough thinking of new concepts and technology. Its use facilitates the process of concurrent engineering and encourages teamwork to work towards a common goal of ensuring customer satisfaction.

A House of Quality (HOQ) is not QFD, it is just a tool. The House of Quality converts each customer requirement into one or more engineering characteristics in the first phase of QFD, because the voice of the customer is essential, The main goal of HOQ is to identify customer requirements and weights for the product (WHATs) and then to convert these needs into engineering characteristics (HOWs). In addition, the same technique can extend the method into the constituent product subsystems, configuration items, assemblies, parts and service deployments. From these detail level components, these process QFD charts can be developed to support statistical process control techniques [5, 6]. The components of HOQ are shown in Figure 1.

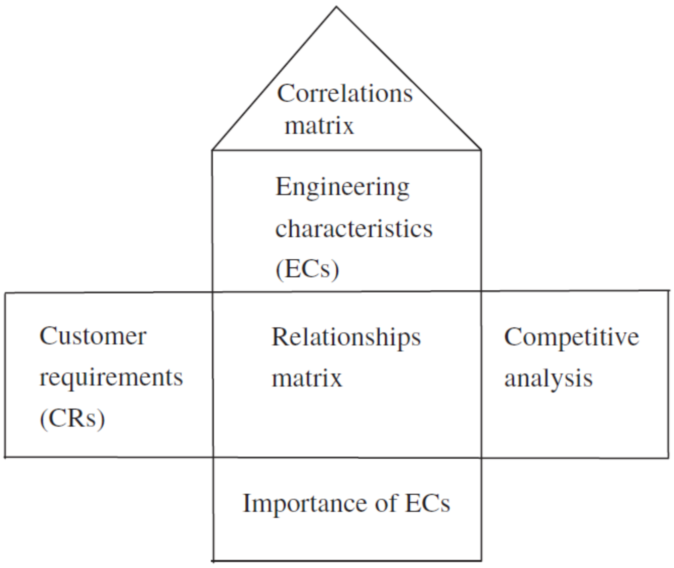

Fig. 1 The components of house of quality (HOQ).

2.2 Life Cycle Assessment

Keys [22] explained that various design models of the product are generated during the conceptual model phase. From these conceptual models, requirements, and specifications will evolve decisions for breadboard and brassbound models.

Zust and Wagner [29] explained four phases of the product life cycle: (1) product definition, (2) product development, (3) product manufacturing and marketing, and (4) product usage. At each of these phases, there exists a definition of objectives, activities, and deliverables for the next phase. The greatest challenge is the assessment of the impacts associated with environmental releases during the manufacturing, transportation, use and disposal of products within the LCA framework. Also, the Hewlett-Packard addressed the life-cycle issue by prototyping software, defining development and phases, and standardizing modules and packages [33].

3 Data Mining and Time Series analysis

In order to identify significant patterns or rules [10, 25], Berry and Linoff defined data mining as the analysis of huge amounts of data by automatic or semi-automatic means. Furthermore, time series analysis is one of the most important data mining techniques. Time series data often arise when monitoring tracking corporate business metrics or industrial processes [27].

It can be used to accomplish different goals by applying time series analysis:

(1). By plotting or using more complex techniques, descriptive analysis determines what trends and patterns a time series has.

(2). Explanative analysis using one or more variable time series, a mechanism that results in a dependent time series can be estimated [16].

(3). Forecasting can do 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.

(4). Intervention analysis can explain if there is a certain event that occurs that changes a time series. This technique is used a lot of the time in planned experimental analysis.

(5). Spectral analysis is carried out to describe how variation in a time series may be accounted for by cyclic components. This may also be referred to as "Frequency Domain". With this an estimate of the spectrum over a range of frequencies can be obtained and periodic components in a noisy environment can be separated out [28].

The double exponential smoothing is the most important trend forecasting technique for time series analysis when there is a trend in the data mining, because simple exponential smoothing does not do well. Double 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. Double exponential smoothing is designed to address this type of data series by taking into account any trend in the data.

There are some equations associated with double exponential smoothing that showed as follow.

$$s_o = x_o \tag{1}$$

$$s_t = \alpha \times x_t + (1-\alpha) \times F_t \tag{2}$$

$$b_t = \beta \times (s_t - s_{t-1}) + (1-\beta) \times b_{t-1} \tag{3}$$

$$F_{t+m} = s_t + m \times b_t \tag{4}$$

The raw data of observations sequence is represented by $\{x_t\}$, beginning at time $t = 0$. We use $\{s_t\}$ to represent the smoothed value for time t, and $\{b_t\}$ is best estimate of the trend at time t. The output of the algorithm is written as F_{t+m}, an estimate of the value of x at time $t+m$, $m>0$ based on the raw data up to time t. Double exponential smoothing is given by the formulas. where α is the *data smoothing factor*, $0 < \alpha < 1$, β is the *trend smoothing factor*, $0 < \beta < 1$, and b_0 is taken as $(x_{n-1} - x_0)/(n - 1)$ for some $n > 1$, thus further values can be evaluated [16, 17, 28]. The higher the value of alpha the more weight is given to current values [17].

The application domain of data mining is quite broad in many fields. However, little research has been applied to forecast dynamic and future customer requirements and engineering characteristics for the life cycle assessment-based green supply chain of green product. This study applied a proposed approach of using double exponential smoothing-based data mining in QFD to forecast dynamic and future customer requirements and engineering characteristics. By applying the proposed approach, the future trends of customer requirements and engineering characteristics of green products can be found from a large marketing database to enhance green competitiveness.

4 An Empirical Example

This study uses data mining cycle to identify the future trends of customer requirements and engineering characteristics 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 [10, 25]. The previous steps can be served as the baseline reference for the next steps, and the steps for the dynamic trend forecasting of LCA-based green supply chain are described as follow.

4.1 Defining the problem for data mining

A large marketing database was created by a professional notebook computer manufacturer in Taiwan owing to unknown weights for future customer requirements. This resulted in a huge amount of data continuously based on many customer questionnaires.

The intent of this study was to explore and analyze a huge amount of data, by employing a double exponential smoothing-based data mining cycle in QFD, so as to identify the weights within customer questionnaires in each period. Based on these the weights of customer requirements, the dynamic trend forecasting of future customer requirements and engineering characteristic may be discovered for the life cycle assessment-based green supply chain of green product, so the results and discoveries can be beneficial and encouraged the computer designers and manufacturers.

4.2 Data preparation and analysis for data mining

The data was processed, and analyzed in order to enhance the efficiency and ensure the accuracy of the results. It had to be checked and processed before mining the data, with all abnormal or missing data being separated out [19]. As a result, of the 18,000 questionnaires, 363, which had missing or abnormal data, were deleted. Also, the green QFD matrix for the notebook computer is shown in Figure 2. There are nine customer requirements for each customer questionnaire and ten engineering characteristics for the life cycle assessment-based green supply chain of notebook computer as shown in Table 1 and Table 2.

		Product Life Cycle-based Green Supply Chain									
		Raw Material		**Manufact uring**		**Disassem-bly**		**Transpor-tation**	**Usage**		**Disposal**
	Weights	**EC1**	**EC2**	**EC3**	**EC4**	**EC5**	**EC6**	**EC7**	**EC8**	**EC9**	**EC10**
CR1			**3**			**9**	**3**		**9**	**1**	**1**
CR2		**9**		**3**	**9**	**9**	**1**	**9**	**3**	**9**	**9**
CR3		**3**		**1**	**9**	**9**		**3**	**9**	**9**	**1**
CR4		**1**			**3**	**9**	**3**		**1**	**3**	**3**
CR5		**3**	**1**	**1**	**3**	**3**	**9**		**3**	**9**	**9**
CR6		**1**	**9**	**9**		**1**	**1**			**9**	**3**
CR7		**3**			**1**		**1**	**3**	**9**	**3**	**3**
CR8						**1**	**3**		**3**	**3**	
CR9		**9**			**3**	**1**	**1**	**1**	**9**	**3**	**9**
Importance of EC											

Fig. 2 The green QFD matrix for the notebook computer.

Table 1 The definitions of customer requirements (CRs)

Voice of customer	Customer Requirements
CR1	**Price or cost**
CR2	**Operating quality**
CR3	**Size or weight**
CR4	**No toxical material released**
CR5	**Easily disassembly**
CR6	**Easily maintenance**
CR7	**Energy saving**
CR8	**Recyclable**
CR9	**Speed**

Table 2 The definitions of design requirements

		Voice of Engineering	Engineering Characteristics
Life Cycle Assessment-based Green Supply Chain	Raw Material	EC1	Material reduction
		EC2	No dangerous material
	Manufacturing	EC3	Pollution control
		EC4	Low energy exhausting
	Disassembly	EC5	Modularization
		EC6	Tools usage
	Transportation	EC7	Package reduction
	Usage	EC8	Energy saving
		EC9	Maintenance
	Disposal	EC10	Reuse or recycle

4.3 Data mining by time series analysis

Next we want to list the weights for the customer requirements. To determine the weights this study would do a survey of the target market. The survey asked computer customers to rank the importance of the defined customer requirements on a 1-10 scale – with 10 being a very important requirement. The averages of those results are then listed in Table 3.

It is essential to reflect customer requirements for the designers and manufacturers by corporate language and then fulfil those engineering characteristics to satisfy customer requirements. The designers and manufacturers have to check the relationship between WHATs and HOWs, when customer requirements are translated by HOWs. The weights of four periods for each customer requirement are periodically mined in Table 3.

Table 3 The weights of customer requirements (CRs)

	Period 1	Period 2	Period 3	Period 4
CR1	6.9	6.4	5.7	5.2
CR2	5.5	5.8	6.3	7.1
CR3	5.8	6.5	6.2	6.8
CR4	4.9	5.8	6.9	7.6
CR5	5.3	5.2	5.4	5.1
CR6	7.2	7.5	7.8	7.6
CR7	6.5	6.8	7.4	8.2
CR8	5.8	6.2	6.4	6.6
CR9	5.7	6.2	6.7	6.4

QFD represent the respective weak relationship (with a weight of 1), moderate (with a weight of 3), and strong (with a weight of 9) while the blank is zero [20, 24]. Taking period 1 as an example, the matrix relationship between customer requirements and engineering characteristics is shown in Table 4.

Table 4 The HOQ of period 1

	Weights	EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10
CR1	**6.9**	**9**	**3**	**1**	**3**	**3**	**1**	**3**	**9**	**3**	**3**
CR2	**5.5**				**1**	**1**	**3**		**3**	**9**	
CR3	**5.8**	**3**	**1**	**1**		**9**	**1**	**3**	**3**	**3**	**3**
CR4	**4.9**	**3**	**9**	**9**	**1**	**1**	**1**	**3**	**3**	**3**	**9**
CR5	**5.3**	**1**			**3**	**9**	**9**		**1**	**9**	**9**
CR6	**7.2**	**3**		**1**	**3**	**9**	**9**		**9**	**9**	**3**
CR7	**6.5**	**3**		**1**	**9**	**9**		**3**	**9**	**9**	**1**
CR8	**5.8**	**9**	**1**	**9**	**3**	**9**	**3**	**3**	**9**	**9**	**9**
CR9	**5.7**		**3**	**1**	**1**				**3**	**3**	**1**
Importance of EC		**192.8**	**93.5**	**128.4**	**150.2**	**306.5**	**164**	**89.7**	**308.6**	**342.6**	**215.9**

The matrix relationship between customer requirements and engineering characteristics were determined through checking the relationship between WHATs and HOWs. Subsequently, data mining was undertaken, using double exponential smoothing-based data mining cycle, to mine the weights and determine the trend of each customer requirement for the next period.

The predicted weights of customer requirements in the next period (period 5) would be estimated according to the data mining cycle as shown in Table 5. As shown, the weight of CR1 in the period 5 is 5.0; thus, these predicted weights of the customer requirements were chosen for the next stage of processing.

Table 5 Predicted weights for the customer requirements in the period 5

	Period 1	Period 2	Period 3	Period 4	Period 5 predicted weights
CR1	**6.9**	**6.4**	**5.7**	**5.2**	**5.0**
CR2	**5.5**	**5.8**	**6.3**	**7.1**	**7.7**
CR3	**5.8**	**6.5**	**6.2**	**6.8**	**6.9**
CR4	**4.9**	**5.8**	**6.9**	**7.6**	**7.9**
CR5	**5.3**	**5.2**	**5.4**	**5.1**	**5.3**
CR6	**7.2**	**7.5**	**7.8**	**7.6**	**7.4**
CR7	**6.5**	**6.8**	**7.4**	**8.2**	**8.6**

CR8	**5.8**	**6.2**	**6.4**	**6.6**	**7.1**
CR9	**5.7**	**6.2**	**6.7**	**6.4**	**6.3**

4.4 Evaluation and Application of Results

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 mean squared error is the average of the squared forecast errors. Forecast error is defined as the difference between actual value and the forecast. The MSE equation is shown as follow.

$$MSE = \sum_{i=1}^{n} \left(A_i - F_i\right)^2 \Big/ n-1 \qquad (5)$$

Taking the CR1 as an example, the mean squared error is 1.7. 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 tracking signal, and let fix the upper limit at 2.61 and the lower limit at -2.61: 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 customer requirements are less than the double control limit. Thus, the double exponential smoothing analysis is clearly quite accurate.

To gain a better insight into the predicted weights among the nine customer requirements resulting from the double exponential smoothing-based data mining cycle, a bar chart was drawn of the weights of the customer requirements. As can be seen in Figure 3, the weights of customer requirements bear marked differences for each period. The trend for each customer requirement can be understood and controlled by the designers and manufacturers with the well information. The weight trend of each customer requirement can be considered to know the future trends of customer requirements. The designers and manufacturers can design and plan green computer to satisfy with future customer requirements in advance.

This study used double exponential smoothing-based data mining cycle in QFD to predict the weights and determine the trends of customer requirements and engineering characteristics. In addition, the time series-based data mining cycle can be applied to predict the weights and determine the trend of each customer requirement for the next period. The use of time series-based data mining cycle to predict the weights is advantageous because it can (1) find the future trends of customer requirements and engineering characteristics; (2) provide the designers and manufacturers with reference points to satisfy customer requirements and engineering characteristics in advance.

The results of this study can provide an effective procedure of identifying the trends of customer requirements and engineering characteristics. Furthermore, it enhances customer relationship management in the notebook computer marketplace.

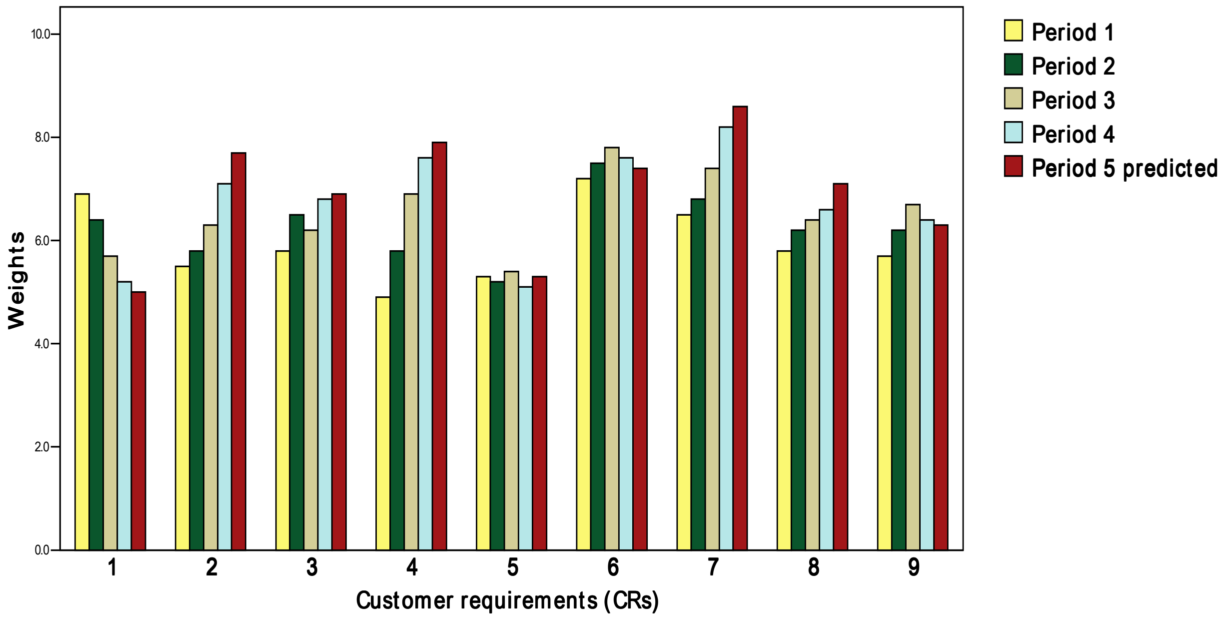

Fig. 3 Dynamic trend forecasting of the nine customer requirements (CRs).

In addition, the future trends of engineering characteristics to satisfy future customer requirements can be analysed in Table 6. According to the future trend of each engineering characteristic, many engineering characteristics should be closely noticed since its importance has increased and could become the most important engineering characteristics to satisfy customer requirements in the future. Different engineering characteristics should be considered differently for the computer designers and manufacturers with the more information.

Table 6 Dynamic trend forecasting of the ten engineering characteristics (ECs)

	EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10
Period 1	**192.8**	**93.5**	**128.4**	**150.2**	**306.5**	**164**	**89.7**	**308.6**	**342.6**	**215.9**
Period 2	**198.4**	**102.7**	**141.4**	**154.9**	**320.6**	**169**	**95.1**	**320.2**	**358.2**	**229**
Period 3	**199.2**	**111.9**	**153.5**	**162.4**	**329.1**	**175.7**	**97.8**	**329.4**	**376.2**	**241.5**
Period 4	**201.9**	**116.6**	**162**	**168.4**	**339**	**175**	**103.2**	**337.2**	**389.4**	**247.1**
Period 5 prediction	**206.6**	**119**	**169.2**	**173.7**	**348.3**	**178.5**	**106.5**	**344.6**	**403.2**	**255.5**

The double exponential smoothing-based data mining cycle in QFD emphasizes the dataset information by repeating interaction activities. Since customer requirements can change rapidly, the database of customer requirements must be updated continually; therefore, the time series-based data mining cycle, proposed in this study, will continually update the database and continually identify the future trends of customer requirements for the designers and manufacturers. These revised engineering characteristics will exactly satisfy with customer requirements, allowing the computer designers and manufacturers to the latest customer requirements, thus facilitating advanced design for green notebook computers. As future research researchers can use agent based modeling to model the supply chain domain as this techniques provided significant results in other complex domains such as financial markets [14].

5 Conclusions

Because green product design has high risk and challenge, the understanding of customer requirements becomes a critical issue for the designers and manufacturers. This study proposed an approach of using double exponential smoothing-based data mining cycle in QFD to forecast dynamic and future customer requirements for the LCA-based green supply chain. An empirical example is provided to demonstrate the application of the proposed approach. The use of proposed approach to predict the weights is advantageous because it can (1) find the future trends of customer requirements and engineering characteristics for green product design; (2) provide the designers and manufacturers with engineering characteristics reference points for green product design to satisfy customer requirements in advance.

Furthermore, double exponential smoothing is a powerful technique for tracking the trends. This paper uses double exponential smoothing-based data mining cycle in QFD to analyse customer dynamic and future requirements instead of using static and present customer requirements. Obviously, understanding dynamic and future engineering characteristics, developing a green product that meets or exceeds customer requirements, and even preparing customers in advance could significantly improve customer satisfaction and enhance a company's green competitiveness in the marketplace.

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