APPROXIMATE LIFE CYCLE ASSESSMENT OF DESIGN CONCEPTS FOR PRODUCT GROUPS

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ABSTRACT

Many companies are beginning to change the way they develop products due to increasing awareness of green product development. To copy with this trend, designers are being asked to incorporate environmental criteria into the design process. Recently Life Cycle Assessment (LCA) is used to support the decision-making for product design and the best alternative can be selected based on its estimated LCA and benefits. Both the lack of detailed information and time for a full LCA for a various range of design concepts need the new approach for the environmental analysis. This paper explores an approximate LCA of design concepts for product groups according to their environmental characteristics. An artificial neural network approach is developed to estimate an approximate LCA for classified products with product attributes and environmental impact index identified in this paper.

KEYWORDS: design concept, product group, artificial neural networks

INTRODUCTION

The ability of a company to compete effectively on the increasingly competitive global market is influenced to a large extent by the cost as well as the quality of its products and the ability to bring products onto the market in a timely manner. Traditionally, manufacturers focus on how to reduce the cost the company spends for materials acquisition, production, and logistics, but due to widespread consciousness of global environment problems and environmental legislative measures, companies also should take environmental considerations into their decision making process of product development. These trends are driving many companies to consider environmental assessment during product development. Product designers are challenged with questions of what and how to consider environmental issues in relation to the products they are developing. In particular, it is quite relevant to understand how design changes can affect the environmental performance of product concepts in the early design process.

Life Cycle Assessment (LCA) is now the most sophisticated tools to consider and quantify the consumption of resources and the environmental impacts associated with a product or process. By considering the entire life cycle and the associated environmental burdens, LCA identifies opportunities to improve environmental performance. Conceptually, a detailed LCA is an extremely useful method, but it may be rather costly, time consuming and sometimes difficult to communicate with non-environmental experts. Further the use of
LCA poses some barriers at the conceptual stage of product development, where ideas are diverse and numerous, details are very scarce, and the environmental data for the assessment is short. This is unfortunate because the early phases of the design process are widely believed to be the most influential in defining the LCA of products. Therefore, a new methodology for estimating the environmental impacts of products is required in early design phase.

This paper explores an approximate LCA for products in early conceptual design phase by classifying products into groups according to their environmental and product characteristics. Artificial neural networks (ANNs) and statistical analysis is applied to the proposed approach. The statistical analysis is used to check the correlation between product attributes and environmental impact drivers (EIDs) derived from environmental impact categories (Goedkoop et al., 1999). An ANN is trained on product attributes typically known in the conceptual phase and the LCA data from pre-existing detailed LCA studies.

THE PRODUCT GROUPING METHOD

The purpose is to develop a product grouping method that supports the appropriately specialized approximate LCA models based on ANNs. The method may learn faster and more effectively if the learning space is narrowed into general but coherent product categories. The categorization should be based on properties that potentially create common dominant environmental impacts or similar scaling trends so that the proposed models are better able to emulate impacts of specific products within the group.

Products have been classified in several different ways (Hartmut and Virginia, 2000; Park et al., 2001; Sousa et al., 2000). Different perspectives on what a product is and the purpose of the classification lead to distinct methods. A total of 150 products including various types of electronic appliances, vehicles and other goods were collected and evaluated. The methods are briefly described as follows:

The first classification attempt was done by ranking the impact indicators of the life cycle phases. Using the actual LCA results from pre-existing LCA studies, three major clusters were recognized.

1) Group 1: The impact indicator of material phase provides the dominant indicator.
2) Group 2: The impact indicator of usage phase represents more than 50% of the total impact.
3) Group 3: The material and usage phase are equally weighty.

The second grouping attempt was made by grouping the products according to the top impact indicator classes. All the products were grouped into 5 groups, which are the greenhouse effect, acidification, winter/summer smog, eutrophication and ozone depletion categories.

The third clustering attempt (Sousa et al., 2000) provided a basis for a product classification
according to functional properties. Group criteria used for this classification focused on a product’s use phase, and product attributes that are a potential cause for dominant environmental impacts. The product groups by product categories of potential classification are shown as below.

1) Group 1: In use energy conversion - Product does or does not transform energy when in use.
2) Group 2: In use mobility - Product is or is not mobile or transported when in use.
3) Group 3: Durability - Product is durable or consumable.
4) Group 4: Service system - Product is or is not designed as a service.

The fourth classification attempt was performed by applying hierarchical grouping analysis which uses multiple variables that are characteristics of associations between these variables. The variables are product attributes which are related to environmental categories. The grouping results give 2 major groups.

1) Group 1: The environmental impact at the usage phase is intensive.
2) Group 2: The impact in the material phase is intensive.

AN APPROXIMATE LIFE CYCLE ASSESSMETN FOR PRODUCT GROUPS

In this section, the reasonable EIDs and the meaningful product attributes are introduced and identified in product groups. The EIDs stand for environmental impact categories and the product attributes are meaningful to designers during conceptual design. The approximate LCA of group members is performed by artificial neural networks with product attributes as inputs and EIDs as outputs.

Environmental Impact Drivers (EIDs) and Product Attributes

In order to estimate the environmental impact of products for the entire life cycle, environmental impact drivers (EIDs) are introduced in this section. EIDs represent the key environmental characteristics that determine the environmental impact of products and must have a good correlation with the total environmental impact of the products. EIDs eventually mean the environmental impact categories such as greenhouse effect, acidification, winter/summer smog, eutrophication, ozone depletion, solid material and energy, which were identified by the test of confidence interval or hypothesis between the full and abbreviated LCI data (Sousa et al., 2000). The estimating results of LCA are provided by ANNs and it gives the process for testing the validity of the abbreviated LCI. These EIDs are to be identified for each product group, and then be used as the basis for an approximate LCA of all group members.

In order to estimate the environmental impact, the suitable EIDs are introduced and identified in product groups. If the first clustering method in section 3 were used as the basis, the three groups would be the beginning. For example, EIDs for group 1 would have
to be material based and for group 2 energy based. In this section, energy that is the one of environmental impact categories is shown as an example to identify the EIDs and product attributes. For group 2, a suitable EID was energy, noted EID$_{energy}$. The EID$_{energy}$ is a function of product attributes in this group as follows.

$$EID_{energy} = f (x_1, x_2, x_3, x_4, x_5)$$

(1)

where $x_1$ is lifetime,

$x_2$ is use time,

$x_3$ is mode of operation,

$x_4$ is in use energy source,

and $x_5$ is in use power consumption.

The product attributes need to be both logically and statistically linked to EID$_{energy}$ and also be readily available during the conceptual design phase of products. Design checklists and design improvement strategies (Brezet and Hemel, 1997; Clark and Charter, 1999) provided a starting point for product attributes and other research works were also reviewed. After candidate product attributes are selected, they were grouped for organizational purposes and reviewed for conceptual linkages to the EID$_{energy}$. The product attributes are chosen, by potentially identifying strong relationships between candidate product attributes and the EID$_{energy}$. Conceptual relationships between attributes and EID$_{energy}$ are induced by the quality function deployment (QFD) (ReVelle and Moran, 1998). The correlation analysis shows that the selected product attributes are strongly correlated with the EID$_{energy}$ as expected. The multiple regression analysis with candidate attributes and EID$_{energy}$ were then performed. The analysis result was shown in table 1.

<table>
<thead>
<tr>
<th>Table 1. The results of multiple regression analysis between 5 parameters and EID$_{energy}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Statistics of regression analysis</strong></td>
</tr>
<tr>
<td>multiple coefficient 0.99</td>
</tr>
<tr>
<td>R-squared 0.99</td>
</tr>
<tr>
<td>adjusted R-squared 0.99</td>
</tr>
<tr>
<td>Obs 30</td>
</tr>
<tr>
<td><strong>ANOVA Table</strong></td>
</tr>
<tr>
<td>Source            DF</td>
</tr>
<tr>
<td>Model       5</td>
</tr>
<tr>
<td>Error        24</td>
</tr>
<tr>
<td>Total        29</td>
</tr>
</tbody>
</table>

In table 1, the multiple regression analysis shows a very good correlation of $R^2 = 0.99$ for all products in group 2. In addition, the linear regression equation provided a model that
accounted for 95% of the variability in the estimation for LCA of products. The F value (1234.31) of this multiple regression model is larger than that of F (5, 24, α=0.05) by analysis of the variance. Given the value of the F test statistics, it can be concluded that the coefficients of the model are not equal to zero and the coefficients of the model are significant.

We can repeat the same procedure for defining the other EIDs and product attributes. For example, when a new EID of impact category for green house effect, noted EID_{greenhouse}, is introduced in the second clustering attempt and the correlation between EID_{greenhouse} and product attributes is checked.

It is possible to group products into groups by product and environmental characteristics. In addition, the reasonable EIDs of product groups and product attributes related with EIDs can be identified.

An Approximate LCA of Classified Products using Artificial Neural Networks

In this section, an approximate LCA for the grouping members is performed by ANNs. The identified products attributes in group 2 are used to input of an ANN model and EIDs represented impact categories are used to output. The architecture for a backpropagation (BP) neural network is developed to estimate the results of LCA. The structure of the BP neural network consists of an input layer with 5 nodes (x₁, x₂, x₃, x₄ and x₅), a hidden layer with 10 and 15 nodes and an output layer with one node (EID_{energy}) as shown in figure 1. Training data with product attributes and corresponding energy were gathered for 40 products in the group.

Figure 1. Structure of the BP neural network to estimate the product LCA

The estimated results of group members are shown in Table 2. The approximate LCA using
ANNs with the identified EIDs and product attributes gives good results except for heater. It is shown that a grouping of products is possible and reasonable for the use of LCA of the group members. The identified EIDs and product attributes can be used to estimate the product’s environmental impact of group elements.

Table 2. The estimated results of group members by using ANN

<table>
<thead>
<tr>
<th>Product</th>
<th>Actual LCA</th>
<th>Predicted LCA</th>
<th>Relative error (%)</th>
<th>Predicted LCA</th>
<th>Relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1 hidden layer</td>
<td></td>
<td>1 hidden layer</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>with 10 neurons</td>
<td></td>
<td>with 15 neurons</td>
<td></td>
</tr>
<tr>
<td>Vacuum cleaner</td>
<td>5110</td>
<td>3910.68</td>
<td>23.47</td>
<td>3846.30</td>
<td>24.73</td>
</tr>
<tr>
<td>Mini-Vacuum Cleaner</td>
<td>176</td>
<td>130.70</td>
<td>25.74</td>
<td>126.30</td>
<td>28.24</td>
</tr>
<tr>
<td>Radio</td>
<td>207</td>
<td>182.68</td>
<td>11.75</td>
<td>185.43</td>
<td>10.42</td>
</tr>
<tr>
<td>Heater</td>
<td>24800</td>
<td>35498.72</td>
<td>-43.14</td>
<td>36014.56</td>
<td>-45.22</td>
</tr>
<tr>
<td>Coffeemaker</td>
<td>3980</td>
<td>4604.86</td>
<td>-15.7</td>
<td>3995.12</td>
<td>-0.38</td>
</tr>
<tr>
<td>Washing Machine</td>
<td>54500</td>
<td>54036.75</td>
<td>0.85</td>
<td>53786.05</td>
<td>1.31</td>
</tr>
<tr>
<td>Refrigerator (small)</td>
<td>2686.19</td>
<td>2431.54</td>
<td>9.48</td>
<td>2475.06</td>
<td>7.86</td>
</tr>
<tr>
<td>Refrigerator (large)</td>
<td>18777.79</td>
<td>20165.47</td>
<td>-7.39</td>
<td>18496.12</td>
<td>1.5</td>
</tr>
<tr>
<td>TV</td>
<td>24320.37</td>
<td>24325.23</td>
<td>-0.02</td>
<td>23653.99</td>
<td>2.74</td>
</tr>
<tr>
<td>LCD TV</td>
<td>24813.73</td>
<td>25324.89</td>
<td>-2.06</td>
<td>24625.15</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Average absolute error 13.96 12.32
Maximum absolute error 43.14 45.22

* Training sample size is 30, ** Test sample size is 10

CONCLUSIONS AND FUTURE WORKS

The lack of analytic LCA for early conceptual design stage motivated the development of this estimation method. This paper proposed the possibility of the approximate LCA for the conceptual design phase by classifying products into groups according to their environmental and product characteristics. Different grouping criteria and clustering approaches were discussed. It was shown that it is possible to estimate environmental impacts of the products group. Additionally, the identified EIDs and product attributes can be used to estimate the product’s environmental impact. Then a neural network approach with product attributes as inputs and impact categories as outputs was developed to estimate the results of LCA of grouping members and the estimated results seemed to be satisfactory. The estimation method by EID_{energy} gave good results for the estimation of the results of LCA. The proposed approach does not replace a full LCA but designers can use this guideline to optimize their effort and guide their decisions at the conceptual design phase of environmentally conscious product design.

In future, the identification of EIDs will be refined and the various grouping criteria be developed. The various product attributes are also introduced.
REFERENCES


