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APPROXIMATE LIFE-CYCLE ASSESSMENT IN CONCEPTUAL PRODUCT DESIGN

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ABSTRACT

Prior work has demonstrated the integration of detailed life-cycle assessment into a traditional design modeling process. While a full life-cycle assessment provides insight into a product's potential impact on the environment, it is often too time consuming for analysis during conceptual product design, where ideas are numerous and information is scarce. The work presented in this paper explores an approximate method for preliminary life-cycle assessments without detailed modeling requirements. Learning algorithms trained on the known characteristics of existing products allow the environmental impacts of new products to be approximated quickly during conceptual design. Artificial neural networks train on product attributes and environmental impact data from pre-existing life-cycle assessment studies. The product design team queries the trained artificial model with new high-level product attribute data to quickly obtain an approximate impact assessment for a new product concept. Tests based on simplified inventory data have shown it is possible to predict impacts on life-cycle energy consumption, and that there is a basis for the method to be used in also predicting solid material, greenhouse effect, ozone layer depletion, acidification, eutrophication, winter smog, and summer smog.

Keywords: approximate life-cycle assessment, artificial neural networks, product design, integrated design.

INTRODUCTION

The detailed life-cycle assessment (LCA) of a product provides insight into a product's potential impact on the environment, yet also requires a large amount of time—so much so that it is usually too slow for many product development cycles. To increase the accessibility of LCA in product development, it is important to discover ways to maintain the rigor of the analyses while significantly reducing the modeling time required. General parametric LCA models for defined classes of products are of value for this purpose during detailed design.

Time and information availability become even more critical when LCA is used in the conceptual phase of product design. Change is rapid during this phase, detail is limited, budgets are tight, and a diverse set of solutions may be considered. General parametric LCA models are somewhat limited in this context. However, researchers state the need for LCA implementation at this design phase (Bhamra *et al.*, 1999; Fiksel, 1996; US Congress, 1992)—it is the phase of development most receptive to changes such as those indicated by LCA results. As development proceeds toward production, the product launch deadline is also approaching; deep conceptual changes will less and less likely take place to ensure meeting this deadline.

Solutions for saving LCA modeling time and expenses are divided into two categories (Linton, 1999). The first strategy is to increase the accessibility of LCA studies by compiling a

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database of published data, comprised of reliable information that may otherwise require a large investment to obtain. The second solution is simply to get 'the most bang for your buck' by conducting abridged, approximate, or streamlined LCA studies. Although the simplified methods are criticized from a scientific approach, their obvious advantage of reduced resources makes them an attractive solution (Brezet *et al.*, 1999) in conceptual product design. Later in the design process when there are fewer concepts and more product data, a more detailed LCA can be conducted.

The need for design tools that support a team-oriented, distributed, multidisciplinary design process, and assist designers in balancing complex performance tradeoffs, including environmental characteristics is widely recognized (Kitzmiller and Jagannathan, 1989). Communication, although necessary in this type of process, is often a barrier as it takes time to establish and maintain adequate synchronization of information between designers and environmental analysts. Prior work (Borland *et al.*, 1998) in the DOME (Distributed Object-based Modeling Environment) project (Abrahamson *et al.*, 2000; Pahng *et al.*, 1998) has demonstrated the effectiveness of a tool that both supports integrated environmentally conscious design and facilitates timely communication.

This paper explores a simplified LCA approach, called a learning surrogate LCA, which can work in conjunction with an integrated design process demonstrated in the work by Borland *et al.* (1998). The background section reviews prior work to support integrated environmentally conscious design and several different simplified LCA methods. Then, the paper presents the learning surrogate LCA model, preliminary tests, and obstacles to be overcome before practical application.

BACKGROUND

Integrated Design Using Traditional LCA

The push for sustainable development has changed the way companies develop products. Traditional product designers are being asked to judge the environmental impact of the products they are developing. Not only is this an additional task for the designer, but it also is not necessarily something they are qualified to do.

Although it is a good idea for product designers to have some environmental knowledge, it is not and should not be their area of expertise. Ideally, the services of an environmental expert should be extended to the designer. A computer-based method to provide such an extension has been proposed (Borland and Wallace, 1999; Borland *et al.*, 1998) to provide designers with real-time environmental impact assessment based upon LCA models. The prototype system, developed in the MIT CADLab (Computer-aided Design Laboratory), is called DOME.

DOME allows the traditional designer and the environmental expert to collaboratively work together to develop a product design. Expertise is distributed, allowing each person to concentrate on the fields they know best. After the initial exchange of information, an interface is negotiated among all involved parties.

The negotiated interface is simply an agreement as to what data will be exchanged and in what form. The designer's model likely depends on some results from the environmental expert, just as the life-cycle model requires inputs from the designer. The interface provides the opportunity for concurrent modeling while maintaining any proprietary data, models, or tools with its owner.

After the interface is defined and information is exchanged, the designer constructs an engineering model while separately, the environmental expert builds a life-cycle model. This life-cycle model may be built from scratch, by modifying an existing model, or by reusing an existing model depending on the circumstances. The complete model may be anything from a detailed LCA to a straight materials analysis. A detailed model built from scratch is obviously preferred for accuracy, but time and proprietary information may be limiting factors in building such a model.

The environmental expert will then publish his/her data as distributed objects on the Internet. The designer integrates these objects into their design and immediately gains the services of the environmental expert's life-cycle model.

The designer now has the ability to evaluate and compare the impacts of many parametric variations to the initial design. Moreover, this stage can take place completely without the environmental expert and continue only using the services already extended through the life-cycle model. For example, if the designer makes a change by adding a part, then the additional part is translated through the interface as an input to the life-cycle model, perhaps as added mass of a particular material. The designer will then obtain rapid quantitative feedback about the environmental impact of the increase in mass. Thus, a decision can be made on the importance of the added part with respect to its environmental impact.

This computer-based method has significant benefits. It is capable of supporting the distributed, multidisciplinary, collaborative approach needed in solving large and complex design problems. The method allows for tradeoff evaluation of any number of simple, parametric variations in concept. Even so, it is still of limited value for conceptual design because of the amount of time and information needed to develop parametric LCA models for new design concepts.

Simplified LCA Methodologies

In order to reduce modeling time an obvious solution might be to perform a simplified assessment. Simplified assessments may be qualitative or quantitative, ranging from checklists, matrices, abridged LCA, and LCA streamlining, to a variety of other forms of approximate LCA.

Checklists are qualitative approaches that target distinct environmental design strategies such as material conservation, energy efficiency, and pollution prevention guidelines (Lindahl, 1999). Although an excellent starting point to raise environmental awareness, checklists are quite general and their use lacks the thought process that may lead designers to new opportunities. Also, checklists do not readily support subtle tradeoff analysis.

Qualitative matrices (Allenby, 1992) also promote life-cycle thinking. Matrices provide an illustrative means for evaluating tradeoffs and interactions among design criteria. However, their form limits the manipulation of information to assess new design strategies quickly when tradeoffs involve complex multi-objective functions.

Abridged LCA (Graedel *et al.*, 1995) is a semi-quantitative matrix approach. Like qualitative matrices, it highlights only the most significant of concerns. An additional benefit of abridged LCA is its numerical basis, allowing for matrix manipulation and improved, but perhaps inconsistent, tradeoff analysis as the quantitative elements are based on heuristics.

LCA streamlining (SETAC, 1999) refers to the design of LCA in terms of what is included in the study and what is not. SETAC views streamlining as “an inherent element of the of the scope-and-goal definition process” of an LCA, determining what is necessary to support its use. Streamlining removes portions of an LCA deemed non-critical to a specific product's environmental impact profile. SETAC has found that the more streamlined an LCA becomes, the less accurate its results.

LEARNING SURROGATE LCA MODEL CONCEPT

The learning surrogate LCA model proposed by Sousa *et al.* (1999) is a different approach to approximate LCA. Unlike the others, it does not require any LCA modeling at the time of use. Learning algorithms train artificial neural networks (ANNs) using high-level product attribute and corresponding environmental impact data from pre-existing life-cycle assessment studies.

The product design team queries this trained artificial model with high-level product attribute data for a new concept to quickly obtain an approximate impact assessment for the design. For example (see Figure 1), product attributes can come from other models integrated within the system, such as obtaining volume from a CAD model, or from the environmental expert, such as recyclability. Together, all the attributes are presented to the previously trained neural network to gain the required environmental performance indicators needed for tradeoff analysis.

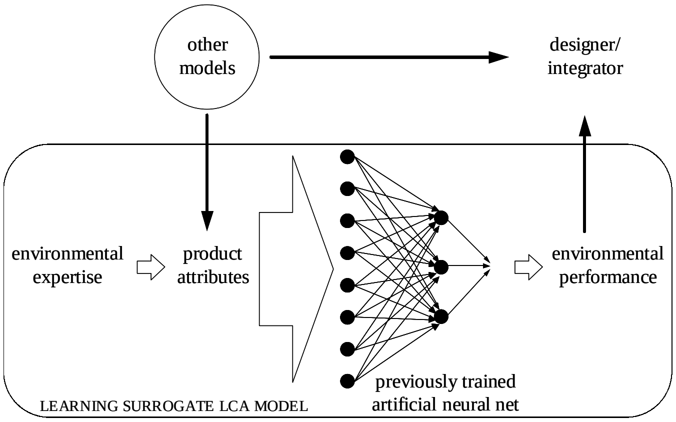

Figure 1: The learning surrogate LCA model within the construct of integrated design.

The surrogate LCA model uses artificial neural network training algorithms to learn by example (Masters, 1993). The learning process begins when the ANN is provided a set of product descriptors from previously analyzed existing products and corresponding full LCA results. The training algorithms adjust parameters within the network so that its output better emulates the actual impact results of the training data products. The process continues until the network converges, or the two output match. Effective learning requires a training set representing a reasonable distribution of products.

After the completion of training, the ANN is ready for use. Designers need to simply provide high-level descriptions of new product concepts to gain LCA predictions based upon trends inferred from the real products and LCA studies used as training data. A new model does not have to be constructed to analyze a new concept. However, the results of new detailed LCA studies should be continually added to enhance the training data set.

The surrogate LCA model learns from detailed LCA studies, yet possesses a high-level interface allowing it to operate with the limited data available in conceptual design. It has the flexibility to learn and grow as new information becomes available, but does not require the creation of a new model to make LCA predictions for a new product concept. Also, it does not delay product development by supporting extremely fast comparison of the product concepts. At later stages of development when fewer concepts are under consideration, a more detailed parametric LCA approach can be applied as described in the work by Borland *et al.* (1998).

The capabilities of this surrogate LCA approach are not fully known, but this work raises and addresses a number of questions that must be answered before the approach can be relied upon in practice. It is important to develop an appropriate form for the product attributes and LCA results used as the training database. Studies are needed to determine what product attributes should be used as inputs and what type of output we can reasonably expect to predict using these high-level descriptors. Then, sufficient LCA training data must be gathered for the learning system so that the effectiveness of the approach can be tested for the chosen impact areas. These subjects are addressed in the following sections of the paper.

Product LCA Database Interface

The basic element to a surrogate LCA model is the product LCA database, from which it learns. The database is made up of a series of product descriptors, or key words describing a product, and the product's corresponding environmental performance. It is necessary to establish a set of high-level product descriptors that both are easily known to designers in conceptual design, and provide reason to believe they may correlate with the chosen environmental performance indicators.

A pilot study completed by De Schepper (1999) was utilized to gain experience in determining which environmental impact categories might reasonably be predicted from a simplified life-cycle inventory (LCI) based upon high-level product attributes. The study will be used as a basis in choosing both the form of the environmental performance indicators and the high-level product attributes.

Abbreviated LCI List. A life-cycle inventory is a full list of all impact substances associated with a product. The LCI data is the most objective and informative form of environmental performance to an environmental expert. Subjectivity increases as these data are classified and aggregated to compute environmental impact categories and single environmental indicators (as would be more comprehensible to the typical designer). Two main points guided De Schepper in developing the list of indicators considered in this work. First, the list should be compact: at a level of resolution that is meaningful to designers, and not so large as to avoid increased architecture complexity of the surrogate model. On the other hand, highly aggregated performance measures are less objective and convey less information.

Based on these competing desires, the decision was made to consider an *abbreviated LCI list.* Ideally the surrogate LCA would predict inventory data so that different impact assessment schemes might be then applied to bring the data to the designer's level. Clearly it would be difficult to predict all inventory data associated with a detailed LCA using the surrogate LCA approach. Therefore, the next step was to determine if a limited set of LCI data could be used to meaningfully predict the environmental impact categories.

Impact Categories. An impact category represents a specific environmental problem. There are many alternative methodologies for developing a list of impact categories, such as: SETAC, Environmental Priority System (EPS), Eco-Points, Eco-Indicator '95, and Eco-Indicator '99. These methodologies are under constant discussion and new methodologies are always being developed.

The main difference among many of the methodologies is the level of characterization, or aggregation, of the list. For example, many approaches result in a single final number, while others may have a long list of impact areas. Table 1 provides a list of impact categories, which were derived from the Eco-Indicator '95 classification with the addition of 'Energy' and 'Solid Material' categories (SimaPro, 1999). This method was used in the study, as more information was available on it than on any other method.

Table 1: List of Impact Categories.

Greenhouse effect	Winter smog
Ozone layer depletion	Summer smog
Acidification	Pesticides
Eutrophication	Energy
Heavy metals	Solid material
Carcinogens	

Testing of the Abbreviated LCI List. The De Schepper study tried to identify a simplified set of inventory data, consisting of only key LCI elements, which could be linked to the impacts in Table 1. This investigation is illustrated in Figure 2. The goal is to then map the simplified inventory list back to derive an appropriate list of high-level product attributes that can be provided by designers in the conceptual phase of design.

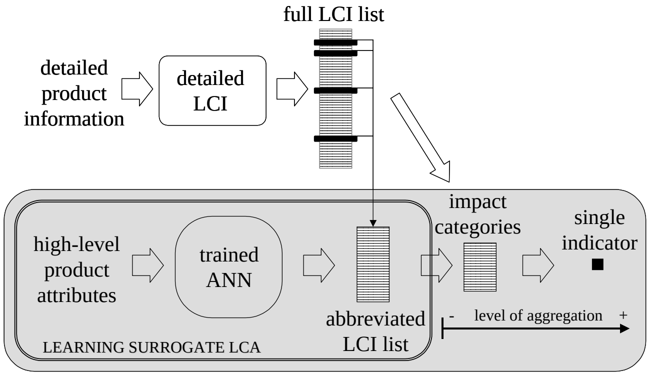

Figure 2: Can the learning surrogate model take the place of a detailed LCA in conceptual design?

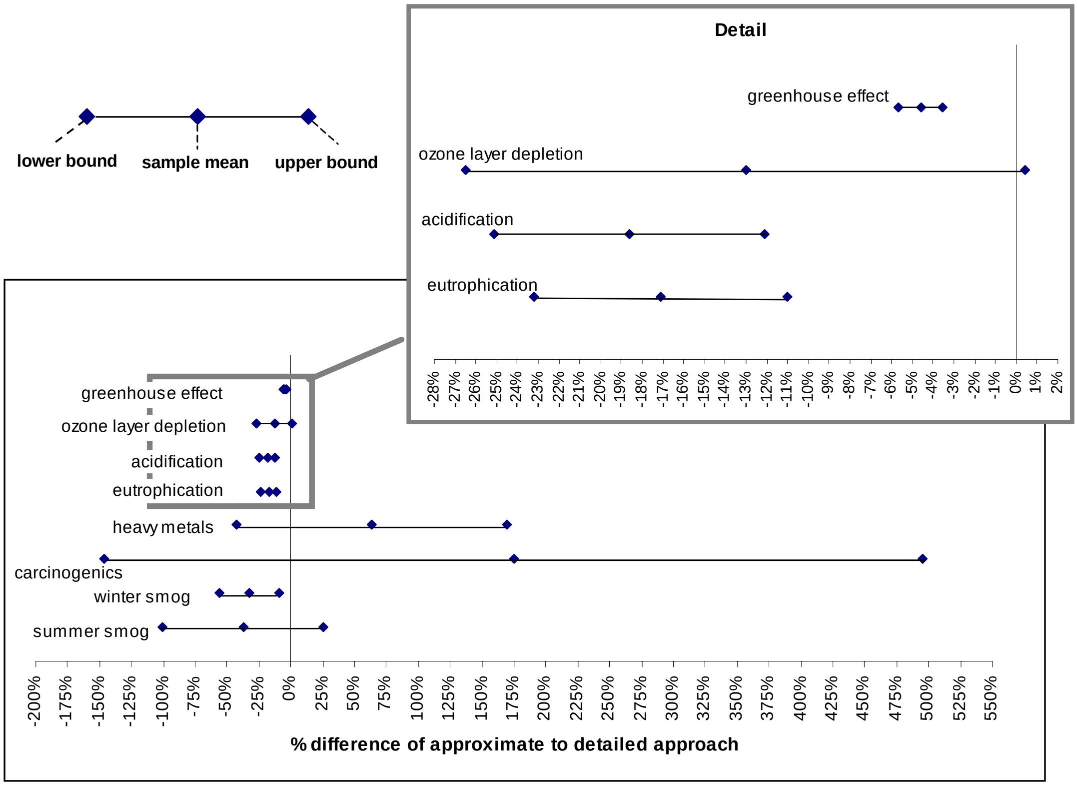

Figure 3: Normalized Data 90% Confidence Intervals.

The full list of LCI elements used to calculate impacts originated from the Eco-Indicator '95 approach. Impacts predicted using the full LCI list were used as a baseline to validate impacts predicted using the abbreviated LCI list, on which the surrogate modeling approach will focus.

The approximate LCI listing, or abbreviated list (Table 2), proposed included only materials that accounted for the majority of environmental impacts.

Table 2: Abbreviated LCI List.

Energy	Cd	CO_2	C_xH_y
Solid Material	PAH	SO_2	COD
CFC	SPM	NO_x	N_{tot}
Pb			

With the two LCI lists defined, 20 different consumer products (listed in Table 4) were assessed using SimaPro 4 (1999). The test resulted in predictions for the Table 1 impact categories with respect to both the abbreviated and full lists. The detailed inventory data for the 20 products tested were obtained from LCA studies conducted at TU Delft (DfS Group, 1994-1997), published studies in the SimaPro 4 User's Manual (1999), and a study by PA Consulting Group (UK Ecolabeling Board, 1992).

The differences between the numerical results produced by the approximate and detailed LCI data were quite large for some categories. Results were normalized and 90% confidence intervals were calculated for each category. These intervals are shown in Figure 3.

It was concluded that certain impact categories—energy[2], solid material[2], greenhouse effect, and ozone layer depletion—were numerically well represented by the abbreviated list while others—acidification, eutrophication, winter smog, and summer smog—were reasonably suited to the simplified LCI. Heavy metals, carcinogens, and pesticides[3] were not.

The final abbreviated list to be used in guiding the identification of key product attributes is shown in Table 3. This list was drawn after several iterations and comparisons to the results predicted by the full LCI list. Chromium, Nickel, and Halon were added to the list. Methane (CH_4) was separated out from the C_xH_y listing. CFC emissions in the list do not include CFC-116 and CFC-14.

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[2] The energy and solid material categories were identical in the two lists.

[3] No material impacts in the study were allocated to the pesticide category. Any such allocation was deemed highly dependent on product and therefore pesticides may not be a useful impact category to use in a more generically based learning surrogate model.

Table 3: Revised Abbreviated LCI List.

Energy	Cr	CO_2	CH_4
Solid Material	Ni	SO_2	COD
CFC	PAH	NO_x	N_{tot}
Pb	SPM	C_xH_y	Halon
Cd			

Additionally, products were ranked from most to least detrimental within each impact category according to their LCA results for that category. Within each category, the rankings resulting from the full and abbreviated lists were compared. The goal of this analysis was to identify any trends in the approximate approach's ability to rank products appropriately with respect to their environmental impacts.

The surrogate tool's ability to appropriately rank products is important in addition to its ability to obtain accurate quantitative results. For the 20 products studied, the energy, solid material, greenhouse effect, and summer smog impact categories were correctly rank ordered. The acidification, eutrophication, heavy metals, and winter smog categories had discrepancies, but they were minor, limited to a shift of no more than two places (e.g. from 3rd to 5th most detrimental product). The ozone layer depletion and carcinogens categories contained more deviations—up to a shift of six places. The carcinogens impact category produced the least consistent results, having only nine matches and the largest shift in product ranking (Café Sima from 13th to 7th), yet the first six products were ranked identically. This is illustrated in Table 4.

Table 4: Rankings for the carcinogens category produced the least consistent of all ranking results.

decreasing detriment

Carcinogens	
Detailed approach	*Approximate approach*
Washing Machine	Washing Machine
Heater	Heater
Vacuum Cleaner 2	Vacuum Cleaner 2
Vacuum Cleaner 1	Vacuum Cleaner 1
Café Pro+	Café Pro+
Café Comfort	Café Comfort
Mini Vacuum Cleaner	Café Sima
Radio 1	Mini Vacuum Cleaner
Juice Squeezer 1	Juice Squeezer 1
Juice Squeezer 2	Radio 1
Oak Chair	Juice Squeezer 2
Silver Chair	Oak Chair
Café Sima	Silver Chair
Radio 3	Showerhead
Radio 2	Radio 3
Radio 4	Radio 4
Paper Bag	Radio 2
PP Crate	PP Crate
Showerhead	PE Bag
PE Bag	Paper Bag

Results of the ranking analysis seem to suggest that the tool could be useful in conceptual design for determining the most environmentally detrimental of concepts. These concepts could then be easily filtered out of the development process or improved. However, further developments are needed in obtaining quantitative results.

The next step, yet to be completed, is to study the relationship between product attributes and the abbreviated list elements in order to systematically develop a set of high-level attributes that will be used to query the surrogate LCA model. However, a preliminary study with the surrogate model (Sousa *et al.*, 1999) has been conducted based on a short list of product descriptors that were determined in an ad-hoc fashion—based mainly on literature review and intuition. Future research will focus on a more methodological way for choosing these descriptors, but the ad-hoc approach was appropriate for preliminary testing.

Surrogate Model Trial

The surrogate model preliminary study (Sousa *et al.*, 1999) was used to see if the results of a single element of the impact category list—life-cycle energy consumption—could be predicted using the surrogate modeling approach. The product descriptors used are listed in Table 5.

Table 5: High-level Product Descriptors.

Mass	Wood (% mass)
Ceramic (% mass)	Fluids and lubricants (% mass)
Concrete (% mass)	Other materials (% mass)
Ferrous metal (% mass)	Durability
Non-ferrous metal (% mass)	Lifetime
Fibers (% mass)	In use energy source
Glass (% mass)	In use hours of operation
Paper (% mass)	In use power
Polymers (% mass)	

Data were gathered for 133 different products and product variations. These data included the product attributes and product life-cycle energy consumption from detailed LCA studies. Results showed that the ANN model was able to learn from these data and accurately predict life-cycle energy consumption. The average difference between the pre-existing LCA life-cycle consumption results and the value predicted by the ANN was ±35% for all products used in training. The accuracy of the predicted value is quite good considering that the precision of life-cycle energy results produced by a real LCA is typically ±30% (UK Ecolabeling Board, 1992).

The trained surrogate model was tested for accuracy by querying it with four products not included in the training data (washing machine, internal combustion vehicle, wood palette, and projector). The correct life-cycle energy consumption levels were known for these products through previously conducted detailed LCA studies. Comparison of results between the detailed study and that of the surrogate model are shown in Figure 4 (Sousa *et al.*, 1999). The predicted values were found to be correct within 12-50% of the published values.

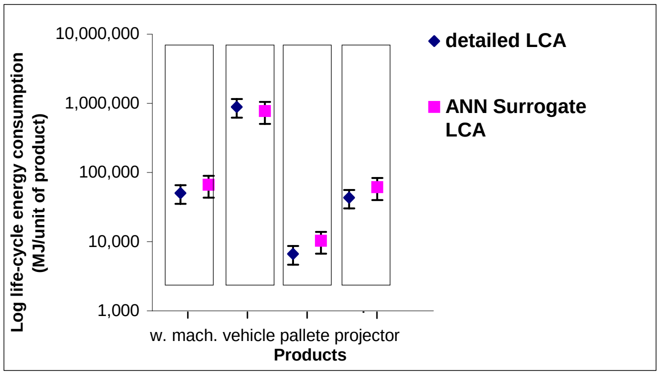

Figure 4: Life-cycle Energy Consumption Calculated by the Detailed and Surrogate LCA Methods.

The trained ANN was also able to correctly generalize trends. The product descriptor values for the four products not used in the training data were held constant with the exception of product mass. Results indicated that trends predicted by the neural network correspond to expectations.

In conclusion, the surrogate model has been shown to behave well with respect to life-cycle energy predictions in the preliminary study. It is believed that if a set of high-level attributes can be developed to correlate with the abbreviated list elements of Table 3, then the surrogate LCA method also has a good chance of being effective in predicting solid material, greenhouse effect, ozone layer depletion, acidification, eutrophication, winter smog, and summer smog impacts. The approach is not likely to be suitable for predicting heavy metals, carcinogens, and pesticides.

Range of Applicability

The surrogate method shows promise in being suitable to conduct preliminary LCA studies for a certain range of products. As research continues in identifying appropriate high-level product descriptors, this range of applicability should be broadened. Traditional product design is not the only area where this type of method would be helpful in the early stages of development to quickly assess and discard the most detrimental of concepts. Use of the model is aimed beyond traditional consumer product design, at being able to handle construction projects, policy issues, and other developmental ventures.

It is possible that a set of impact categories or product descriptors will not be able to be utilized beyond a certain range of use. In this case, it may be necessary to define classes of products, for which the surrogate method can be applied to separately. For example, in construction project environmental impact assessments, ‘socioeconomic effects’ is a widely used impact category because the public demands it. Frequently, a particular construction project will adversely affect a particular group of people. In contrast, consumer products are typically developed to benefit or aid society in some fashion. Therefore, a product of construction and a consumer product will likely be two different classes of ‘products’ that will require two separate surrogate models to be developed.

Ideally, the same LCA training database would be sufficient and satisfactory in prepping the surrogate model for any type of product—consumable, durable, platform-based, or revolutionary. The extent to which this is actually the case will be tested in future work.

Training Data

The adequacy of the training data used for this approach is questioned frequently as a potential problem. One of the major benefits to using an ANN is its ability to learn from imperfect data. This is possible simply because the most coherent data will dominate training compared to the imperfections. But when do you have enough accurate data? This question is especially important when LCA inputs and results are being used as training data.

LCA approaches are highly dependent on the practitioner. There can be variability in: input parameters, system boundaries, quality of data, and assumptions made (Linton, 1999; Cascio *et al.*, 1996). In taking LCA data from many different sources to amass enough training information, a wide range of these divergences are also collected. How does this affect accuracy of the method?

In retrospect, the Sousa *et al.* (1999) study helped in answering this concern. The study gathered 133 products and product variations from various sources and used a simplified product descriptor list during training. Values and trends in the results were good, yielding predictions within a normal range of accuracy. The method does indeed show promise.

CONCLUSIONS AND FUTURE WORK

The method for integrating LCA with traditional design proposed by Borland *et al.* (1998) supports a collaborative, distributed, multidisciplinary design process. It allows for the evaluation of any number of simple, parametric variations in concept. However, the method's application is still limited by the amount of time that must be invested in constructing parametric LCA models. Also, most LCA methodologies do not easily facilitate the large changes that occur during concept design.

Sousa *et al.* (1999) proposed a learning surrogate LCA method in an effort to make LCA predictions available to the early conceptual stages of design. The neural network trains with a database of product descriptors and corresponding environmental impacts collected from LCA studies on pre-existing products. A design team can then simply query the trained surrogate model with product attributes of a new concept to gain LCA predictions for the new concept. In this way, the method does not require any additional LCA modeling at the time of use.

The learning surrogate model is still under development and hypotheses can only be made about the method's general applicability. However, research to date shows the approach has promise. There is reason to hypothesize that the method can be used independently or within integrated design and will be able to handle approximate parameters for predicting impacts in the following categories: life-cycle energy consumption, solid material, greenhouse effect, ozone layer depletion, acidification, eutrophication, winter smog, and summer smog. The work presented in this paper provides motivation to continue the development of the surrogate LCA model.

The next step in this process is the development of an appropriate set of high-level product descriptors that can be used to query the surrogate model. The descriptors must be systematically selected to relationally link with the abbreviated list of LCI data chosen in the De Schepper (1999) study. Also, further research will look into how the model's range of applicability can be extended to areas of development beyond traditional product design.

Study on the learning surrogate method will continue in the area of training data, its form, and its competence. This research will be conducted with respect to the original concept's intention to provide a learning method to generate approximate life-cycle assessment estimates for evolving design problems in real-time such as those needed in the conceptual phase of product design.

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