Approximate Life Cycle Assessment of Product Concepts Using Multiple Regression Analysis and Artificial Neural Networks

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In the early phases of the product life cycle, Life Cycle Assessment (LCA) is recently used to support the decision-making for the product concepts, 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 a new approach for the environmental analysis. This paper explores a new approximate LCA methodology for the product concepts by grouping products according to their environmental characteristics and by mapping product attributes into environmental impact driver (EID) index. The relationship is statistically verified by exploring the correlation between total impact indicator and energy impact category. Then, a neural network approach is developed to predict an approximate LCA of grouping products in conceptual design. Trained learning algorithms for the known characteristics of existing products will quickly give the result of LCA for newly designed products. The training is generalized by using product attributes for an EID in a group as well as another product attributes for the other EIDs in other groups. The neural network model with back propagation algorithm is used, and the results are compared with those of multiple regression analysis. The proposed approach does not replace the full LCA but it would give some useful guidelines for the design of environmentally conscious products in conceptual design phase.

Key Words : Approximate Life Cycle Assessment, Product Concepts, Environmental Impact Driver, Product Attribute, Multiple Regression Analysis, Artificial Neural Networks

1. 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. It has been recognized that the life cycle or concurrent engineering approach to the design of products has a great potential to achieve these goals. 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 such as take-back and recycling laws, manufacturers also should take environmental considerations into their decision making process of product development. The environmental impacts incurred during a product's life cycle are mostly committed by early design decisions. Therefore,

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designers are in a position to substantially reduce the environmental impacts of products. The research on design methodology for minimizing the environmental impacts of a product also becomes more important and valuable.

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 the study to develop an approximate LCA for products in early conceptual design phase by classifying products into groups according to their environmental and product characteristics. The new approach for the assessment of environmental impacts is proposed by using artificial neural networks (ANNs) and statistical analysis. 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. Multiple regression analysis is performed by using product attributes as independent variables and the LCA data as dependent variables.

The paper is organized as follows: In section 2, the proposed methodology is overviewed. The grouping approach is described in section 3. Different grouping criteria and clustering approaches are discussed. In section 4, the EIDs and product attributes are defined and identified. The test of an approximate LCA of products in groups by using ANNs is then presented. The approximate LCA of group elements are predicted by using a multiple regression model and an ANN model in section 5. The training is generalized by using another product attributes for the other EIDs including product attributes defined for a specific EID. Finally, some conclusions and future works are described in section 6.

2. Overview of the Methodology

In this paper, the possibility of an approximate LCA is investigated by classifying products into groups according to their environmental and product characteristics. This method provides useful LCA results of products in terms of product attributes related with environmental characteristics and corresponding to a detailed LCA. The EIDs are introduced to represent the environmental characteristics of classified products in

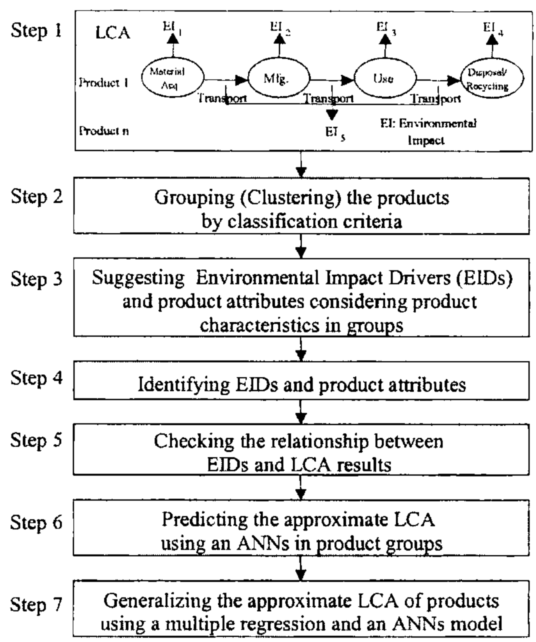

Fig. 1 Procedure of an approximate LCA of products

groups and are identified through analyzing the correlation between EIDs and product attributes. This method aims to investigate whether a reasonable grouping approach of products can be found under consideration of product characteristics and the suggested method can be used for an approximate LCA of products. The detailed procedure of an approximate LCA of products is shown in Fig. 1.

3. The Grouping Approaches

Various methods were attempted to group the products according to their environmental and product characteristics (Hartmut and Virginia, 2000 ; Park et al., 2001 ; Sousa et al., 2000). Different products were used to group by their environmental and product characteristics. 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 grouping 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 weighted.

The second clustering attempt was made by grouping the products according to the top impact indicator classes. All the products were grouped into 5 groups that 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 clustering 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 in 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.

4. Development of an Approximate LCA Method 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 using a neural training with product attributes as inputs and impact categories as outputs.

4.1 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 entire structure of predicting the result of LCA using an ANN is shown in Figure 2 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.

Frist, 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.

$$EID_{energy} = f(x_1, x_2, x_3, x_4, x_5) \quad (1)$$

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

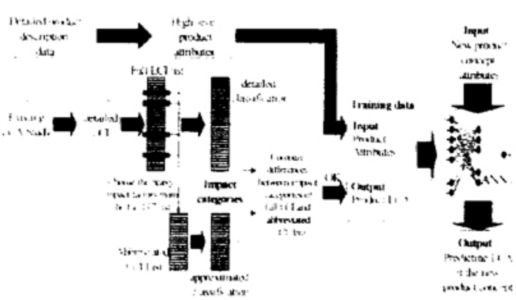

Fig. 2 The structure of training the ANN model and process for testing the validity of the abbreviated LCI

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 EIDenergy are induced by the quality function deployment (QFD) (ReVelle and Moran, 1998). The multiple regression analysis and correlation tests considering candidate attributes and EID_{energy} were then performed. The results of these analyses were shown in Table 1 and 2.

The analysis results in table 1 show that the selected product attributes are strongly correlated with the EID_{energy} as expected. Energy source and power consumption were most strongly correlated with the EID_{energy} and others were strongly correlated.

Table 1 The correlation coefficients and tests between EID_{energy} vs. x_1, x_2, x_3, x_4 and x_5

The parameters	The coefficient of correlation
x_1	0.43
x_2	−0.24
x_3	−0.27
x_4	0.83
x_5	0.99

Table 2 The results of multiple regression analysis between 5 parameters and EID_{energy}

Statistics of regression analysis	
multiple coefficient	0.99
R-squared	0.99
adjusted R-squared	0.99
Obs	30

ANOVA Table

Source	DF	Sum of Squares	Mean Squares	F value
Model	5	3.19651E+12	6.39302E+11	1234.31
Error	24	12430667565	517944481.9	
Total	29	3.20894E+12		

In table 2, 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, $\alpha=0.05$) 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.

The values of the correlation between EID_{energy} and the total impact indicator derived from a detailed LCA are shown in Table 3. The trends show a very good correlation of $R^2=0.99$ for all products in group A in Table 3. The total impacts (TI) can be calculated by equation (2). Using this equation for the estimation of total impacts of all products in the group, the good impacts can be expected.

Table 3 The results of multiple regression analysis between a detailed LCA and EID_{energy}

Statistics of regression analysis	
multiple coefficient	0.99
R-squared	0.99
adjusted R-squared	0.99
Obs	30

ANOVA Table

Source	DF	Sum of Squares	Mean Squares	F value
Model	1	6.02304E+12	6.02304E+12	108796.33
Error	28	1550099841	55360708.62	
Total	29	6.02459E+12		

$$TI=74.8+1.3EID_{energy} \tag{2}$$

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 clusters by considering product and environmental characteristics. In addition, the reasonable EIDs of product groups and product attributes related with EIDs can be identified.

4.2 Approximate LCA of classified products using artificial neural networks (ANNs)

In this section, the approximate LCA for the grouping members is performed by using ANNs. The identified products attributes in group 2 are used as input to an ANN model, and EIDs represented impact categories are used to output. The architecture for a backpropagation (BP)

Table 4 The predicted results of group members by using ANN

Product	Actual LCA	Predicted LCA 1 hidden layer with 10 neurons	Relative error (%)	Predicted LCA 1 hidden layer with 15 neurons	Relative error (%)
Vacuum Cleaner	5110	3910.68	23.47	3846.30	24.73
Mini-Vacuum Cleaner	176	130.70	25.74	126.30	28.24
Radio	207	182.68	11.75	185.43	10.42
Heater	24800	35498.72	−43.14	36014.56	−45.22
Coffeemaker	3980	4604.86	−15.7	3995.12	−0.38
Washing Machine	54500	54036.75	0.85	53786.05	1.31
Refrigerator (small)	2686.19	2431.54	9.48	2475.06	7.86
Refrigerator (large)	18777.79	20165.47	−7.39	18496.12	1.5
TV	24320.37	24325.23	−0.02	23653.99	2.74
LCD TV	24813.73	25324.89	−2.06	24625.15	0.76
Average absolute error			13.96		12.32
Maximum absolute error			43.14		45.22

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

neural network is developed to predict the results of LCA. The structure of the BP neural network consists of an input layer with 5 nodes (x_1, x_2, x_3, x_4 and x_5), a hidden layer with 10 and 15 nodes and an output layer with one node (EID_{energy}). Training data with product attributes and corresponding energy were gathered for 40 products of the group.

The predicted results of group members are shown in Table 4. 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 predict the product's environmental impact of group elements.

5. Generalizing an Approximate LCA of Products Using a Multiple Regression and an ANN Model

In order to estimate the environmental impacts of group elements as well as others, two methods were used to predict the results of LCA: (1) multiple linear regression analysis, and (2) ANN with BP algorithm. The inputs for the two models are all the product attributes defined previously and the output of these models is the impact driver for energy (EID_{energy}). Especially, the product attributes used in this estimation are checked by correlation test between EID_{energy} and all the product attributes defined as the variables of the other EIDs. Sampling data with product attributes and corresponding energy from past studies were collected for 150 different products.

The multiple linear regression method for predicting the results of LCA is used. The regression model is evaluated and compared with ANN models using the sampling data. The preliminary regression model for the prediction of the results of LCA is introduced.

$$y=\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4+\cdots+\beta_{21}X_{21}+\varepsilon \quad (3)$$

where y is the predicted results of LCA; X_1 is normalized mass (kg) of products; X_2 is ceramic (% mass); X_3 is fibers (% mass); X_4 is ferrous metal (% mass); X_5 is non-ferrous metal (% mass); X_6 is plastics (% mass); X_7 is paper/cardboard (% mass); X_8 is chemicals (% mass); X_9 is wood (% mass); X_{10} is other materials (% mass); X_{11} is assemblability (binary); X_{12} is the manufacturing process (dimensionless), X_{13} is the normalized lifetime; X_{14} is normalized use time; X_{15} is operation mode (dimensionless); X_{16} is additional consumable (binary); X_{17} is energy source (dimensionless); X_{18} is normalized power consumption; X_{19} is modularity (binary); X_{20} is serviceability (binary); X_{21} is disassemblability (binary) and the coefficients β_i ($i=1, 2, \cdots, 21$) represent the corresponding constant. The SAS system was used for developing the multiple regression model.

The inputs in the ANN experiments consist of 21 neurons and the output consist of one neuron used in the regression analysis. The same independent variables are used so that a direct comparison can be made with the results obtained from the regression model. More than 50 experiments were performed to determine the best combination of the learning rates (α), momentum (η), number of hidden layers, number of neurons in hidden layers, learning rules and transfer functions. The resulting network has a hidden layer with 16 neurons. The most popular learning rules, generalized delta rules and a sigmoid transfer function are used for the output node. Fig. 3

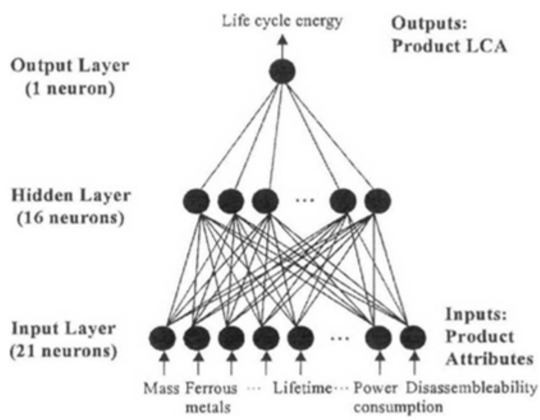

Fig. 3 Structure of the BP neural network to predict the product LCA

Table 5 Comparison of the predicted results of LCA between the multiple regression and ANN model

Product	Actual LCA	Predicted LCA		Relative error (%)	
		Regression	ANN	Regression	ANN
Vacuum Cleaner	5110	4893.85	4686.84	21.38	4.23
Mini-Vacuum Cleaner	176	129.62	122.21	26.35	5.72
Radio	207	170.94	164.53	17.42	3.75
Heater	24800	35235.84	39471.19	−42.08	−12.02
Coffeemaker	3980	4844.85	5097.76	−21.73	−5.22
Washing Machine	54500	49627.70	49682.29	8.94	−0.11
Refrigerator (small)	2686.19	3072.73	3002.98	−14.39	2.27
Refrigerator (large)	18777.79	20762.60	20507.22	−10.57	1.23
TV	24320.37	26047.12	26807.69	−7.1	−2.92
LCD TV	24813.73	24553.19	24430.42	1.05	0.5
Average absolute error				17.1	3.79
Maximum absolute error				42.08	12.02

* Training sample size is 140, ** Test sample size is 10

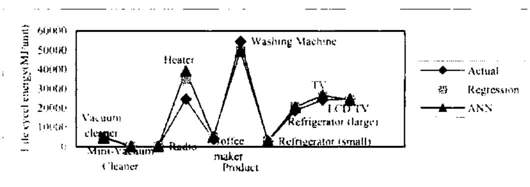

Fig. 4 Comparison results of LCA of products

shows the structure of the BP neural network used in this study, which consists of an input layer with 21 nodes, a hidden layer with 16 nodes and an output layer with one node.

The training of the BP neural network took 3,588 seconds for 150 leaning patterns on a 500 MHz Pentium III processor. When η and α were 0.6 and 0.35 respectively, the number of iteration was 60,000, and the MSE was 0.00011.

The predicted results of LCA by the regression and ANN model and the comparisons for ten products are shown in Table 5 and Fig. 4. In Table 5, it can be observed that the ANN model generally outperformed the regression model. The BP network-based model resulted in a lower average absolute error than the linear regression model. The BP neural network has also a lower maximum absolute error than the linear regression model. The absolute errors of LCA predicted by the ANN model ranged from 0.11 to 12.02 percent of the levels given by the actual LCA. During the early conceptual design stages of product development, available data are limited, so it is not easy to estimate environmental impacts of products for the entire life cycle. The accuracy of predicted energy consumption in the conceptual design phase is typically between −30% and +30% (UK Ecolabeling board, 1992), so the results obtained by this ANN model seem to be satisfactory.

To compare the performance, only the results of approximate LCA of group members are shown in Table 5. Comparing the results in Table 4 and 5, we realize that the results of Table 5 are superior to those of Table 4. These results mean that the predicted result including another product attributes defined by the other EIDs outperform that of product attributes defined by only the EID_{energy} in a group.

6. Conclusions and Future Works

The lack of analytic LCA for early conceptual design stage motivated the development of this estimation method. This paper explored the possibility of using an approximate approach of 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 predict the product's environmental impact. Then a neural network approach with product attributes as inputs and impact categories as outputs was developed to predict the results of LCA of grouping members and the predicted results seemed to be satisfactory.

Finally, the neural network model with BP algorithm was applied to predict the results of LCA for group elements as well as the others and the results were compared to those of multiple regression analysis. These methods were applied to all the product attributes identified by correlation test between EIDs and product attributes. It was found that the neural network model was superior to the regression approach. It is concluded that the predicted results including another product attributes defined by the other EIDs were better than that of product attributes only defined by EID_{energy}. Consequently, the value of proposed EID_{energy} in the group can represent the results of LCA.

The estimation method by EID_{energy} gave good results for the prediction of the results of LCA, and the approximate LCA including another product attributes for the other EIDs also could give more accurate results.

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 depicted by the product characteristics would be investigated. The various product attributes are also introduced.

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