Approximate Life-Cycle Assessment of Product Concepts Using Learning Systems

by

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ABSTRACT

This thesis develops an approximate, analytically based environmental assessment method that provides fast evaluations of product concepts.

Traditional life-cycle assessment (LCA) studies and their streamlined analytical versions are costly, time-consuming, and data intensive. Thus, they are not practical to apply during early concept design phases where little information is available and ideas change quickly. Alternatives currently used are mostly qualitative, ad-hoc approaches that often provide overly simplistic assessments difficult to trade-off with other design objectives.

The Learning Surrogate LCA method is an alternative approach that uses simple, high-level, and accessible descriptive information about a product to provide approximate, yet useful, analytical LCA results during early concept design stages. The method relies on a general artificial neural network (ANN) trained on high-level product descriptors and environmental performance data from pre-existing detailed life-cycle assessment studies or related data. To quickly obtain an approximate environmental impact assessment for a product concept, the design team queries the trained artificial model with new set of descriptors, without requiring the development of a new model. The predicted environmental performance, along with other key performance measures, can be used in tradeoff analysis and concept selection.

Foundations for the approach were established by investigating: (1) model inputs in the form of a compact, and meaningful set of product concept descriptors; (2) ability to gather data and appropriately train an ANN-based surrogate LCA model. Proof-of-concept tests on life-cycle energy consumption showed that ANN-based surrogate models were able to: (a) match detailed LCA results within the accuracy of typical LCA studies; (b) predict relative differences of distinct product concepts; (c) correctly predict and generalize trends associated with changes for a given product concept. A product classification system based upon concept descriptors was developed to improve performance.

The method was then applied to a case study with a heavy truck manufacturing company. A demonstration example was used to illustrate application scenarios for tradeoff analysis within DOME (Distributed Object-based Modeling Environment). The study suggested that high-level, customizable simulation interfaces of learning surrogate LCA models are likely to have a significant practical impact in the early decision making process.

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1 INTRODUCTION

The push for sustainable development has begun to change the way many companies design products. Product design teams are being asked to judge the environmental impact of the products they are developing. Furthermore, it is key to understand how design changes can affect the life-cycle environmental performance of a product during evaluation of concept feasibility, together with the other traditional design criteria, such as technical performance and cost. This prevents environmental impacts that may not be corrected or mitigated later from occurring in the first place. However, conceptual design creates particular challenges for environmental assessment. How can product design teams quickly evaluate and tradeoff competing product concepts that are numerous and often dramatically different using only the scarce information available at early conceptual design stages? Motivated by the lack of methods for integrated, early conceptual, environmentally-conscious design this thesis proposes the learning surrogate LCA method to apply on approximate life-cycle assessments early on in the product design process.

1.1 MOTIVATION

Today's patterns of consumption, energy production and waste generation must be dramatically changed. The world population is growing along with our increased quality-of-life expectations.

Industry plays a key role in determining the sustainability of development. Further, the need to change consumption patterns while meeting the needs of people, economies and natural systems through less wasteful processes and life-enhancing goods and services creates new business opportunities. This in turn requires technology innovation and the adoption of new business models (WRI, 2002).

In order to commit to such changes one must be able to understand their implications, including the environmental impact of designed and manufactured products. When defining and adopting strategies, we must be aware that every product we design and manufacture causes environmental impacts during all stages of its entire life-cycle.

Design for environment (DFE) or environmentally-conscious design is a product design strategy widely recognized to be useful to industry in acquiring long-term competitive advantage under the "new rules of the game." These new rules developed greatly during the 1990s through factors, such as an increasing societal awareness of environmental issues, increased pressure from environmental legislation or anticipated legislation, competition, and consumer demand (Lewis et al, 2001; McAloone, 2000; Graedel, 1998; Fiksel, 1996).

DFE considers life-cycle environmental attributes as design objectives together with other conventional design goals rather than as constraints (Berkel et al, 1997). Life-Cycle Assessment (LCA) is a popular DFE analytical methodology that has been proposed to identify and assess the environmental aspects and potential impacts associated with a product throughout its life cycle. By tackling environmental issues in a product's life cycle, potential for cost savings are likely to be found, such as using fewer raw materials and less energy or reducing waste management and emission control costs.

Environmentally-conscious design in-itself may promote sustainability, but it is not necessarily actively aiming at sustainability (McAloone, 2000). In contrast, sustainable design or sustainable product development actively broadens the design activity scope to collectively consider equity, ethical and social impacts and total resource efficiency. The ultimate goals are to achieve inter-generational equity and to maximize robust system-wide solutions in pursuit of more sustainable modes of production and consumption (Lewis et al, 2001; McAloone, 2000; Thomas and Weinberg, 1999).

In order to achieve this holistic goal, it is essential to consider many factors during the front-end of the design process, and to use them in the evaluation of concept feasibility along with other requirements. This means product design teams must be able to evaluate the approximate environmental performance of many product concept systems – solution concepts and their upstream influences and downstream impacts – early in the design process. Further, these evaluation techniques must be operable within the constraints of real-world product development and provide credible information that is sufficient for decision-making. This is a central issue addressed in this thesis.

1.2 PRODUCT CONCEPT SYSTEMS – OPPORTUNITY AND CHALLENGE

Environmental impacts occur at all stages of a product's life-cycle, and different types of products create impacts at different stages of the life-cycle (Lewis et al, 2001). Regardless, the largest part of environmental impact is "locked-in" into the product at the conceptual design stage of product development (Lewis et al, 2001; U.S. Congress, 1992).

The conceptual design stage defines the basic characteristics of a product, ranging from cost (Ulrich and Eppinger, 2000) to environmental aspects (Bhamra et al, 1999). Decisions that emerge from the conceptual phase are often locked-in because of to the large amount of resources – time, manpower, and money – needed to change path as launch deadlines approach. In particular, early design decisions have environmental implications at each stage of the product life cycle from extraction of raw materials, processing and manufacturing, to product use and final disposal. At early design stages, critical decisions are made on product key attributes, such as the materials used, energy requirements, recyclability, and longevity, which ultimately determine its life-cycle performance. Figure 1.1 illustrates the environmental "lock-in" concept over the life cycle of a product and maps the various strategies industry can potentially adopt throughout the product's development cycle.

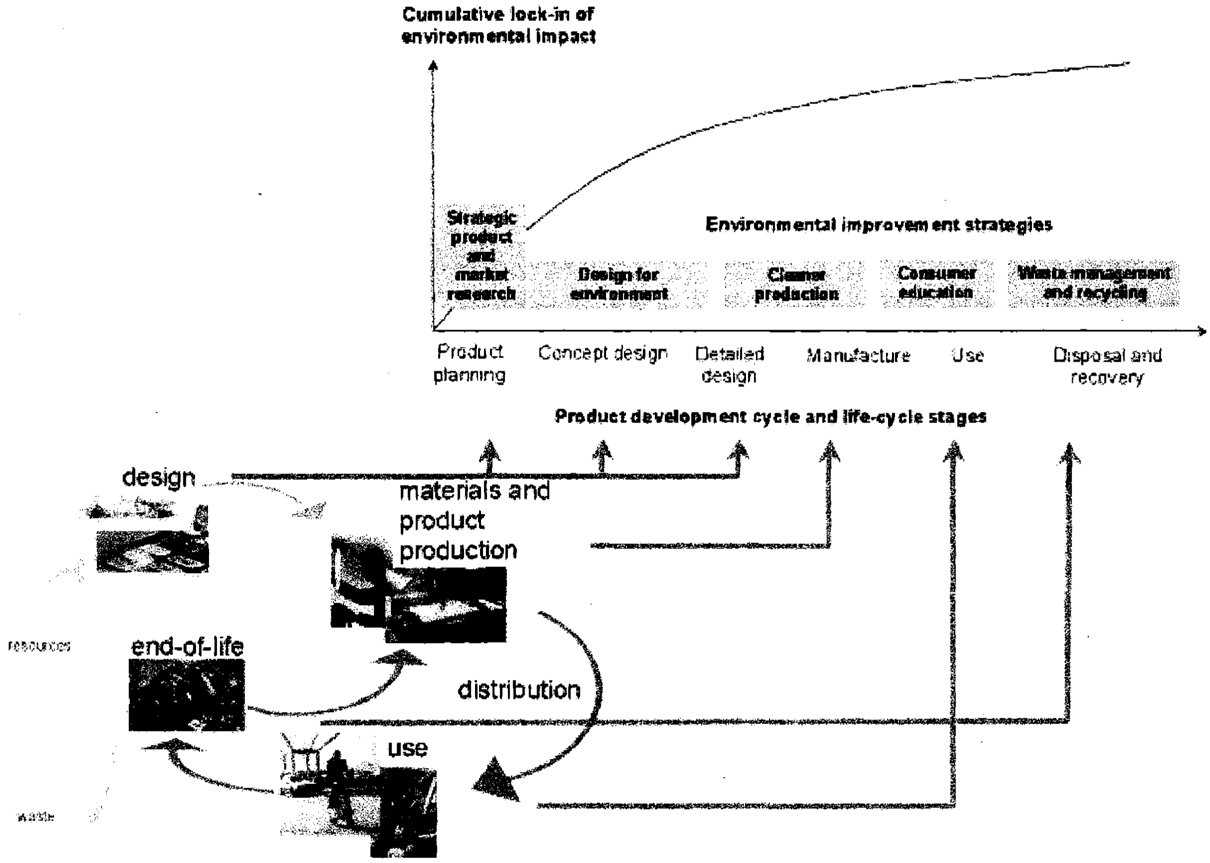


Figure 1.1 Early design stages define key attributes that ultimately determine the environmental performance of a product throughout its life-cycle. Adapted from Lewis et al (2001).

Therefore, it is key to bring environmental considerations into the front end of the design process and use them in the evaluation of concept feasibility along with other requirements, such as operational performance and price. The product design team must then be able to evaluate the approximate environmental performance of many alternative concepts early in the design process.

Conceptual design creates particular challenges for environmental assessment. Time is usually a scarce resource during the product development cycle. Development time can mean the difference between leading or following in an industry, and thus it limits the ability to create detailed models for many different concepts. Competing product concepts are numerous and have dramatic differences. The lack of information is a significant barrier to the creation of models needed to evaluate different concept ideas, and multi-attribute tradeoffs and decisions must be made quickly.

Previous work by Borland and Wallace (2000) illustrated how the capabilities of parametric life-cycle assessment (LCA) models developed by environmental experts could be integrated with traditional design models and made available on demand using an Internet-based framework called DOME (Distributed Object-based Modeling Environment). The approach seamlessly linked parametric design models for rapid integrated tradeoff analysis. They propose and demonstrate a vision for practicing environmentally conscious design where teams of designers and environmental experts collaborate during the product design process. Expertise is distributed, allowing each party involved to concentrate on the fields they know best. In this paradigm, the focus shifts from providing techniques that let designers make environmental assessments to providing tools that facilitate timely communication and information transfer between designers and environmental experts. However, the use of detailed parametric models is still of limited value for early conceptual design because of the amount of time and information needed to develop the parametric LCA models. Thus, both the overhead in developing parametric LCA models for a diverse range of product concepts, and the lack of detailed information make the integration of traditional LCA models impractical.

Several methods, qualitative and quantitative, have been proposed to simplify and significantly reduce the amount of resources required for LCA modeling. They range from checklists (Clark et al, 1999; Fiksel, 1996), qualitative matrices (Allenby, 1992), abridged LCA (Graedel et al, 1995), and LCA streamlining (Mueller and Besant, 1999; SETAC, 1999), to a variety of other forms of approximate LCA. Although these existing methods are all useful, they are not ideally fitted for early conceptual design in an integrated modeling context. Qualitative information is difficult to use in highly dimensional, fast-paced tradeoff analyses, and the streamlined analytical techniques are still somewhat prohibitive from a modeling effort viewpoint.

Empirical studies performed at companies, such as the one described by McAloone (2000), have been substantiating the present lack of tools for environmentally-conscious design decision-making at early conceptual stages. Existing methods and tools do not match at all the nature of product concept systems to be able fully incorporate environmental aspects during early conceptual design stages. They do not fulfill the need for:

- Conceptually support life-cycle thinking with lack of detailed, accurate information on ill-defined product concepts, and their upstream and downstream influences;
- Credible information for decision-making in the design process within the time, data and cost constraints of real-world product development;
- Analytically support highly dimensional multi-attribute tradeoff analysis on traditional and environmental design goals, when designing a particular system;
- Simulation interfaces between environmental experts and the other product design team members in a systems modeling context.

1.3 Reframing Environmentally-Conscious Design of Product Concept Systems: The Learning Surrogate LCA Concept

The lack of analytically-based methods capable of supporting environmentally-conscious design at early conceptual stages motivated a search for alternative evaluation techniques that better suit the needs of early product development. This lead to the question:

> *Can life-cycle assessment using learning algorithms emulate existing heterogeneous knowledge and generalize trends to allow fully integration of environmental assessment into early conceptual design stages?*

The hypothesis is that models built upon learning surrogate LCA approaches can efficiently provide, in a system-modeling context, approximate, quick and integrated environmental analysis of new product concepts. The *learning surrogate LCA concept* developed and tested in the thesis supports this hypothesis.

The learning surrogate LCA concept suggests the use of an approximate LCA model based on learning algorithms that learns from existing detailed LCA studies. Yet, the model possesses only a high-level input interface – *product concept descriptors* – allowing it to operate with the limited data available in early conceptual design stages to meaningfully predict environmental impacts for a wide variety of concepts. The model has the flexibility to learn as new information becomes available, but it does not require the creation of a new model to make LCA predictions for a new product concept. In addition, the surrogate model does not delay product development as it supports the extremely fast comparison of the environmental performance of product concepts and facilitates simulation interaction between designers and environmental experts.

It is proposed that existing environmental and product data are brought into early design stages through heuristic abstraction (see Figure 1.2). Pahl and Beitz (1999) discuss heuristic abstraction as a key cognitive strategy to support both creativity and systematic thinking of designers at early conceptual design stages. In the course of doing abstraction, designers find higher level – generic and comprehensive – interrelationships, reduce complexity and emphasize essential characteristics of the problem. In a similar way, both designers and environmental experts can use abstraction to identify essential product and environmental assessment features ignoring particular or incidental information stored for existing products and emphasizing what is general.

The abstracted information is the used in learning cycles of LCA models based on artificial neural networks (ANN) for quick and approximate preliminary analysis of product concept systems' environmental performance, as illustrated in Figure 1.2. ANNs are first trained to generalize on high-level characteristics of product concepts, typically known in the conceptual design phase, and environmental data from pre-existing LCA studies. The product design team then queries the trained artificial model with high-level attribute data of new product concepts to quickly obtain the corresponding approximate environmental performance, without the overhead of defining new LCA models. The product design team can apply the predicted environmental performance along with key performance measures from other models in tradeoff analysis and concept selection.

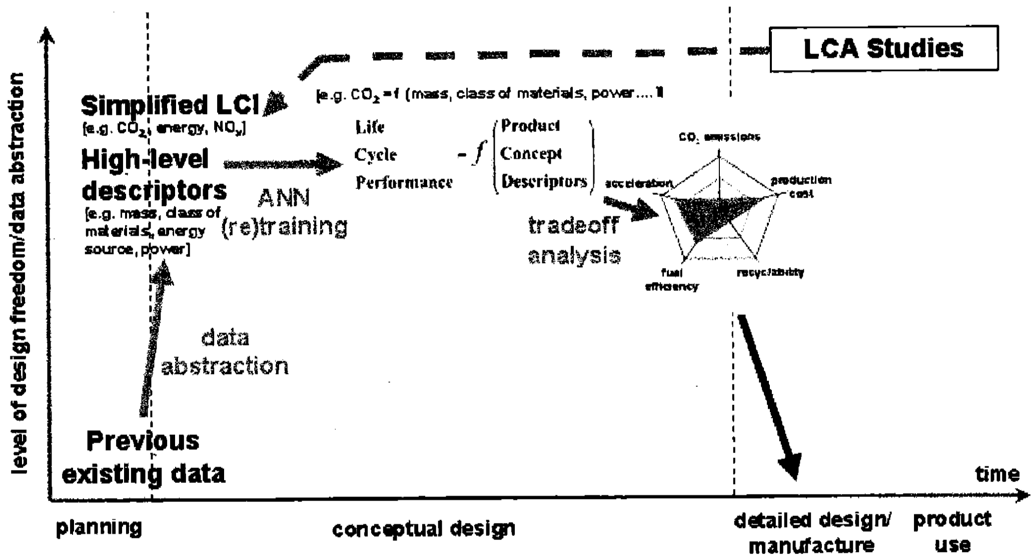


Figure 1.2 The learning surrogate LCA concept.

In supporting a team-oriented, multidisciplinary design process at early conceptual stages, this new method assumes that environmental experts and design engineers are specialists in their own fields. Learning surrogate LCA models should be created, validated and maintained by environmental experts. They are meant to be used by designers or by environmental experts as a service provided to designers. Product descriptors are the simulation interface between environmental experts and designers for this new approach, understood by designers in relation to preliminary product concepts, and meaningful for an approximate environmental impact assessment of product concept systems.

The learning system architecture of the surrogate LCA method has also been extended to include a tree-based classifier to perform an initial product categorization based on the product descriptors and direct the analysis to broad product category-based neural networks to approximately predict environmental performance. The goal of the classification step is to narrow down the learning space to enhance the prediction performance of ANNs specialized in different types of products.

1.4 THESIS OUTLINE

Chapter 2 first provides an overview of the design process and highlights key features that make the design activity such an ambiguous yet critical activity in the product development cycle. The second part of the chapter introduces the standard methodological process for LCA and alternative streamlined approaches that have been proposed to address some of the limitations of the LCA detailed approach. Fundamental gaps of existing DFE methodologies are identified. These approaches are mapped together with the learning surrogate LCA concept to methodological attributes that are key to early conceptual design stages.

Chapter 3 introduces the learning surrogate LCA concept and relevant background for the developed method. It first explains the overall concept. Then it provides the basis from which the learning system to support the concept was selected. Finally, it gives an overview of the

DOME (Distributed Object-based Modeling Environment) simulation framework through which environmental assessment services from learning surrogate LCA models can be extended to a World-Wide Simulation Web (WWSW) for integrated design and tradeoff analysis.

Chapter 4 focuses on the proof-of-concept work that was performed to establish the learning surrogate LCA method. The first part goes through the investigation of key questions critical to the validation of the learning surrogate LCA concept: (1) What is a meaningful set of product attribute descriptor inputs?; (2) Can a trained ANN quickly provide reasonable estimates when queried with descriptors? The second part of the chapter describes research performed to explore product classification schemes to support learning surrogate LCA models specialized in different general classes of products.

Chapter 5 presents an application study to a specific product development context in a Swedish heavy truck manufacturing company. The process of customizing the learning surrogate LCA approach in a company-targeted product concept system was explored. The implementation of a demonstration example illustrated potential application scenarios for tradeoff analysis using integrated simulation.

Chapter 6 summarizes the main ideas developed in this thesis, key contributions and broader implications of the work. A future work section includes methodological improvements, further research on implementation and investigation of new application areas.

2 NEED FOR LIFE-CYCLE THINKING IN PRODUCT CONCEPT SYSTEMS

McAloone (2000) presents an interesting perspective on how life-cycle thinking is considered in product design. McAloone realizes that there is a significant gap between the theory dictated by concurrent engineering literature and design practice. While definitions of concurrent engineering extend the term to consider a product throughout its life cycle, from concept to end-of-life, many design models and design practice do not go further than manufacturing and selling the product, after which the company's responsibility ends. So why expect designers to have a life-cycle philosophy and understand about the whole life of the products they design?

Interestingly enough, there is also a significant inconsistency between the academic theoretical view of environmentally-conscious design and design practice. Life-cycle thinking is theoretically embedded in the framework of environmentally-conscious design and detailed analytical approaches such as Life-Cycle Assessment (LCA) (a widely accepted method of assessing the environmental impacts of a product throughout its life-time). However, environmentally-design process in practice (or a life-cycle philosophy) is absent in the most critical phase – the early conceptual design stages. The lack of realistic structured approaches to help incorporate environmental considerations into early design stages can be viewed as an important factor that drives this gap (McAloone, 2000). Qualitative research by McAloone (2000) tackled this problem by developing a conceptual model of the transition from design to environmentally-conscious design for the electronics industry organizational structure. Although necessary, his research path was not sufficient to eliminate the gap. I believe the "established" environmental-conscious design theoretical and methodological framework is an equally relevant barrier. It does not match the particular nature of the design process, especially at early conceptual stages. Life-cycle thinking is not happening in practice at the conceptual design stage given currently available environmentally-conscious design framework and methods. This idea is further illustrated in Figure 2.1.

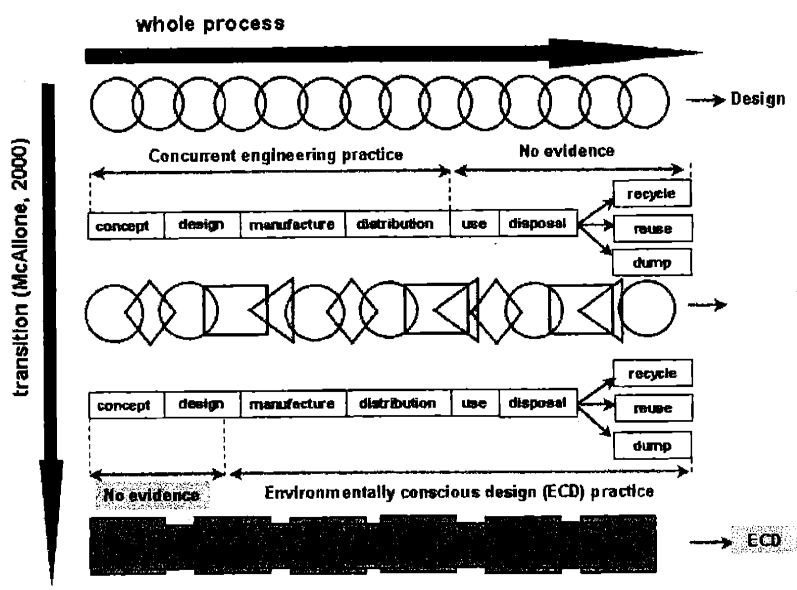


Figure 2.1 Environmentally-conscious design practice does not happen up-front.

This chapter reviews key literature to develop the rationale of this argument. In the first two sections, an overview of the early design process and the key features that make it so challenging to the development of methods for environmentally-conscious design are provided. The third section presents an overview of the LCA methodology, its streamlined forms, and discusses key limitations of the framework when applied during the design process. Finally, the chapter closes by discussing fundamental methodological gaps found in existing environmentally-conscious design approaches that make them inappropriate for early design stages and ultimately contribute to the lack of consideration of environmental issues in mainstream design activities.

2.1 THE DESIGN ACTIVITY

A wide variety of models intended to systematically describe the design process have been proposed by several authors (Pahl and Beitz, 1999; Ulrich and Eppinger, 2000; Clausing, 1995; Ullman, 1992; Hoffmann III, 1997; Pugh, 1996). These models, although recognizing the iterative nature of the design activity, propose systematic interpretations of the process by dividing it into distinct phases. Based on the various existing approaches, the design process can be generally outlined as follows:

1. Planning and clarification of task. The goal is to formulate a clear statement of the product requirements that looks promising given the current market situation, company needs and economic outlook. During this phase, the company decides development strategies related with supply chain, life cycle support and manufacturing management.
2. Conceptual design. In this phase, the product is conceived in conceptual terms emphasizing the purpose that the product will fulfill. It involves the identification of the essential problems through abstraction, the establishment of function structures and the search for the appropriate solution principles and their combination. The design tools used at this phase in product design must be general in nature, questioning past design approaches and directing the design team to new, improved design options.
3. Embodiment design. During this phase the designer, starting from the selected concept, defines the layout and forms, and develops a technical product or system according with technical and economic considerations.
4. Detail design. In this phase, the concept and the part structure have been well defined and attention shifts to the design of individual parts. The arrangement, form, dimensions, and surface properties of all the individual parts are finally laid down, the materials specified, the technical and economic feasibility re-checked and all drawings and other production documents produced.

Cagan and Vogal (2002) propose a new systematic approach – user-centered, integrated new product development – to clarify the early phases of new product development, traditionally perceived as the "fuzzy front end" of product development. They define four phases: identifying the opportunity, understanding the opportunity, conceptualizing the opportunity, and realizing the opportunity. The first three phases are the ones where the problem definition is still uncertain and vague. The fourth phase is a transition phase into the more concrete and analytical stages of product development.

Throughout the design process, the design activity is a combination of many different factors, such as creativity, technical knowledge, mathematical knowledge, and team dynamics. Pahl and Beitz (1999) view the design activity through different perspectives: psychological, systematic and organizational.

Psychologically, design is a creative activity that requires sound knowledge in various scientific and engineering disciplines as well as knowledge and experience in the domain of interest. Initiative, resolution, economic insight, tenacity, optimism and teamwork are essential qualities of a good designer. Designing is also a systematic activity that optimizes given objectives given partly conflicting constraints in a particular set of circumstances. From an organizational perspective, design is a key piece of the product life cycle where designers must understand their role in close collaboration with specialists in a wide range of disciplines and expertise.

During the design process, designers have to determine a path that maps the need for a specific object to the final product (see Figure 2.2). Many different solutions (paths) that meet the need can be devised depending on the designer's knowledge of the process and problem domain (Ullman, 1992).

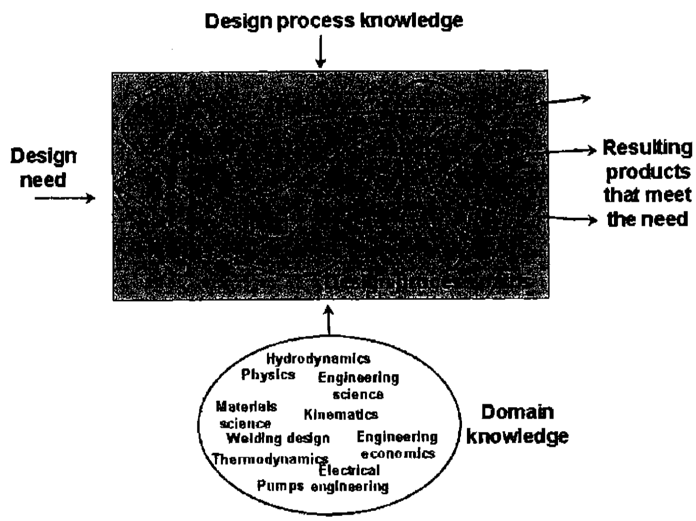


Figure 2.2 Knowledge used in the design process. Source: Ullman (1992).

Design is a problem solving activity that deals with ill-defined problems with many potential solutions and no clearly best solution (Ullman, 1992). Using available or easily accessible information to help understanding the problem and generate potential solutions, designers evaluate the solutions by comparing the alternatives and deciding which is the best. Four basic actions are involved: (1) establish the need or realize there is a problem to be solved; (2) understand the problem; (3) generate potential solutions; (4) evaluate the solutions by comparing the potential solutions and deciding for the best; (5) document the work.

Through this problem design activity, design reveals to be fundamentally a learning process. Figure 2.3 shows a typical learning curve in a scenario known as the design process paradox (Ullman, 1992). Throughout most of the design process the learning rate is high. The steeper the slope the more knowledge gained per unit time. The design freedom curve illustrates that as design decisions are made, the ability to change the product becomes increasingly limited because of time and cost, typically the main drivers of design projects. While at the beginning the designer has a high degree of freedom (few decisions have been made and little capital has been committed), by the time the product is about to go to production, any change is an expense, limiting the designer's freedom to make further changes.

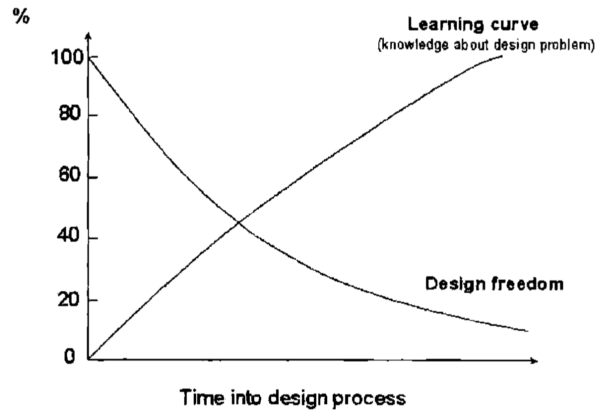


Figure 2.3 The design process paradox. Source: Ullman (1992).

This effect of cost commitment by the design process is directly represented in Figure 2.4. As shown in the figure, one can rapidly realize that cost is most committed *early* in the design process. Typically 75% of the manufacturing cost is committed by the end of conceptual phase in the design process (Ullman, 1992). This means decisions made after this point in the design process can determine only 25% of the product's manufacturing cost.

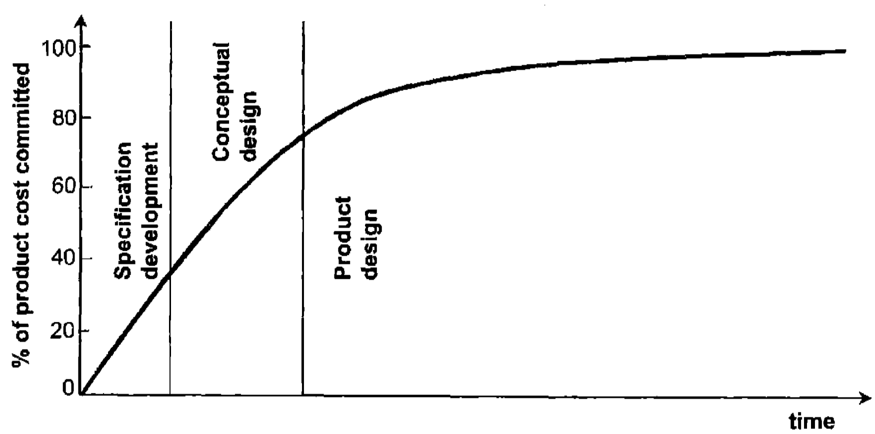


Figure 2.4 Design effect on manufacturing cost. Source: Ullman (1992).

Likewise, the environmental performance of a product is largely locked-in into the product at the early stages of the design process (Lewis et al, 2001; U.S. Congress, 1992, McAloone, 2000). During these early stages, critical decisions are made on product key attributes, such as the materials used, energy requirements, recyclability, and longevity, which ultimately determine the life-cycle performance of the product. Figure 2.5 shows the environmental "lock-in" concept over the life cycle of a product.

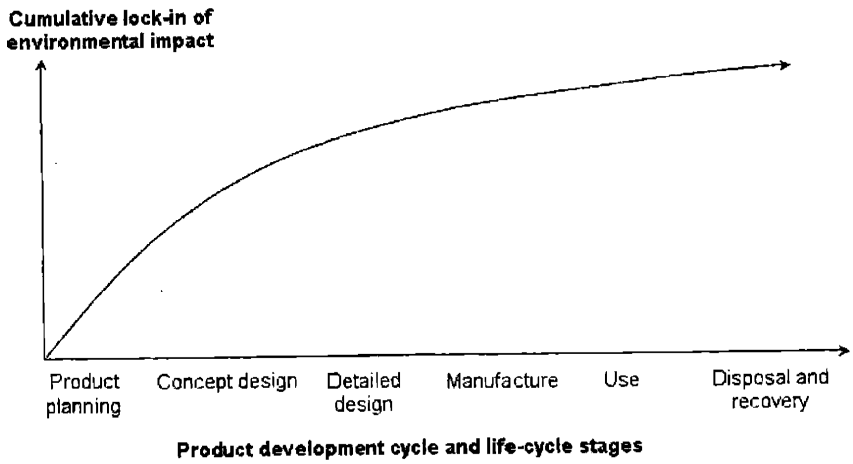


Figure 2.5 Environmental "lock-in" by design activities over the various stages of product development and life-cycle. Adapted from Lewis et al (2001).

Thus, at early stages, product designers should have access to relevant environmental information so that they can make appropriate decisions and tradeoffs with other design requirements, allowing a wide range of environmental concerns to be incorporated into the decision-making process.

2.2 PRODUCT CONCEPT SYSTEMS

Product concept systems is a term used throughout this thesis to help position, define, and characterize the research problem domain into the design process framework. From the literature reviewed, the systems architecture framework proposed by Crawley and de Weck (2001) is the one most appropriate for this purpose.

The close interaction between systems architecture and systems design as described by Crawley and de Weck (2001) fits well with the conceptual interface model of the learning surrogate method. The system architecture scope – embodiment of the concept and the allocation of functionality and definition of interfaces among elements – manipulates architectural variables (e.g. number of satellites, constellation type). The systems design scope manipulates design variables (e.g. optical parameters, thermal strategy detector). Changes in the design variables can have large consequences at the architecture level and influence decisions, especially in high performance complex systems. The simulation interface of the learning surrogate LCA concept (product concept descriptors) operates in this boundary by incorporating a high level description of the concepts while at the same time accommodating a (high) level of parameterization.

The problem domain of this thesis consists of a product concept system. The concept – a vision, idea or mental image of a product – maps function, i.e. how the product behaves, to form, i.e. where the chunks are. Based on a framework proposed by Crawley and de Weck (2001) the product concept can be viewed as a system which interfaces with both upstream and downstream influences of a whole product system, as illustrated in Figure 2.6.

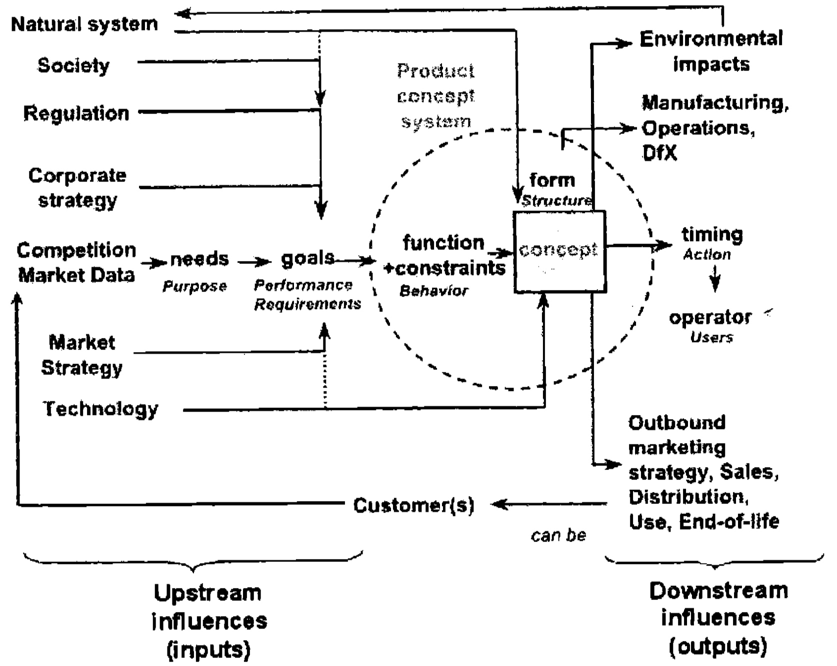


Figure 2.6 Product concept system interfaces with upstream and downstream influences. Adapted from Crawley and de Weck (2001).

Product concept systems are key for the design and development process to the extent of being able to shape cost, technical and environmental performance of products throughout their life-cycle. Figure 2.7 maps levels of complexity, ambiguity and creativity to the CDIO (Conceive – Design – Implement – Operate) generic product development process model developed at the MIT Department of Aeronautics and Astronautics. Product concept systems and high level trades occur and evolve at the conceive phase, characterized by:

Incomplete knowledge
Design concepts have little detail. Specific forms of linear or non-linear functionalities are unknown or ill-defined. The complexity – defined here as the amount of information required to fully describe the system – is then low (see Figure 2.7) and systems are defined and simulated at a high, abstract and approximate level.

Uncertainty
Upstream influences on product conceptual systems are "not designed," rather they occur with incomplete, uncertain, overlapping or conflicting outcomes. Downstream influences are themselves ambiguous because they are "in the future." This lack of information and incomplete knowledge about the systems leads to high levels of ambiguity or uncertainty (see Figure 2.7).

Design freedom
The creativity process can be very active (see Figure 2.7). Design concepts evolve rapidly in innovative combinations of different pieces of information or ideas. Design freedom at this stage can lead to architectural innovation – by further exploiting existing technology – or radical innovation – by replacing existing technology (Henderson and Clark, 1990).

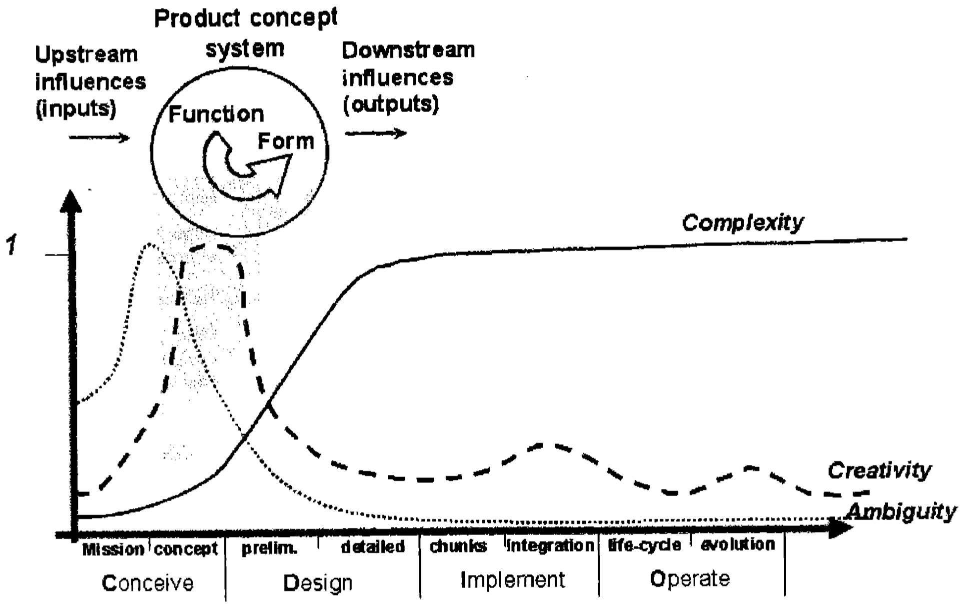


Figure 2.7 Ambiguity, complexity and creativity throughout product development. Adapted from Crawley and de Weck (2001).

2.3 LIFE-CYCLE ASSESSMENT

2.3.1 OVERVIEW OF STANDARDIZED LCA APPROACH

Life-Cycle Assessment (LCA) is a "cradle-to-grave" approach for assessing the environmental performance of a product, process or service system from raw material acquisition through production, use and disposal. The method systematically examines environmental impacts by: (1) compiling an inventory of energy and material inputs and outputs of the product system, (2) evaluating the potential impacts on resource use, human health and ecological systems associated with those inputs and outputs, and (3) interpreting and communicating the results of the assessment relatively to the goals of the study, which covers the whole life-cycle of the system, from raw material acquisition through production, use and disposal (ISO, 1997; SETAC, 1993). Figure 2.8 illustrates the possible life-cycle stages considered in an LCA process and the typical inputs and outputs measured.

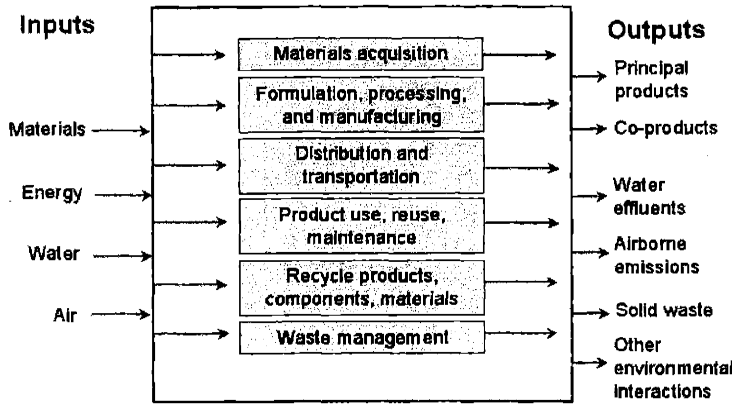


Figure 2.8 Life-cycle stages and life-cycle flows typically considered in LCA.
Source: Graedel and Allenby (1995)

The LCA methodology has evolved over the past two decades, predominantly in Europe but also in the USA and more recently in Asia (Lewis et al., 2001). The International Organization for Standardization (ISO) developed the currently agreed international standard for the LCA process (ISO, 1997). LCA principles and framework as well as methodological details are documented in four environmental management standards (ISO 14040-14043).

The LCA process consists of four components: definition of the goal and scope, life-cycle inventory analysis, life-cycle impact assessment, and life-cycle interpretation. This phased approach is illustrated in Figure 2.9, and generally outlined in the following paragraphs. A basic yet comprehensive introductory overview of the LCA process is provided by U.S. EPA (2001).

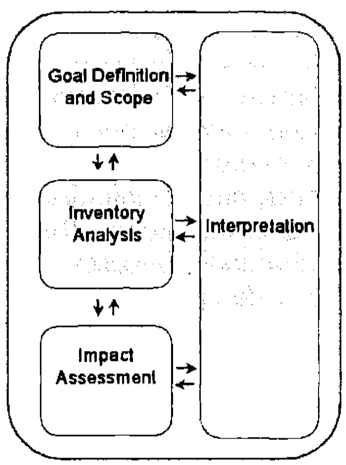


Figure 2.9 The standardized LCA process. Source: ISO (1997).

- Definition of goal and scope. This phase determines the direction and depth of the study. The purpose of the study is defined by stating clearly the reason for conducting the LCA, and the intended use of results. The scope of the LCA defines the system, boundaries, data requirements, environmental effects to be reviewed, assumptions, and limitations.

The system to be assessed is defined in terms of a "functional unit," a measure of performance that the system delivers. This functional unit is specified as a basis for comparison: of a product before and after improvement; a comparison of several design alternatives of a new product; or a comparison between different products with the same function. Specific data-quality goals should be clearly established, including the degree of confidence in the data, and ultimately in decisions that will be based upon the data.

- Life-cycle inventory (LCI) analysis. In this phase, the unit processes of the system are analyzed to identify and quantify energy, water and materials use and environmental releases (e.g., air emissions, solid waste disposal, wastewater discharge). The unit processes are then linked together in process flow charts, and mass balance equations are used to calculate the net flows of inputs and outputs of the system. The result of this analysis is a long list of resources used and emissions to the environment. Detailed data are required and the quality of the data should be consistent with the purpose and scope of the study, including variability, uncertainties, and gaps. The degree of sub-division of the total system into individual processes is frequently determined by the availability of data and the requirements defined in the goal and scope of study.
- Life-cycle impact assessment. A stand-alone LCI can provide useful information for product improvements, benchmarking, energy savings, and emission reduction, but it does not place the inventory data and information into perspective for the comparative assessment of product systems. To better understand the relative environmental significance of the inputs and outputs of the system, environmental impacts associated with the inventory are estimated and evaluated in three main steps:
    (1) Classification. The data collected in the inventory stage are grouped together into a number of impact categories (e.g. global warming).
    (2) Characterization. All the inventory elements within each impact category are translated into a common metric or equivalency factor (e.g. global warming potential in CO_2-equivalents, where, for example, carbon dioxide affects global warming by a factor of 1 and methane affects global warming by a factor of 22). A further development of the characterization step is to normalize the aggregated data per impact category in relation to the actual magnitude of the impacts within this category in some given area, to facilitate the comparison of the data from the different impact categories.
    (3) Valuation. The impact categories are weighted so that they can be compared and trade-offs can be performed. The weighted impact can then be summed to determine a single score or "eco-indicator". In principle, this assessment reflects social values and preferences.
- Life-cycle interpretation. In this phase, the results of the inventory analysis and impact assessment are evaluated and tested to check their validity before making and reporting the conclusions, with a clear understanding of the uncertainty and the assumptions used to generate the results.

By promoting the life-cycle thinking, LCA supports a holistic, systems-based view, which is required for properly assessing and reducing environmental impacts of products (Bras, 1997). A systems approach is needed to avoid transfer problems between life-cycle stages. For example, lead-acid battery-powered vehicles that may be considered to reduce emissions may increase lead burdens to the environment (Rydh, 2001; Lave et al, 1995), or changes in material composition of cars to improve fuel economy may increase the amount of automobile shredder residue (which is not recyclable), leading to disposal concerns, or generate new emissions in the production phase (e.g. SF6 emissions from magnesium production and manufacturing of magnesium components) (Rebitzer and Fleischer, 2000), or may not yield a better life-cycle energy benefit (Sullivan and Hu, 1995).

LCA is one of several approaches for supply environmental information to the decision-making process in industry, governmental and non-governmental organizations. Other methods, such as risk assessment, environmental impact assessment, cost benefit analysis, and environmental audit, are often applied for different purposes and using different technical approaches. For example, risk assessment uses stochastic techniques for evaluating the probability of catastrophic events at specific facilities to reduce risks to workers and community. CHAINET (1998) provides a framework for structuring how different concepts (e.g. life-cycle thinking), technical elements to obtain and process data (e.g. mass balance models), and analytical and procedural tools (e.g. LCA and environmental management system) are related to the decision process.

LCA has been perceived as a useful DFE analytical approach to select environmental areas of attention and to support environmentally conscious product design options. For environmental validation and prioritization of design options and environmental performance of products, this approach provides a satisfactory performance, as long as it is applied transparently, with acknowledgment of assumptions and methodological limitations (Newell, 1998).

2.3.2 LIMITATIONS

The LCA methodology has a number of limitations and therefore it must be used with caution (Ehrenfeld, 1997; Owens, 1997). The following are key limitations of the method:

- Defining the system boundaries is an arbitrary and controversial task that depends on many subjective judgements involving ambiguous analytical and conceptual compromises in the inventory phase (Newell, 1998). The specification of the functional unit is also not obvious and it is hard to recommend a consistent approach to either procedure (Graedel, 1998). In addition, building the complete system model within the defined boundaries is difficult and often impossible, especially if supplier data is proprietary (Arnold, 1993).
- Data collection and analysis are also limitations to accuracy and completeness of the LCA approach (Graedel, 1998). Although databases are being developed in various countries, in practice data are frequently obsolete, incomparable or of unknown quality at the level of building blocks (combinations of processes, such as electricity production or aluminum production) rather than on individual processes (Guinée et al, 2001). As a result, different assessments can produce different although perhaps with equally valid results.
- LCA is time-consuming, data-intensive and expensive to conduct. Often, LCA studies get obsolete for the decision making process for which they were conducted in the first place because the LCA process takes too long (Rebitzer and Fleischer, 2000).
- Moving from inventory to impact assessment in LCA is fraught with scientific difficulties (Owens, 1997). Limitations imposed by the inventory (LCI) are loss of spatial, temporal, dose-response, and threshold information, varying widely according to the environmental issue in question and models used to extrapolate the inventory data. As a result, LCA may have limited value in local and/or transient biophysical processes, and issues involving biological parameters, such as biodiversity, habitat alteration, and toxicity.

- The impact assessment phase is an area of significant debate in the LCA community with no commonly agreed-to methodologies to apply in practice. Variations in temporal scale, spatial scale, and locale as well as questions of valuation based on subjective elements of societal structure and preference are main limitations (Owens, 1997; Graedel, 1998; Boustead et al, 2000).

In examining the appropriate uses of LCA one may adopt two main perspectives on the methodology (Fava, 1997; Owens, 1997): (a) a thought process that guides the selection of options for design and improvement, providing a spectrum of useful insights on a system; (b) as a sound, complete characterization useful for all types of comparisons and judgments of environmental performance. The difference between these points-of-view may also be interpreted as whether LCA is a stand-alone tool, sufficient for making definitive comparisons, or must be integrated with non-LCA complementary tools, such as risk assessment and environmental impact assessment, to provide meaningful and relevant answers. The scientific and technical limitations inherent to LCA limits this approach for making comparisons in a stand-alone fashion, and therefore its broad screening capabilities need to be integrated with other environmental tools in an overall environmental management framework (Owens, 1997; Fava, 1997; Ehrenfeld, 1997).

The use of LCA in a "toolbox" of environmental assessment tools (Guinée et al, 2001) is then the appropriate approach to support the decision process. The goal is to have each tool performing the task and providing the information to which it is best suited, while other complementary tools address its weakness and limitations (Fava, 1997). For example, if one were trying to assess the efficient use of resources in a product system, LCA could provide information internally to a company to identify opportunities to improve the efficiency. But, if the goal were to address customer concerns on health and toxic effects, the problem could be addressed by conducting a human health and ecological risk assessment. Finally, if one were trying to address "overall environmental preference" of one product system over another, a variety of tools, including site-based assessments and LCA could be suitable.

Newell (1998) proposes a decision-oriented LCA tool called "Explicit LCA" (XLCA) as a quantitative LCA methodology suitable to, at the most, environmentally rank alternative technologies. In early design phases, a low precision assessment tool is appropriate and sufficient for ranking technologies, so long as it addresses the objective and subjective elements of LCA explicitly in order to explore their effects on the outcome (Newell, 1998). This perspective on a low-resolution approach to meaningfully incorporate LCA into the design process agrees with the methodological strategy proposed in the present research.

In any case, comparisons and choices have to be made in product design, and LCA, if used appropriately and consciously regarding methodological limitations, can potentially add important environmental content and context to other factors, such as performance and price (Ehrenfeld, 1997). Although it does not provide the right answer, this methodology has the potential for identifying environmental issues from a system-wide perspective, helping to achieve better understanding of the problems.

In practice, however, experience has shown that a product-level comprehensive LCA with its scoping, impact, and interpretation phases is infeasible, at least as a routine, useful tool to apply in product development cycles in industry (Rebitzer and Fleischer, 2000; Graedel, 1998; Graedel and Allenby, 1995; O'Connor and Blythe, 1997). There are key practical barriers:

- High completion costs, time required, labor intensive: the staff time and expense needed to complete a comprehensive assessment is often prohibitive.
- Unavailability of the required assessment data: much of the data are difficult or impossible to acquire, e.g., factory energy use may not have been allocated to specific products, and residue streams may have been merged.
- An assessment taking several months to perform makes no sense, with product life-cycles and design-to-market intervals of several months to 2 or 3 years.

2.3.3 STREAMLINING LCA

To simplify and significantly reduce the amount of time and information required for the detailed standardized LCA process, simpler approaches have been developed, both in academia and in industry. Most corporations and many other organizations have adopted the LCA philosophy but have implemented it in a practical form adapted to their own needs and constraints in the product development process (Graedel and Allenby, 1995; O'Connor and Blythe, 1997; Eagan and Weinberg, 1997; Hoffman III, 1995). Simplified approaches include qualitative matrices, abridged LCA, and a variety of other forms of simplified or streamlined LCA.

In general, LCA streamlining refers to the design of LCA in terms of what is included in the study and what is not (SETAC, 1999). Streamlining removes portions of a LCA deemed non-critical to a specific product's environmental impact profile and can be performed within the existing LCA framework or through alternative streamlining approaches based on life-cycle concepts.

Typically, streamlining approaches within the standardized LCA framework have included: (a) simplification of the LCI phase through the elimination of life-cycle stages (e.g. cradle-to-grave studies that ignore activities after the production phase), also referred by Fleischer et al (1998) as restricted LCA; (b) reducing the data required on the unit process networks (e.g. by applying thresholds or cutoff criteria or by limiting the analysis to first tier contributions), or focusing on specific flows at the inventory level (e.g. life-cycle energy) or on specific impacts (e.g. global warming), generally referred by Fleischer et al (1998) as screening LCA. .

SETAC (1999) compared several streamlining approaches and found that the more streamlined a LCA becomes, the less accurate its results when compared with a full LCA, especially when streamlining decisions are ad-hoc. However, depending on the goal of the study these results may still be just as useful as the full, detailed LCA.

Figure 2.10 shows the "assessment continuum" proposed by Graedel (1998) that frames the scope of the streamlining activity. The region referred as extensive LCA corresponds to detailed, quantitative LCAs. The scoping or eco-screening regions are those that are "quick and dirty" to guarantee that no truly bad design choices have been made or to investigate the need for additional assessment. The ideal point is within the SLCA region, where the assessment is complete and rigorous enough, yet not so detailed as to be difficult or impossible to perform.

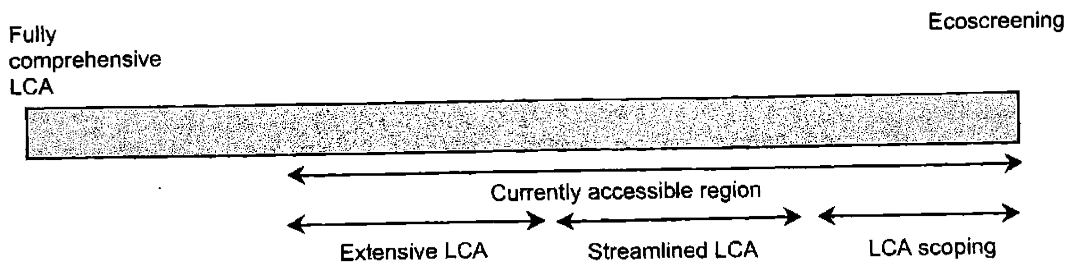


Figure 2.10 The assessment continuum. Source: Graedel (1998)

Overall, a streamlined LCA (SLCA) is considered valid if all relevant life cycle stages and environmental stressors are evaluated in some manner, and the LCA's four elements methodological steps are included, not necessarily in a quantitative manner (Graedel, 1998).

Several different techniques for SLCA have been proposed and used in academia, government, industry, consulting firms, and professional associations (Graedel, 1998). An ideal goal has been to keep the LCA concept and sufficient accuracy to obtain credible results while at the same time meeting the scientific and logistical constraints. Some of these different SLCA approaches are presented below. This is not as a comprehensive list, but an illustration of some of the benefits and shortcomings of presently used SLCA techniques.

Matrix-based life-cycle assessment

Matrix-based LCAs can be performed through a sequence of steps equivalent, yet less data-intensive and time-consuming, to the standardized LCA process, as shown in Table 2.1.

Table 2.1 Comparison of full LCA versus matrix-based streamlined LCA. Source: Lewis et al (2001)

Full LCA	Matrix-based LCA
Goals, scope and definition.	Flowchart or process tree, with a design or product development brief.
Inventory of (almost) all processes, with data taken back to basic materials (e.g. ores, coal, CO_2).	Inventory matrix, which is a list of materials and energy used by the product throughout its life-cycle and the associated emissions.
Impact assessment.	Impact assessment matrix, which simplifies the inventory information into groups of emissions or potential impacts. The information entered in the matrix can be qualitative or may include a ranking of the impacts.
Interpretation.	Design strategies and practicality versus efficacy matrix.

Several variations of the matrix-based LCA approach have been developed by academia and in industry to meet specific environmental assessment demands (Eagan and Weinberg, 1997; O'Connor and Blythe, 1997; Graedel, 1998).

In a qualitative matrix approach proposed by Allenby (1992), to include the Environment in its broadest sense, environmental issues are proposed to be further classified and analyzed under four different category matrices for each design alternative - manufacturing issues like materials, cost, energy; environmental impacts e.g. on air, water and soil, toxicity and exposure impacts and socio-political impacts. Any scheme can be adopted so long as the items under each category created can all be consolidated into a single impact for a summary of the analysis. A summary matrix is proposed which brings together for all design alternatives, the essence of each of these categories and permits the comparison of alternatives for each category of environmental impact.

In the rating system suggested by Allenby (1992), slightly modified for the sake of illustration, inapplicable or inappropriate elements are denoted by a dash and beneficial impacts by a '+' or '++', depending on the relative degree of benefit. Where there is an environmental 'concern', a system of ovals is used with the darkness of shading representing concern, and the extent of filling, the uncertainty. For example, in cell phones the 900 MHz electromagnetic radiation is a suspected carcinogen but evidence is slim. So while the concern is serious, fetching a black shading, it is highly uncertain and to that extent only a quarter of an oval for certainty. The ranking system and a hypothetical environmental matrix are shown in Figure 2.11.

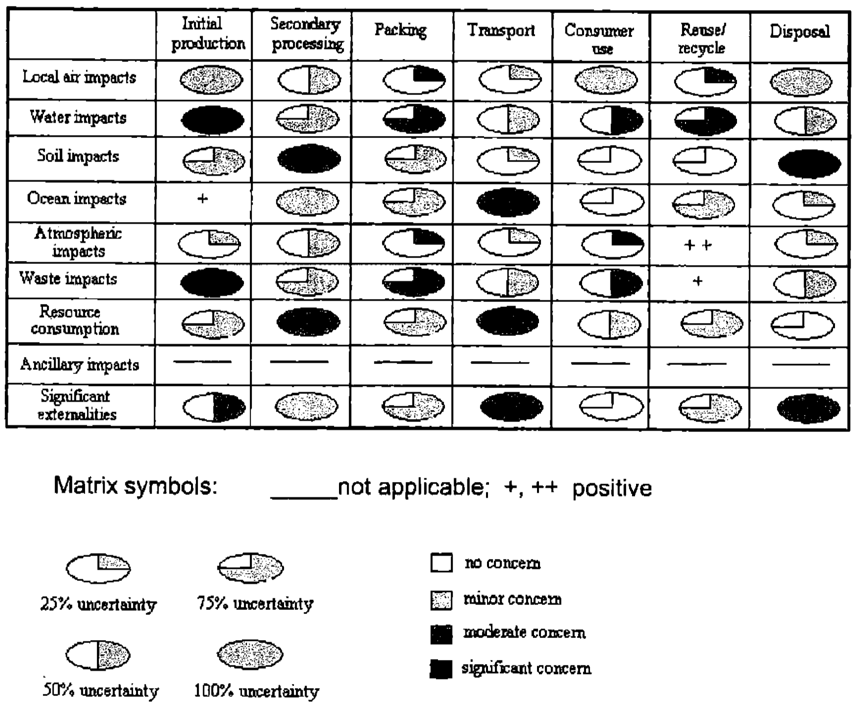


Figure 2.11 Ranking system and hypothetical environmental matrix.

Each matrix is given an overall degree of concern/certainty in the assessment. The hypothetical matrix shown in Figure 2.12 summarizes these grouped assessments for comparing different design alternatives. In assessing an individual matrix element, or in offering advice to designers exploring the rating of new design options, the environmental expert can refer to experience, appropriate checklists, design and manufacturing surveys and other protocols for guidance (Graedel and Allenby, 1995).

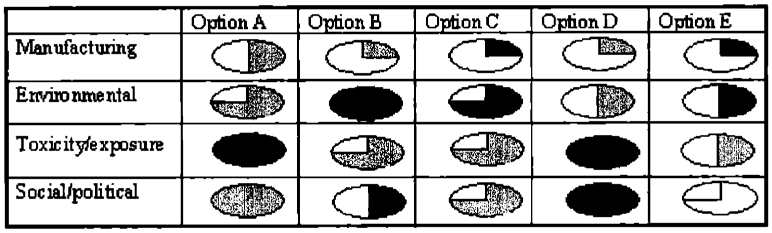


Figure 2.12 Summary matrix for comparing between design alternatives.

The matrix approach presented herein is a framework that incorporates the life-cycle thinking into the design process by manipulating data and analysis in a qualitative fashion. This is of great importance for the product design area. There are aspects in product design that are critical and cannot be ignored, such as consumer preferences, quality, and aesthetics, for which data in many cases are not quantifiable or not available to merit a probabilistic analysis. Also environmental and social impacts are poorly understood and suffer from fundamental data and methodological deficiencies (Graedel and Allenby, 1995). This gives rise to the notion of uncertainty where there is a suspected effect but which isn't known to a reasonable degree of confidence to assert it as a fact. Consequently, some aspects, even if important, are relegated to the qualitative world, particularly during conceptual phases. Therefore, relevant advantages of qualitative matrix approaches are:

- They incorporate representation and manipulation of qualitative data and value judgments in the product design process;
- Qualitative matrices highlight the existence of uncertainties in the analysis. They can help account for uncertainties in the environmental area, namely risks, potential costs, and potential environmental impacts.
- They make life-cycle thinking more accessible and practical by simplifying the LCA methodology. They reduce data and time required to perform an LCA and overall life cycle assessment is less thorough.
- They bring effectiveness to design evaluations by estimating the first-order environmental effects, capturing the essential points. Qualitative matrices help to focus on key issues.

However, the limitations associated with this approach are felt when the trade-offs to be made are complex, the "what-if" analysis involve multi-objective functions and several constraints that are hard to manipulate. Although it provides a macroscopic comprehensive view of the problems enabling comparative analysis, this approach limits the manipulation of the information to assess new design strategies and corresponding scenarios in a fairly quick fashion. Indirectly, this has the potential to affect the quality of the analysis since it may limit the number of scenarios to explore due to time constraints.

Abridged LCA (Graedel et al 1995) is a semi-quantitative matrix approach. The use of ALCA is demonstrated in Graedel et al (1995) through a comparison of consumer products. Hoffman III (1997) also refers to abridged LCA tools to be useful in the conceptual phase, as opposed to employing traditional LCA for the prototype manufacture, when more design details become available. Like qualitative matrices, ALCA highlights only the most significant concerns. An additional benefit of abridged LCA is its numerical basis. The simplified LCA process can be represented and handled mathematically through matrix manipulation. The ALCA matrix-algebra computation is capable of generating a numerical rating for design or alternative designs providing specific targets for analysis. To some extent, this approach may minimize the limitation mentioned previously for qualitative matrices on performing efficient trade-off analysis and decision-making analysis. At the same time, the associated numerical bases can improve the effectiveness in capturing the essential points by allowing graphical representations.

On the other hand, the determination of the values of the matrix elements as quantitative indices based on the combination of heuristics (rules of thumb of knowledgeable practitioners) with precise information data might be controversial. There is the question of in what extent they are reasonable and consistent enough to perform the analysis.

Simplified LCI modeling

Reducing the effort in modeling the product system affects the time and cost associated with the inventory phase as data requirements can be decreased significantly. Rebitzer and Fleischer (2000) developed a methodological approach that facilitates the set up of a simplified system LCI model. The goal is to have a (semi-) automatic procedure that helps to decide whether further inclusion of processes and therefore further gathering and computing of data in the LCI model is necessary for the specific study.

In this approach, simplified models of product systems are derived from those of detailed studies through a systematic procedure based on recursive modeling by path analysis. Starting from the finished product, the flows into the final manufacturing process (level 0) are followed and the processes having those flows as output (level 1) are determined and so on, ending at the resources entering the system as elementary flows. The idea is to show a correlation between the levels (or other criteria such as mass) included or the magnitude of cut-off criteria to the results of the LCA. Mathematical indicators such as first and/or second derivative of the correlation function can be used to identify the product system model that defines 80 or 90% of the total impacts. The level of confidence in the simplified model is based on the probability of occurrence of relevant function maximums with increasing number of levels. This can be estimated based on a qualitative screening LCA, which screens specifically for hot-spot emissions or inputs in the complete system.

Rebitzer and Fleischer (2000) tested this approach in two material options for a front sub-frame system of a Ford passenger car. The approach has potential for greatly simplify, with a certain level of confidence, the LCI model, and consequently allocate more efficiently the resources for data gathering and computing. However, it still requires a significant modeling effort that in early phases of the product development cycle such as early conceptual design is not cost-effective to invest in. At this stage, it might even be impossible to develop such simplified models, as these still require an explicit knowledge of the system. Another issue to consider is how general these simplified models can be applied seamlessly in different types of systems, without additional modeling tasks.

Canter et al (2000) propose a screening methodology for the inventory stage that uses the linear structure within the deterministic LCI model. Each input data element is ranked and sorted in descending order based upon its contribution to the final output. Percentages of the top ranked data elements are then selected, and their corresponding data quality index (DQI) value is upgraded in the stochastic LCI model. The output variance of the original stochastic model and the one of the modified stochastic model are compared using Monte Carlo computer simulations. Similarly to the method described previously, the modeling effort involved and the limited generalization ability are still barriers to perform quick and approximate environmental assessments of various concepts at early design stages.

A method proposed by Mueller and Besant (1999) models life-cycle parameters (LCP) in terms of design parameters (DP) to present information that is required for the environmental assessment in a more condensed manner. The analyst will have the LCI-data represented in form of relationships and thus the amount of the data gathering effort is largely reduced. Once the models are determined they will form the basis for a generic LCA, although their development requires an even larger amount of data. The first step is to select the parameters. Design parameters (e.g. power output and speed of an electric motor) are physical characteristics of the design that can be determined or are known with a certain degree of accuracy. They must have a significant relationship to at least one LCP. Life-cycle parameters (e.g. mass and size of the product) can be linked to the LCI and/or one or more life cycle stages. They should be an accessible data source, describe features that change within the product range in a continuous manner, and if described by qualitative data, the discrete levels should be limited to a sensible number based on valid assumptions.

The second step is to define the relationships between the DPs and the LCPs in the form of $LCP = f(DP_1, DP_2, \ldots, DP_n)$, based on theoretical reasoning, common practice and practical considerations (such as standardization), empirical observations or combinations of those. The accuracy of these models is considered by associating an error function with the actual model. The life cycle parameters can be optimized by choosing different combinations of the design parameters. Finally, the LCI data of the product described by the LCP's can be used to perform the environmental impact assessment phase, which may not be limited to a particular method and various methods may be applied. By highlighting the most important parameters of the total life cycle, this analysis can be used for focusing design efforts to maximize improvements in the design of the product.

This approach ultimately supports the development of modeling interfaces between traditional design and environmentally-conscious design. However, the modeling step required to estimate environmental performance using the LCPs is not explicitly addressed other than just selecting relevant life-cycle parameters that help confining the design efforts to important elements of the system.

2.4 FUNDAMENTAL GAPS OF EXISTING DFE METHODOLOGIES FOR EARLY DESIGN STAGES

Limitations of LCA have determined many potential users in product development to exploit LCA streamlined forms (such as the ones discussed in section 2.3) for conducting a simpler and cost-effective assessment process. A variety of other DFE methodologies have been proposed and used in practice for support the identification and evaluation of the environmental impact of a product. They include team brainstorming sessions, environmental performance checklists at certain points of the design process (e.g. waste reduction or material recycling), design standards, design guidelines, and chemical and material databases. Although there are some LCA success stories in industry (Wenzel and Alting, 1999), several studies performed at companies (e.g. Evans et al, 1999; Grüner et al, 1999, Mizuki et al, 1996) reveal a general agreement upon the valued use of "quick and dirty" analysis tools.

Still, “quick and dirty” tools currently available are of limited use or even impractical if one needs to address the analytical requirements of early conceptual design stages.

Table 2.2 provides a comparison between the learning surrogate LCA approach and other approaches based on methodological, data, decision support and practicability criteria.

Table 2.2 Comparison of the learning surrogate LCA method with other DFE methodologies.

	Checklists	**Qualitative matrix-based**	**Abridged matrix-based**	**Detailed LCA**	**Simplified LCI model**	**Learning surrogate LCA**
			Methodology			
Mode of analysis	descriptive	descriptive	descriptive	descriptive/prescriptive	descriptive/ prescriptive	descriptive/ prescriptive
Depth of analysis	none	superficial	superficial	deep	medium	superficial
Precision in analysis	low	low	low	higher	medium, sufficient for early design	medium, sufficient for early design
Technical approach	quality assessment	quality assessment	quality assessment	allocation, mass balance models	allocation, mass balance, empirical models	ANN, tree-classifier models
			Data			
Quantification of data	qualitative	qualitative	qualitative/ quantitative	quantitative	quantitative	qualitative/ quantitative
Specificity of data	generic	generic	generic/ averages	typically primary	typically secondary	generic/ averages
Data quality	high uncertainty	high uncertainty	high uncertainty	measured/ lower uncertainty	estimates/ high uncertainty	estimates/ high uncertainty
			Decision making support			
Support life-cycle thinking	no	yes	yes	yes	yes	yes
Model retains causal chain	no	no	yes	maybe, depends on transparency of method)	maybe, depends on transparency of method)	no
Assist in ranking environmental alternatives	no	only in low-dimension problems	only in low-dimension problems	yes	yes	yes
Support trade-off analysis with other design goals	no	only for obvious tradeoff scenarios	only for obvious tradeoff scenarios	maybe, if flexible to be implemented in integrated simulation frameworks	maybe, if flexible to be implemented in integrated simulation frameworks	yes, at early conceptual design stages
			Practicability			
Modeling effort required	none	low	low	high	medium	none
Resource requirements – time, expert knowledge and money	lowest	low	low, but with environmental expertise required	highest	high	low, but with environmental expertise required
Intended user	designer	designer (or environmental experts)	environmental expert (in product design team)	environmental expert (in product design team)	environmental expert (in product design team)	environmental expert in product design team

Figure 2.13 maps the methodologies and the learning surrogate approach according to key properties of product concept systems.

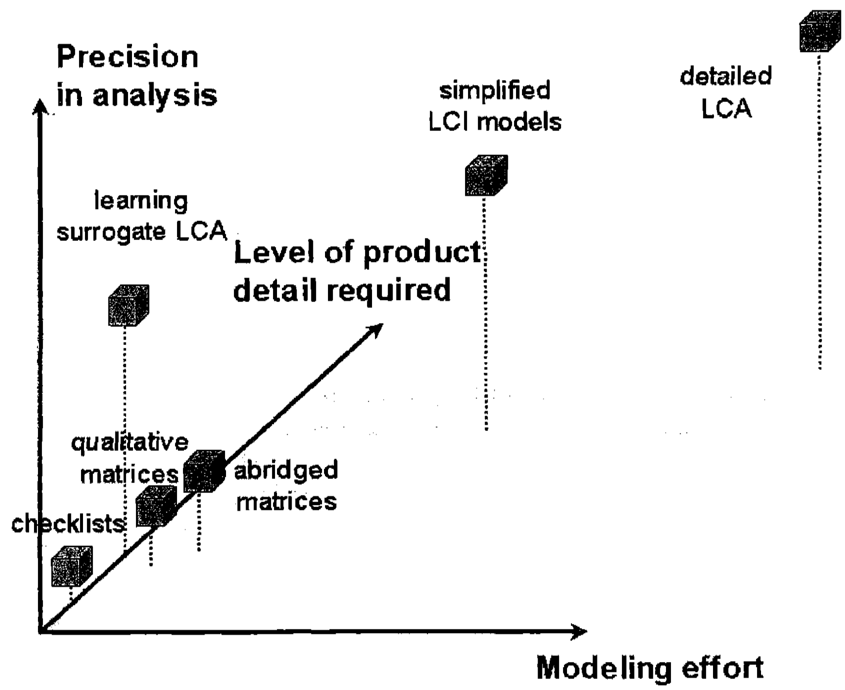


Figure 2.13 Mapping the learning surrogate LCA method and other methodologies to modeling effort, level of product detail required, and precision in analysis.

As illustrated in Figure 2.13, the learning surrogate LCA method is isolated in a space defined by key attributes for product concept systems. While maintaining technical credibility with sufficient precision in analysis for early conceptual stages, the learning surrogate LCA approach is highly cost-effective with low data requirements and no modeling effort. Ultimately, these methodological attributes allow feasible and timely life-cycle environmental assessment at early design stages.

3 LEARNING SURROGATE LCA FOR PRODUCT CONCEPT SYSTEMS

3.1 THE LEARNING SURROGATE LCA CONCEPT

The lack of analytically based methods for incorporating environmental aspects into product concepts motivated the development of the learning surrogate LCA concept (Sousa et al, 2000; 1999). The approach facilitates an integrated system design process, allowing the approximate and rapid assessment of environmental impact based on high-level information typically known in the conceptual phase.

An artificial neural network (ANN) is trained to generalize on characteristics of product concepts typically known in the conceptual design phase, and environmental data from pre-existing LCA studies. The approach is illustrated in Figure 3.1. The product design team queries the trained artificial model with high-level attribute data of new concepts – *product descriptors* – to quickly obtain an approximate environmental performance for a new product concept. This is done without the overhead of defining new LCA models on a product-by-product basis. The product design team can then apply the predicted environmental performance along with key performance measures from other models in tradeoff analysis and concept selection.

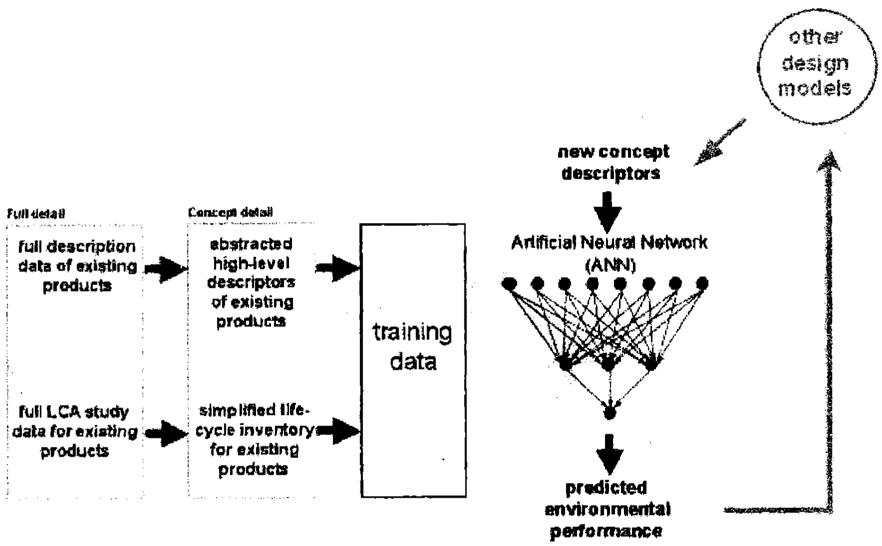


Figure 3.1 Training the learning surrogate LCA model.

The learning process of the ANN begins when it is provided a set of product descriptors and corresponding detailed LCA results from previously analyzed existing products. The training algorithms adjust parameters within the network so that its output better emulates the actual environmental impact results of the training data products. The process continues until the network converges, or the two outputs – actual and predicted environmental performance – match. ANNs do not require an explicit functional model for relationships between the system variables and they can learn from incomplete, inaccurate, and noisy data. However, 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. The new values for the product descriptors can come from other models integrated within a system model, such as obtaining volume from a CAD model, or from the environmental expert, such as recyclability. A new LCA model does not have to be constructed to analyze a new concept. However, results of new detailed LCA studies should be continually added to enhance the training data set.

Although it is a good idea for product designers to have some environmental knowledge, it is not and should not be their area of primary expertise. Ideally, the services of an environmental expert should be extended to the designer. Communication, although necessary for such an extension, is often a barrier as it takes time to establish and maintain synchronization of information between designers and environmental analysts. Prior work (Borland and Wallace, 2000; Borland et al, 1998) has demonstrated the effectiveness of an Internet-based prototype software called DOME (Object-based Modeling Environment) (Wallace et al, 2002; Abrahamson et al, 2000; Pahng et al, 1998) in providing designers with rapid environmental impact assessment based upon LCA models and tradeoff analysis with other design models.

In supporting a team-oriented, multidisciplinary design process at early conceptual stages, this new learning surrogate LCA method assumes that environmental experts and design engineers are specialists in their own fields. They exchange their simulation-based services through an integration framework such as DOME. Learning surrogate LCA models should be created, validated and maintained by environmental experts. They are meant to be used by designers or by environmental experts as service provided to designers. Product descriptors are the communication-simulation interface between environmental experts and designers for this new approach. Designers naturally think in terms of materials, processes and form (Kljajin, 2000). By considering these in the form of high-level product descriptors that potentially influence environmental performance of product concepts, this method can be thought as a natural extension of the designer's world to the environmental expert's world. Product descriptors are then a set of keywords both understood by designers in relation to preliminary product concepts, and meaningful in an approximate environmental impact assessment of product concept systems.

The purpose of the learning surrogate LCA method is not to explore environmental causalities in the product concept system. The idea is that designers use it to better relate design changes with approximate environmental performances, internalizing environmental effects of their decision making in a holistic sense under the guidance of an environmental expert. They follow the design path, not the environmental path. In product concept systems, high level information and parameters are not suitable for timely and significant explicit modeling. However, there is a need for approximate, fast answers for preliminary trade-off analysis with traditional design goals. In addition, the learning surrogate LCA concept has an analytical purpose by helping identify weaknesses and strengths rather than to suggest improvement strategies. It is important to be able to separate analysis from improvement activities. The latter can be supported with informed analysis provided by the learning surrogate LCA models but also may need other type of inputs to be carried on.

The learning surrogate LCA model is envisioned to complement traditional full LCA, not to replace it. In early design stages the learning surrogate LCA, trained on previously conducted detailed LCA studies, provides rapid feedback on a wide variety of concepts. In later design stages, when a smaller range of concept variations is under consideration, full parametric LCA models can be used as envisioned in the work by Borland and Wallace. (2000), when fewer concepts are under consideration and more detailed parametric LCA approaches provide the appropriate support. Results from the detailed LCA models are then added to the training database to enhance the training data set of the surrogate model. The simplicity of the learning surrogate method is distinct however from the one of ad-hoc rules, which cannot generalize. Even at early design stages, general environmental guidelines can be misleading when designing and assessing a particular system.

Proposal of a hybrid learning system

Surrogate model tests that were performed using ANNs (Sousa et al, 2000), to be further discussed in 4.1, showed that the implemented learning algorithm had difficulty predicting characteristics for an extremely diverse range of products (for example, predicting the life cycle energy consumption of a coffee filter and an automobile). Performance increased significantly when small mass products and products that do not transform energy when in use were trained and tested separately from medium to large mass products that transform energy when in use.

These results suggest that it is unlikely that a single universal neural network will be able to generalize well for an overly large range of products. A product categorization system based on a decision tree classifier proposed in Sousa and Wallace (2002) was considered to be a viable strategy to make the ANN learn faster and more effectively, as it narrows down the "learning space", into general product categories, prior to the prediction phase. The learning architecture will then be a combination of a tree-based classifier, to perform the initial product categorization, with "category-based" neural networks, to approximately predict environmental performance in the subsequent step. The goal is to incorporate capabilities inherent to distinct methods that complement each other, in order to reach better learning performance.

Classification criteria are based upon the product concept descriptors that are used to train and query the learning LCA models. The prediction step takes place using neural networks, previously and separately trained using products from one single category. This hybrid approach is schematically represented in Figure 3.2.

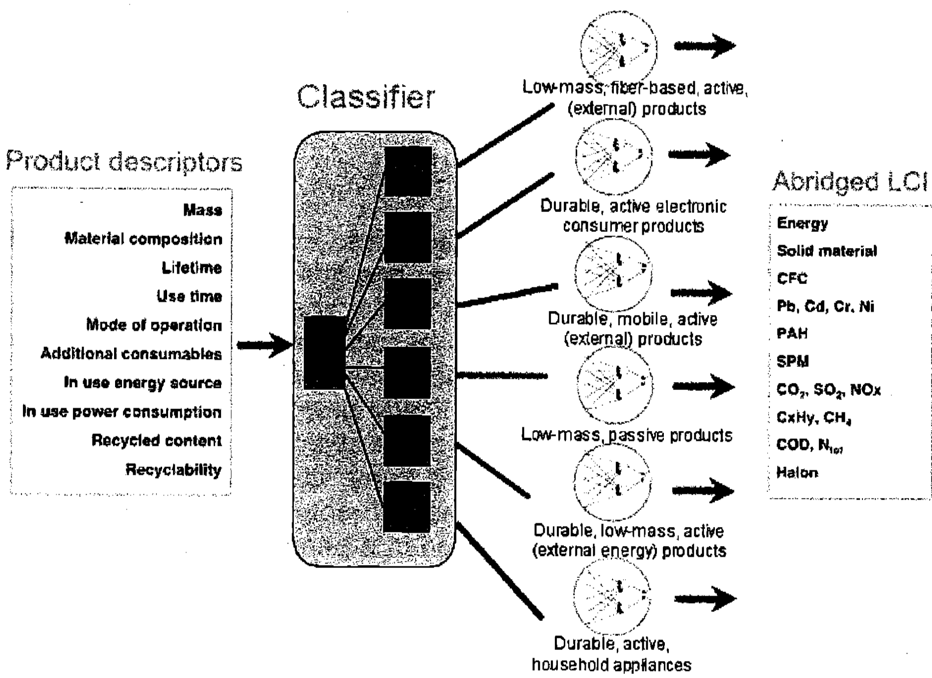


Figure 3.2 The hybrid learning system.

The use of a classifier, in this case a decision tree, allows the automation of the classification step. This potentially brings two main advantages: speed on the process and consistency in the data for training and using the specialized neural networks.

As it will be described in Chapter 4, the set of product descriptors was systematically and devised as a general set that can characterize many different products. However, there is no universal set of attributes that fully represents every possible product. Therefore, the hybrid-learning concept should accommodate the need for customizing general descriptors for specific categories of products (e.g. lifetime drive distance and drive cycle for durable, mobile, active (external energy based) products). Group-specific product descriptors can then be incorporated accordingly in the training cycles and query tasks of each of the specialized learning surrogate LCA models (see Figure 3.2).

3.2 Machine Learning to Support a Surrogate LCA Model

There are several machine learning algorithms and reasoning mechanisms that have been proposed, developed and used in various fields of application. The goal here is not to exhaustively review them all. Instead this section provides a review of eight existing methodologies that were selected as being relevant to consider for supporting the learning surrogate LCA method.

Each methodology is explored in qualitative terms by its definition, main properties and basic functionality. The idea is to use relevant background to properly identify advantages and disadvantages associated with each methodology, given the problem domain and research goals of this thesis. This discussion provided the basis for ultimately selecting artificial neural networks and decision trees as suitable methodologies to form the hybrid learning architecture proposed for the learning surrogate LCA model.

3.2.1 NEURAL NETWORKS

Definition and general properties

Artificial Neural Networks (ANN), (or neural networks, neurocomputers, parallel distributed processing systems and connectionist systems) are intended to model the organizational principles of the central nervous system (Haykin, 1999). The motivation for the approach is that the brain, a highly complex, nonlinear, and parallel computer, has the ability to perform certain computations (e.g., pattern recognition, perception, and motor control) many times faster than the fastest digital computers. For example, an image processing task, such as recognizing a simple object projected against a background of other objects, can be solved by a small child's brain in a few tenths of a second. However the same child might not be able to solve the addition problem 3+3=6, while a serial machine can solve it in a few nanoseconds. A key difference is that image recognition is best solved in a parallel fashion (brain is believed to be similar to a massively parallel analog computer containing about 10^{10} simple processors, each requiring a few milliseconds to respond to input) while simple mathematics is best done serially (McCollum, 1998). The biologically inspired computing capabilities of ANNs are thus believed to perform cognitive and sensory tasks more easily and satisfactorily for solving real-word problems than conventional serial processors (Bose and Liang, 1996).

An ANN is an interconnected assembly of simple processing logic units, nodes or neurons, usually connected in layers. The knowledge of an ANN is stored in inter-unit connection strengths, or weights, generated by a process of adaptation to, or learning from, a set of experimental training patterns. There are several learning tasks that apply to the use of neural networks. The classification and multivariate function mapping are learning tasks that are relevant to a large number of problems.

A neuron is the information-processing unit that is fundamental to the operation of a neural network. A basic model of a single neuron is shown in Figure 3.3. There are three basic elements on the neuronal model:

1. Synapses, each of which characterized by a weight. A signal x_j at the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj}. There might exist a fictitious or internal constant input signal called bias.
2. Adder or summer, which sums the input signals, weighted by the respective synapses of the neuron.
3. Activation or threshold function, which yields an output to a respective input. The function limits the permissible amplitude range of the output of a neuron to some finite value. Typically, normalized amplitude range of the output of a neuron is considered in the closed unit interval [0,1] or alternatively [-1,1].

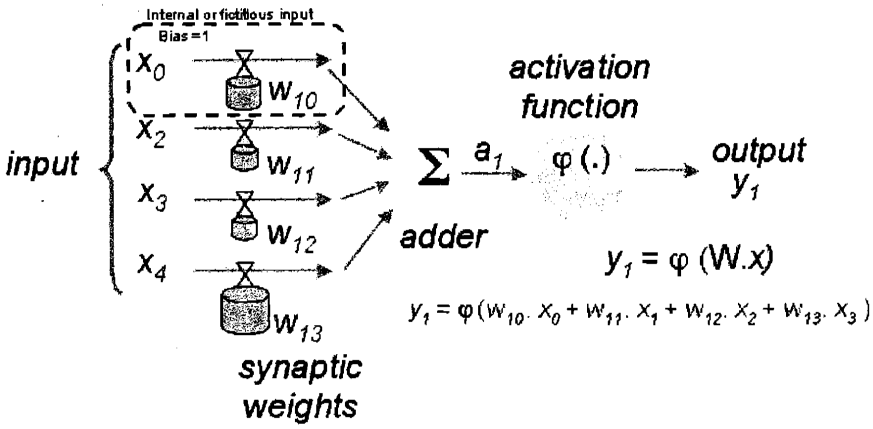


Figure 3.3 A nonlinear model of a neuron. Adapted from Haykin (1999).

There are different ways in which the neurons of a neural network can be structured. The multilayer feed-forward network is a popular type of neural network architecture. The network is arranged in layers of neurons or units: an input layer, to take input values from the outside; one or more hidden layers, which extracts useful features from the input data; an output layer, to report the final answer. A schematic diagram of a multilayer feed-forward architecture, with one hidden layer and one output layer, is shown in Figure 3.4. Each neuron or unit has activation flowing into it from the preceding units, which is multiplied by the weight along which it flowed. The vector of resultant inputs is summed and passed through the unit's activation function before being passed onto the next layer.

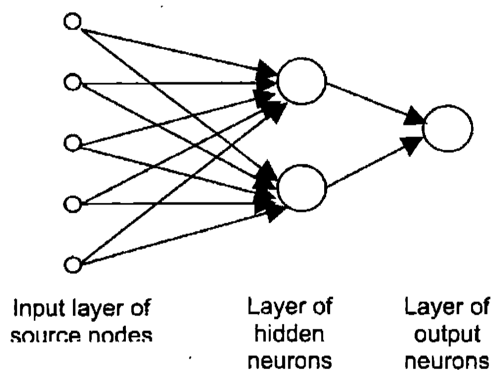


Figure 3.4 A feed-forward neural network with topology 5-2-1.

A neural network is supposed to learn a model of the world (environment) in which it is embedded and to maintain sufficient consistency with the real world in order to achieve the specified goals of its application of interest. The training of an ANN is based on a simple idea - learning through example. The neural network is provided input data for known problems and its outputs are compared to the known answers. Training algorithms use this information to adjust the weights of each connection to better match the target output. It is important to note that in order for a neural network to learn effectively the examples in the training set should represent a reasonable distribution over the system space.

There is a diverse variety of training algorithms for the design of neural networks, each of which offers different advantages. They differ from each other in the way the adjustment to a synaptic weight of a neuron is formulated. The most commonly used method is called back-propagation-of-error, a form of supervised learning which generally works well, is simple to understand, and can be easily implemented as a software simulation. A multi-layer perceptron, back-propagation network or feed-forward network is mathematically represented by:

$$y_k = \phi_o(\alpha_k + \sum_j w_{jk}\phi_h(\alpha_j + \sum_i w_{ij}x_i)) \qquad \textbf{Equation 3.1}$$

where i is the number of neurons in the input layer, j is the number of neurons in the hidden layer, k is the number of neurons in the output layer, the parameters w_{ij} and α_i are the weights and:

- ϕ_h is usually the logistic $\phi_h(x) = e^x/(1+e^x)$
- ϕ_o is linear, logistic or threshold
- the biases α_i can be replaced by weights to +1

In concept, the back-propagation method involves changing the values of the connection weights according to their effect on the rate of change in output error. The error measurement is initiated at the output neuron and back-propagates through the network to the input neurons. Once the rate of change is calculated then each connection weight value is modified. The mean-square error (MSE) or the sum of squared errors over the training sample may be used as a performance measure for the ANN, defined as a function of the free parameters of the network and visualized as an error surface with the free parameters as coordinates. For the ANN to improve performance over time, it has to move down successively toward a minimum point of the error surface, which may be a local or a global minimum. To minimize the MSE for the whole training set of input/output vector pairs the gradient of the error is calculated in the whole weight space. Partial derivatives and the chain rule are used to calculate the contribution that each of the weights makes on the total error. A downside of gradient descent optimization is that it can be prone to converging to a local minimum instead of the global minimum (Zaknich, 1998). There are a number of techniques (e.g., simulated annealing and genetic optimization) that have been proposed to address this problem (Masters, 1993). Also, a number of heuristics have been suggested to accelerate the convergence of back-propagation learning (Haykin, 1999).

A neural network has the ability to learn and therefore to generalize (Haykin, 1999). A neural network generalizes well when producing reasonable outputs for inputs not encountered during training (learning). There is a trade-off between building a neural network model that generalizes well and is robust, and one that is more accurate but more brittle. The more complex, accurate, yet brittle a model is, the more closely it will fit to the data points in the training set. A more general model describes a smoother curve through the training data points, missing some, but not incorporating the effect of noise or peculiarities that might be present within the training data. Figure 3.5 shows some of the decisions involved when dealing with the generalization-accuracy tradeoff.

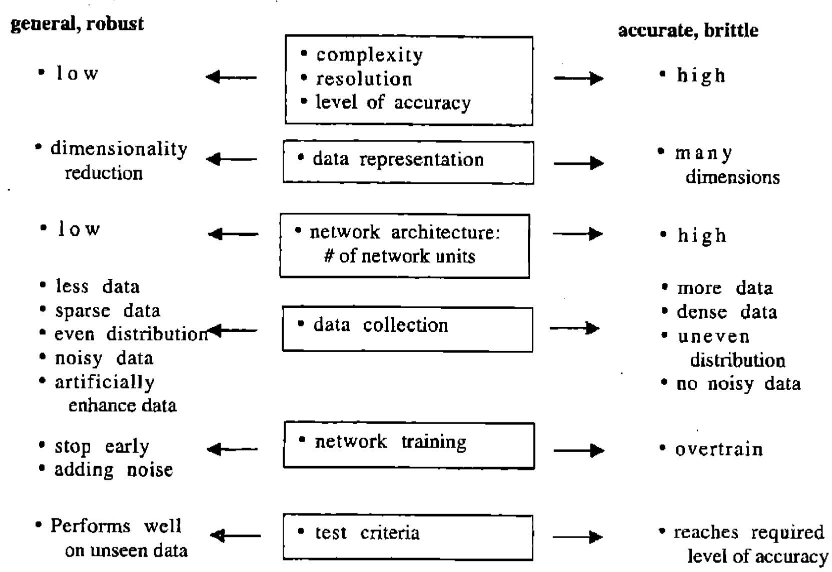


Figure 3.5 Constraints and techniques that determine the complexity of a neural network model. Source: Swingler (1996)

Neural networks and statistical methods

ANNs can emulate some of common statistical techniques such as: generalized linear models, polynomial regression, non-parametric regression and discriminant analysis, projection pursuit regression, kernel regression, principal components and cluster analysis.

However, a neural network and its learning process may be statistically interpreted in the sense that it is merely a form in which "empirical knowledge" or a set of measurements about a physical phenomenon or environment of interest may be encoded through training. In this context, the interest is not in the evolution of the weight vector *w* as a neural network is cycled through a learning algorithm, but rather on the deviation expressed in statistical terms between a target function *f(x)* and the actual function *F(x,w)* realized by the ANN, where the vector *x* is the input signal. Most neural networks that can learn to generalize effectively from noisy data (statistical inference) are similar or identical to statistical methods. For example, feed-forward networks with no hidden layer are basically generalized linear models – linear combination of the predictor variables transformed via a nonlinear transformation; feed-forward networks with one or more hidden layers adopt this as the basic element where, instead of using just one element, they use multiple layers of many elements with the outputs from one layer (transformed linear combinations from each basic element) serving as inputs to the next layer. In addition, many of the traditional statistical estimation and optimization techniques (e.g., the incorporation of Bayesian priors into the score function to drive small weights to zero) or the use of more sophisticated multivariate optimization procedures (e.g., conjugate gradient techniques during weight search) are used in training neural network models. The original contribution of the neural network modeling approach lies in the nonlinear multilayer nature of its underlying model structure (Hand et al, 2001).

Neural networks, contrary to many claims, can thus involve the same type of distributional assumptions as statistical models (Bishop, 1995). However, while statisticians study the effects of these assumptions, many neural networkers ignore them. For example, least-squares training methods are widely used by both statisticians and neural networkers. Under specific distributional assumptions – normally distributed noise with equal variance for all training cases and independent between different cases – least-squares training originates least-squares estimates with certain optimality properties. These optimality properties are consequences of the fact that, under those conditions, least-squares estimation is the maximum likelihood. If distributional assumptions are studied, one can recognize and deal with violations of the assumptions. For example, if a training data set has normally distributed noise but some training cases have greater noise variance than others, then the weighted least squares instead of ordinary least squares can be used to obtain more efficient estimates.

Feed-forward neural networks can be viewed as a subset of the class of nonlinear regression and discrimination models. In consequence, many concepts and results from the statistical theory of nonlinear models can be applied directly to feed-forward neural networks to provide more powerful solutions with reduced computational load (Ripley, 1997). Bishop (1995) and Ripley (1996) explore in detail the application of statistical theory to neural networks.

The bias/variance tradeoff in non-parametric estimation, a statistical concept, is relevant for neural networks when addressing the problem of over-fitting. A model with too little flexibility (e.g., linear polynomial) has a high bias, while a model with too much flexibility (e.g., 10^{th}-order polynomial) has a high variance. The best generalization performance is determined by the tradeoff between these two competing, and is achieved when the number of degrees of freedom in the model is relatively small compared to the size of the data set (Bishop, 1995). A highly complex (measured by e.g. the order of the polynomial) model that fits the data almost perfectly can give a poorer representation of the systematic aspects of the data than would a simpler model. On the other hand, a model that is too simple is not appropriated as it can fit the data very poorly. These compromises occur with neural network models where the complexity of the model can be controlled by structural stabilization (e.g., changing the number of free parameters in the network). Generalization performance can also be optimized with different forms of regularization (e.g., feature selection; weight decay target models with small weight values and unnecessary weights become zero during training; models trained by using weight decay are less prone to over-fitting since the approximated functions become smoother) and early-stopping, as discussed by Bishop (1995). By using a sequence of successively larger data sets and a corresponding set of models with successively higher complexity, both bias and variance can be reduced simultaneously and therefore improve the generalization performance of the network. Ultimately, generalization performance is limited by the intrinsic noise on the data.

The probabilistic and statistical characterization of neural networks is part of an important area of study called statistical learning theory, which addresses the fundamental issue of how to control the generalization ability of a neural network in mathematical terms. In the context of supervised learning, the question "do training examples contain sufficient information to construct a learning machine capable of good generalization performance?" is answered by the emerging theory of so-called support vector machines. In general terms, the supervised learning problem is viewed as an approximation problem, involving finding the function $F(x,w)$ that is the best possible approximation to the desired function $f(x)$.

Benefits and limitations of neural networks

The massively parallel-distributed structure and the ability to generalize from noisy or incomplete data are two information-processing capabilities inherent to neural networks that allow them to solve complex problems. The following points are relevant properties and capabilities of neural networks (Haykin, 1999; Zaknich, 1998).

- Functional use of knowledge based on experience. An artificial neuron can be linear or nonlinear and a neural network, as an interconnection of nonlinear neurons, is itself nonlinear, with the nonlinearity distributed throughout the network. Because of their nonlinear nature, ANNs are often capable of performing functions beyond the capability of optimal linear or conventional rule based processing techniques. Although ANNs lack the exact precision and formal rigor of the traditional computing approach, they may be powerful enough to allow construct near perfect approximations to systems about which there is insufficient knowledge to allow an explicit, fully specified solution. A rule-based approach to many problems such as an expert system is often difficult or even impossible to apply as the rules are not easily obtained or defined, as in nonlinear systems, are too many, or are not even known. Neural networks are generalizable models with no explicit rules that overcome this problem by extracting relevant rules, in a relatively short time, from a set of training data through learning. They are very flexible techniques, which may develop intuitive concepts where the nature of computations required in a task is not well understood or is poorly defined. ANNs are sensitive to statistical regularities in large data sets so they can derive knowledge from actual relationships implicit in the data. There are other methods for extracting rules from a set of example data points. Decision trees, discussed next, are rule-based systems that are popular for deriving rules from a data set. They are able to model nonlinear data with the superposition of hierarchically arranged linear decisions. But they lack incremental induction, relevant for changing environments, an inherent feature of ANNs. Neural networks also allow for a fusion of diverse input measurements from various domains.
- Input-output nonparametric mapping. The close analogy between the input-output mapping performed by a neural network in supervised learning and nonparametric statistical inference suggest a fair comparison of the neural networks with conventional, parametric regression techniques. The term parametric means that no prior assumptions are made on a probabilistic distribution model for the input data. Regression, for example, requires conformance to the assumptions of a statistical model (e.g., independent variables are not correlated, errors of prediction for individual observations are independent and normally distributed with a zero mean and constant variance) to be applied; neural network models do not, being less sensitive to e.g., multi-colinearity. Due to its nonparametric and nonlinear nature, neural networks can better provide suitable solutions for problems generally characterized by nonlinearities, high dimensionality, noisy, complex, imprecise, imperfect, limited, discontinued data (Gubta and Lam, 1996; Kuo and Reitsch, 1995), and a lack of a clearly stated mathematical solution or algorithm. When the sample size is very small, the functional relationship is known and data explanation is required, multivariate regression methods perform better.
- High dimensional spaces. Neural networks are greatly suited for function approximation in spaces of many dimensions (Bishop, 1995). They deal with the problem of scaling with dimensionality in a different way from what other general non-linear models in multidimensional spaces (e.g., polynomials) do. Neural networks models represent nonlinear functions of many variables in terms of superpositions of non-linear functions of a single variable – hidden functions or units – which are themselves adapted to the data as part of the training process. As a result, the number of these functions only needs to grow as the complexity of the problem itself grows, and not as dimensionality grows. The number of free parameters in such models typically only grows linearly, or quadratically, with the dimensionality of the input space for a given number of hidden

functions, in contrast with the d^M growth for a general *Mth*-order polynomial. Barron (1993) showed that the sum-of-squares error of neural networks falls as $O(1/M)$ where M is the number of hidden units in the network, irrespective of the number of input variables. For polynomials (or any other series expansion in which it is the coefficients of linear combinations of fixed functions which are adapted) the error only decreases as $O(1/M^{2/d})$, where d is the dimensionality of input space.

- Context sensitive. A neural network is context sensitive. This is relevant to nonlinear systems as nonlinearities in a system introduce the need for local, ungeneralizable rules. Contextual information is naturally incorporated in a neural network because knowledge is represented by the structure and activation state of the network, where every neuron is potentially affected by the global activity of all other neurons in the network.
- Adaptivity. Neural networks are able to adapt their synaptic weights to changes in the surrounding environment. ANNs trained to operate in a particular environment can be easily retrained to deal with minor changes in the operating environmental conditions. Additionally, an ANN can be designed to change its synaptic weights in real time when operating in a non-stationary (time-dependent statistics) surrounding environment.
- Robust computation. A neural network is potentially able to exhibit a graceful degradation in performance under adverse operating conditions rather than a catastrophic failure due to the distributed nature of information stored in the network through a large number of connections. If some of the processing elements are destroyed the system will continue to function with only a minimal reduction in overall performance. Therefore, ANNs are tolerant to errors or distortions in the input they receive, losing little accuracy if model assumptions are violated (Gubta and Lam, 1996; Kuo and Reitsch, 1995). In order to control fault tolerance, it may be necessary to incorporate corrective measures when designing the algorithm used to train the network.
- Fast computation. The massively parallel nature of a neural network allows a very fast computation of final results.
- Simplicity. Neural networks require minimal programming and algorithmic development.
- Uniformity of analysis and design. Neural networks are universal as information processors. Documentation is readily available through an expansive research community and the same notation is used in all domains involving the application of neural networks. Neurons represent an ingredient common to all neural networks, which make it possible to share theories and learning algorithms in different applications of neural networks.

One of the main criticisms of neural networks is that is not possible to discover why they produce the answers they do. Neural networks are black boxes that are simply fed in with inputs and miraculously provide outputs. Swingler (1996) describes some methods for deriving explanations of a neural network's outputs, based on the derivatives of the outputs with respect to the inputs that caused them. These and other methods for the extraction of rules from neural networks are important to:

- Validate neural network components in software systems by making the internal states of the neural network accessible and understandable to users.
- Improve the generalization performance of neural networks by identifying regions of the input space where the training data are not adequately represented, or indicate the circumstances where the neural network may fail to generalize.
- Discover salient features of the input data for data exploration.

Still, the mathematical representation and manipulation of ANNs will not yield to intuition even by examining the weights, architecture and nodal transfer functions associated with the final trained model (Smith and Mason, 1997). Explaining in logical terms to the user how the ANN arrived at its answer could be much like explaining how one plays tennis by doing a dissection of the brain tissue of the tennis player.

A substantial quantity of quality training data is needed for a neural network to learn. Generalization in a neural network is a non-linear averaging over a set of examples, and therefore noise, bad and insufficient data do have an effect on its performance. Rules of thumb have been proposed to be used in practice to define the training sample size for a given network architecture and/or desired generalization performance (Masters, 1993; Haykin, 1999). Although this size depends also on the complexity of the problem at hand, these rules tend to point to hundreds or even thousands of samples needed to train a given network to generalize well.

Neural networks are limited to available data. The main methodological risk associated with a neural network based approach is that either the data will not contain the information required to carry out the task to the required degree of accuracy, or that the network will be unable to extract that information. Assuming that a solution is possible, there is the risk that it will prove impossible for sufficient data to be collected, or that the balance between generalization ability and accuracy is difficult to optimize. Neural networks can also be ineffective when dealing with certain numerical and symbolic manipulations (Deniz, 2000). For example, when one of the inputs of the network is a discrete value (e.g. a word), it has to be indexed into a number to allow the network interpret it. However, the indexed input might loose the influence it has on the system, or gain an unnecessary one.

The efficient scaling with dimensionality of a neural network due to the nonlinear functions of the adaptive parameters costs a number of additional complications associated with nonlinear optimization such as the presence of multiple minima in the error function. In feed-forward neural networks it is very easy for gradient algorithms to get stuck in local minima when learning the network weights. There is no universal fast and reliable training algorithm that will guarantee the convergence of a global minimum (Masters, 1993).

ANNs are then purely data driven models that iteratively change from a random state to a final model through training. Two-layer feed-forward networks can be trained to approximate arbitrarily well any functionally (one-one or many-one) continuous mapping from one finite dimensional space to another, *provided* the number of neurons in the hidden layer is sufficiently large (Bishop, 1995). Bishop (1995) outlines a simple theoretical proof of this universality property for a two-layer network having sigmoidal hidden units and linear output units. However, this result of universality property (Hornik et al. 1989) is of more theoretical than practical interest. Theory may show that one hidden layer (with enough nodes in that layer) is sufficient to model any continuous function, or any function with a finite number of discontinuities, but in practice this will depend on the available data, or whether memory or training requirements for that structure to solve a particular problem would be impractical.

There is no widely accepted method for determining the appropriate structure for feed-forward multilayer perceptrons (Hand, et al, 2001). In practice, ANN structures are often determined by a trial-and-error procedure of manually adjusting the number of hidden nodes until satisfactory performance is reached on a validation data set (not used in training). Masters (1993) discusses some rules of thumb for choosing an appropriate multiple-layer feed-forward network model and defining specific characteristics of that model (how many hidden layers?, how many hidden neurons?, how many training iterations?). Haykin (1999) presents a model selection procedure that provides a principled approach guided by statistical learning theory to determine the number of hidden neurons in a multilayer perceptron.

It is important to recognize that a neural network is far from having a performance that mimics a human brain. Neural networks may be used to approach complex problems but, in practice, they cannot provide the solution on its own by working individually (Haykin, 1999). Neural networks should be integrated into a consistent system engineering approach, where the complexity of a problem is decomposed into a number of relatively simple tasks. ANNs are then assigned a subset of the tasks that match their inherent capabilities – they are applied in their "field of expertise".

For example, let us compare symbolic Artificial Intelligence (AI) and neural networks cognitive models. Symbolic AI can be described as the formal manipulation of a language of algorithms and data representations in a top-down fashion. Neural networks, however, are parallel-distributed processors with a natural ability to learn, and which usually operate in a bottom-up fashion. The neural rules are local and simpler and the hoped-for emergent behavior is sophisticated pattern recognition and learning (Mitchell, 1996). For the implementation of cognitive tasks, rather than seek solutions based on symbolic AI or neural networks alone, a potentially useful approach could be to build hybrid systems that integrate them together. The desirable features of adaptivity, robustness, and uniformity offered by neural networks would be combined with the representation, inference, and universality that are inherent to symbolic AI.

Appropriateness for the learning surrogate LCA method

Artificial neural networks have properties considered relevant to address the problem domain – product concept systems with product descriptors as inputs and prediction of environmental performance as outputs – and specific research needs:

- Nonlinearity, high-dimensionality, uncertainty and incomplete knowledge of the system. Product concepts systems have to incorporate a diverse number of factors dictated by uncertain upstream conditions and downstream effects, spanning its whole life-cycle (see section 2.2). Design concepts have little detail, and change rapidly and widely at a high level of parameterization. Approximate predictions are needed quickly to assess downstream (environmental), complex effects. Although lacking exact precision and formal rigor (which actually is not a requirement for the purpose of the learning surrogate LCA method), neural networks allow through learning from experience construct approximations to nonlinear, high-dimensional systems about which we have insufficient knowledge and don't need clearly stated mathematical solutions. Inputs can be independent or highly correlated.
- Adaptivity. A neural network trained to operate in a specific environment can be easily retrained to deal with changes in the surrounding environment and can be designed to change its synaptic weights in real time. This feature is relevant to the present problem domain as design concepts evolve rapidly and therefore there is a need for a readily adaptation of the learning system to a new analysis scenario, without the overhead of new modeling efforts.
- Robustness. If appropriate corrective measures are incorporated in the learning algorithm, a neural network exhibits a graceful degradation in performance under adverse operating conditions rather than a catastrophic failure due to the distributed nature of information stored in the network. This fault tolerance is important for the present problem domain, as it enables the neural network not to be highly sensitive to

errors or distortions that are frequent in "informed guessed" product data at the conceptual level and in environmental data from LCA studies.

- Continuous numeric prediction. Neural networks are able to learn continuous numeric functions and predict numerical real values. This is relevant for the approach, since the output of the learning system, the approximate environmental performance of a product concept, should be in a real-valued form for the purpose of simulation.
- Fast computation. The parallel nature of a neural network makes it potentially fast for the computation of certain tasks. In addition, training cycles are attainable in acceptable times given the computational performance of today's personal computers. This is important, as quick analysis tasks are required at the conceptual design phase.
- Simplicity. One can easily build, train and test ANNs without extensive mathematical or programming background by using currently available plug-ins for mathematical analysis tools (e.g. Matlab®), which provide all required functions and routines for designing and applying ANNs in a transparent manner.

As mentioned previously, neural networks are often criticized as black boxes that are simply fed in with inputs and miraculously provide outputs without revealing causal paths. This criticism should be balanced with other methodological arguments and specifics of the research goals. There are methods for deriving mathematical explanations of neural networks' outputs, for example, based on the derivatives of the outputs with respect to the inputs that caused them. Probabilistic and statistical characterization of a neural network also makes internal states of the neural network more accessible and understandable. Still, the weights learned by ANNs are often difficult for humans to interpret, for example, learned ANNs are less easily communicated to humans than learned rules.

However, the goal of this research it is not creating a comprehensive and exhaustive causal model of the system. Given the purpose for which this methodology is being developed, it is rather relevant trading-off full explanatory models with the possibility of rapidly and dynamically obtain approximate predictions, appropriate to the practical problem being solved, without compromising the necessary understanding of the system, which is not learning the target function. At the conceptual stage, high level information and parameters are not suitable for timely and significant explicit modeling. The real need goes into support designers to better relate design changes originated by their decisions with corresponding approximate environmental performances, under the guidance of environmental experts. These are the ones who should be focused in exploring environmental causalities when creating, maintaining and validating the surrogate LCA model based on existing detailed LCA studies. The ANN is therefore a "suitable black box" for the purpose of its application in this context.

Along with useful features and capabilities that are relevant for the purpose of this research, neural networks also have their own limitations. A substantial quantity of training data for a neural network to learn is required. Despite the potential robustness, generalization in a neural network is a non-linear averaging over a set of examples, and therefore noise and bad data do have an effect on its performance. Thus, there is a great effort in the design of a neural network model and the preprocessing of data. Dealing with outliers, scaling, averaging, normalizing the data and choosing a set of coding functions are used to smooth inputs for better training results.

Nevertheless, there is still the risk of it being impossible for: sufficient data to be collected; to obtain the level of information required for a certain degree of accuracy; or the neural network to extract the desired information. Curran (1999) reports that of the approximately 200 LCAs studies that Franklin Associates has conducted over the years, only a very small number have been presented publicly. However there is an increasing movement among different institutions (e.g., SETAC, US EPA, OECD, UNEP) to join efforts in facilitating data exchange around the world, working together with academia, government and industry. Still, great effort must be devoted in establishing the necessary levels of collaboration and communication with industry and consulting companies to overcome proprietary issues.

3.2.2 DECISION TREES

Definition and general properties

Decision trees represent attribute-value information about concepts for the purpose of classification. They provide a particular way of breaking up data into classes or categories, defined as structures that are either: a leaf node, representing a class after categorization; or a decision node, specifying some test to be carried out on a single attribute value of the data, with one branch for each possible outcome of the test (Quinlan, 1993). A simple example of a decision tree is shown in Figure 3.6.

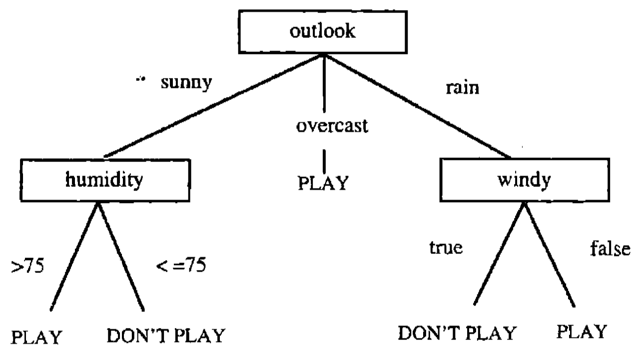


Figure 3.6 A simple example of a decision tree. Source: Quinlan (1993).

The classification of a case by a decision tree starts at the root of the tree and navigates through the tree until a leaf is encountered. At each decision node, the case's outcome for the test at the node is determined. The process then shifts to the root of the sub-tree corresponding to this outcome. When a leaf is finally reached, the class of the case is predicted to be that recorded at the leaf.

C4.5 is a software extension of the ID3 decision tree algorithm (Quinlan, 1993). C4.5 inductively constructs classification models in the form of decision trees by discovering and analyzing patterns found in given data with known classification. The program also contains a module that generates rules from a decision tree. The underlying algorithm in C4.5 is simple and computationally efficient. Given a set of disjoint target classes $\{C_1, C_2, \ldots, C_k\}$ and a set of training data, S (containing cases of more than one class), a divide and conquer algorithm uses a series of statistical tests to refine S into subsets that contain cases of only one class. This procedure builds a decision tree, where decision nodes correspond to tests on a single attribute of the data, and leafs are classified subsets of the data set. An information gain ratio criterion is used to consistently choose the best possible test to decide which attribute will be tested. The information gain criterion measures the ratio of information relevant to classification that is provided by the division (information gain) to the information produced by the division itself (split information).

C4.5 also contains heuristic methods for pruning (simplifying) decision trees to create more comprehensible structures without compromising accuracy on unseen cases. Pruning is done by replacing a whole sub-tree by a leaf node if the expected error rate in the sub-tree is greater than in a single leaf.

Benefits and limitations

The underlying algorithm in C4.5 for taking a training set and deriving a decision tree that will correctly classify unseen objects is simple and computationally efficient. Its final product, the decision tree, is an explicit model of the problem being solved. The time to build such tree only increases linearly with the size of the problem. The system has also been adapted to cope with noisy and incomplete data. The simplicity and efficiency of the algorithm make it a feasible alternative to knowledge elicitation in expert systems if sufficient data of the right kind are available (Jackson, 1998).

In comparison with more conventional statistical methods, there are a number of advantages in electing to use decision tree methods over more conventional statistical methods. Methods like C4.5 make no assumptions about the distribution of the attribute values (for example, that they are normally distributed) or about the conditional independence of attributes (as would be required by Bayesian classifiers). Studies have concluded that tree-based classifiers compare favorably with other methods, in terms of accuracy, robustness across different tasks, and speed of computation (Jackson, 1998).

The decision tree approach, or the particular algorithms embodied in C4.5, are not always appropriate to be used as a classification task. The following requirements, which might translate into limitations, are key for successful application of decision trees:

- Attribute-value description. The data must be in a regular attribute-value format, meaning that each datum must be characterized in terms of a fixed set of attributes and their values, whether symbolic, ordinal or continuous. This restriction rules out domains in which data have inherently variable structure. C4.5 handles missing attributes by assuming that unknown test outcomes are distributed probabilistically according to the relative frequency of outcomes that are known.
- Predefined classes. The classes or categories into which data will be divided must be established ahead of time. C4.5 will not discover groupings of data.
- Discrete classes. The classes must be sharply delineated and must be disjoint – a case either does or does not belong to a particular class – and there must be far more cases than classes.
- Sufficient data. Large data sets are required, the larger the better. Training sets that are too small will lead to over-fitting. The classification will be too heavily influenced by individual data points, and the performance will be bad on unseen data. The amount of data required is affected by factors such as the number of attributes and classes and the complexity of the classification model. A simple model may be identified with a small number of cases, but a detailed classification model usually requires hundreds or even thousands of training cases. C4.5's pruning heuristic methods for simplifying decision trees to produce more comprehensible structures, without compromising accuracy on

unseen cases, will not correct for the problems cause by a small sample containing atypical data.

- "Logical" classification models. C4.5 constructs only classifiers that can be expressed as decision trees or sets of rules. This restricts the description of a class to a logical expression with statements about the values of particular attributes.

From these requirements, it should be noted that the method lacks incremental learning and the inability to predict numerical real values like neural networks. Additional training data cannot be incorporated without reconsidering the classification of previous data. Another practical distinction between neural networks and decision trees is that the tree algorithm is able to automatically search through models of different complexities while there is no widely accepted procedure for determining the appropriate structure for a neural network, as mentioned before (Hand et al, 2001).

C4.5 is not guaranteed to find the simplest decision tree that characterizes the training data, because the information-theoretic evaluation function for choosing attributes is only a heuristic. Nevertheless, as mentioned previously, experience with the algorithm has shown its decision trees are relatively simple and perform well in classifying unseen data. The search for the "best" solution would increase the complexity of the algorithm and it is sometimes better to choose a satisfying solution to a hard problem.

Appropriateness for the learning surrogate LCA method

C4.5 and its derived decision trees cannot be used for the purpose of learning quantitative environmental performance from product concept descriptors, as the technique is only suitable for learning predefined and discrete classes. However, this method was found to be useful for performing the initial product categorization.

For product categorization it makes sense to have an explicit description of a product concept in terms of its attributes and path used to classify it. Designers are familiar with, among other methods (e.g. intuitive), systematic search with the help of classification systems to find and evaluate design solutions and the combination of their essential characteristics (Pahl and Beitz, 1999). Decision trees, by providing a simple hierarchical multi-perspective view of the classification problem, follow cognitive patterns, which are familiar not only to designers but also to environmental experts who often use systematic, hierarchical presentation of data.

In addition, the C4.5 underlying algorithm is simple and computationally efficient. Tree-based classifiers have been favorably compared with other methods in terms of accuracy, robustness and speed of computation. C4.5 has also been adapted to cope with noisy and incomplete data. The lack of incremental learning that requires reconsidering the classification of previous data when incorporating additional training data might not be a relevant limitation in this case. The initial product categorization, once satisfactory for the purpose, is meant to be final, even if more training data is used to update the remaining learning system.

One limitation, especially for innovative design, might be the fixed structure and lack of incremental learning in the classification step, as new cases emerge. However, this should not compromise the whole learning system for incremental product concepts.

3.2.3 GENETIC ALGORITHMS

Definition and general properties

Genetic algorithms (GA) are adaptive methods that may be used to solve search and optimization problems, based on the genetic processes of biological organisms. By mimicking the evolution process of the natural selection and "survival of the fittest", genetic algorithms may be able to "evolve" solutions to real world problems (Beasley et al, 1993).

GAs are not the only algorithms based on an analogy with nature (Beasley et al., 1993; Mitchell, 1996). Evolution strategies and evolutionary programming also draw inspiration from the natural search and selection processes leading to the survival of the fittest individuals. Neural networks are based on the behavior of neurons in the brain, as previously described. Their area of application partly overlaps that of GAs.

A number of other techniques have been traditionally proposed for use in connection with search and optimization problems (Goldberg, 1989). There are many optimization techniques, some of which are only applicable to limited domains, for example, the enumerative scheme of dynamic programming. Some of the more general techniques are calculus-based gradient methods, and random search. Simulated annealing is another popular search mechanism that uses random processes as GAs to help guide its form of search.

Simulated annealing, genetic algorithms and evolutionary strategies are similar in their use of probabilistic search mechanism directed toward decreasing cost or increasing payoff. These three methods have a high probability of locating the global solution optimally in a multimodal search landscape. Although these methods have different approaches, several hybrids of these techniques have been proposed (Srinivas and Patnaik, 1994).

Genetic algorithms have been used for many machine learning applications, including classification and prediction tasks. Particularly, they have been used to evolve aspects of particular machine learning systems, such as weights for neural networks, and rules for learning classifier systems, where GAs try to evolve (i.e. learn) a set of *if...then* rules to deal with some particular situation (Mitchell, 1996).

In general, the basic elements of GAs are as follows, based on a direct analogy of natural behavior of biological organisms (Beasley et al, 1993):

- Initially, there is population of "individuals", each representing a possible solution to a given problem. Each individual is assigned a "fitness score" according to how good a solution to the problem it is.
- The highly fit individuals are given opportunities to "reproduce", and "cross breeding" with other individuals. This produces new individuals as "offspring", which share some features taken from each "parent". The least fit members of the population are less likely to get selected for reproduction, and so "die out".
- A new population of possible solutions is thus produced by selecting the best individuals from the current "generation", and mating them to produce a new set of individuals. This new generation contains a higher proportion of the characteristics possessed by the good members of the previous generation.

- Over many generations, good characteristics are spread throughout the population, being mixed and exchanged with other good characteristics as they go. If the GA has been designed well, the population will converge to an optimal solution to the problem.

The first step in preparing to solve a GA problem is the identification of a representation scheme, where a suitable coding or representation for the problem must be defined. A potential solution to a problem may be represented as a set of parameters or "genes", which are joined together to form a string of values or a "chromosome". For example, if a problem is to maximize a function of three variables, $F(x,y,z)$, each variable might be represented by a 10-bit binary number (suitably scaled). The chromosome would therefore contain three genes, and consist of 30 binary digits. A fitness function must also be devised. For a particular chromosome, the fitness function returns a single numerical "fitness", which is supposed to be proportional to the "utility" or "ability" of the individual, which that chromosome represents. (Beasley et al., 1993).

A simple GA is mainly composed of three operators to solve the problem:

- Reproduction. The reproduction operator is a process in which individual strings in the current population are copied into the next generation according to their fitness function values, meaning that strings with a higher value have a higher probability of reproducing. This has an effect of improving the average fitness of the population at the expense of its genetic diversity.
- Crossover. The crossover operator randomly chooses a position along a string and exchanges subsequences before and after that position between two strings or chromosomes, which are selected to be "parents" based on their fitness values. Figure 7 illustrates a basic form of crossover.
- Mutation. The mutation operator randomly flips some of the bits in a chromosome with some probability, usually very small (e.g., 0.001). Figure 3.7 illustrates with an example a single mutation. The traditional view is that while crossover is more important for rapidly exploring a search space, mutation provides a small amount of random search, and helps ensure that no point in the search space has a zero probability of being examined, potentially restoring lost diversity in a population.

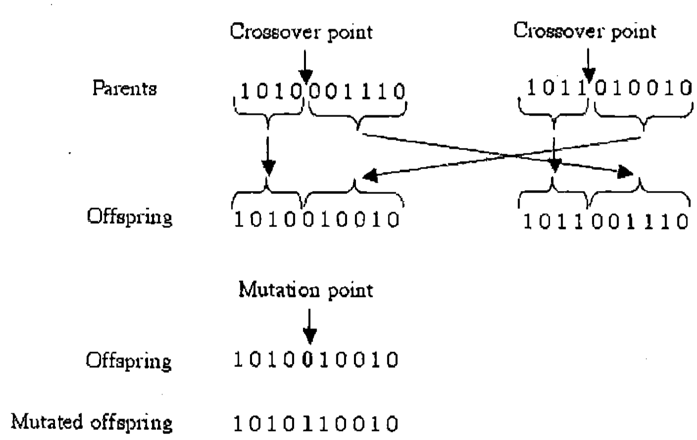


Figure 3.7 Single-point crossover and a single mutation. Source: Beasley et al. (1993).

Given a clearly defined problem to be solved and a bit string representation for candidate solutions, a simple GA may work as follows (Mitchell, 1996):

1. Start with a randomly generated population of n l-bit chromosomes, which are the candidate solutions to the problem.
2. Calculate the fitness $f(x)$ of each chromosome x in the population.
3. Repeat the following steps until n offspring have been created:
   (a) Select "with replacement" a pair of parent chromosomes from the current population, the probability of selection being an increasing function of fitness.
   (b) Crossover with probability p_c the pair at a randomly chosen point (with uniform probability) to form two offspring. If no crossover takes place, form two offspring that are exact copies of their respective parents.
   (c) Mutate the two offspring at each position with probability pm and place the resulting chromosomes in the new population.
4. Replace the current population with the new population. If n is odd one new population member can be discarded at random.
5. Go to step 2.

A GA is iterated (1 iteration = 1 generation) until some termination criterion is satisfied, typically from 50 to 500 or more generations. If the GA has been suitably implemented, the population will evolve over successive generations so that the fitness of the best and the average individual in each generation increases towards a global optimum, in a run (set of generations). Due to randomness, two runs may produce different detailed behaviors. Statistics, such as the best fitness found in a run and the generation at which the individual with that best fitness was discovered, are therefore often reported, averaged over many different runs of the GA on the same problem.

There is no accepted "general theory" which explains exactly why GAs have the properties they do. Nevertheless, several hypotheses have been put forward, which can partially explain the success of GAs and be used to implement good GA applications. Holland's schema theorem and the building block hypothesis (Goldberg, 1989) are two important "theories" that have contributed for explaining how GAs work.

On the practical side, each GA application needs its own fitness function. However, there are less problem-specific practicalities to deal with. For example, different parent selection techniques have been proposed to overcome the fitness range problems of premature convergence and slow finishing.

Benefits and limitations

Genetic algorithms are a powerful optimization technique. This technique is theoretically and empirically proven to provide robust search in complex spaces, and therefore can deal successfully with a wide range of problem areas (Goldberg, 1989). Genetic algorithms are computationally simple yet powerful in their search for improvement, and are not limited by restrictive assumptions about the search space, such as continuity, existence of derivatives, and unimodality. GAs therefore provide an alternative to traditional optimization techniques by using directed random searches to locate optimal solutions in complex landscapes. Specifically, GAs have been shown to be able to outperform conventional optimization techniques in numerical function optimization on difficult, discontinuous, multimodal, noisy functions.

Genetic algorithms are not guaranteed to find the global optimum solution to a problem. Specialized techniques that exist for solving particular problems are likely to out-perform GAs in both speed and accuracy of the final result. GAs are however generally good at finding quickly a "satisficing" level of performance. Where existing techniques work well, improvements have been made by hybridizing with GAs to combine the best of the local search method with the more general robust scheme of the GA.

Appropriateness for the learning surrogate LCA method

Genetic algorithms could be used to improve the learning system. They could be applied to evolve the weights of the neural network. GAs could also evolve the rules for the learning classifier system performing the automatic product categorization. This additional optimization feature could be added as a refinement of the method.

3.2.4 CASE-BASED REASONING

Definition and general properties

Case-based reasoning (CBR) model of reasoning incorporates problem solving, understanding, and learning, and integrates all with the memory processes (Kolodner, 1993). A reasoner remembers previous situations similar to the current one and uses them to help to solve the new problem by: adapting old solutions to solve new problems; using old cases to explain new situations or critique new solutions; or reasoning from precedents to interpret a new situation or create an equitable solution to a new problem.

Learning is an emergent behavior, it occurs as a natural consequence of reasoning, when a case-based reasoner that remembers its experiences learns as it reasons. The learning process is incremental, resulting in the learning of new procedures embodied in the cases, their refinement, and the learning of when each procedure is appropriately used. Feedback and analysis of feedback through follow-up procedures (e.g., explaining failures and attempting to repair them) and explanatory reasoning are necessary parts for the complete reasoning/learning cycle. Learning could not happen and references to previous experiences during reasoning would be unreliable without evaluation processes based on feedback (Kolodner, 1993).

A case is a contextualized piece of operational knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner (Kolodner, 1993). Cases are indexed by combinations of their descriptors that predict the situations in which they can be appropriately used. They can present different shapes and sizes, covering large or small time slices, associating solutions with problems, outcomes with situations, or both.

There are two different types of case-base reasoning: problem-solving and interpretive. In problem solving CBR, cases are used to propose solutions, while in interpretive CBR cases are used to provide context for understanding or assessing a situation. In the case-based reasoning cycle (see Figure 3.8), both these two styles of CBR require at first case retrieval to facilitate reasoning. To guarantee that poor solutions are not repeated along with the good ones, both styles of case-based reasoning evaluate their solutions.

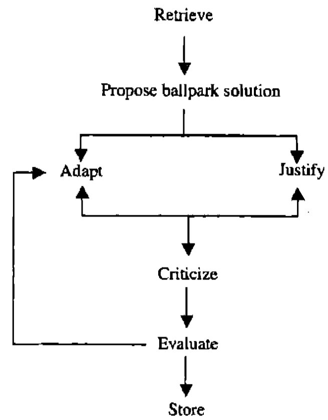


Figure 3.8 The case-based reasoning cycle. The steps involved are recursive.
Source: Kolodner (1993)

The two styles, however, require that different reasoning be done once cases are retrieved:

- In problem-solving, a ballpark solution to the new problem is proposed by extracting the solution from some retrieved case. Then follows adaptation, the process of fixing an old solution to fit a new situation, and criticism, the process of critiquing the new solution before trying it out.
- In interpretive CBR, a ballpark interpretation or desired result is proposed, sometimes based on retrieval cases, sometimes imposed from the outside. This is followed by justification, where an argument is created for the proposed solution, done by looking for similarities between the new situation and others that justify the desired result and differences that imply that other factors must be taken into account. Sometimes justification is followed by a criticism step in which hypothetical situations are generated and the proposed solution applied to them in order to test the solution.

The quality of a case-based reasoner's reasoning depends therefore on: the experiences it has had or those that have been put into its case library; its ability to understand new situations in terms of those past experiences; adeptness at adaptation, evaluation and repair; and its ability to integrate new experiences into its memory appropriately.

CBR's model uses the specific and the biggest chunks of knowledge available to reason before attempting to apply more abstract and smaller chunks of knowledge. Comparing with rule-based reasoning, case-based reasoning is a process of adapting small numbers of large chunks, while rule-base reasoning is a process of composing large numbers of small chunks to get to a solution. Comparing with model-based reasoning, both were created to avoid reasoning from scratch, and reason with large chunks. The knowledge they use, however, is quite different, with models representing general knowledge while cases represent specific knowledge.

Benefits and limitations

The combination of reasoning and learning behavior in a case-based system, the use of cases as the preferred form of knowledge, and the ability of cases to hold experience-acquired associative knowledge leads this methodology to provide several advantages (Kolodner, 1993):

- Solutions to problems are proposed quickly, avoiding the time necessary to derive those answers from scratch. Case-based reasoning gives the reasoner a way of reusing hard reasoning done in the past, making it possible not having to redo time-consuming computations and inferences.
- Solutions to problems are proposed in domains that are not completely understood. Case-based reasoning provides a method for dealing with incomplete knowledge by basing reasoning on experience in the domain, with cases capturing an informal understanding of the domain at a concrete level, rather than on formal models. A case-based reasoner makes assumptions to fill in incomplete or missing knowledge on what its experience tells it, based on what worked in the past, and goes on from there. Resulting solutions will not always be optimal, or even right, but if proposed answers are carefully evaluated, this methodology gives it a way to generate solutions easily.
- Solutions are evaluated when no algorithm method is available for evaluation. Using cases to aid in evaluation is particularly helpful when there are many unknowns, making any other kind of evaluation impossible or hard. In case-based reasoning, solutions are evaluated in the context of previous similar situations, based on what worked in the past.
- Cases are useful in interpreting open-ended and ill-defined concepts.
- Cases help a reasoner to focus its reasoning on important parts of a problem by pointing out what features of a problem are the important ones.
- Previous experiences are particularly useful in warning of the potential for problems that have occurred in the past, alerting a reasoner to take actions to avoid repeating past mistakes.

In comparison with other reasoning methodologies, some case-based systems have outperformed traditional expert systems. An interpretation for these results is that if a causal model is not well known, a case-based system can perform better than the traditional model-based one, and if problem situations are incompletely described, then case-based methods work better than other classification methods.

There are also disadvantages or barriers associated with case-based reasoning that are important to recognize. One disadvantage might be that CBR does not fully explore its solution space, and therefore some optimal solutions might not be found. But, as mentioned in the GA section, a goal might be getting answers "good enough" and some fine-tuning can be done to make sure a system gets to answers that are "good enough". Another disadvantage is that a case-based reasoner requires a large memory to hold its cases, and this is a problem for memory-limited systems.

In general, only common sense or guidelines have been provided to address fundamental issues related with the capabilities of a case-based reasoning, namely, indexing issues, case manipulation, and case representation. There is a need for better methodologies to overcome performance barriers and enhance those capabilities. In particular, adapting rules for new domains is a question that still remains to be fully answered. Although there are several adaptation methods that have been developed and listed in literature, they are not enough yet to cover all the kinds of adaptations special-purpose heuristics need to cover. The adaptation problem becomes even more relevant in domains where knowledge is incomplete, interpreting new data and adapting the old solutions with little domain information.

Appropriateness for the learning surrogate LCA method

Case-based reasoning was also ruled out as a method to support this research, although it could be explored and tested for its performance. In effect, I am not disregarding its relevant benefits, such as ability to reuse hard reasoning previously completed, avoiding redoing time-consuming computations and inferences, and to handle domains that are not completely understood.

For the classification task in the learning surrogate LCA method, the human cognitive patterns mentioned previously to support the use of decision trees make decision trees a more appropriate approach.

In addition, although practical retrieval technologies are available for adapting old solutions in case-based reasoning, general adapting rules for new domains is though a question that still remains to be fully answered. This becomes quite relevant if new design concepts are being analyzed with little domain information.

Nevertheless, Soibelman (1998) applied case-based reasoning in conceptual structural building design, acknowledging particularities of his design problem that would allow a successful implementation. He used GAs to perform adaptation of the objective standards provided by case-based reasoning. Rivard (1998) also implemented a computer-based building design environment using case-based reasoning to help designers remember and quickly retrieve appropriate cases at early phases of building design.

Rombouts (1998) applied case-based reasoning using product categories and attributes to obtain environmental profiles of products in some form of aggregated quantitative loads. An expert system is then applied to the environmental profiles to rank environmental improvement strategies, as the final output. However, in the predictive phase of the learning surrogate LCA method, low aggregated and quantitative output is preferred, as opposed to strategy ranking, to provide greater flexibility for further analysis and the quantitative results necessary for integrated conceptual design. I question into what extent this may compromise developing an appropriate case library for the required system output.

3.2.5 EXPERT SYSTEMS

Definition and general properties

An expert system is a form of knowledge-based system defined as a computer program that represents and reasons with knowledge of some specialist for solving problems or giving advice. It may completely fulfill a function that normally requires human expertise, or it may play the roles of an assistant to a human decision maker (Jackson, 1998). The following general features characterize an expert system:

- It simulates human reasoning about a problem domain, rather than simulating the domain itself. The goal is to emulate an expert's problem solving abilities by performing some portion of the relevant tasks as well as, or better than, the expert.
- It performs reasoning over representations of human knowledge, in addition to doing numerical calculations or data retrieval. The knowledge in the program is normally represented in a special-purpose language and kept separate from the code that performs the reasoning.

- It solves problems by heuristic or approximate methods. A heuristic is a rule of thumb that encodes a piece of knowledge about how to solve problems in some domain. Methods are approximate because they do not require perfect data and the solutions derived by the system may be proposed with varying degrees of certainty.

An expert system is built by assembling a knowledge base, which is then interpreted by an off-the-shelf program that contains an inference engine (see Figure 3.9). An empty knowledge base comes with the program, typically called a shell. The end user of the application interacts with the shell via the inference engine, which uses the knowledge put in the knowledge base to answer questions, solve problems, or offer advice.

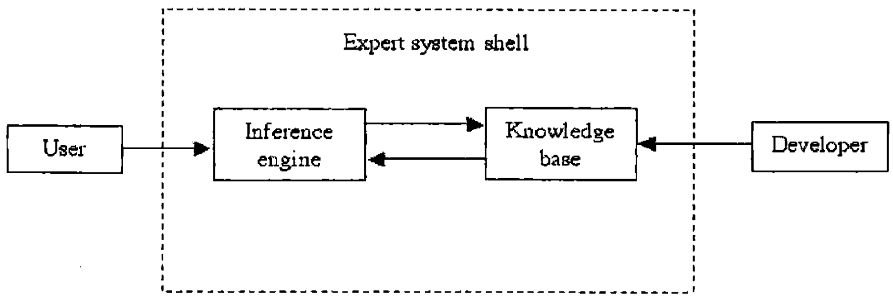


Figure 3.9 The structure of an expert system shell. Source: Jackson (1998).

In expert systems, knowledge representation focus on finding ways in which large bodies of useful information can be formally described in an unambiguous language or notation with a well-defined syntax and semantics, for the purposes of symbolic computation. This computation is non-numeric in which symbols and symbol structures can be created as representing various concepts and relationships between them.

Several conventions for coding knowledge have been suggested, including production rules, structured objects, and logic programs. Production rules, intended as generative rules of behavior, have become a mainstay of expert systems design and development. They determine how the symbol structures that represent the current state of the problem should be manipulated in order to bring the representation closer to the solution.

Benefits and limitations

Expert systems are best applied to problem areas that are objective, easily broken down to specific components, and have well defined outcomes, providing straightforward answers in situations where the rules are well defined. They then provide a greater accessibility to human expertise to solve problems that cannot be solved by conventional data processing techniques, along with a consistent application of rules and procedures.

Although expert systems can become highly intelligent systems to solve problems in a very restricted domain, past experiences in expert systems, and other knowledge-based systems, indicate that scaling up to broader scopes is extremely difficult, and as a consequence, poor results have been obtained (Soibelman, 1998).

Expert systems show inflexibility, as they are unable to handle data or problems that fall outside of the parameters built into them. Also they do not change with changing conditions, meaning that they do not "learn" as, for example, neural networks do.

Knowledge acquisition is known as "the bottleneck problem" of expert systems applications. The transfer and transformation of potential expertise from a human expert to a program is usually accomplished by a series of lengthy and intensive interviews between a knowledge engineer, normally a computer specialist, and a domain expert who is able to articulate his expertise to some degree. The productivity of this task is estimated to be typically very poor. Some reasons for this limitation are that experts have their own jargon, it is difficult to them to communicate their knowledge in everyday language. Also facts and principles of many domains of interest cannot be characterized precisely in terms of a mathematical theory or a deterministic model whose properties are well understood. Experts need to know more than the mere facts or principles of a domain in order to solve problems. Also it is often difficult to delineate the amount and nature of general knowledge needed to deal with a specific problem as human expertise is often set in a broader context that involves a good deal of common sense knowledge. A variety of tools and methods for knowledge acquisition have been proposed but none of these eliminate the need for significant human labor.

Research in expert systems has been trying to address these limitations. One approach has been considering hybrid systems that would combine an expert system with another problem solving method, resulting in applications that take advantage of the strengths of each approach. A learning component capable of learning concepts from example is often considered to be included. These hybrid systems could extend and refine expert system architectures for solving problems.

Appropriateness for the learning surrogate LCA method

Expert systems are not suitable for the current research purpose. The problem domain is sufficiently complex, not perfectly understood and nonlinear to cause difficulties in acquiring and codifying all the necessary knowledge from the experts. Expert systems would not support the evolution of design concepts, as they do not change with changing conditions, meaning that they do not "learn" as, for example, neural nets do. Expert systems would also be inflexible with incomplete and noisy environmental product data, as they are unable to handle data that fall outside the parameters built into them. Not coping with noisy and incomplete data makes this mechanism also inefficient to complement the neural network in product categorization.

3.2.6 Qualitative Reasoning

Definition and general properties

Qualitative reasoning is a framework that aims to formalize the ability to focus on the important distinctions between deterministic systems and ignore the unimportant ones, in order to cope with incomplete knowledge. This methodology addresses both the problems of model building and model simulation, based on the belief of the value of a model representation that captures incomplete, qualitative knowledge of continuous quantities (Kuipers, 1994). Qualitative differential equations (QDEs) are qualitative abstractions of the ordinary differential equations (ODEs), and are used for such representation (see Figure 3.10).

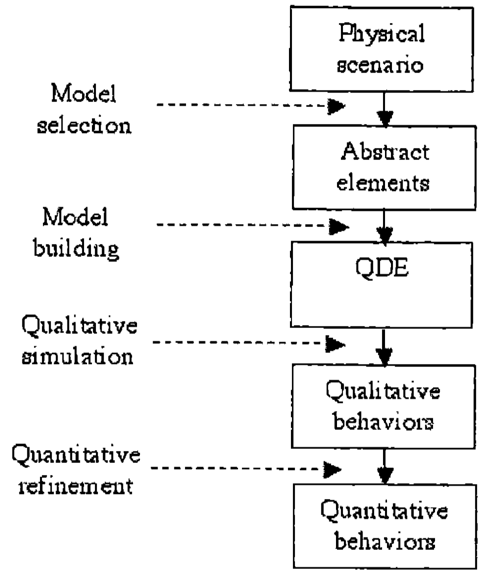


Figure 3.10 Qualitative reasoning framework. Adapted from Kuipers (1994).

For example, consider a deterministic system such as a structural system of specific beams, columns, connections, and applied forces, where the fundamental physics necessary to analyze possible outcomes and the differential equations representing the physics are well known (Soibelman, 1998). The quantitative knowledge of its physical parameters (lengths, cross-sections, materials, and forces) makes it a deterministic system, as its behavior may be completely analyzed and accurate behavior predictions derived. The knowledge of such physical parameters, however, may be incomplete (e.g. early in the design process), and therefore conventional analysis, which relies upon solution of systems of differential equations, becomes limited if some of the variables are unknown, and must be repeated if any of the variables change in value. The system, with unknown variable values, is no longer deterministic because multiple outcomes are possible, depending on the values of the unknown variables. Qualitative reasoning models this system using QDEs instead of ODEs to automatically simulate all of possible outcomes, and to discover the dependencies of events in the system.

Qualitative reasoning methods are based primarily on ordinal knowledge of real-valued quantities. The motivation is that human perception and memory seem to be particularly sensitive to ordinal relationships, especially with "landmark" values or "natural joints" that break a continuous set of values into qualitatively distinct regions (Kuipers, 1994).

The use of the language of differential equations provides the "expressive power" to state models that capture the dynamic character of the real world, and the "inferential power" to derive predictions from those models. The abstraction from ordinary to qualitative differential equations allows: (a) a functional relationship between two variables to be incompletely known, specified as being in the class of monotonically increasing (or decreasing) functions, with behavior inferred for the entire class; (b) the real number line in which variables take their values to be described in terms of a finite set of qualitatively significant "landmark values" and the intervals between them.

Benefits and limitations

Qualitative reasoning is appropriate for situations where all of the possible outcomes of a deterministic system must be inferred. The system operates in accordance with known functions of time but the quantitative knowledge of some of the parameters is incomplete.

Limitations for the application of this methodology occur when the underlying mechanisms of the system are not sufficiently known or well understood to develop the appropriate qualitative differential equations systems.

Appropriateness for the learning surrogate LCA method

Qualitative reasoning is also eliminated as an alternative or complementary method for the current research purpose. The problem domain is not sufficiently well understood and deterministic to develop the appropriate qualitative differential equation systems.

3.2.7 FUZZY SYSTEMS AND FUZZY LOGIC

Definition and general properties

Classical set theory is based on two-valued logic: expressions of the form *a* and *A*, where *a* is a constant representing an individual and *A* denotes a set of individuals, are either true or false. This crispness of the classical set theory cannot deal with concepts that are not sharply defined. Fuzzy set theory is a formalism developed to deal with such imprecise or approximate concepts and relationships.

Lofti Zadeh, its inventor, believes that humans reason not in terms of discrete symbols and numbers but in terms of general categories, but not rigid, fixed collections – fuzzy sets (Cox, 1994). A fuzzy set is a function that maps a value that might be a member of the set to a number between zero (value is not in the set) and one (value is completely representative of the set) indicating its actual degree of membership. This produces a curve across the members of the set. A simple example is illustrated in Figure 3.11.

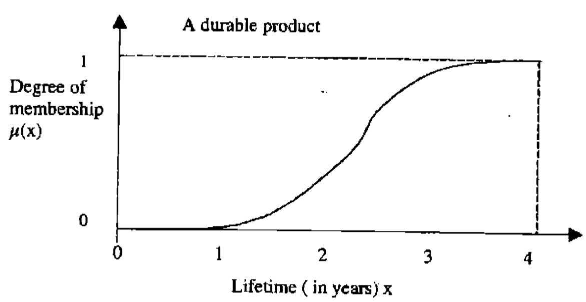


Figure 3.11 Idea of a durable product.

The members of the fuzzy set "durable products" in Figure 3.2.7.1 are duration periods, in years, for a specific product. The fuzzy set indicates to what degree a product of a specified duration or lifetime is a member of the set "durable products". A product that lasts less than one year would not be considered "durable", a product with 2 years would have a moderate membership in the set of "durable products", and a product of more than 3.5 years is most certainly a "durable product". The actual definition depends on the context in which is used, in this case for example, the type of product.

The center of the fuzzy modeling technique is the idea of a linguistic variable. A linguistic variable is the name of a fuzzy set. In the previous example, the fuzzy set "durable" is a simple linguistic variable and could be used in a rule-based system to make decisions based on the lifetime of a particular product.

Fuzzy set qualifiers or hedges change the shape of fuzzy sets in predictable ways and function in the same fashion as adverbs and adjectives in the English language. This allows writing expressive statements about related concepts. For example, the following are linguistic variables using the fuzzy set "durable": "very durable," "somewhat durable", "minimally durable".

The theory of fuzzy sets supports the more general theory of fuzzy logic, which in turn supports the logical constructs used to create and manipulate fuzzy systems. Fuzzy logic is a calculus of compatibility. Unlike probability, which is based on frequency distributions in a random population, fuzzy logic deals with describing the characteristics of properties. Much of the descriptive power of fuzzy logic comes from the fact that its semantic partitions of values can overlap. This overlap corresponds to the transition from one state to the next, which arises from the natural ambiguity that exists in intermediate states of the semantic partitions. Fuziness is therefore a measure of how well an instance (value) is compatible to a semantic ideal or concept, assessing the degree of ambiguity or uncertainty attached to each value.

Benefits and limitations

Fuzzy set theory and fuzzy logic have been successfully applied in existing methods for decision support, control and knowledge systems. In general, the membership functions or fuzzy sets are easy to understand, can be deduced from situations and created with logical reasoning. Therefore, some benefits of using fuzzy system modeling are:

- Modeling highly complex problems. Fuzzy systems are able to approximate the behavior of systems with a variety of poorly understood and/or nonlinear properties.
- Improving cognitive modeling of expert systems (Jackson, 1998). For many knowledge engineers fuzzy system modeling provides the ability to encode knowledge directly in a form that is very close to the way experts themselves think about the decision process.
- Improving neural networks (pre-processing and post-processing data) and genetic algorithms (improving the objective function) performances (Soibelman, 1998).
- Reducing model complexity. Fuzzy models require fewer rules than conventional systems and these rules are closer to the way knowledge is expressed in natural language. Fuzzy rule-based systems usually execute faster than conventional rule-based systems and require fewer rules.
- Handling uncertainty. Fuzzy logic provides a way to represent uncertainty and imprecision as an intrinsic part of the model. Park et al. (1999) applied a fuzzy clustering approach to classify disposal products into recycling parts families as an alternative approach to conventional clustering techniques.

These benefits, however, may not be fully provided for certain applications. There are projects where knowledge acquisition for the definition of meaningful fuzzy sets is still a major barrier for implementation (Soibelman, 1998). Also, the fuzzy representation of uncertainty and the fuzzy interpretation of the way experts think are areas of continual debate, confronted with other existing approaches such as the probabilistic interpretation. Wallace (1994) discusses main semantic differences between fuzzy theory and probability theory (based upon classical set theory) in the context of decision making in product design. Following the fuzziness interpretation, designers have a fuzzy internal concept of acceptability of design specifications. However, given that all designs must belong to the unambiguous sets of needing improvement (unacceptable) or not needing improvement (acceptable), and consequently designers have only these crisp courses of action, Wallace (1994) concludes that the probabilistic interpretation of decision making in product design seems more appropriate.

Appropriateness for the learning surrogate LCA method

Fuzzy logic is not considered for the approach as well. Given the problem domain and also some experience already gained from contacts with experts, I think it would be difficult in acquiring the necessary knowledge for the definition of meaningful fuzzy sets for its effective use.

3.2.8 TRUTH MAINTENANCE SYSTEMS

Truth maintenance systems are support algorithms, a group of algorithms dedicated to give justifications to the decisions adopted by the different reasoning mechanisms. The following overview is based upon Jackson (1998), Soibelman (1998) and Winston (1993).

Definition and general properties

Truth maintenance systems are mechanisms for keeping track of dependencies and detecting inconsistency, by focus on beliefs and constraints that a set of beliefs must satisfy in existing reasoners. Functions of a truth maintenance component in the context of a larger problem solving program are:

- Maintenance of a cache of inferences. The purpose is to cache inferences made by the problem solver, so that conclusions that have once been derived need never be derived again.
- Identification of assumptions and conclusions. The purpose is to allow the problem solver to make useful assumptions and see if useful conclusions can be derived from them. By providing explanations on the conclusions the problem solver enables the user (or itself) to know what to change when things go wrong
- Handle the problem of inconsistency. This is done by either by maintaining a single consistent world model, or managing multiple contexts, which are internally consistent but which may be mutually inconsistent.

There are several different types of truth maintenance systems, with a large number of design alternatives. In general, the process involves proof by constraint propagation that makes it easy to keep track of justifications enabling truth-maintenance procedures to withdraw assumptions in the context. Expressions are used to built a truth-propagation net consisting of truth boxes, which contain true and false values, and truth-propagation boxes, which propagate truth values.

Benefits and limitations

Truth maintenance systems keep track of dependencies and detect inconsistency. This additional functionality in a reasoner prevents deriving expressions all over again by tracking dependencies, and accounts for influences and constraints that always exist in a system and that should not be ignored to avoid inconsistency.

Truth maintenance systems deal with propositional calculus only. Therefore, they cannot deal with expressions containing variables, unless the problem is such that there is a way to transform the variable-containing expressions into a finite number of variable-free expressions. Also, it can be shown that truth propagation cannot prove all true expressions, thus it is not a complete proof procedure.

Appropriateness for the learning surrogate LCA method

Truth maintenance systems could eventually be implemented as a "quality maintenance" structure, if reasoning mechanisms were chosen to be applied. In this case, I would add this additional feature as a refinement of the methodology.

3.3 Extending Sustainable Product Concept Systems Modeling Using DOME

The learning surrogate LCA method was developed under the assertion that environmental issues can be successfully incorporated into product design only if balanced with the existing traditional design criteria. Product concept descriptors are the feature in the method that can facilitate the required integration efforts by providing a flexible, high-level simulation interface between designers, environmental experts and other parties involved in the early design process. This section starts by discussing why an integrated, emergent modeling approach is critical for early design synthesis, particularly in environmentally-conscious design. Then the World-Wide Simulation Web (WWSW) and its software infrastructure – Distributed Object-based Modeling Environment (DOME) – are presented as a new approach proposed by Wallace et al. (2002) to model and simulate integrated product systems over the Internet. The last section explains how such a framework can be used to allow LCA models communicate with other design models, providing product designers with real-time environmental impact assessment. In particular, an example will illustrate how DOME can be used to extend the simulation interface capabilities of learning surrogate LCA models at early conceptual design stages.

3.3.1 Need for integrated, emergent modeling approach

Environmentally-conscious design only truly happens when environmental issues are viewed as design goals to be traded-off against other, traditionally considered design goals, such as cost, technical performance, and aesthetics. This is a key requirement for environmentally conscious design approaches to actually be useful in practice. A mal-functioning, over-priced or unattractive product that customers won't buy or use inappropriately is definitely not a successful "sustainable product".

The need for integrating environmental assessment into product design is closely related with the need for designers to interact and collaborate efficiently by sharing common information, reaching agreements in an integrated, concurrent design environment. This is important since product design problems require specialized knowledge from many different fields, such as functional, aesthetic, and environmental, each of them characterized by different viewpoints, goals and constraints that have to be balanced with appropriate tradeoffs (Jackson and Wallace, 1997a; Senin et al, 1997; Borland et al, 1998).

In sustainable product development, such integration needs to be further extended to account for many more stakeholders early on. When addressing sustainability issues at early conceptual stages, evaluations and decisions have a social, political and environmental relevance, besides the traditional technical and economical. Designers and engineers, although focusing their effort on their own expertise, must internalize in their mental model this holistic view of product systems to be able to collaborate with the other parties. This way chances of designers and engineers effectively address current pressures to innovate with eco-efficient forms of production get substantially higher. Communication and collaboration with the value creation chain (e.g. supply chain) as well as with authorities (e.g. governmental agencies) and others external to a company must then be enabled to pro-actively filter preliminary decisions and support informed decision-making overall.

An integrated modeling approach in design allows us to predict the overall product performance through mathematical analysis and simulation of integrated product behavior. It provides a system perspective in a rational manner, by making technical, economical and environmental dependencies more transparent and accessible (Wallace, 1994). As a consequence, informed and more reliable decisions can be made and quality and speed in product development can be improved, for example by reducing costly design, build, test, and refine cycles in the process (Abrahamson et al, 1999).

In particular, integrated simulations facilitate an early, less costly detection of environmental impacts to be measured against environmental goals and in relation to other traditional design goals. The number of factors to be considered in economical, social and natural systems is such that it is impossible to evaluate and make decisions intuitively or on the basis of simple (linear) connections (Saur et al, 2000). Through integrated simulations, product concept systems can be explored inexpensively and quickly with a multitude of what-if scenarios and iterations. In addition, up-front integrated design on the basis of integrated simulations is an incentive to try more innovative solutions, as these bring no costly effects if they don't work (Wallace et al, 2002). This potentially will yield higher quality products with better environmental performance.

Research groups in both academia and industry have been proposing and developing integrated modeling environments. Borland et al (1998) and Wallace et al (2002) refer to existing concurrent and integrated design modeling approaches. Wallace et al (2002) argue they all have in common a major barrier for addressing integration challenges during design synthesis – they all use some form of an up-front, consolidated explicit description of the complete integrated system model. In contrast, product systems and design activities are generally evolving and have high levels of uncertainty, with rapid – and often unplanned – synthesis and evaluation cycles, involving many participants using different modeling tools (e.g., spreadsheet applications and CAD systems) in different geographical locations; therefore making it inefficient to be modeled and supported by strict, centralized top-down explicit consolidated approaches that in the same way don't emerge with the design process.

This barrier is particularly relevant when predicting the integrated behavior in the design of complex "sustainable-to-be" product concepts ranging from home air conditioners and other household appliances, to automobile, aircraft, urban environments, and industrial ecosystems. Such large systems usually emerge from individual actions and locally defined exchange relationships and incorporate complex technology, economic and natural systems with informal, dynamic, heterogeneous, and evolving characteristics.

For example, imagine the following hypothetic scenario:

A car design firm realized the growing governmental, market and public pressure on automotive companies to innovate towards the production of more eco-efficient automobiles – new standards for life-cycle environmental performance of cars are expected to be phased in over the next ten-year period. Industrial design solutions are already being explored internally but other issues need to be concurrently addressed, such as:

- What are combinations of weight reduction, fuel types, power train changes that can meet the new requirements with the present design proposals?
- What are alternatives of weight reduction that can provide life-cycle energy and material efficiency with the present design proposals?
- How should recycling strategies be traded off with weight reduction strategies?
- What are the corresponding production, operational and end-of-life costs?
- What are car concepts that best fit existing or predicted market niches?
- What OEM (original equipment manufacturer) should be targeted to commit with production and penetration in the market?
- How will the existing industrial design solutions evolve to cope with all the other design requirements in previous questions that need to be explored?

The company formed a partnership to pursue the project in collaboration with other interested parties. It made sense to bring in other areas of expertise for technical and financial support. Together they have to somehow integrate the first answers to these and many more questions – and the sooner and faster the better – to filter down essential preliminary decisions to move forward to get further funding for a more detailed study and attract an OEM to "adopt" the idea. Figure 3.12 illustrates the scenario.

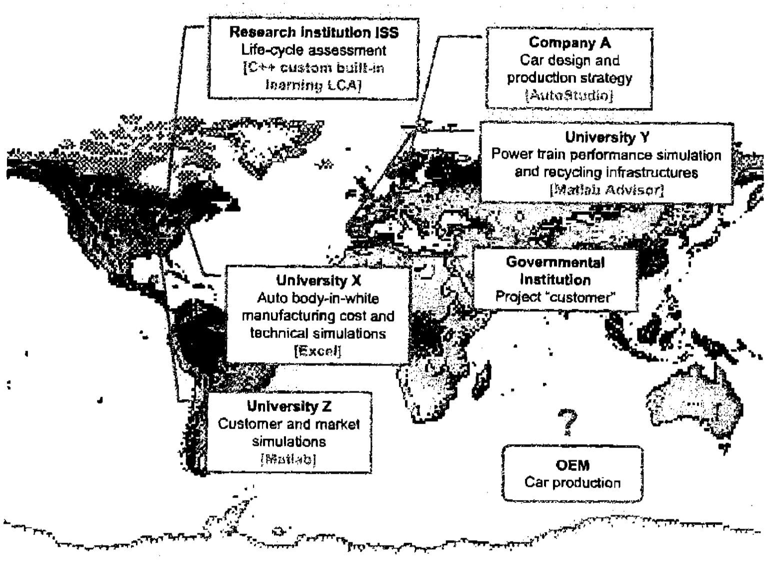


Figure 3.12 Hypothetical scenario

This hypothetical scenario exemplifies some of the complexity, heterogeneity and uncertainty that need to be addressed in product concept systems. The partnership, which includes several participants located in different parts of the world, focused on different pieces of the problem, and using different tools and proprietary information, hasn't decided yet which OEM is going to be targeted.

This means that at this point they need to delivery a convincing, profitable and feasible idea for "marketing" it to a potential OEM and guarantee further funding with the governmental institution (whose in turn is interested in attracting the OEM to the country for economy enhancement) for follow up with more detailed studies. However, to deliver such a proposal without knowing who is going to take on the production of the car, they will have to deal with a high degree of uncertainty and still do a good job in the feasibility study: the car design will only include style proposals with minimal information on structure dimensions and lack of detail in material choices for the interior and other sub-systems, components and parts as it is not known who is going to supply them – it will greatly depend on which OEM will be responsible for the manufacturing. This lack of information and ill-defined scenario propagates uncertainty to the network of the other partners who will have to provide their approximate assessments based only on their previous experience in the area of expertise and the high level information of this project they can get at this point in time. In particular, the research institution ISS will only be able to deliver approximate environmental assessments using very high-level information provided by the other participants on material composition, mass and dimensions, use of the car, power train alternatives and plausible recycling scenarios.

This scenario will evolve with the desirable future interactions and negotiations amongst the stakeholders. The partnership must be prepared with flexible assessment and decision-making capabilities to deal with the resulting emergent situations in a similar organic, yet reliable, path as the project moves along.

3.3.2 DOME FOR A WORLD-WIDE SIMULATION WEB

A World-Wide Simulation Web (WWSW) is a concept inspired by the vision of the World-Wide Web as an emergent information-network building environment. Wallace et al (2002) proposed this new concept for defining an emergent, integrated, simulation-building environment that could overcome the barriers associated with the traditional explicit, procedural process of modeling integrated systems. The WWSW concept envisions a global community, or marketplace, of individuals offering access to simulation services related to their own expertise, much as the WWW has enabled world-wide access to information. Within this envisioned simulation network, it will be possible to quickly create and holistically assess technology systems from many viewpoints, thereby helping individuals to make informed tradeoffs related to complex sustainability issues.

DOME (Distributed Object-based Modeling Environment) is an ongoing project to develop and test a computational infrastructure for the WWSW concept. DOME first-generation implementation was developed in 1996 and emphasized computation, decision support, and optimization (Panhg et al, 1998). The second-generation implementation focused on simulation marketplace concepts using CORBA as a distributed communication protocol (Abrahamson et al, 2000; Senin et al, 2000). The DOME project is now in the early stages of its third generation implementation focusing on combining http protocol-based simulation service marketplace concepts with the efficient solving of emergent integrated simulations. The kernel runs on any platform (Windows® (NT/2000/XP), Mac® OSX, Linux® and Unix®) supporting Python® 2.1 or higher. The graphic user interface components are Java Bean-based to easily write custom interfaces for 3rd party application models. Distributed communication uses XML-RCP, which is based upon http.

DOME allows participants interact and act locally to define and create a complex whole, incorporating much more systemic knowledge than all the individual pieces of the system model. Participants can offer their capabilities digitally through simulation service interfaces instantiated by object models accessible over the Internet. They can define and publish parametrically operable interfaces to their sub-system simulations on the Internet, much like html pages are published in the WWW. Participants can also independently negotiate and form local relationships between their simulations and those of other participants by defining mathematical links between interface parameters without requiring a centralized understanding of the global structure or execution sequence of the integrated simulation. The resultant simulation network becomes an emergent distributed computational system capable of solving decentralized relationships while maintaining overall mathematical consistency and proprietary information through a federated parametric solving mechanism. Service state changes, rather than data models, are propagated to rapidly predict the integrated behavior of the emergent system.

Publishing over the Internet and integrating 21 heterogeneous distributed simulations for a full door glass drop proof-of-concept pilot study conducted at Ford Motor Company required less than one person-month (Abrahamson et al, 2000). As a general benchmark to measure against it several similar or smaller size integrated simulation environments have been observed to require on the order of person years to construct (Wallace et al, 2002). A fully integrated simultaneous design cycle required roughly 20 seconds to 1 day in comparison to a week to three months in the traditional design cycle. These cycles typically occur nearly 20 times. In addition, the opportunity for performing integrated, emergent simulation foster an iterative process that improves systemic design by allowing many more learning and improvement cycles while still reducing product development time.

A more detailed description of the process of building an emergent system simulation, using the Ford pilot study as an application example, as well as of the federated parametric solving mechanisms can be found in Wallace et al (2002). Several other DOME pilot applications both in industry and academia are summarized in the same paper.

Tools for optimization, simulation structure analysis and tradeoff analysis have been developed and incorporated in DOME. The optimization engine is based on genetic algorithms (GA) to automatically search for model states that best meet design goals. In particular, the Struggle GA have the potential to locate several locally optimal design alternatives in addition to the global solution, in a single optimization, which provides designers with insight into the design space and freedom to select from a number of possibilities (Senin et al, 1999). Simulation structure analysis can be performed using a design structure matrix object to visualize service interactions as they evolve (Abrahamson et al, 1999).

Decision-making support

DOME supports decision-making based on a goal-oriented design evaluation model (Kim and Wallace, 1997). An evaluation model includes both the definition of the designer's preference structure and the comparison of design performance variables to this preference structure, with the possibility of associating uncertainty and evolving as the understanding of a design problem changes over time. According to the goal-based approach, design solutions are evaluated against a set of designer's goals stated as requirements or specifications. These goals are defined in terms of acceptability functions, which indicate the subjective probability that the designer will judge values of a quantity as "acceptable", to indicate desired performance levels.

A specification-like acceptability function is represented as a piecewise linear function of its associated attribute, ranging from 0 (reject the performance variable value with certainty) to 1 (accept the performance variable values with certainty). A design criterion evaluates a performance variable against a specification to determine its acceptability, meaning to compute the probability that the current value of the quantity will be deemed acceptable. This goal-based acceptability design evaluation is illustrated in Figure 3.13. The overall probability of acceptance for a design is assessed by aggregating the probabilities of acceptance for all the individual requirements.

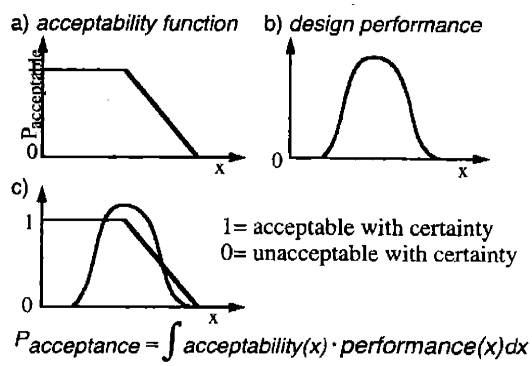


Figure 3.13 Goal-based acceptability design evaluation. Source: Jackson and Wallace (1997).

The decision support object in DOME provides a real-time view of system-wide tradeoffs as different participants make local design changes. Spider diagrams visualize performance assessments on different axes axes, while expanded detail window show performance predictions relative to the design specifications.

3.3.3 PROVIDING LIFE-CYCLE ASSESSMENT IN A WWSW

The DOME modeling infrastructure has been conceived to support environmentally conscious design. It is currently being used to facilitate the construction of "virtual Tokyo" – a simulation platform for evaluating holistically the tradeoffs between various technologies for reducing the emission of greenhouse gases (Kraines et al, 2001).

DOME has been explored for supporting life-cycle assessment modeling capabilities distributed over the Internet in a collaboration environment between product designers and environmental experts. It provides two types of approaches to facilitate the incorporation of LCA into product design: (1) modular method; (2) collaborative method. These approaches are not necessary mutually exclusive so that a design problem modeling may involve both methods combined in a flexible way that fulfill the goals and scope of the study.

In the modular method, generalized modules may be used to represent the product life-cycle using DOME environment. Jackson and Wallace (1997b) describe an approach for modeling product life-cycles in order to create time-dependent inventories for use in environmental impact assessment. A general process module is defined relating resource inputs and outflows, based upon an embedded mathematical model. The generality of the process module defined allows sections of a network to be embedded within larger modules, thus facilitating the re-use of network sections in different product life-cycles. A specific model used within modules represents average process behavior as a function of a set of empirical process parameters for simulating a variety of life-cycle processes, such as material processing, transportation, and assembly. By linking process modules together, the designer can represent complete manufacturing networks for product life-cycles, and specify the required system output or product demand as a function of time. The integrated network calculates the necessary time-dependent resource flows throughout the network, and this time-based inventory information can be used in conjunction with existing LCA tools to perform an environmental impact assessment that accounts for time-related effects.

The collaborative method uses 3rd party LCA applications to be incorporated into modules so that they become part of an integrated design model. This method is based upon the collaborative modeling concept proposed by Borland and Wallace (2000). In this approach, an expert-based collaborative structure allows environmental experts to rapidly provide an impact assessment to product designers, based on a given set of inputs. The collaborative approach assumes that product designers and environmental experts are specialists in their own fields, each may have some knowledge of and training in the other's field, but neither is capable of doing the other's job in a thorough way.

This communicating object architecture for integrated environmental assessment has been demonstrated successfully in prior work using DOME infrastructure (Borland et al, 1998; Borland and Wallace, 2000; Abrahamson et al, 1999). The environmental experts build life-cycle models, and designers separately build appropriate engineering models. Through an internet-based communication using an interface negotiated between the environmental experts and the designers, the two groups exchange relevant information, allowing for concurrent modeling even though their proprietary data, specialized models and tools are separate. This method has the advantage of timely distributing expertise and keeping models proprietary, yet integrated (Borland et al, 1998).

LCA - based comparisons using DOME framework, if used appropriately acknowledging LCA methodological limitations, can be a valuable interactive design tool in providing insight into a product's potential impact in the environment and balancing a wide variety of design goals. LCA models can communicate with other design models on the same numerical basis of material and energy flows, providing product designers with real-time environmental impact assessment.

The following steps are a general description of the process:

1. First, an interface is negotiated among all involved parties, after the initial exchange of information. The negotiated input-output interface is an agreement as to what data will be exchanged and in what form, maintaining however any proprietary data, models, or tools with its owner. The designer's model likely depends on some results from the environmental expert and the life-cycle model requires inputs from the designer's model.
2. Both the designer and the environmental expert build their own models. The LCA model may be built from scratch, by modifying an existing model, or by reusing an existing model. It also may be anything from a detailed LCA to a straight materials analysis, depending on the amount of information provided to the environmental expert. Time and proprietary information might prevent building a detailed model built from scratch.

3. The environmental expert makes his/her data available as distributed objects on the WWSW. The designer integrates these objects into the product system model and immediately gains the services of the environmental expert's LCA model.
4. The designer now is able to evaluate and compare the impacts of many parametric variations to the initial design. For example, when the designer changes the design by adding a part, this additional part is translated through the established interface over the WWSW as an input to the life-cycle model, e.g. as added mass of a particular material. The result of the added mass is increased environmental impact of the design and the quantitative result is propagated back to the designer. A decision will have to be made on the importance of the added part with respect to its environmental impact.

In a similar fashion, learning surrogate LCA models can use DOME to extend sustainable product concept systems modeling services to other models (see Figure 3.14). At conceptual design phases, with limited data available, wide solution space and need for fast, approximate analysis, a learning surrogate LCA model has a high level interface (product concept descriptors) that can support through the WWSW almost real-time fast comparison of different design concepts. Comparisons may be based on changes broader than just low-level parametric variations as in detailed LCA.

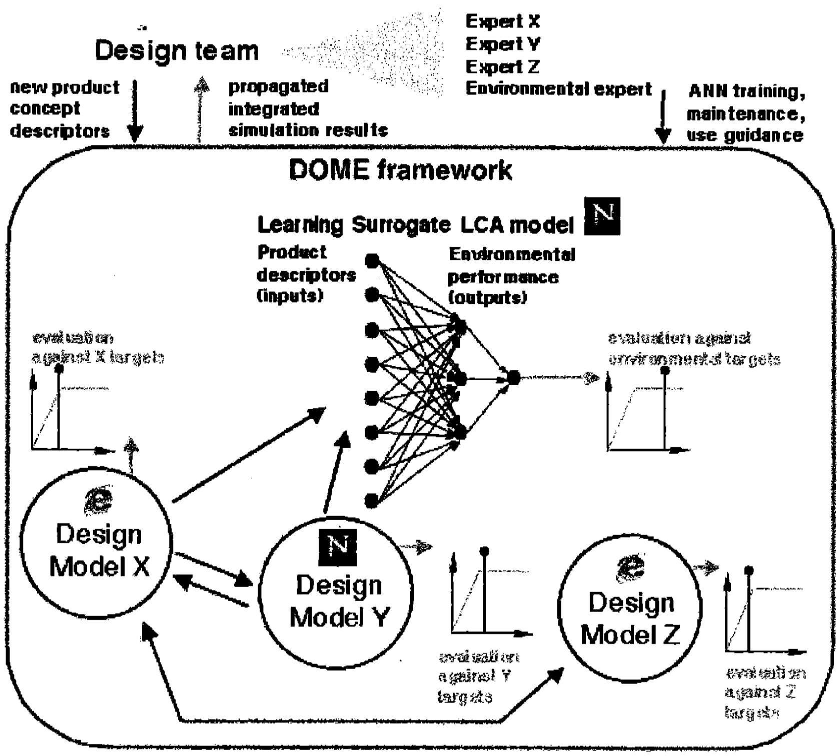


Figure 3.14 Extending sustainable product concept systems modeling in WWSW using DOME framework

4 IMPLEMENTATION AND RESULTS

4.1 DEVELOPING THE LEARNING SURROGATE LCA MODEL

In proof of concept work, foundations for the learning LCA approach are established, and then a surrogate model testing is performed within DOME integrated modeling environment (Sousa et al, 2000). Key questions critical to the validation of the learning surrogate LCA concept are investigated:

- What is a meaningful set of product attribute descriptor inputs?

The product attribute descriptor inputs must be meaningful to and known by designers during conceptual design and, as a set, span the scope of the product life cycle. In particular, these conceptual descriptors should map to a set of key environmental impact categories of a product's life cycle. A life-cycle inventory (LCI) could provide the most flexibility for testing those relationships and as the model output – different aggregation schemes can then be applied subsequently. However, the inventory also needs to be compact to increase the chance that the learning surrogate LCA model will be effective. Therefore, the feasibility of establishing a compact LCI – abbreviated LCI list – that can represent key environmental impact categories must be tested. A list of reasonable product attributes must be identified and correlated with LCI data to create a set of meaningful product descriptors.

- Can a trained ANN quickly provide reasonable estimates when queried with descriptors?

The training database must represent a range of products and contain many complete samples of input product attribute data and corresponding LCI outputs. Data transparency should be maintained as with any LCA by fully stating in writing any assumptions, estimations, or uncertainties. Finally, the structure of the learning surrogate model must be chosen, trained, and validated to effectively emulate LCI results. In application, the surrogate model must be fast and provide reasonable LCI estimates.

Figure 4.1 highlights the main components of the surrogate LCA model that were explored to answer these questions. The training database will be developed through the course of gathering information to assess the three questions.

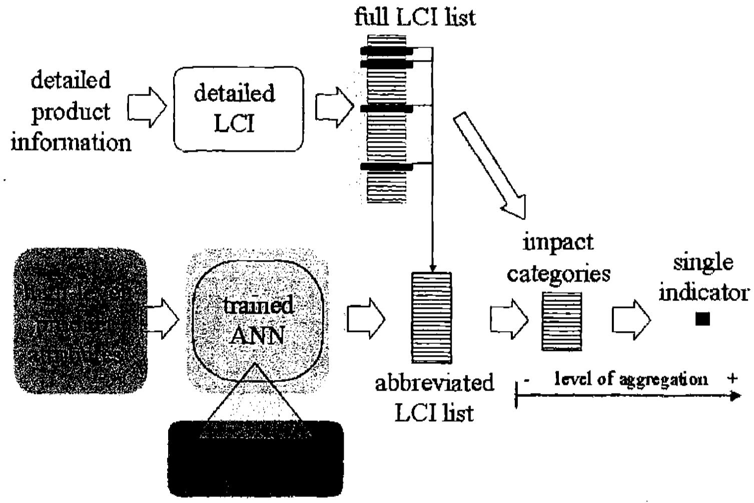


Figure 4.1 Key components of the learning surrogate concept model.

4.1.1 THE ABBREVIATED LCI LIST (MODEL OUTPUT)

A life-cycle inventory (LCI) is a very long and comprehensive list of different raw materials, energy, and releases to air, land and water, over the entire life-cycle of the product. The LCI data are used to estimate and evaluate the environmental impacts associated with the product. It is the most objective and informative form of environmental performance to an environmental expert. Situational values and subjectivity increases as these data are then aggregated to compute environmental impact categories and the high-level environmental indicators that are more comprehensible and useful to the typical designer. Thus, the most versatile solution would be for the surrogate model to provide inventory data as its output, and to leave aggregation to be determined on a case-by-case basis to bring the information back to the designer's level.

It is not feasible to gather sufficient information to train a surrogate model to predict all inventory data associated with a detailed LCA, and substantial complexity would be added to the learning architecture of the model. Therefore, an abbreviated LCI list was proposed and evaluated for its ability to meaningfully predict different environmental impact categories.

The framework for the abbreviated LCI study is schematically shown in Figure 4.2. Inferences were drawn on the validity of the abbreviated LCI list by comparing results of statistical and product ranking analyzes using a simplified approach and a detailed LCI approach. For this purpose, three lists were defined and used for comparative analysis:

- Simplified list of LCI elements, the abbreviated LCI list, which only includes key LCI elements deemed relevant to the majority of environmental impacts;
- Comprehensive list of LCI elements, the full LCI list, to be used as a baseline to validate environmental impacts predicted using the abbreviated list;
- Impact categories list to be calculated by both the abbreviated and the full LCI lists in order to compare differences in impact results.

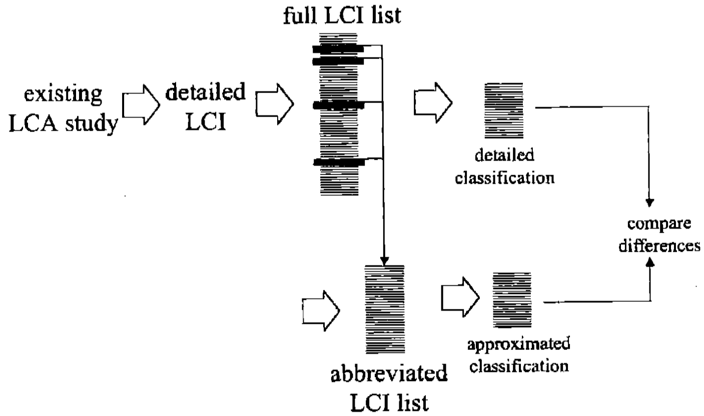


Figure 4.2 Testing the validity of the abbreviated list

Table 4.1 provides a list of the environmental impact categories that were used to assess the abbreviated LCI list. The categories are based on the Eco-Indicator'95 classification scheme used in SimaPro 4.0 (PRé Consultants, 1999) and are named and computed according to this method. Eisenhard et al. (2000) performed experiments to identify a simplified set of inventory data, consisting of only key LCI elements, which could be linked to the impacts in Table 4.1.1.1.

Table 4.1 Impact categories used to assess the abbreviated LCI list.

Greenhouse effect [kg eq. CO_2]	Winter smog [kg eq. SPM]
Ozone layer depletion [kg eq. CFC11]	Summer smog [kg eq. C_2H_4]
Acidification [kg eq. SO_2]	Pesticides [kg act.s]
Eutrophication [kg eq. PO_4]	Energy [MJ LHV]
Heavy metals [kg eq. Pb]	Solid material [kg eq. waste]
Carcinogens [kg eq. B(a)P]	

Detailed LCI data were obtained for 20 different consumer products (see Table 4.2). These data were obtained from three sources: LCA studies conducted at TU Delft (DfS Group, 1994-1997); published studies in the SimaPro 4 User's Manual (PRé Consultants, 1999); and a study by PA Consulting Group (UK Ecolabeling Board, 1992).

Table 4.2 Product used in the abridged LCI study.

1 washing machine	1 oak chair
1 heater	1 silver chair
2 vacuum cleaners	1 paper bag
1 mini vacuum cleaner	1 PP crate
3 coffee machines	1 showerhead
4 radios	1 PE bag
2 juice squeezers	

The impact categories identified in Table 4.1 were predicted using full LCI data for each of the products. Through an iterative experimental process analyzing classification schemes of different environmental evaluation methods, discussing with experts and performing data inspection, the abbreviated LCI list in Table 4.3 was proposed (De Schepper, 1999). This list incorporates inventory elements identified as commonly used in existing evaluation methods to calculate impact categories.

Table 4.3 The abbreviated LCI list

Energy [MJ LHV]	Carbon dioxide [kg CO_2]
Solid material [kg waste]	Sulfur dioxide [kg SO_2]
Chlorofluorocarbons (CFC)	Nitrous oxides [kg NO_x]
Lead [kg Pb]	Hydrocarbons [kg C_xH_y]
Cadmium [kg Cd]	Methane [kg CH_4]
Chromium [kg Cr]	Chemical oxygen demand [kg COD]
Nickel [kg Ni]	Total nitrogen [kg N Total]
Polycyclic aromatic hydrocarbons [kg PAH]	Polyhalogenated carbons [kg Halons]
Dust [kg SPM]	

Finally, the abbreviated LCI list was used to compute the impact categories for each product, and then compared with impact predictions based upon the full LCI. The differences between the numerical results produced by the abridged and detailed LCI data varied widely between categories. Results were normalized around the detailed LCI approach and 90% confidence intervals using a t-distribution were plotted to graphically show the difference between impacts predicted using the two LCI approaches. These intervals are shown in Figure 4.3.

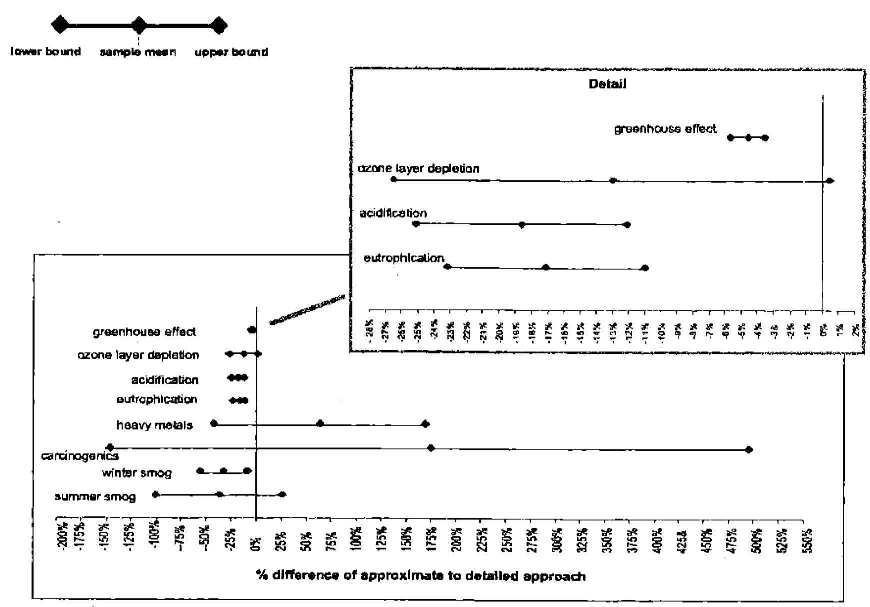


Figure 4.3 Normalized 90% confidence intervals comparing impact categories based upon a full LCI and the abbreviated LCI.

Based upon the confidence intervals, it was concluded that certain environmental impact categories – energy[1], solid material[1], greenhouse effect, and ozone layer depletion – were numerically well represented by the abbreviated list while others – acidification, eutrophication,

[1] The energy and solid material categories were identical in the two approaches

winter smog, and summer smog – were reasonably suited to the abbreviated LCI. Heavy metals, carcinogens, and pesticides were not. This result seems reasonable given that one might expect heavy metals, carcinogens, and pesticides to be determined by trace details. Note that 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.

Additionally, products were ranked within each impact category to see if the full LCI and the abbreviated LCI led to the same ordering of products within an impact category. For the 20 products studied, the energy, solid material, greenhouse effect, and summer smog impact categories were identically rank-ordered. The acidification, eutrophication, heavy metals, and winter smog categories had discrepancies, but they were very 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 four and six places, respectively. 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 most detrimental products were still ranked identically. This worst case for carcinogens is illustrated in Table 4.4. When the rank order of variations of products with similar functions was considered, several discrepancies were observed within the heavy metals and carcinogens categories, while only a single instance was observed in both acidification and winter smog categories.

Table 4.4 Rankings for the carcinogens category produced the least consistent of all results. Product ordering based upon energy, solid material, greenhouse effect, and summer smog were identical.

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

Based upon the two studies, it was concluded that the abbreviated LCI, needed to reduce demands on the surrogate model outputs, could potentially be used to predict life-cycle energy consumption, solid material waste, greenhouse effect, ozone layer depletion, acidification, eutrophication, winter smog, and summer smog levels. The remaining three categories – heavy metals, carcinogens, and pesticides – were not well represented by the abbreviated LCI in all cases. For these categories a checklist developed by an environmental expert may be a more appropriate conceptual design tool.

4.1.2 PRODUCT CONCEPT DESCRIPTORS (MODEL INPUT)

After defining and bounding the prediction scope of the surrogate model, product attributes, or descriptors, must be identified for use in training and querying the surrogate model. It is hypothesized that when a set of basic product properties, extended from those of traditional design, is defined meaningfully for both product designers and environmental experts any product can be thoroughly described from an environmental viewpoint (Eisenhard, 2000).

The attributes need to be both logically and statistically linked to elements in the abbreviated LCI list, and also be readily known during product concept design. They must be sufficient to discriminate between different concepts and be compact so the input demands on the surrogate model are reasonable. Finally, the attributes must be easily understood by designers and, as a set, span the scope of the product life-cycle. These criteria were used to guide the process of developing a product descriptor list systematically.

Defining a set of candidate product attributes

First, a set of candidate product attributes, based upon literature and the experience of experts, was formed. Ecodesign checklists and design improvement strategies (e.g., Alting and Legarth (1995), Fiksel (1996), Brezet and Hemel (1997), Sfantsikopoulos and Pantelis (1997), Hanssen (1999), and Clark and Charter (1999)) provided a starting point to identify product attributes. For example, checklist questions like "What type of energy is required when using the product?" suggest in use energy consumption and in use energy source as possible attributes characterizing the product use phase.

Other researchers (Rombouts, 1998; Mueller and Besant, 1999) also specifically addressed the problem of defining product attributes for environmental evaluation. Rombouts (1998) derived a list of descriptors from the Ecodesign Checklist defined by Brezet and Hemel (1997), while Mueller and Besant (1999) modeled life-cycle parameters as functions of design parameters. For example, mass, material composition, and efficiency are functions of the power of a standard motor.

Experts in both product and environmentally-conscious product design were interviewed or contacted through email to augment candidate descriptors derived from the literature. A common view (Baumann, 2000) was that, in practice, product descriptors at the conceptual stage are few, simple, and expressed in a product-specific language. For example, frequently used environmental descriptors in the automotive industry are weight and fuel consumption. Also, different levels of information are available and used at the early stage of product design, depending on the purpose of the design – improvement or innovation (Potts, 2000).

Based upon literature and the experience of experts, a set of candidate product attributes was then identified (see Table 4.5). Definitions of all attributes along with examples can be found in Appendix A.

Table 4.5 The initial candidate product descriptor set.

Mass	Transport distance	In use energy source	Recycled content
Volume	Transport means	In use power consumption	Recyclability
Materials	Lifetime	Modularity	Biodegradability
Durability	Use time	Upgradeability	Disassemblability
Distribution mass	Mode of operation	Serviceability	Reusability
Distribution volume	Additional consumables	In use flexibility	

Conceptual linkage with the abbreviated LCI

With candidate attributes identified, they were grouped for organizational purposes, reviewed for conceptual linkages to the abbreviated LCI, and for potential coverage of the entire life-cycle.

The attributes were first grouped according to the method developed by Hubka and Eder (1992), which is based on recognized phases of the life-cycle and the nature and purpose of technical systems. The defined groups are: general design; elementary design; functional; operational; distribution; end-of-life. Table 4.6 lists the six groups defined – general design; elementary design; functional; operational; distribution; end-of-life – along with corresponding attributes.

Table 4.6 Organizational grouping of the product attributes.

Group	Attributes
General design	Biodegradability, durability
Elementary design	Material content, recycled content
Functional	Mass, volume
Operational	Life time, use time, energy source, mode of operation, power consumption, in use flexibility, upgradeability, serviceability, modularity, additional consumables
Distribution	Distribution mass, distribution volume, means of transport, transport distance
End-of-life	Recyclability, reusability, disassemblability

In Figure 4.4 the grouped candidate attributes are provided, along with efforts to qualitatively identify potentially strong links amongst attributes and between attributes and the abbreviated LCI list. The representation in Figure 4.4 is based upon the house-of-quality (Hauser and Clausing, 1988).

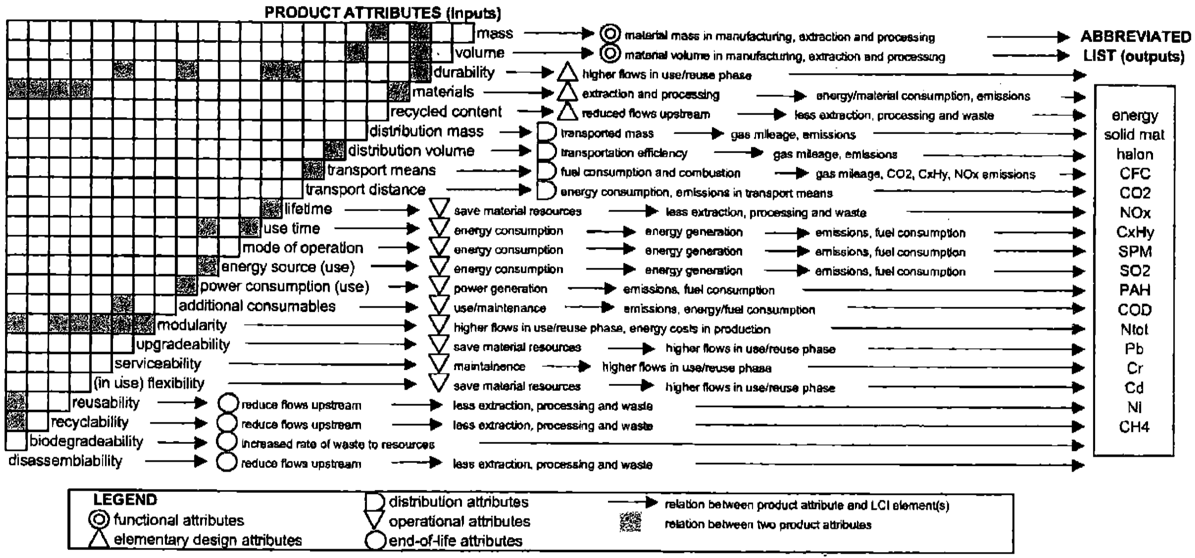


Figure 4.4 Conceptual relationships among product attributes and between product attributes and elements of the abbreviated LCI list.

Level of information in conceptual design

Once satisfied that the candidate descriptors were appropriate conceptually, an online survey (see Appendix B) was distributed to designers to verify what descriptors are likely to be known during conceptual design. The survey provided clear definitions for each of the candidate descriptors to sixteen practicing product designers working on products ranging from industrial equipment to very new consumer goods. The majority of the designers worked for firms specializing in product design, and thus had experience designing a wide range of products.

If the designer was able to specify or estimate a descriptor in an appropriate qualitative or quantitative sense, the attribute was deemed specified. If the designer could not specify the descriptor, but could typically rank order concepts, the attribute was deemed ranked. If an attribute of could not be specified or ranked, but the designer could provide a yes or no type of answer, the descriptor was deemed binary. For example, the designer might know a concept will contain polymers, but not be able to specify or rank the amount used. If the designer could typically provide no information about a descriptor, it was deemed unknown. Finally, if a descriptor did not apply to the class of products designed by the participant, the attribute was categorized as not applicable (N/A). Results assessing descriptors based upon operational grouping are shown in

Figure 4.5. The complete set of results can be found in Eisenhard (2000).

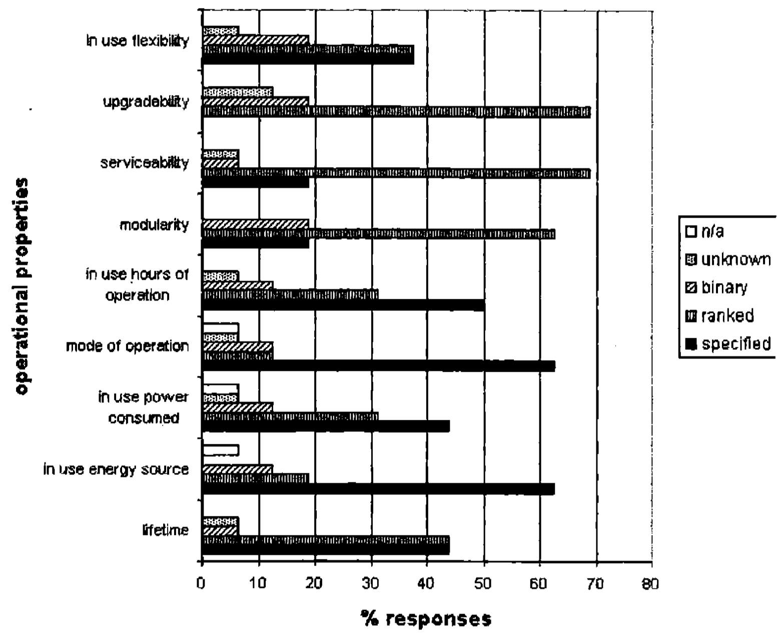


Figure 4.5 Survey results for operational properties.

This study helped the authors identify descriptors that designers could both understand and had knowledge of during conceptual design. For example, descriptors such as in use energy source and mode of operation were readily specified, whereas upgradeability and serviceability are more likely to be ranked with respect to other concepts. A ranking system, however, was considered difficult to be implemented within the learning surrogate LCA method – what would the baseline product be for such a system? Therefore, all attributes pointed by designers as rank-specified were brought down to the binary information level.

While some attributes, such as material content, can be commonly found in existing studies or easily estimated from other existing information, some qualitative properties may not even be discussed in those studies or there is not sufficient information or common perceptions on what they might be to perform reasonable "informed guesses". This could cause largely inconsistent estimates entering the training database for some of the qualitative attributes, leading to poor predictions of the surrogate model when queried.

Thus many of the product attributes were analyzed more thoroughly in an attempt to avoid inconsistencies when building the training data set. For example, upgradeable products can also be thought of as reusable – the parts that are not upgraded are reused to form an improved product. And if a product is reusable or serviceable, it can be thought of as having an extended lifetime. In use flexibility and modularity can convey impact information at a very high level. However, they can be too ambiguous to be consistently captured from existing information.

Further, it was possible to assess what attributes are likely to vary significantly from concept to concept. For example, while in practice the ranked attribute disassemblability may provide meaningful information, collapsing it to a binary level of information will carry little meaning.

Binary information does not convey the degree to which a product can be disassembled, just that it is or is not disassembled. Therefore there will be little variation from concept to concept with regard to disassemblability. Table 4.7 shows a refined product descriptor set.

Table 4.7 Refined candidate product descriptor set. [Q] means quantitative level of information and [B] means binary qualitative level of information

[Q] Mass (kg)	[Q] Transport distance (km)	[B] In use energy source
[Q] Volume (m^3)	[B] Transport means	[Q] In use power consumption (W)
[Q] Materials (various) (% mass)	[Q] Lifetime (hours)	[B] Recycled content
[B] Durability	[Q] Use time (hours)	[B] Recyclability
[Q] Distribution mass (kg)	[B] Mode of operation	[B] Biodegradability
[Q] Distribution volume (m^3)	[B] Additional consumables	

Test for first order relationships

The refined candidate descriptor set was then tested for first order relationships with the abbreviated LCI list. In addition to the 20 products used for the study to define the abridged LCI list, data for 28 other products (see Table 4.8) were included from studies provided by TU Delft (DfS Group, 1994-1997) and nonproprietary studies conducted by the Research Triangle Institute (Sharma et al 1996a; 1996b; Peters, 1996) and Franklin Associates, Ltd. (1990; 1994). Linearity and bivariate normality in the data was assumed in checking for trends.

Table 4.8 Additional products used in the correlation tests.

1 coffee filter	2 newsprint productions
1 vacuum dustbag	2 coatings
2 towels	2 antifreeze solutions
5 refrigerators	3 diaper systems
10 televisions	

Bivariate Pearson product-moment correlations were computed, and correlation tests to 95% statistical significance were performed between quantitative descriptors and the abbreviated LCI data for the 48 different products. The Pearson correlation coefficient, *r*, was calculated by

$$r = \sum_{i=1}^{N} \frac{(x_i - \bar{x})(y_i - \bar{y})}{(N-1)s_x s_y} \qquad \textbf{Equation 4.1}$$

where *N* is the number of data points and $\bar{x}$ and s_x are, respectively, the mean and standard deviation of variable *x*, and likewise for variable *y*. If *p*-value (correlation significance) is less than 5% (0.05) then independence is rejected and *x* and *y* show linear correlation.

This first order examination required careful interpretation and grouping of products. For example, the data in table 9 suggest that mass is not correlated with many of the abbreviated LCI list elements as expected. However, when the same test was preformed including only durable goods, indeed the correlation with many of the LCI categories is strong (see Table 4.9). These results suggest grouping products to train specialized surrogate LCA models might then improve prediction performance of the ANNs.

Table 4.9 Correlation coefficients and tests: mass vs. abbreviated LCI list elements. Highlighted results indicate correlation.

Abbreviated LCI list elements	Correlation coefficients (p-value)	
	all products	durable products
Energy	.348 (0.015)	0.749 (0.000)
Solid waste	.663 (0.000)	0.730 (0.000)
Chlorofluorocarbons (CFC)	-0.024 (0.874)	0.415 (0.016)
Lead (Pb)	-0.015 (0.919)	0.690 (0.000)
Cadmium (Cd)	-0.047 (0.749)	0.611 (0.000)
Chromium (Cr)	-0.04 (0.788)	0.663 (0.000)
Nickel (Ni)	-0.036 (0.807)	0.669 (0.000)
Polycyclic aromatic hydrocarbons (PAH)	-0.027 (0.855)	0.577 (0.000)
Dust (SPM)	0.948 (0.000)	0.488 (0.000)
Carbon dioxide (CO_2)	0.485 (0.000)	0.694 (0.000)
Sulfur dioxide (SO_2)	0.835 (0.000)	0.521 (0.002)
Nitrous dioxide (NO_x)	0.629 (0.000)	0.704 (0.000)
Hydrocarbons (C_xH_y)	0.969 (0.000)	0.838 (0.000)
Chemical oxygen demand (COD)	-0.077 (0.601)	-0.101 (0.574)
Total nitrogen (N Total)	0.165 (0.262)	0.830 (0.000)
Polyhalogenated carbons (halons)	-0.041 (0.78)	0.691 (0.000)
Methane (CH_4)	-0.036 (0.809)	0.663 (0.000)

Lifetime, power consumption, and material composition were most strongly correlated with the abbreviated LCI elements. These attributes are correlated with almost all abridged inventory elements. The effect of qualitative descriptors on the abbreviated LCI was assessed visually using scatter plots. In general, these descriptors influence product's environmental performance (Eisenhard, 2000). For example, product LCA studies taking into account the use of additional consumables showed a trend in producing larger COD values.

Overall, the product attributes seem likely to provide adequate life-cycle coverage. Every category in the abridged LCI was correlated with at least one product descriptor. Additionally, it is believed that some correlations were not apparent because of potentially non-linear relationships between descriptors. Inconsistency in data should also be taken into account. For example, the lack of a COD significant correlation in Table 4.1.2.6 is thought to be due to differences in system boundaries – some studies looked farther upstream than others.

Table 4.10 shows the final list of product descriptors chosen for using the learning surrogate LCA model. The analysis provided a basis for belief that that descriptor list could span the elements in the abridged LCI, and insight for ways that surrogate models might be specialized on different product groupings. Note that durability was removed from the list to be considered in a higher level for product classification purposes, as it will be explained next. Transport mean and transport distance were also excluded as they are not "intrinsic" to a product, its design or intend for design. Volume and biodegradability, although considered as part of the final list, were not thoroughly tested due to lack of data.

Table 4.10 Product descriptor list used in testing the surrogate model.

Descriptor	Unit	Level of Information
Mass	kilogram	quantitative, specified
Ceramics	%mass	quantitative, specified
Fibers	%mass	quantitative, specified
Ferrous metals	%mass	quantitative, specified
Nonferrous metals	%mass	quantitative, specified
Plastics	%mass	quantitative, specified
Paper/Cardboard	%mass	quantitative, specified
Wood	%mass	quantitative, specified
Chemicals	%mass	quantitative, specified
Other materials	%mass	quantitative, specified
Recycled content	%mass	quantitative, specified
Recyclability	%mass	quantitative, specified
Lifetime	hours	quantitative, specified
Use time	hours	quantitative, specified
Operational mode	dimensionless	qualitative, specified (no power, manual, standby, sensor)
Additional consumables	dimensionless	qualitative, binary (yes, no)
Energy source	dimensionless	qualitative, specified (none, human, batteries, electric, solar, solar/electric, hydro, gasoline)
In use power consumption	Watt	quantitative, specified

Preliminary product classification based on product descriptors

The analysis on first order relationships provided insight about product groupings as a structure for specializing the surrogate LCA models to improve results. Although the goal is to develop a surrogate LCA that is as general as possible, it may also be necessary to specialize surrogate LCA models for different classes of products. The classification of products into general categories may lead to more specific relationships between product attributes and LCI elements of the abbreviated list.

Rombouts (1998) uses a case-based product classification scheme in an expert system for ranking ecodesign strategies. Research work using results of 18 different LCA studies of product systems carried out by Østfold Research Foundation (Hanssen 1996) provided a basis for a product classification according to functional properties. Criteria used for this classification focused on a product's use phase, and product attributes that are a potential cause for dominant environmental impacts. A first exploration of potentially useful classification schemes suggested a preliminary binary classification structure, shown in Figure 4.6. The binary categories are described in Table 4.11. For each category's definition, negation leads to products that cause opposite trends in the way product attributes mentioned in the category generate significant impacts.

Table 4.11 Preliminary product classification into general categories.

Product Categories	Description
A. In use energy conversion	**Product does or does not transform energy when in use.** The majority of environmental impacts caused by this type of product, frequently estimated at more than 90%, are related to energy conversion for consumption in the use phase (Alting and Legarth, 1995; Hanssen, 1999). Consequently, lifetime, use time, mode of operation, energy source, and power consumption are dominant product attributes in causing significant impacts.
B. In use mobility	**Product is or is not mobile or transported when in use.** This type of product will exhibit dominant influence on the indirect effects of mass and materials: weight of the product in part determined by type and properties of materials is proportional to emissions and energy source consumption generated by the transportation activity.
C. Durability	**Product is durable or consumable.** These products are expected to create higher flows in the use/reuse stage than if they were consumable. Therefore, they will make a relative difference on the direct and indirect impacts related with materials and all the attributes listed as operational. Consumable products are expected to produce higher flows in the upstream and downstream stages than if they were not consumables. Thus, they will cause materials and the attributes listed as end-of-life to dominate in causality of environmental impacts.
D. Service system	**Product is or is not designed as a service.** This type of product is expected to create higher flows in the use/reuse stage and significantly reduce upstream and downstream flows. Dominant product attributes are the same as those mentioned for category C. However, as services, these products potentially have typical ranges of impacts that are distinct (and likely less) from those caused by durable products.

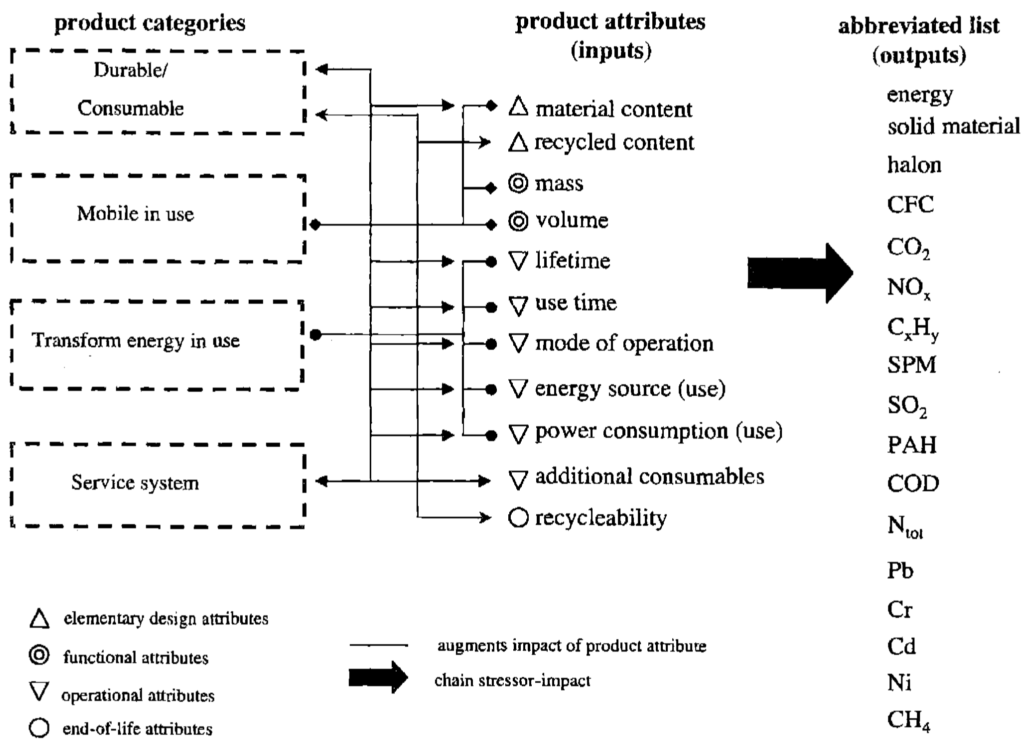


Figure 4.6 Product categories and corresponding relations with product attributes.

4.1.3 SURROGATE MODEL TESTS

With product descriptors and abridged LCI defined, ANN-based surrogate LCA models were trained in an effort to validate the method. Tests were focused only on the total life-cycle energy consumption component of the abridged LCI list. Training data with product attributes and corresponding life-cycle energy consumption from true LCA studies were collected for 158 products (see Table 4.12). These data were obtained from the same sources as the data used in the development of the abridged inventory list and product attribute list with additional studies provided by Keoleian (1997; 1998), Schuckert (1996), and TEAM® databases (Ecobilan, 1996).

Table 4.12 Additional product types used in surrogate models tests (175 total training and testing data points).

1 instrument panel	1 transformer
7 vehicles	1 speaker
42 metals	1 keyboard
9 paper products	3 communication cables
36 plastics	2 light bulbs
3 glass fibers	12 LCD projectors
3 batteries	6 wood products

Through the data collection process using the available studies, a common bottle-neck was to find the data necessary to specify the product descriptors. In the available documentation, some of these were not explicit or in the form of assumptions made in the studies. Some "detective work" was required to get an "engineering estimate" to replace the missing data. The idea was to use these "educated guesses", although not accurate data, to end up with a figure "in the right ball court" (Kljajin, 2000). When data were not available, generic data on similar products or from the same brand were searched on the Web or existing catalogs and databases. These were used to get the values directly or to use related data to make an engineering estimate of the missing data.

In this process, the detailed accuracy that is lost (also when estimating missing environmental data) is more than compensated by the ability of the design team to intrinsically incorporate environmental issues at very early stages in the design phase.

A general artificial neural network was implemented in C++ as an object in the DOME system and used to develop the surrogate models. A detailed discussion on implementation, benchmarking and application of the DOME ANN object is provided by Deniz (2000). The design of the ANN-based LCA model involved the tasks illustrated in Figure 4.7.

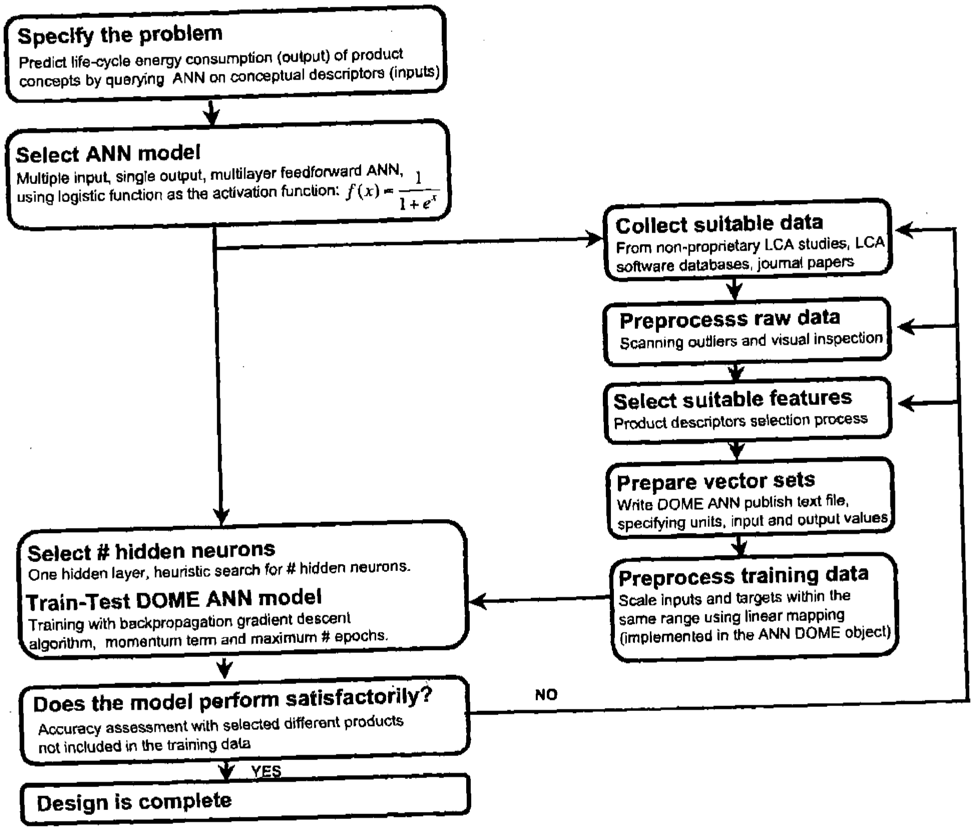


Figure 4.7 ANN design procedure.

A multiple input, single output, feedforward two-layer ANN with back propagation training was used (see Figure 4.8). Architectures with one hidden layer and 5 to 20 neurons were tested in several training sessions. ANNs with fifteen hidden neurons performed best. Training for 2 million epochs required 32 minutes on a 233 MHz Pentium" II processor.

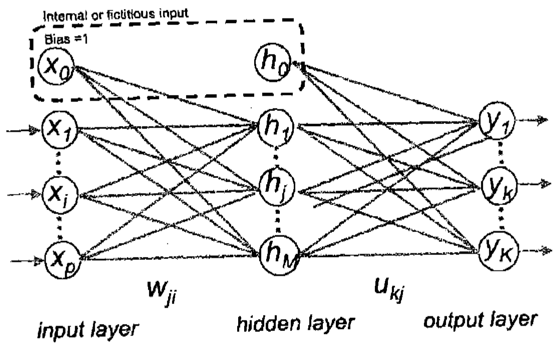


Figure 4.8 Schematic representation of the ANN model, with p=18, M=15, and K=1. Adapted from Zaknich (1998).

The backpropagation training was performed using a mathematical framework as described next. To minimize the mean square error for the whole training set of input/output vector pairs, the two sets of network weights – output layer weights and hidden layer weights – need to be adjusted and so the gradient of the error in the whole weight space needs to be calculated. Partial derivatives and the chain rule are used to calculate the contribution that each of the weights makes on the total error (see Appendix C).

Figure 4.9 shows a screen image of the surrogate LCA object in the DOME environment. The ANN runs its learning cycle by reading a text file containing the training data. Once trained, users can log into the surrogate model over the Internet using a web browser, and set the model inputs (product descriptors) to values corresponding to a product concept. The input product descriptors or attributes are shown in the upper right of

Figure **4.9**. The surrogate model then immediately provides the predicted life-cycle energy output (lower right).

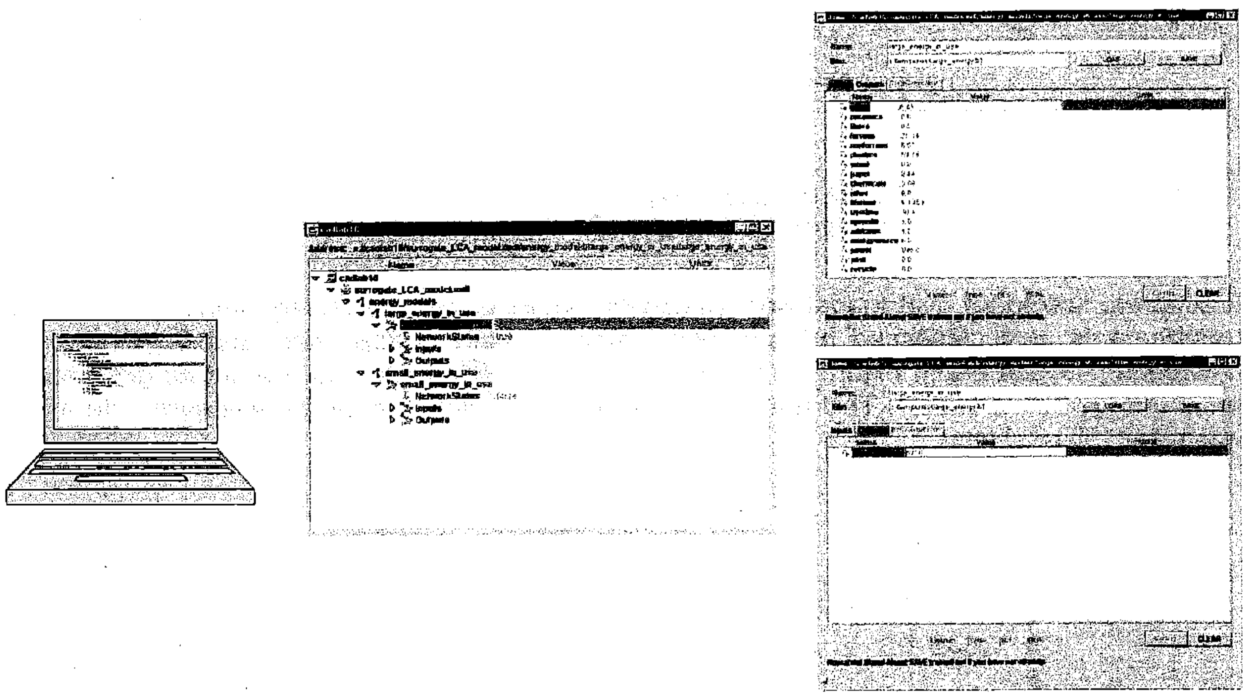


Figure 4.9 Surrogate LCA model as a DOME object.

The trained neural network was evaluated using products with known LCA results, but on which the ANN had not been trained. The surrogate LCA model was assessed in three different ways: absolute accuracy; precision in predicting relative differences; and ability to generalize trends. Six different products were used in the assessment.

The accuracy comparisons for goods with large in-use energy requirements (vacuum cleaner, refrigerator and vehicle) are provided in Figure 4.10. Life-cycle energy predictions were between 0.4 and 41 percent of the levels given by the true LCA analyses. The accuracy of a life cycle energy assessment from real LCA is typically ±30% (UK Ecolabelling Board 1992; Franklin Associates Ltd. 1994), so these results seem satisfactory.

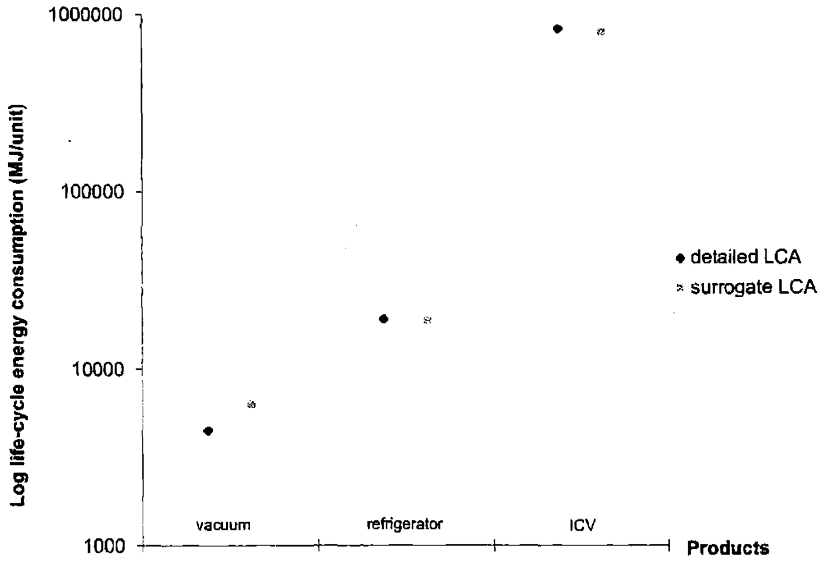


Figure 4.10 Comparison of the life cycle energy consumption of products with large in-use energy requirements as predicted by the surrogate LCA with results from detailed LCA studies.

A separate surrogate LCA model was trained for products with no or very small in-use energy requirements, and assessed for accuracy using a chair, coffee filter, and 3.785 liters of antifreeze. Results are in Figure 4.11. The results seem adequate, but are not as good as the large energy use products. This may be because the training sample for this surrogate model was small (55 products).

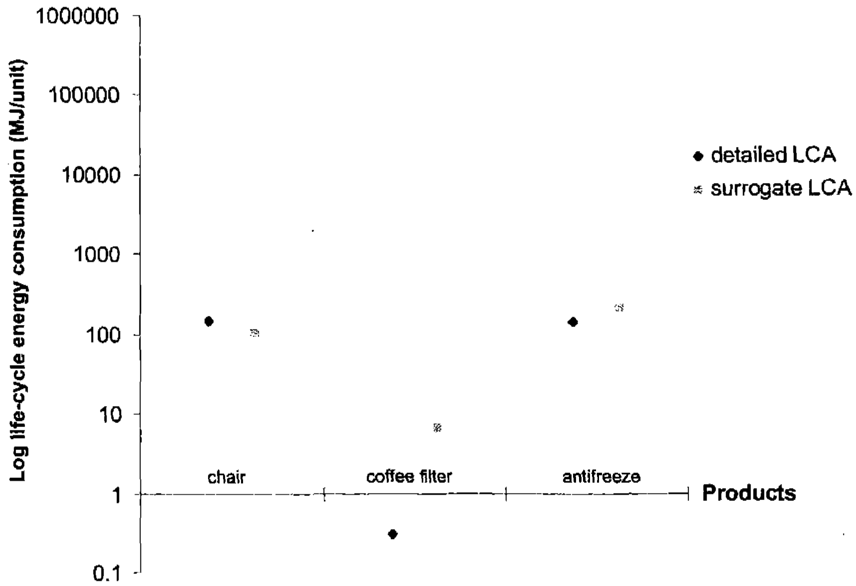


Figure 4.11 Comparison of the life cycle energy consumption for low in-use energy products predicted by the surrogate LCA with results from real LCA studies.

A second test compared how the trained surrogate models would rank the different products in a relative sense. This test is important for cases where designers are comparing very different design concepts. In Figure 4.12, the six products are compared relative to the energy consumed by the refrigerator. Detailed LCA results are relative to the detailed refrigerator LCA, and surrogate results are relative to the surrogate refrigerator LCA. Rank order remains the same for all products except the antifreeze and chair. However, the energy consumption ratios for the chair and antifreeze are almost identical, so one is likely to interpret the chair and antifreeze as being about the same.

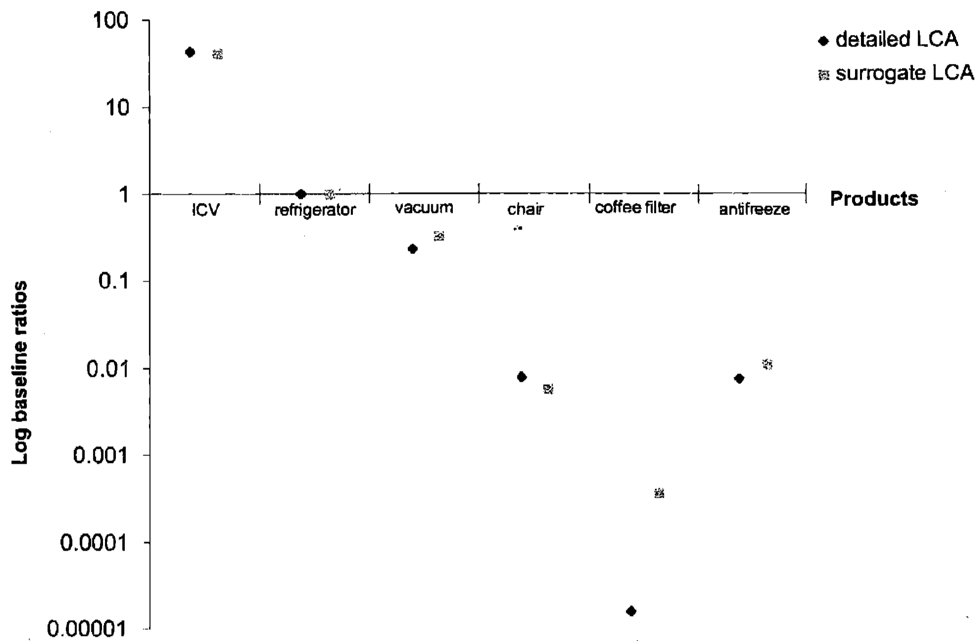
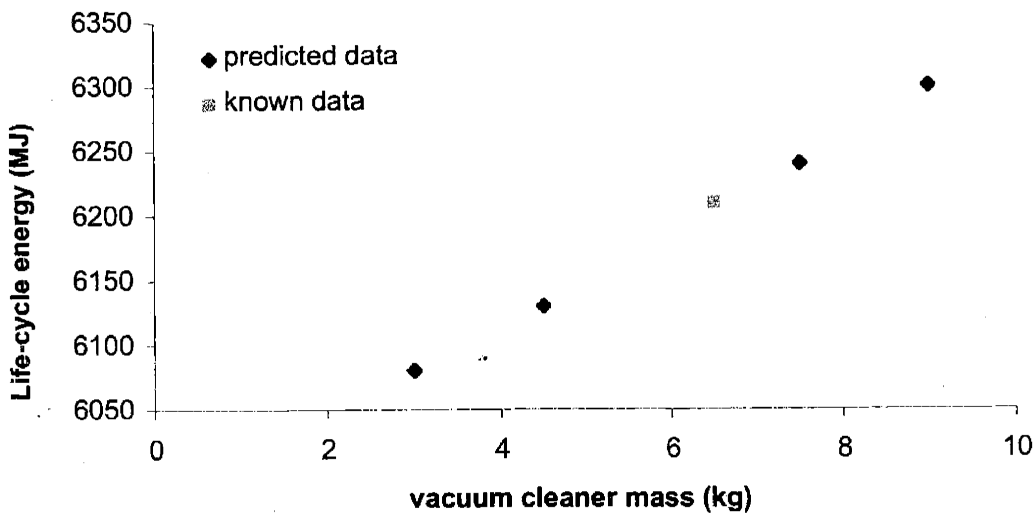


Figure 4.12 Ranking different products with the detailed and surrogate LCA results using the refrigerator as the baseline product.

The ability to assess very different products consistently is necessary during early stages of design when wildly different approaches might be under consideration for achieving the product's goals. For smaller parametric variations of a given product, ideally parametric LCA models would be used as described in our earlier work (Borland and Wallace, 2000), but tests were also performed to determine consistency of the method in maintaining rank order of product variations of the same type. Rank order of life-cycle energy consumption was maintained for the three vacuum cleaner products and for the three coffee maker products tested. Of the four different radios also evaluated, the rank order of only one of the similarly performing products was inconsistent. Thus, the surrogate LCA was quite successful at rank ordering the test cases. However, the ANN can only reflect the trends of the technologies used in the training data. Thus, when a refrigerator using new technology was introduced it did not rank well because it was an anomaly to the trends the ANN inferred for the traditional goods used for training.

Finally, the six products were used to test the surrogate model's ability to generalize and predict trends correctly for a given product concept. The characteristics of each test-case product were held constant, with the exception of the attribute for which trends were being assessed—mass, power consumption, energy source, and use time. The mass and power consumption results for the vacuum cleaner, shown in Figure 4.13, are representative in illustrating trends as predicted by the surrogate LCA.



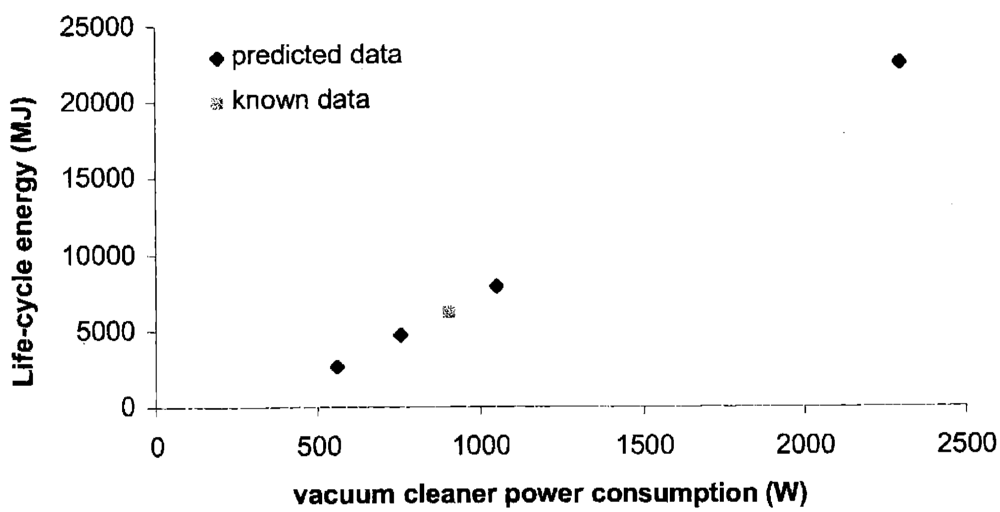


Figure 4.13 Results of power consumption and mass trends for the vacuum cleaner.

The trends predicted for energy source and use time are shown in Figure 4.14 and Figure 4.15. The use time results were generally as expected. However, only very large changes in use time caused life-cycle energy to vary. The wide variety of use time values in the training data set is one possible explanation for this insensitivity. For example, for products using an electric energy source, refrigerators are on all day, during their entire lifetime, while vacuum cleaners are used infrequently, i.e. for a smaller percentage of their lifetime.

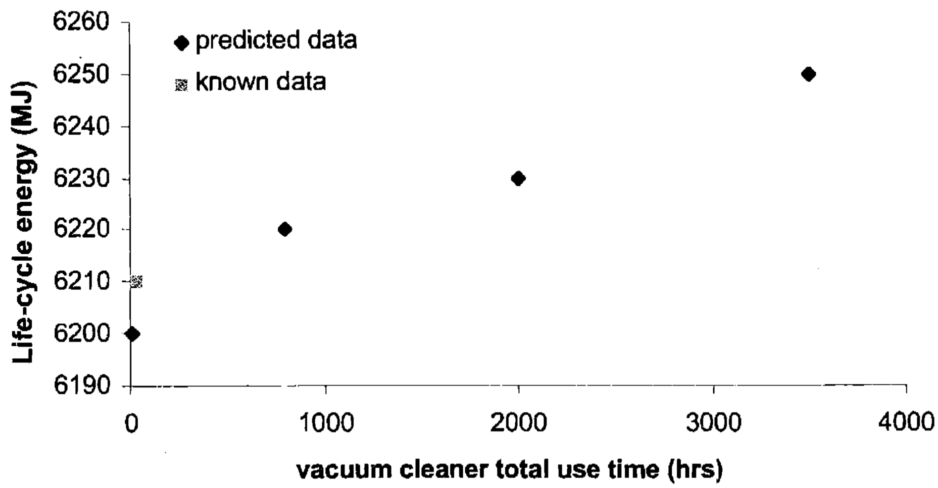


Figure 4.14 Use time trends predicted by the surrogate model for the vacuum cleaner.

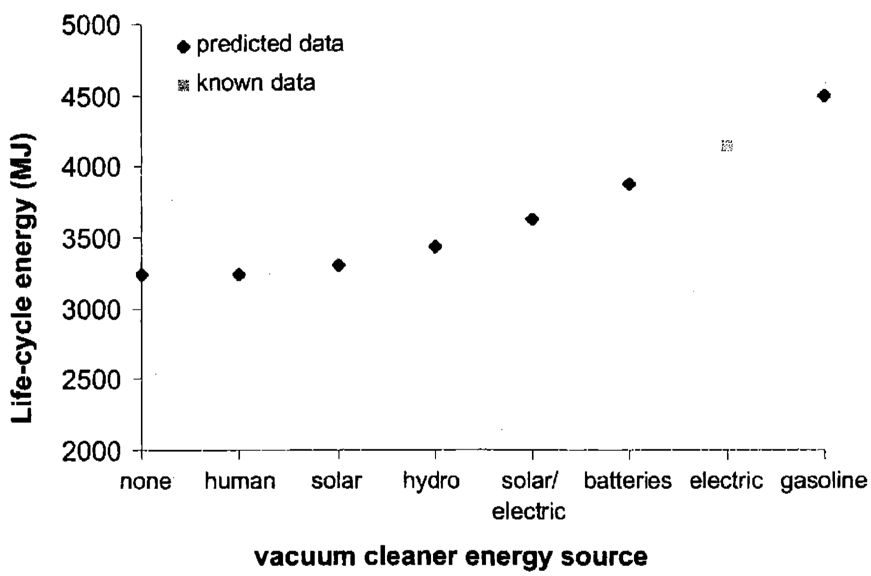


Figure 4.15 In use energy source trends predicted by the surrogate model for the vacuum cleaner.

The results generalizing trends for different energy sources are less certain as only a few products in the training data set used each source. It should also be noted that the LCA studies used for training did not account for food eaten by humans as part of human power, or the energy used to produce photovoltaic panels as part of solar power. Thus, it seems plausible that the no energy, human power, and solar vacuum scenarios are very similar.

4.2 PRODUCT CLASSIFICATION FOR LEARNING SURROGATE LCA MODELS

Insight gained in proof-of-concept testing about the effect of product groupings suggested it might be necessary to specialize surrogate LCA models for different classes of products. This section presents further work to develop an automated classification system to support the specialization of surrogate LCA models for different groups of products (Sousa and Wallace, 2002). Hierarchical clustering is used to guide a systematic identification of product groups based upon environmental categories. These groupings are then used to create automated classification schemes using the C4.5 decision tree algorithm.

4.2.1 PRODUCT CLASSIFICATION

Products have been classified in several different ways. Product classifications vary in their application, completeness and specificity. Reuleaux (1904) devised one of the first product classification systems after recognizing the identicalness among various properties of different products. Reuleaux categorized machine elements with respect to shared properties, something that was previously thought to be impossible.

Different perspectives on what a product is and the purpose of the classification lead to distinct classification systems. Krishnan and Ulrich (2001) refer to at least four perspectives in the research community on what products are within different product development decision frameworks:

- *Marketing:* product is a bundle of attributes; product attribute levels and price are examples of decision variables.
- *Organizations:* product is an artifact resulting from an organizational process; product development team structure and incentives are examples of decision variables.
- *Engineering design:* product is a complex assembly of interacting components; product size, shape, function, dimension are examples of decision variables.
- *Operations management:* product is a sequence of development and/or production process steps; development process sequence and schedule and point of differentiation in production process are examples of decision variables.

Decision variables within and across different product perspectives can be used as classification criteria. For example, economic classifications are often based on a demand-side/market-oriented classification framework to coordinate the collection, tabulation, and analysis of output and price data for products (ECPC, 1993). From an organizational perspective, distinct incentives on product development can drive the classification of products into technology-push products (e.g., Gore-Tex), platform products (e.g., instant films used in Polaroid cameras), process-intensive products (e.g., chemicals) and customized products (e.g., motors) (Ulrich and Eppinger, 2000). From an engineering design perspective, products can be seen as engineered (e.g., computer peripherals) vs. non-engineered (e.g., sweaters), discrete (e.g., power tools) vs. non-discrete (e.g. gasoline), physical (e.g., bicycle) vs. non-physical (e.g., services). Specific engineering variables such as type of materials, size or lifetime can also serve as a basis for different classification systems. When adopting an operations management perspective, manufacturing processes can be used as the classification criteria.

Environmentally-conscious product design can be thought of as a fifth perspective. Examples of decision variables are product characteristics (e.g., mass), level of environmental impacts (e.g., impact indicators) and types of environmental improvement strategies (e.g., material use, efficiency, end-of-life strategies). Several environmental product classification systems can be developed driven by distinct classification purposes. Table 4.13 lists possible environmental classifications of products proposed or inspired by work found in literature.

Table 4.13 Examples of environmental classifications of products

Classification purpose	Classification criteria	Product categories	Source
Simplify environmental assessment of products for the conceptual design phase	Product's characteristics (e.g., mass) and presence or absence of environmental issues (e.g. acidification)	• Products with greater impacts at use phase (energy driven) • Products with greater impacts in material phase (material driven)	Kaebernick and Soriano (2000)
Identify environmental improvement strategies for distinct types of products	Product's functional and life-cycle properties related with significant environmental impacts (e.g., raw material production and maintenance generate the significant impacts for stationary products without energy consumption in use)	• Products being chemically transformed in use (e.g. solvents) • Stationary inert products without internal energy consumption in use (e.g., electric cables). • Stationary products with internal energy consumption in use (e.g., lighting armature) • Transportable products without internal energy consumption in use (e.g. food packaging). • Transportable products with internal energy consumption in use (e.g. boat with outboard motor).	Hanssen (1999)
Enhance knowledge-based system performance for ranking ecodesign strategies	Aspects of product use which are answered by yes or no	• Product does [does not] transform energy when is use • Product does [does not] transform materials when in use • Product is [is not] transported during use	Rombouts (1998)
Determine products' feasible end-of-life strategies early in the design cycle	Technical product's characteristics that affect product's end-of-life treatment (e.g. number of parts, wear-out life)	• Reuse • Service • Remanufacture • Recycle (separate first) • Recycle (shred first)	Rose et al (1998, 1999, 2000)
Design recycling cellular system	Design attributes (e.g., material composition), usage attributes (e.g., breakage of parts) and recycling attributes (e.g., condition of thermostat)	• Subassemblies for reuse • Subassemblies for special reprocessing • Subassemblies for recycling with existing technologies	Park et al (1999)
Select products with superior environmental performance	Targeted life-cycle stage (e.g., use phase) and/or design approach for superior environmental performance (e.g., resources used to deliver service)	• Disposable goods • Durable goods • Packaging systems • Production process • Agricultural products • Product systems	Gallery of Environmental Preferably Goods and Services (http://tbe.mit.edu)
Rate products' contribution to progress towards sustainable development	Level of environmental performance (number of targeted life cycle stages) and/or level of rethinking the product as a service (e.g., product designed primarily to deliver service)	• Strong • Moderate • Weak • None	Gallery of Environmental Preferably Goods and Services (http://tbe.mit.edu)

Hanssen (1996) investigated environmental impacts related to specific product groups using results of 18 different LCA studies of product systems. Criteria used for classification focused on functional properties during the use phase and included chemical transformation, energy conversion, and transportable vs. stationary products (see Table 4.13). Although the validity and generality of the LCA results were questioned due to uncertainty and variation in the studies, relevant trends were identified:

- The importance of environmental impacts differed among product types. Depletion of fossil fuel energy sources, global warming and acidification were most significant for stationary products and transportable products with energy conversion. Photochemical oxidation and human toxicity were most important for products being chemically transformed and transportable products with energy conversion. Solid waste generation was also significant for transportable products without energy conversion.
- The most important life-cycle stages were generally raw material production and product use. For both life-cycle phases, conversion of fossil energy to electricity, process energy, heat or transport was a dominating factor. The production phase, distribution phase and production of packaging were in most product types of very low relevance.
- Raw material production was dominant for products being chemically transformed, stationary products without energy conversion, and transportable products without energy conversion. Use phase was important for products being chemically transformed, stationary products with energy conversion, and transportable products with energy conversion. Waste generation was relevant for products being chemically transformed, and stationary products with energy conversion.

Research work using results of 18 different LCA studies of product systems carried out in Østfold Research Foundation provided a basis for a product classification (Hanssen, 1996), according to their functional properties. Criteria used for classification focused in product's application phase and included chemical transformation, energy conversion, and transported vs. stationary products. Based on the LCA studies, the most significant environmental impacts as well as the contribution to different impacts from different life-cycle phases for each type of product were analyzed. Although the validity and generality of the LCA results were discussed due to uncertainty and variation in the studies, important trends that were found are as follows:

- The importance of environmental impacts differed among product types: depletion of fossil fuel energy sources, global warming and acidification were most significant for stationary products without and with energy conversion, and transport products with energy conversion; photochemical oxidation and toxicity were most important for products being chemically transformed and transport products with energy conversion; solid waste generation was also significant for transport products without energy conversion.
- The most important life-cycle stages were generally raw material production and use of products. For both life-cycle phases, conversion of fossil energy to electricity, process energy, heat or transport was a dominating factor. The production phase, distribution phase and production of packaging were in most product types of very low relevance.
- Raw material production was the dominating life-cycle for products being chemically transformed, stationary products without energy conversion, and transport products without energy conversion. Use phase was important for products being chemically transformed, stationary products with energy conversion, and transport products with

energy conversion. Waste generation was relevant for products being chemically transformed, and stationary products with energy conversion.

Kaebernick and Soriano (2000) assessed 33 products. Different product groupings were investigated according to:

- Rank of the life cycle phase impact indicators. Three major groups were identified: (1) material phase produces dominant impacts; (2) use phase produces dominant impacts; (3) material and use phase are of equal importance.
- Contribution of material types to the top 70% of material impact. Two major groups were identifies: (1) materials with impact contribution proportional to product mass contribution; (2) materials with significant impact despite the almost negligible contribution to product mass.
- Top impact indicator classes. Five clusters were identified.
- Degree of association between multiple variables including product variables (mass, service life, frequency of use, energy requirement) and environmental variables (presence or absence of environmental impacts). Two major clusters were identified: (1) intensity of impact in the material phase; (2) intensity of impact in the use phase.

4.2.2 TREE-BASED CLASSIFICATION FOR LEARNING SURROGATE LCA MODELS

Purpose of classification

The goal is to develop a systematic product classification system that supports the development of appropriately specialized learning surrogate LCA models.

Framework for environmental performance of product concepts

The system 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 surrogate models are better able to emulate impacts of specific products within the group. Figure 4.16 shows a conceptual framework for environmental performance of product concepts, driven by the product descriptors of the learning surrogate LCA models.

– **Environmental performance** +

negative impacts	Product descriptors	positive impacts
↑ energy, material consumption emissions	*mass*	↓ energy, material consumption emissions
↑ energy, material consumption emissions	*material composition*	↓ energy, material consumption emissions
↑ downstream energy consumption, emissions (air, water)	*recycled content*	↓ upstream energy, material consumption, emissions, downstream solid emissions
↑ downstream energy consumption, emissions (air, water)	*recyclability*	↓ upstream energy, material consumption, emissions, downstream solid emissions
↑ downstream energy, material, consumption, emissions	*life time*	↓ upstream and/or downstream energy, material consumption, emissions
↑ energy consumption, emissions	*use time*	↓ energy consumption, emissions
↑ energy consumption, emissions	*operational mode*	↓ energy consumption, emissions
↑ energy, material consumption emissions	*additional consumables*	↓ energy, material consumption emissions
↑ energy consumption, emissions	*energy source*	↓ energy consumption, emissions
↑ energy consumption, emissions	*power consumption*	↓ energy consumption, emissions

Figure 4.16 Conceptual framework for environmental performance of product concepts, driven by product descriptors.

Classification criteria should be based upon the product concept descriptors that are used to train and query the learning LCA models. Instead of a single general surrogate LCA model for every product there would be a number of surrogate LCA models, still general yet specialized, trained to cover different categories of products. A simple example to illustrate the idea for a hybrid learning system with automated classification is provided in Figure 4.17.

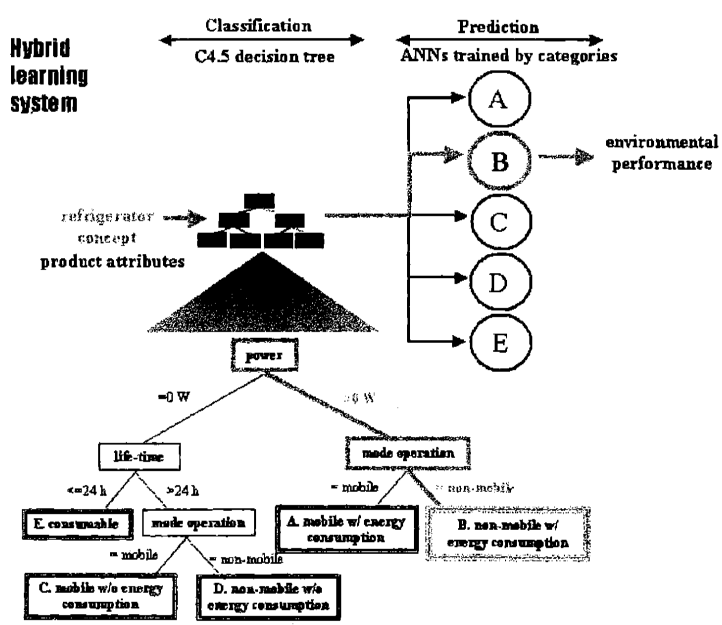


Figure 4.17 Simple example to illustrate a classification scheme preceding the prediction phase.

Preliminary development of an automated classification system

Product data and LCI data were collected for 61 different products (see Table 4.14) from several sources: LCA studies conducted at TU Delft (DfS Group, 1994-1997) and KTH (Eriksson and Izar, 2000); studies published in SimaPro 4 User's Manual (1999); a study by PA Consulting Group (UK Ecolabeling Board, 1992); a case study of an entire automotive body-in-white (BIW) and car fenders (Newell, 1998); and nonproprietary studies conducted by the Research Triangle Institute (Sharma et al, 1996a, 1996b) and Franklin Associates, Ltd. (1990, 1994).

Table 4.14 Products used in the classification study

1 washing machine	1 oak chair
1 heater	1 silver fir chair
2 vacuum cleaners	1 paper bag
1 mini vacuum cleaner	1 PP crate
3 coffee machines	1 showerhead
4 radios	1 PE bag
2 juice squeezers	1 coffee filter
1 vacuum dustbag	2 newsprint productions
2 towels	2 coatings
5 refrigerators	2 antifreeze solutions
10 televisions	3 diaper systems
6 Body-In-White (BIW)	4 sauce pans
3 car fenders	

<u>Conceptual grouping</u>

Hierarchical clustering techniques have been used in several applications (e.g. gene expression data and market segmentation) to suggest potentially useful ways of grouping objects based on their proximity (similarity) with each other. Hierarchical clustering procedures are among the most widely used methods, in part due to their conceptual simplicity and graphical dendrogram representations (Duda et al 1997).

Agglomerative hierarchical cluster analysis of the 61 products using the Ward method was carried out to help identify environmentally-driven product categories. This technique has been applied as a useful procedure to classify products into similar groups that can be profiled for environmental similarities and differences (Kaebernick and Soriano, 2000). The product descriptors were used as the clustering variables. The resulting clusters of products are then formed based on product descriptors but conceptually should be groups of which we can "environmentally think" in the same way.

These multivariate statistical procedures for clustering units on a battery of variables have inherent problems with multi-colinearity and autocorrelation. It is also recognized that other approaches might provide different "lenses" to view data patterns. However, the goal was to use cluster analysis as an exploratory data method to provide systematic qualitative guidance in defining product categories. There is no expectation of a unique and definite solution.

Hierarchical clustering analysis was performed using Matlab®. An improved version of the Matlab® routines was implemented to deal with mixed qualitative and quantitative data, and to balance over-weighting of material composition caused by the many material attributes. This improvement was based on a combined distance matrix approach proposed by Romesburg (1984), and is symbolically written in Equation 4.2.2.1.

$$R = w_1 R_1 + w_2 R_2 + w_3 R_3 = \sum_{q=1}^{3} w_q R_q \qquad \textbf{Equation 4.2}$$

where R is the combined distance matrix; R_1 is a distance matrix using z-score-standardized quantitative material attributes and squared Euclidean distance; R_2 is a distance matrix using z-score-standardized quantitative non-material attributes and squared Euclidean distance; R_3 is a distance matrix using qualitative attributes and Jaccard coefficient; w_1, w_2 and w_3 are the corresponding weights, which are nonnegative and sum to 1.0.

There is no single method for selecting the candidate cluster solution. In this study, a number of options were explored by analyzing the agglomeration schedule and dendrogram to identify marked increases in the value of the distance coefficient between stages. The final cluster solutions were chosen according to the desired level of classification (general vs. specific), interpretability of the clusters (mean profiles of clusters), and the number of observations in each cluster. Clusters with very few products (1 or 2) were considered probable outliers and/or not representative enough for classification purposes.

Figure 4.18 shows the dendrogram produced by cluster analysis.

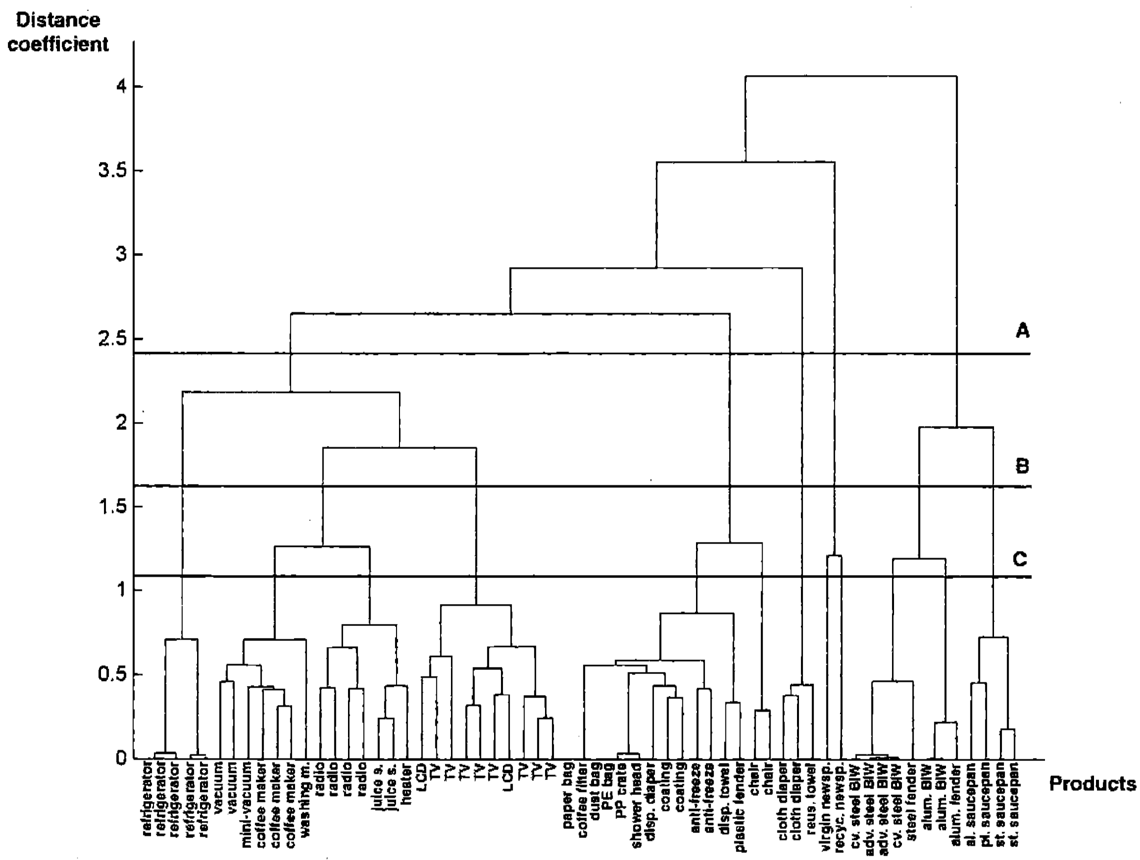


Figure 4.18 Hierarchical clustering tree (dendrogram).

The dendrogram shows evidences of sudden increases in distance values – ranges of the distance coefficient for which the number of clusters remains constant. These indicate stages at which well-separated clusters are being brought together, and thus suggest the number of clusters to consider. Newsprint, forming clusters with 2 elements (in cuts A and B) and 1 element (in cut C) were discarded. Newsprint data are very atypical with respect to the other values in the data set. Due to its material and operational properties, one would expect them to be included in other clusters.

In an attempt to capture patterns of the clusters from different cuts in the dendrogram, the corresponding mean profiles of the quantitative variable z-scores were computed. Clusters originated by cut C were considered too specific for our classification needs. Mean profiles obtained by cuts A and B are illustrated in Figure 4.19. Table 4.15 presents a summarized interpretation.

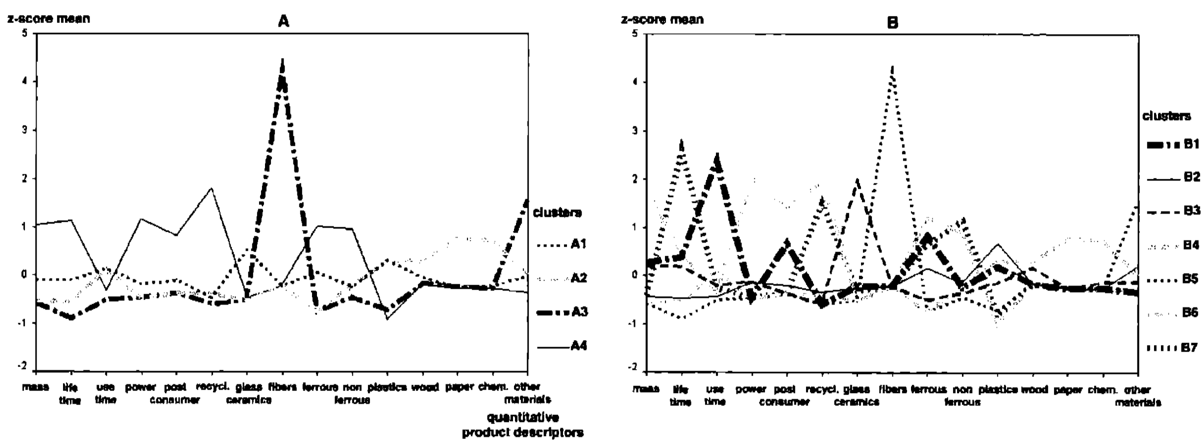


Figure 4.19 Mean profiles of product groups originated by cuts A and B in dendrogram.

Table 4.15 Summarized interpretation of mean profiles for cuts A and B.

Cluster		Interpretation	Sample products
A	1	Durable products, with a significant amount of plastics or ceramics/glass, and with power consumption.	Refrigerators, vacuum cleaners, mini-vacuum cleaner, coffee makers, washing machine, radios, juice squeezers, heater, LCDs, TVs.
	2	Generally non-durable, low-mass products, and with no power consumption [a].	Paper bag, coffee filter, dust bag, PE bag, PP crate, showerhead, disposable diaper, coatings, antifreezes, disposable towel, chairs, plastic fender.
	3	Low-mass products, with a significant amount of fibers materials in their composition, and with no (internal) power consumption.	Home and commercial washed cloth diapers, reusable towel.
	4	Durable, recyclable products, made primarily of metals, and with (external) power consumption[b].	BIWs, car fenders, sauce pans.
B	1	Durable products, with a significant amount of ferrous, plastic and recycled materials, and with (efficient) power consumption.	Refrigerators.
	2	Durable products, with a significant amount of plastic materials, and with power consumption.	Vacuum cleaners, mini-vacuum cleaner, coffee makers, washing machine, radios, juice squeezers, heater.
	3	Durable products, with a significant amount of ceramic/glass materials, and with power consumption.	LCDs, TVs.
	4	Generally non-durable, low-mass products, and with no power consumption [a].	Paper bag, coffee filter, dust bag, PE bag, PP crate, showerhead, disposable diaper, coatings, antifreezes, disposable towel, chairs, plastic fender.
	5	Low-mass products, with a significant amount of fibers materials in their composition, and with no (internal) power consumption.	Home and commercial washed cloth diapers, reusable towel.
	6	Durable, recyclable products, made primarily of ferrous and/or non-ferrous material, with (external) power consumption during use [c].	BIWs and car fenders
	7	Durable, low-mass, recyclable products, made primarily of ferrous and/or non-ferrous material, with (external) low power consumption during use.	Sauce pans

a. among highest average values for use time due to chairs;
highest average values for wood, paper, and chemicals due to chair, paper-based disposables, coatings and antifreezes, respectively;
b. highest average values for lifetime due to saucepans; sample products are all highly recyclable and partially recycled;
c. highest average values for mass due to BIWs; highest average values for post consumer materials due to steel BIWs.

In addition to the mean profiles, basic cross tabulation tables that relate the clusters previously defined with the categorical product descriptors were also analyzed. While none of these results are unexpected, they do serve to make more explicit differences/similarities between/within clusters (i.e., do the relations make sense?) and can provide useful information on how to reach the cluster members. Table 4.16 shows the percentage breakdown of each cluster group into the specific sources of energy during the use phase.

Table 4.16 Sources of energy cross table.

		Clusters A					Clusters B							
Type		1	2	3	4	**Total**	1	2	3	4	5	6	7	**Total**
none	count	2	14			16		2		14				16
	%	6.9	93.3			27.1		14.3		93.3				27.1
solar	count	2				2			2					2
	%	6.9				3.4			20					3.4
hydro	count	1				1			1					1
	%	3.4				1.7			100					1.7
solar-electric	count	1				1			1					1
	%	3.4				1.7			100					1.7
batteries	count	2				2		2						2
	%	6.9				3.4		14.3						3.4
electricity	count	21		3	4	28	5	10	6		3		4	28
	%	72.4		100	33.3	47.5	100	71.4	60		100		100	47.5
gasoline	count		1		8	9				1		8		9
	%		6.7		66.7	15.2				6.7		100		15.2
Total	count	29	29	3	12	59	5	14	10	15	3	8	4	59
	%	100	100	100	100	100	100	100	100	100	100	100	100	100

The majority of products in cluster A1 and all the products in cluster A3 (B5) use electricity (wall outlet) as the source of energy. In cluster A1, there are also products that do not consume energy during the use phase (self-powered radios) or use renewable energy sources (solar-powered LCDs and TVs). In cluster A3 (B5) electric energy is accounted for as externally consumed in washing operations. The majority of products in cluster A2 (B4) do not consume energy during use (confirming their lowest average values for power consumption). The car plastic fender is an exception. Material composition and recycleability properties dominated the grouping in this case, separating the car plastic fender from the other car fenders. In cluster A4, electric energy and gasoline are accounted for as externally consumed in heating the saucepans and in influencing the mobility of the cars. All the products of clusters B1 and B7 and the majority of products in clusters B2 and B3 use electricity as the source of energy. In clusters B2 and B3 there are also products that do not consume energy during use (self-powered radios in B2) or use renewable energy sources (solar-powered LCDs and TVs in B3), lowering the groups' average values for power consumption. In cluster B7, electric energy is accounted for as externally consumed in washing the diapers and towel. Products of cluster B7 are BIWs and car fenders that externally drive the consumption of gasoline (and high power consumption).

Results for operation mode showed that all the products in clusters A2 (B4), A3 (B5), A5 (B7, B8) do not have any operation mode. Although mode of operation can partially encode level of performance in energy efficiency, it was not considered a property for products that, nevertheless, induce energy consumption during use. In clusters B2 and B3, the majority or all of the products are on/off manually operated. This potentially causes a greater influence of different patterns of consumer usage in use time and power consumption trends. Percentage breakdown for additional consumables showed that the majority of products do not add consumables during the use phase. All products in cluster A4 (B6, B7) add consumables during the use phase.

The grouping of products defined by cuts A and B in the dendrogram maps partially to the ones defined by Kaebernick and Soriano (2000) (who used hierarchical clustering). Kaebernick and Soriano (2000) grouped products using both product characteristics and environmental performance indicators as the clustering variables. Two major clusters were formed: one including products that manifest intensity of impact at the use phase (cluster A1 contains the same or similar type of products, e.g., coffee makers, refrigerators, TVs, washing machine, heater); and the other including products with the main impact intensity in the material phase (cluster A2 contains the same or similar type of products, e.g., paper bag, PE bag, chairs, coffee filter, other disposable products). Cluster A1 contains products (self-powered radios and solar-powered TVs and LCDs) likely to have less impact intensity in the use phase than in the material phase (as they are eco-designed products with "non-traditional properties" positively relevant to the environment) due to a smaller effect on clustering of the energy consumption properties relatively to other properties (e.g., material composition). Cluster A2 contains other types of products (e.g., antifreezes, coatings, chairs), even though one can also consider them as material-based products. The car plastic fender is an exception, as explained previously. In addition to these groupings, clusters A3 and A4 were created. A plausible interpretation is that in these products, although expected as being material-based, indirect (external) energy consumption during the use phase is accounted for. Cluster A3 is strongly isolated also due to the particular material composition, with a high percentage of fibers.

The groups defined by cuts A and B in the dendrogram also follow general patterns proposed by Hanssen (1996), for example: A1 are "stationary products with energy consumption"; A2 are "stationary products without energy consumption"; A3 and A5 are products "without internal energy consumption". A4 further specializes into cluster B6 – "moveable products without internal energy consumption" – and cluster B7.

For specific-purpose use the dendrogram should be cut to produce groupings that are maximally related to other specific variables of interest (Romesburg, 1984) – in this case environment-related variables. The cluster solution generated by cut B was then chosen for its level of specificity and interpretability. Table 4.17 summarizes a final conceptual grouping of products, guided by the previous clustering exploratory analysis, to be used for further analysis.

Table 4.17 Final conceptual grouping of products.

Group	Definition	Sample Products
1	**Durable, high-mass household appliances, with efficient energy consumption during use (active).**	Refrigerators
2	**Durable, (generally) low-mass consumer products, (generally) with a significant amount of plastic materials, and with energy consumption during use (active).**	Vacuum cleaners, mini-vacuum cleaner, coffee makers, washing machine, juice squeezers, heater, radios
3	**Durable electronic consumer products, (generally) with a significant amount of ceramic/glass materials, and with energy consumption during the use phase (active).**	LCDs, TVs
4	**(Generally) non-durable, low-mass consumer products, with no energy consumption during use (passive).**	Paper bag, coffee filter, dust bag, PE bag, PP crate, shower head, disposable diaper, coatings, antifreezes, disposable towel, chairs, radios *
5	**Low-mass consumer products, with a significant amount of fiber materials, and with external energy consumption for maintenance during use (active).**	Home and commercial washed cloth diapers and reusable towel.
6	**Durable, recyclable products, with external energy consumption for mobility duringuse phase (active).**	BIWs and car fenders **
7	**Durable, low-mass, recyclable products, with a significant amount of metals, and with external energy consumption for maintenance during the use phase (active).**	Sauce pans

* self-powered radios included in category 4 for further analysis in classification.
** plastic fender included in category 6 for further analysis in classification.

Product classification system

Product descriptors data and environmentally driven categories were then used to develop an automated classification system based on decision trees algorithms applying C4.5, a software extension of the basic ID3 decision tree algorithm (Quinlan, 1993). C4.5 is both well documented and publicly available (http://www.cse.unsw.edu.au/~quinlan/).

The method implemented in C4.5 by Quinlan (1993) for constructing a decision tree is simple, yet fairly efficient. Given a set T of training cases let the classes be denoted $\{C_1, C_2,...,C_k\}$ one of the following is true:

- T contains one or more cases, all belonging to a single class Cj. This corresponds to the situation where the decision tree for T is a leaf identifying class Cj.
- T contains no cases. Here the decision tree is a leaf but the class to be associated with the leaf must be determined from information other than T. For example, some background knowledge of the domain (e.g. overall majority class) might choose the leaf. C4.5 uses the most frequent class at the parent of this node.
- T contains cases that belong to a mixture of classes. In this case the algorithm refines T into subsets of cases that are or seem to be heading towards single-class collections of cases. A test is chosen, based on a single attribute, that has one or more mutually exclusive outcomes $\{O_1, O_2, ..., O_n\}$. T is partitioned into subsets $T_1, T_2, ..., T_n$ where T_i contain all the cases in T that have outcome O_i of the chosen test. The decision tree for T consists of a decision node identifying the test, and one branch for each possible outcome. The same divide and conquer algorithm is applied recursively to each subset of training cases, so that the ith branch leads to the decision tree constructed from the subset T_i of training cases.

This method highly depends on the choice of appropriate tests, which should lead to a partition that reveals the structure of the domain and so has predictive power. In C4.5 the selection of the test – decide which attribute will be tested – is made on the basis of the information-based gain ratio criterion. It is assumed that the information conveyed by a message depends on its probability and can be measured in bits as minus the logarithm to base 2 of that probability. The message of selecting one case at random from a set S of cases and reporting that it belongs to some class C_j has probability:

$$\frac{freq(C_j,S)}{|S|},$$

where $freq\ (C_j,S)$ is the number of cases in S that belong to class C_j and $|S|$ is the number of cases in set S. Therefore the information it conveys is:

$$-\log_2\left(\frac{freq(C_j,S)}{|S|}\right) \text{ bits.}$$

The expected information from such a message pertaining to class membership is found by summing over the classes in proportion to their frequencies in S:

$$info(S) = -\sum_{j=1}^{k} \frac{freq(C_j, S)}{|S|} \times \log_2\left(\frac{freq(C_j, S)}{|S|}\right) \text{ bits.}$$ **Equation 4.3**

It follows then that *info(T)* measures the average amount of information needed to identify the class of a case in *T*. Considering a similar measurement after *T* has been partitioned in accordance to the *n* outcomes of the test *X*, the expected information required can be found as the weighted sum over the subsets:

$$\text{info}_X(T) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} \times \text{info}(T_i)$$ **Equation 4.4**

The quantity:

$$gain(X) = info(T) - info_X(T)$$ **Equation 4.5**

measures the information that is gained by partitioning *T* in accordance with the test *X*. The gain criterion selects a test to maximize this information gain. To avoid a bias in favor of tests with many outcomes *gain(X)* is normalized as follows. By analogy with the definition of *info(S)*:

$$split\ info(X) = -\sum_{i=1}^{n} \frac{|T_i|}{|T|} \times \log_2\left(\frac{|T_i|}{|T|}\right)$$ **Equation 4.6**

which represents the potential information generated by dividing *T* into *n* subsets, different from the information gain which measures the information relevant to classification that arises form the same division. Then,

$$gain\ ratio(X) = \frac{gain(X)}{split\ info(X)}$$ **Equation 4.7**

represents the proportion of information generated by the split that is useful – expected helpful for classification. To avoid unstable ratios (when split is near-trivial) the gain ratio criterion selects a test to maximize the gain ratio, subject to the constraint that the information gain must be at least as great as the average gain over all tests examined.

Once the attribute is chosen, if the attribute is discrete, the test creates one outcome and branch for each possible value of that attribute. If the chosen attribute *A* has continuous numeric values, a binary test with outcome $A<Z$ and $A>Z$ is performed, based on comparing the value *A* against a threshold value *Z*. To find the appropriate value of the threshold *Z*, the training cases *T* are first sorted on the values $\{v_1, v_2, \ldots, v_m\}$ of the attribute *A*. The *m-1* possible splits on A are all examined. C4.5 chooses the largest value of A as the threshold in the entire training set that does not exceed the midpoint of each interval $\frac{v_i + v_{i+1}}{2}$, rather than the midpoint itself, to ensure that all threshold values appearing in trees and/or rules actually occur in the data.

Given that only a small data set was available to construct the decision tree, cross-validation was used to more robustly estimate the accuracy for unseen cases. In this procedure, the available data were divided into *N* blocks to build *N* different classification models, in each of which one block is omitted from the training data. The resulting model is then tested on the cases in that omitted block. Provided that *N* is not too small – 10 is commonly used– the average error rate over the *N* unseen test sets is considered as a good predictor of the error rate of a model built from all the data (Quinlan, 1993). The following parameters were considered in analysis of the average pruned tree:

- *Grouping attribute values.* This was done to address two types of concerns: (1) one consequence of partitioning the training set into numerous subsets is that as each subset is small useful patterns in the subsets may become undetectable because of an insufficient data; (2) if discrete attributes vary greatly in their number of values, it is highly uncertain that a selection criteria such as gain ratio is assessing them equitably. The denominator of this ratio grows rapidly as the number of subsets increases and therefore biases against attributes with many values. If the number of outcomes from testing a multi-valued attribute is to be reduced, one or more outcomes must be associated with a collection of attribute values rather than a single value. The default procedure forces the partition to a binary split. If there are numerous discrete attributes with 3 or more values, it is worth trying to group attribute values.
- *Minimum cases.* C4.5 requires that any test used in the tree must have at least 2 outcomes with a minimum number of cases. Situations where tests in which almost all the training cases have the same outcome may lead to odd trees with little predictive power. The default minimum can be changed to a higher value when there is a lot of noisy data. This constrains the degree to which the initial tree can fit the data.
- *Size.* The number of nodes of the average simplified decision tree.
- *Observed error rate for unseen cases.* Error, defined as the average of the observed error rates of the *N* classification models generated by cross-validation. Each observed error rate is the total number of observed errors in each classification model divided by the total number of unseen cases in that model.
- *Expected error rate for unseen cases*: Error, estimated as the average of the expected error rates of the *N* classification models generated by cross-validation. Each expected error rate is the sum of the predicted errors at the leaves in each classification model divided by the total number of training cases in that model. For a given confidence level, the predicted errors at the leaves are found from the confidence limits for the binomial distribution, assuming that the classification tree has been constructed to minimize the observed error rate.

To run C4.5, a file with definition of attributes, attribute values and classes was first created (see Figure 4.20). The quantitative attributes are described as continuous while a list of all possible discrete values are provided for the qualitative attributes

```
classBcomb1.names
|Author: Inês Sousa
|Email: iss@mit.edu
|Date: 4/30/01

|Title: Product classification to support learning surrogate LCA models

|-----------------------------------------------------------------------

|Combination (1)
|Classes: classifies into 7 environmental product categories derived from clustering cut B
|1=Durable, high-mass, efficiently active household appliances
|2=Durable, active, household appliances
|3=Durable,active, electronic consumer products
|4=Low-mass, passive products
|5=Low-mass, fiber-based active (external energy based) products
|6=Durable, mobile, active (external energy based) products
|7=Durable, low-mass, active (external energy based) products

1, 2, 3, 4, 5, 6, 7.

|Attributes:

mass: continuous.
ceramics_glass_concrete: continuous.
fibers: continuous.
ferrous_metal: continuous.
non_ferrous_metal: continuous.
plastics: continuous.
wood: continuous.
paper_cardboard: continuous.
chemicals: continuous.
others: continuous.
lifetime: continuous.
use_time: continuous.
operation_mode: none, sensor, stand_by, manual.
additional_consumables: yes, no.
energy_source: none, solar, hydro, solar_electric, batteries, electricity, gasoline.
power_consumption: continuous.
post_consumer_material: continuous.
recycleability: continuous.
```

Figure 4.20 File classBcomb1.names.

The second step required create a data file containing all the individual cases available in the data set (one line per case), each of which described by corresponding values of each of the attributes and class. Each line contains the values of the attributes in order followed by the case's class, with all entries separated by commas. An unknown value of an attribute is indicated by a question mark "?".

The 10-cross-validation procedure was rerun with a pruning confidence level of 25% for different combinations of parameter options and product descriptors, exploring error estimations associated with different decision trees. Table 4.18 displays the results of some of these combinations: (1) all attributes are included in the analysis; (2) energy source and operation mode were excluded as discrete variables that reveal insufficient data for all categories; (3) energy source is re-introduced in the analysis. Figure 4.21 shows the decision trees corresponding to the highlighted combinations in Table 4.18. The default options of parameters did not group attributes and used 2 minimum cases. Grouping attribute values was considered in other options as there are qualitative product descriptors with three or more values (energy source and operation mode). Table 16 reveals a discrepancy between the observed and expected error rates for unseen cases. This type of results can occur when there is an almost pure partition of the training cases into single-class subsets. However, much of the tree structure induced by this partition is over-fitted, with little predictive power. This often happens when there are many continuous attributes since a single continuous attribute can give rise to numerous possible divisions. By increasing the number of minimum cases overly fine-grained divisions of the training set may be prevented. When the expected error rate for trees is almost exactly correct it indicates an appropriate level of pruning (Quinlan, 1993).

Table 4.18 Error estimations for combinations of parameter options and product descriptors.

Options	Size	Observed error rate %	Expected error rate %
	Combination (1)		
default	15.7	18	6.7
attribute grouping	11.3	16.2	6.7
4 minimum cases	14.9	20.6	13.7
attribute grouping + 4 minimum cases	**9.3**	**19.6**	**18.7**
	Combination (2)		
default	14.6	20.3	13.3
attribute grouping	14.6	20.3	13.3
4 minimum cases	**12**	**26**	**22.3**
attribute grouping + 4 minimum cases	12	26	22.3
	Combination (3)		
default	16.2	17.9	6.7
attribute grouping	12.2	16.2	8.3
4 minimum cases	15.2	21.1	17.7
attribute grouping + 4 minimum cases	**11.6**	**19.1**	**19.3**

In combinations (1) and (3), formation of value groups decreases the observed error rate. Formation of value groups and 4 minimum cases give rise to similar observed and expected error rates at the expense of increased errors rates and smaller simplified decision trees. In combination (2), formation of value groups has no effect on the observed or expected error rates, but 4 minimum cases results in observed and expected error rates which are closer together.

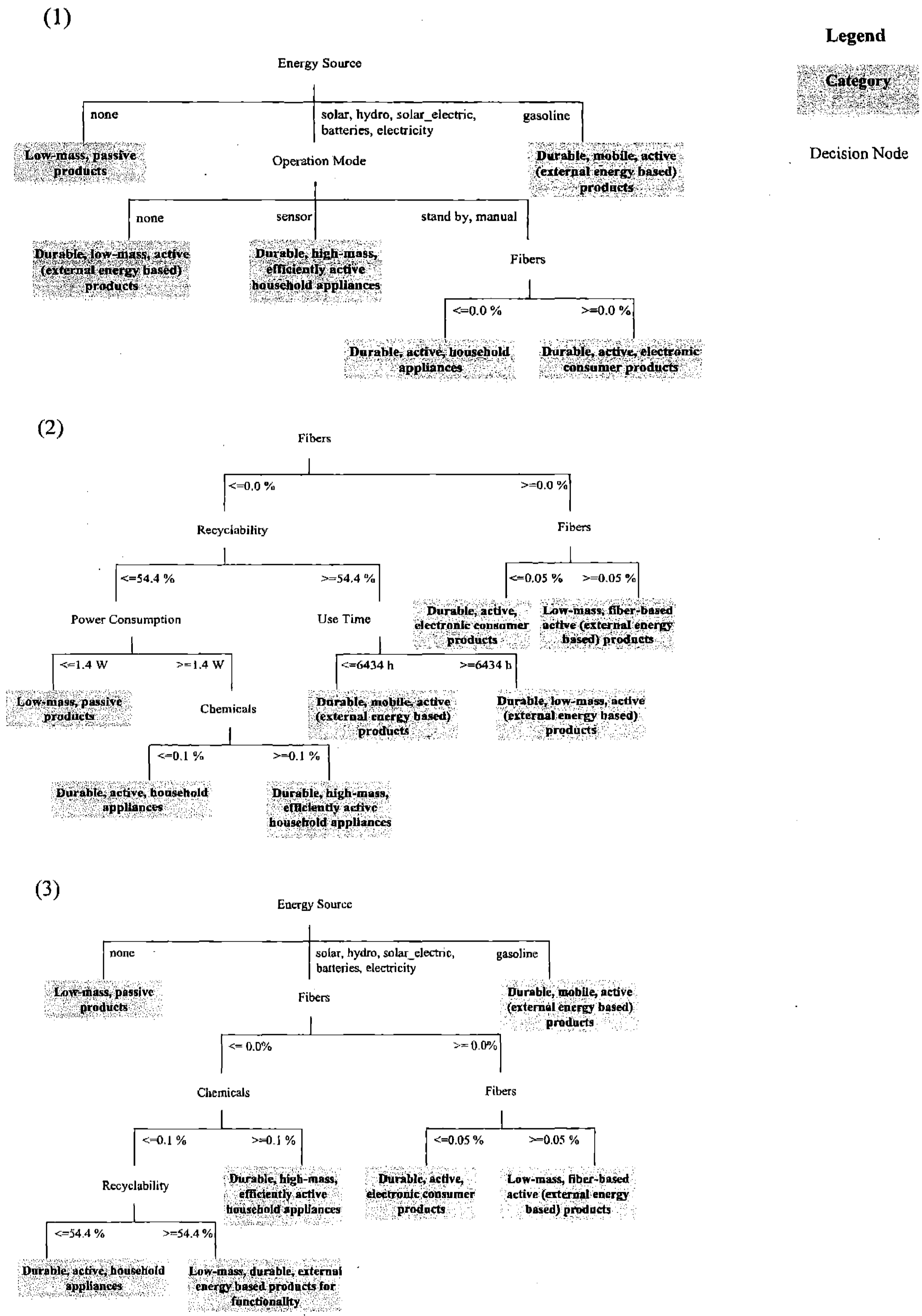


Figure 4.21 Classification systems produced by combinations (1), (2) and (3).

Figure 4.21 shows that the combinations produced by differently structured classification systems. In combination (1), the category *low-mass, fiber-based, active products* was not found by the algorithm. Instead, the training products corresponding to this category were misclassified in the category *durable, low-mass, active products*.

In all three combinations, as well as in other experimented combinations, robust patterns could not be distinguished from chance coincidences. Data were insufficient to induce a good generalization. For example, materials decision nodes and energy source decision nodes were highly biased towards particular patterns in material composition and energy consumption. However, the goal is to explore the viability of a product classification system that could be used to support specialized learning surrogate LCA models. The lack of good generalization does not prevent considering the results of this analysis as relevant for the purpose of this research.

The selection of a suitable classification system need to be done concurrently with tests performed with the specialized trained surrogate LCA models. The best performance of this hybrid learning system would drive the selection of the suitable automated classification scheme

5 APPLICATION STUDY

5.1 GOAL AND SCOPE OF APPLICATION STUDY

The goal of this study was to explore the application of the learning surrogate LCA approach to automotive products within a product development company. The application study was performed to:

- Explore the feasibility and process of customizing the learning surrogate LCA approach for a more narrow class of products - durable, mobile, active (external energy-based) products
- Illustrate the use of the learning surrogate LCA approach in an integrated simulation environment for trade-off analysis in a multiple objective application scenario.

The case study was conducted with a Swedish heavy truck manufacturing company and targeted a pre-development project for a new door concept. An existing detailed environmental assessment of two (present and new) door concepts by Berg and Lindgren (2001) provided detailed product and environmental life-cycle data and a basis for benchmarking the application study.

5.2 BACKGROUND

Product development, methods and tools at the company

At Scania, product development projects involving cross-disciplinary teams are classified as shown in Figure 5.1. Pre-development projects are launched continuously to explore new concepts and test new technologies. The purpose is to create a foundation of projects and knowledge that will be included later on in a Concentrated Introduction project or in product Follow-up. (Berg, 2001). The output is an assignment directive, which triggers either the start of concentrated introduction or product follow-up projects (Schlüter, 2001).

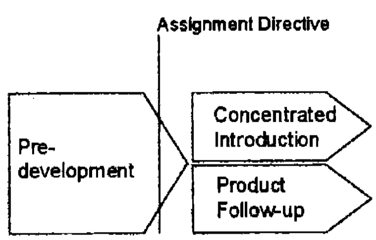


Figure 5.1 Project categories at the company. Source: Schlüter (2001).

Concentrated Introduction projects are based on proven technology and are carried out in five phases: Pre-study, Feasibility study, Development, Implementation, and Termination. Follow-up projects are top-priority projects to ensure fastest possible problem solving to meet quality and customer satisfaction, with no restrictions in introduction date of product/production changes.

In conceptual phases, there is little methodological support available for the designer (Schlüter, 2001). Brainstorming, competitor analysis, TIPS (Theory of Inventive problems solving), re-design of existing products, and discussions with other designers in the team are common approaches. At the system design level, the company uses a modularization method internally developed to maximize product customization with a minimum number of parts. At the detail design level designers use state-of-the art CAE tools.

In the environmentally conscious design arena, the company is using LCA in a small scale (Schlüter, 2001), not systematically applied as a standard procedure to obtain information for design and decision-making. The LCA approach is mostly used for comparing different design concepts for a component, and focusing on inventory results rather than on impact assessment. As in most companies in the industry, the trend at this company is to choose and adopt methods and tools that are perceived as appropriate for their specific needs, based on their understanding and experience with such tools as well as their familiarity with a particular method. Grey and black material lists and DFE training programs for product and manufacturing engineers within the organization are then the common approaches used at the company to promote environmentally conscious design.

Pre-development project for a new lightweight door concept

A pre-development project was carried out to develop a new door concept in collaboration with another company that specialized in door systems. The purpose of the new door concept is to reduce weight – a lighter truck will increase load capacity for the customer and decrease fuel consumption and wear (especially the wear of tires).

A change in materials, using aluminium and plastics instead of steel, was the design strategy selected to achieve weight reduction of the truck cab door. The new door concept only exists as a prototype. It is based on a space frame structure, where a load-carrying frame of aluminium profiles is covered with plastic panels on both the inside (polypropylene) and outside (polyurethane). The total weight of the new door concept is approximately 30% less than the current door, which consists of steel outer and an inner door panels.

Still, it is important to realize that the new light-weight concept has other unintended implications for the environment and natural resource use. Material substitution changes the whole life-cycle system from mining and refining through to manufacturing, use, and disposal/recycling.

A life-cycle perspective is needed to provide the ability to holistically address all these issues. For this purpose, Berg and Lindgren (2001) performed a six-month long detailed life-cycle assessment study to comprehensively compare the current and the new door concepts.

Since concept has been prototyped, quite detailed information is already available. While there is still flexibility to make changes they are confined to a limited solution space because of a significant level of parameterization already applied to the design problem.

Once prototypes have been evaluated, the pre-development project enters a decision making stage. The environmental assessment of the door concepts and recommendations for environmental improvement should complement the information on other design criteria such as safety, economy and customer requirements. All together, they potentially provide an informed and comprehensive basis for the decision-makers evaluate on how to proceed with the project (Berg and Lindgren, 2001).

About the life-cycle assessment study

Berg and Lindgren (2001) conducted the comparative detailed LCA study on the two door concepts at Scania in Södertälje, Sweden, between September 2000 and February 2001, as part of the pre-development project. Six months were required to carry out this study. To define the goals and scope as well as to get relevant background information, several preliminary discussions took place with employees at the company involved with the project.

An extensive search for relevant literature, articles and data followed. Most of the required secondary data was collected at Scania in Södertälje through personal communication, written material and databases. Visits to the company's production plant in Oskarshamn, Sweden, and the development partner company as well as telephone interviews were also required to acquire the necessary data and information. The majority of the primary data (collected specifically for this study) was provided by employees at Scania in Södertälje and Oskarshamn, and some were obtained from the development partner company. Data on fuel consumption and emissions of Scania trucks, an employee at Scania separately ran simulations using a simulation software developed at Scania. When no data was available, assumptions were made in collaboration with experts.

TEAM®, a commercially available LCA software was used to perform inventory calculations amd an impact assessment. Product systems and boundary definitions, allocation procedures, assumptions, data quality issues and methodological limitations underlying this LCA study were carefully documented by Berg and Lindgren (2001).

The results from the inventory analysis on energy use and air emissions (CO_2, CO, NO_x, SO_x and hydrocarbons) showed that:

- The new door concept consumed less energy and causes lower emissions of carbon dioxide, carbon monoxide, nitrogen oxides, hydrocarbons.
- The production of the new door concept requires more energy and causes higher emissions of nitrogen oxides, sulfur oxides, and hydrocarbons than the production of the present door. Production of the present door originates higher carbon monoxide and dioxide emissions.
- The use phase has the largest influence on the results for energy consumption and all emissions (except carbon monoxide) both in the size of the impacts and in the difference between the concepts. The new door concept is about 40% better than the present door due to the difference in fuel consumption.
- The production phase has the largest influence on carbon monoxide and plays a more important role in the new door concept, especially regarding energy consumption.
- In the end-of-life worst-case scenario – 65% steel recycling, 50% aluminum recycling and 100% plastics go to landfill – the present door is the best concept in half of the inventory categories. In the end-of-life best-case scenario – 100% steel, aluminum and polypropylene recycling, and 100% polyurethane incinerated – the new door concept is the best for all but one category (carbon dioxide).

The results from the impact assessment using different valuation methods (IPCC-greenhouse effect, CML-eutrophication, CML-air acidification, CML-depletion of non-renewable resources and EPS-total) showed that:

- For the total life cycle, the new door concept is best concerning all environmental impacts except the depletion of non-renewable resources in the worst-case scenario (large depletion of bauxite due to low recycling rate of aluminum).
- The present door performs best in the production phase for all methods except the IPCC-greenhouse effect and the EPS total.
- The new door concept performs best in the use phase for all methods.
- In the end-of-life phase, the new door concept is the best concerning air acidification and depletion of non-renewable resources, whereas the present door is the best in global warming, eutrophication, and EPS-total.

Berg and Lindgren (2001) conclude that for almost all impacts and effect categories, the new door concept performs better than the present door concept. In addition, the study showed that the use phase is the life-cycle stage with the largest environmental impact (with the exception of depletion of non-renewable resources) and exhibits the greatest difference between the two concepts. A 40% difference in favor of the new door concept is interpreted as resulting from the difference in weight, where the new door concept was modeled as 40% lighter than the present one. The size of the impact from the use phase is interpreted as being related to the total distance driven. Overall, the new door concept is considered to be better than the present one from an environmental point of view. Still, for this conclusion to be true for all the studied emissions and effect categories, the recycling rate for aluminum must be high.

Berg and Lindgren (2001) also proposed improvement strategies for the new door concept based on the findings from the LCA study. They then used the eco-design strategy wheel for qualitatively comparing the improvement proposal with the new door concept. Some recommendations include use of recycled polypropylene instead of virgin material for the inner panel, and aluminum sheets instead of polyurethane for the outer panel.

Finally, Berg and Lindgren (2001) also investigated economical consequences of weight reduction. Based on estimated correlations between fuel consumption and weight for different types of heavy trucks, the investigation showed that 1 kg of reduced weight is worth between 20 and 40 SEK in fuel cost savings during the truck's active lifetime. In addition, tare weight critical customers benefit from the possibility to carry more payload as a result of the reduced weight of the truck. For the company, new light weighting concepts may lead to higher development, implementing and production costs. However, a significant weight reduction may result in a competitive advantage.

5.3 Customization of the Learning Surrogate LCA Method

Here, the customization process will result in the definition of product concept descriptors and key environmental inventory elements tailored to the particular context of the company and its products.

First, a qualitative approach was used to collect data and capture key organizational, methodological and technical aspects of the company's product concept systems (Lagerstedt et al, 2002). The approach used a roadmap proposed by Eisenhardt (1989) for building theories from case study-based research. The case study was conducted targeting two levels of analysis: system (vehicle) and sub-system (door). Interviews, questionnaires, observations, site visits, field notes and company reports were used as data collection methods. The evidence from this iterative process was both qualitative and quantitative. Appendix D summarizes main steps taken in this bottom-up approach.

Customized product concept descriptors set

The general product concept descriptor set (see section 4.1.2) was customized using the criteria listed below. Product concept descriptors should:

- Be relevant to the product design activity: (a) be known and easily understood by design engineers to facilitate readily interface with the product design process; (b) be of high-level information content and parameterization to accommodate the degree of abstraction at early design stages; (c) be sufficient to discriminate between different design concepts.
- Be logically linked to vehicles' environmental performance: (a) span the scope of the life-cycle environmental performance of vehicles; (b) account for functional-environmental synergies between the whole vehicle system and its sub-systems (e.g. fuel consumption of the truck, partially determined by driving behavior, might influence decision-making on mass of the door).
- Be exchangeable within the product design framework to facilitate integrated simulation: (a) span the scope of traditional design decision drivers, which generally are measurable and/or strategic for the company (e.g. cost, fuel economy, power train technology); (b) as a set, form a useful, simple, high-level parameterization structure that facilitates the negotiation of service exchange in the system model.

The final customized set of product descriptors was defined based on data and information provided by this case study research as well as findings from literature (Sullivan and Cobas-Flores, 2001; Lave et al, 2000; McLean and Lave, 2000) and discussions with experts in the automobile industry (Sullivan, 2001) on vehicle attributes and life-cycle environmental performance.

The conceptual framework described next, based on work by Sullivan and Cobas-Flores (2001), was used as a basis to perform the customization. Although proposed for cars, it was considered to be logically extendable to other automotive products (such as heavy trucks and associated sub-systems) for the purpose of the present research.

Consider the total life-cycle burden vector of a vehicle $\overline{\{B\}}_{tot}$ to be defined as follows:

$$\overline{\{B\}}_{tot} = \{B\}_{mp} + \{B\}_{assm} + \{B\}_{op} + \{B\}_{mntn} + \{B\}_{eol} = \overline{\{B\}}_{fxd} + \overline{\{B\}}_{\mathrm{var}} \qquad \textbf{Equation 5.1}$$

where:

- subscripts *tot*, *mp*, *assm*, *op*, *mntn*, and *eol* relate to the vehicle's life-cycle stages and denote *total*, *material production*, *part and product manufacture and assembly*, *operation*, *service and maintenance*, and *end-of-life*, respectively.
- subscripts *fxd* and *var* relate to a conceptual partition of the vehicle's life-cycle burdens and denote *fixed* and *variable* burdens, respectively.

By normalizing the burden vectors with *LTDST*, the life time drive distance for the vehicle (a measure of service rendered), these burdens can then be mathematically written as:

$$\overline{\{B\}}_{tot} = \frac{\overline{\{B\}}_{tot}}{LTDST} \quad \textbf{Equation 5.2}$$

$$\overline{\{B\}}_{fxd} = \frac{\{B\}_{mp} + \{B\}_{assm} + \{B\}_{mntn} + \{B\}_{eol}}{LTDST} \quad \textbf{Equation 5.3}$$

$$\overline{\{B\}}_{\mathrm{var}} = \frac{\{B\}_{op}}{LTDST} \quad \textbf{Equation 5.4}$$

The overall vehicle life cycle performance for a particular data category is the sum of the variable and fixed terms times the vehicle life-time drive distance. Both fixed and variable terms should then be targeted when considering reducing life cycle environmental impacts caused by automotive products. Based on a thoroughly review of vehicle life cycle inventory studies, Sullivan and Cobas-Flores (2001) concluded that:

- The variable term is dominant when considering energy and carbon dioxide during vehicle operation.
- The fixed term is the most or comparably significant when considering solid waste and SO_x emissions during the material production and vehicle manufacturing, maintenance and repair phases.

For energy consumption and CO_2 emissions, the variable terms (operation) increase with increasing mass and at a rate that decreases with increasing power-train efficiency. This is consistent with the expected operational energy equation:

$$E_{op} = \frac{1}{\eta\xi}[A + Bm_T]HHV \quad \textbf{Equation 5.5}$$

where η is power-train efficiency, ξ is fuel production efficiency, m_T is the vehicle total mass, *A* represents parasitic energy dissipation (e.g. aerodynamic drag), *B* is the coefficient of inertial energy consumption, and *HHV* is the high heat value. The same type of equation could be written for $\{B\}_{op}$ in general including CO_2.

Table 5.1 lists the product concept descriptors selected to form the customized set and relates them with the framework just described. Figure 5.2 illustrates how the customized set can be related with the general set of product concept descriptors, and the ones that were selected for the Scania demonstration prototype (due to the company's particularities and data and models availability).

Table 5.1 Customized product descriptors and relation with environmental burdens.

Descriptor	Environmental burdens:	*fix**	*var*
Life time drive distance [km]	Normalization factor. Multiplicative effect for all burdens.		
Mass [kg]	Per-mile vehicle operating energy (inverse of fuel efficiency) and direct CO_2 emissions are expected to increase with mass. Energy (incurred CO_2 emissions) required to move vehicle through drive cycle is dependent (not only) on mass.		
	Energy and CO_2 emissions increase with vehicle mass due to the dominance of energy in material production (e.g. aluminum vehicle/parts have higher fixed term than steel vehicle/parts).		
	For solid waste and SO_x burdens, increasing trends with vehicle mass are expected. Any burden that is proportional to the amount of fuel used should increase with vehicle mass due to reduced fuel efficiency.		
	For solid waste and SO_x burdens, increasing trends with vehicle mass are expected due to material composition and amount.		
Average vehicle fuel efficiency [l/100km]	Per-mile vehicle operating energy and direct CO_2 emissions are expected to decrease with fuel efficiency (inverse of vehicle mass). Energy (incurred CO_2 emissions) required to move it through drive cycle is dependent (not only) on fuel efficiency.		
Efficiency of emission control device [%]	Hydrocarbon emissions might not increase with fuel used due to the effectiveness of the emission control technology used in the vehicle.		
Type of power train	Energy (incurred CO_2 emissions) required to move a vehicle through a drive cycle is dependent (not only) on power train efficiency.		
Type of fuel	Effects due to fuel production efficiency (see Equation 5.5).		
Aerodynamic drag coefficient	Effects due to parasitic energy dissipation (see Equation 5.5)		
Material composition [%]	Effects due to the use (non-use) of significant amount of energy intensive materials and processes.		
Recyclability [%] and Recycled content [%]	Influence life-cycle waste production and resource consumption (materials and energy). Since most materials used in motor vehicles are recycled back onto vehicles again only in small part, open loop recycling may be assumed. However there is no generally agreed upon method for allocating recycling credits to products and their manufacturing systems.		

* According to Sullivan and Cobas-Flores (2001) fixed burden can be approximated by:

$$\overline{\{B\}}_{fxd,i} = \frac{m_T \sum_j B_{ij} D_j + \alpha}{LTDST} \qquad \textbf{Equation 5.6}$$

where:

B_{ij} is the specific burden i (e.g., CO or BOD) originated in the production of material j

D_j is the fraction of material j on the vehicle

α is a constant from service and maintenance and part/product assembly.

General set	Customized set	Demonstration set
mass	mass	[door] weight
material composition	material composition	[door] material composition aluminum steel polypropylene polyurethane
lifetime use time	lifetime drive distance	[truck] lifetime drive distance
power consumption	fuel efficiency	driver factor
recyclability recycled content	recyclability recycled content	[door] recycling rates
energy source	type of fuel	
operational mode	type of powertrain	
additional consumables	efficiency of emission control device aerodynamic drag	

Figure 5.2 Customized set of product concept descriptors.

Customized environmental performance output

The environmental performance output was left at the same level of aggregation as the abbreviated LCI list (see section 4.1.1), with no weighted results. The purpose was to keep enough flexibility so that different valuations could be easily performed if weighting factors and/or regulations change, and decision makers can use their expertise in weighting results according to regional factors and corporate policy (Sullivan et al, 1998). The customization was then carried on such that:

- "Wants" for decision-making are incorporated. For design to be also environmentally driven, there is a need to create environmental drivers:
  - Address company environmental strategy in prioritizing environmental issues
  - Address ways of "lobbying" the core design team
  - Need to be more measurable
  - Team keeps focused only on a few prioritized goals
- "Musts" of regulation are incorporated
- Outputs are LCI-based to be readily used as inputs in existing or company specific aggregation schemes; these should be determined on a case-by-case basis.

The list presented below is a "pool" of environmentally significant metrics for automotive products.

- Life-cycle carbon monoxide [kg CO] [regulated exhaust emissions]
- Life-cycle nitrogen oxides [kg NOx] [regulated exhaust emissions]
- Life-cycle hydrocarbons [kg HC] [regulated exhaust emissions]
- Life-cycle particulate matter [kg PM] [regulated exhaust emissions]
- Life-cycle carbon dioxide [kg CO2] [proactive company strategy]

- Life-cycle strong GHG [SF6, PFCs, HFCs, N2O, CH4] [proactive company strategy]
- Life-cycle sulfur oxides [kg SOx] [proactive company strategy]
- Life-cycle energy [MM BTU] [proactive company strategy]
- Life-cycle solid waste [kg solid waste] [proactive company strategy]
- Life-cycle heavy metals [air, water emissions] [reactive, proactive company strategy]
- Life-cycle Biological Oxygen Demand [kg BOD] [regulated water emissions]
- Life-cycle Chemical Oxygen Demand [kg COD] [regulated water emissions]
- Life-cycle total suspended solids [kg] [regulated water emissions]
- Life-cycle dissolved solids [kg] [regulated water emissions]

At a more aggregated level, the following could be useful indicators:

- Global warming potential, in eq. kg of CO_2 of warming gases, mostly CO2 and CH4
- Acidification potential, in eq. kg SO_2 of acidifying gases (SO_2, NO_x, NH_3, HF)
- Waste index, in % relative to weight of reference system, % of EOL materials that go to landfill.

Environmental performance can potentially correlate well with stock price performance. EcoValue 21 environmental ratings (Innovest, 2001), for example, uncover hidden value potential for investors by identifying environmental risks, management quality and profit opportunity differentials typically not identified by traditional equity analysis. The following are performance indicators that could rate high with these ratings:

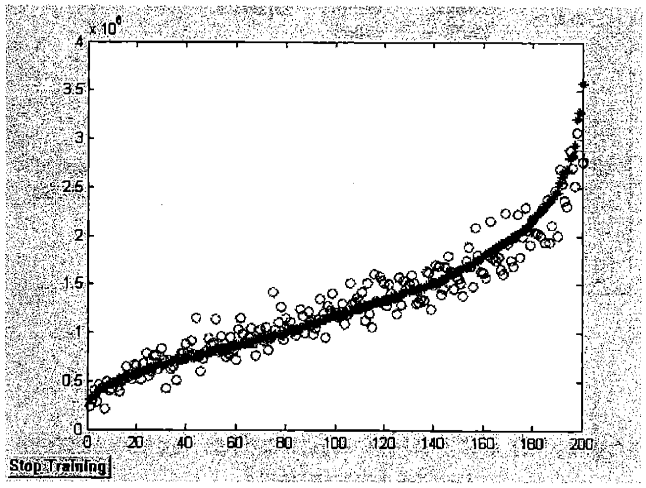
- Global warming [risk factor]:
  - Reactive/proactive to average fleet CAFE in the US (mpg)
  - Reactive/proactive to direct GW risk: reducing total CO2 emissions (%)
- Saving high waste treatment costs [eco-efficiency initiative]:
  - Reduction of non-recyclable waste (% material efficiency)
- Increasing energy efficiency [eco-efficiency initiative]:
  - Reduction of energy consumption per vehicle (%)
- Vehicle recyclability [eco-efficiency initiative]:
  - Reactive/proactive to meet recycling targets (%)

The life cycle CO_2 emissions were selected as outputs of the learning surrogate LCA method for demonstration purposes in the present application study. They were referred in the case study as part of the environmental priorities at the company.

Customized learning surrogate LCA model

The next step focused on building, training and testing a customized learning surrogate LCA model, given the defined set of inputs and outputs. The training and testing data sets were randomly generated using the detailed TEAM® LCI model previously developed at the company for the new door concept pre-development project.

In total, 4 multiple input (9 concept descriptors), single output (each specialized on total, production, use and end-of-life CO_2 emissions) feedforward two-layer (5 hidden neurons) ANNs were implemented using Matlab® Neural Network Toolbox. The log sigmoid and the linear transfer functions were used for the hidden and output layers, respectively. The training and test data sets were pre-processed with normalization to zero mean and unity standard deviation. Each ANN was trained (in batch mode) and tested with 600 training and testing data points. The Lavenberg-Marquardt backpropagation algorithm was used to train the ANNs for faster training cycles. Figure 5.3 illustrates a fairly good function approximation performed by the total CO_2 ANN, when tested with data points corresponding to different concepts of doors.



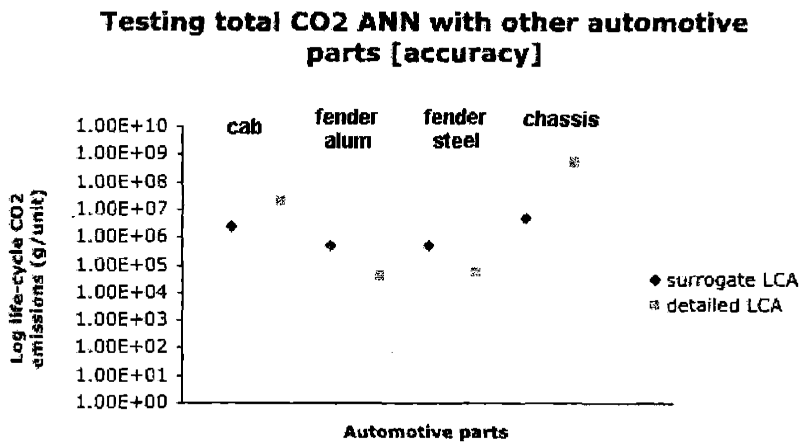
O Life-cycle CO2 emissions predicted by ANN

* "True" life-cycle CO2 emissions

Figure 5.3 Function approximation by the total life-cycle CO_2 ANN

The ANNs were further tested with data points corresponding to other vehicle-type parts or sub-systems – cab, chassis, and car fenders (see Figure 5.4). In terms of accuracy, the ANN did not perform well. Life-cycle CO_2 predictions were between 88% (cab) and 1250% (aluminum car fender) of the levels given by the "true" LCAs. Note, however, that the "true" LCA values for the cab and chassis were calculated by a simplistic mass allocation procedure using the detailed values for the doors. Still the ANN performed better for the cab and chassis predictions than for the fenders predictions. The ANN ranked the concepts (normalized to the emission values of the chassis) correctly except the two car fenders.

The bad performance for the fenders concepts can be interpreted in two ways (not necessarily exclusive). The detailed LCA results for the fenders were estimated using a LCI model developed based on very distinct system boundaries, allocation procedures, assumptions, and primary and secondary data (Newell, 1998); while the total CO_2 ANN was trained using only values generated by the same LCI model (the one developed at Scania). The ANN was trained only on heavy truck-related concepts, while car-related concepts were not part of the training data set. One then can argue that the ANNs are biased towards truck door concepts. The level of specification is too high if the company wants to make a more efficient use of the model, applying it to other truck parts and/or sub-systems assessments. To neutralize this bias effect, the training data set should be updated to include a broader range of automotive products.



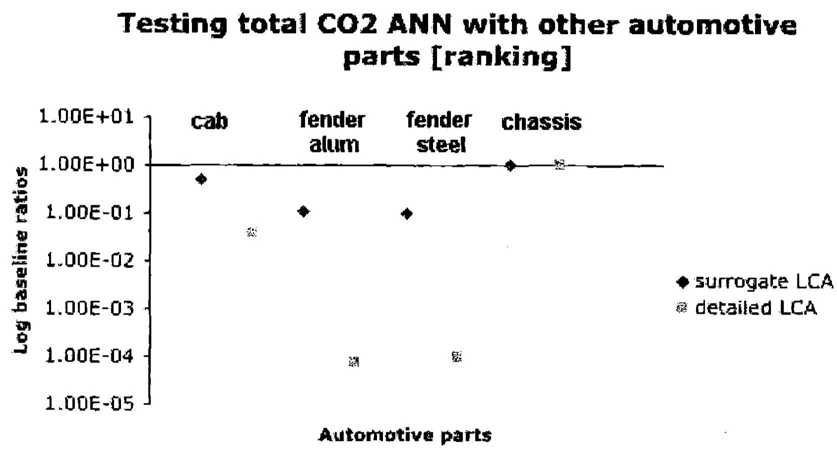


Figure 5.4 Testing the accuracy and ranking performance of the total CO_2 ANN using other vehicle-type concepts not included in the training cycles.

5.4 DEMONSTRATION

A simple illustrative example is herein presented to demonstrate the applicability of the learning surrogate method in the context of an integrated design process. How could a product design team at the company apply the learning surrogate LCA method to make integrated assessments and tradeoffs?

A DOME system model such as the one schematically shown in Figure 5.5 could be useful for this purpose. Due to a limited number of available models for this case study, the implemented system model includes only the models highlighted in Figure 5.5. Still, the implementation example was considered sufficient for demonstration purposes.

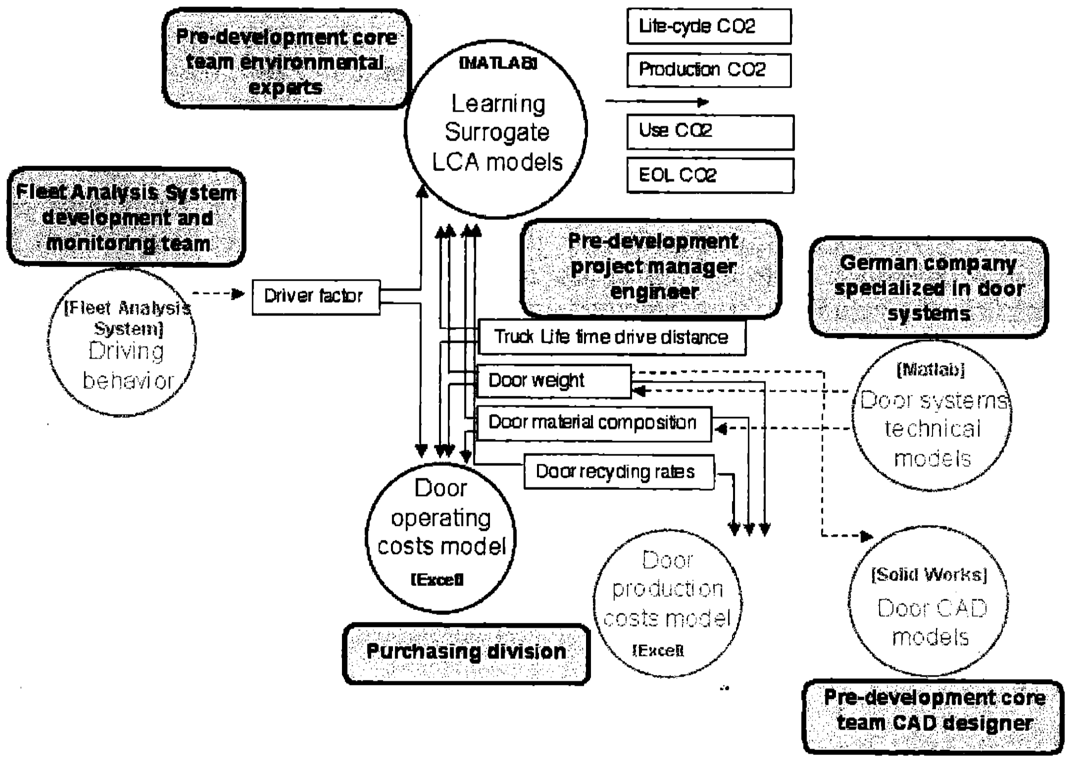


Figure 5.5 Schematic representation of the DOME system model.

The environmental experts built, trained and validated the learning surrogate LCA models in Matlab® and are responsible for maintaining and guarantee their proper use by designers and engineers. To be able to customize the learning surrogate models for their practical use at the company, they played a key role in negotiating useful model interfaces with the other team members, together with the project manager. During data collection and training cycles, environmental experts can best explore and interpret the effects of assumptions and quality of data, understand sensitivity tests to key model parameters, and adjust the training data and learning system accordingly and iteratively. They are the ones in the pre-development project team who have the time and expertise to do so. In pre-development projects, these types of services are extremely relevant for the product development team to be able to early on articulate important environmental issues together with other design goals. The environmental outputs provided by the learning surrogate LCA models, although backed-up with environmental expertise, are of low precision. They are suitable, however, to identify key areas that can be later on analyzed in more detail, when the design systems get further detailed (e.g., in the concentration introduction phases).

There was an initial overhead in setting up and customizing the learning surrogate models but ultimately only future maintenance will be necessary for their use in door systems or other sub-systems.

The operating costs model is a simple Excel® spreadsheet developed for the purpose of the demonstration. It only predicts the operating costs associated with fuel consumption. In a real scenario, cost models – including production costs – could be developed and maintained, for example, by purchase and marketing personnel at the company.

Inputs for the operating costs model are door material composition; door and truck weight (assuming door mass ratios of cab and truck); total distance driven; diesel price; and driving performance. The driving performance, or driver factor, represents the individual driver's driving style. For the company, choosing the right truck engine for a given transport assignment is more important than choosing an engine with the lowest emissions certification rate – the wrong engine has to work harder and consumes more fuel which leads to higher total emissions (Scania, 2000). For example, according to the company experience, the driving style can account for a difference of up to 20% in fuel consumption. In the model, driving performance and is simplistically included in an estimated fuel consumption as follows:

Fuel_consumption [l/km] = *A* [l/km] + *driver_factor* x *A* [l/km] **Equation 5.7**

where $A = 4.85 \times 10^{-6}$ x *truck_weight* [kg] + 0.151 is an empirically estimated linear relation between long-haulage heavy trucks tare weight and fuel consumption (Berg and Lindgren, 2001); and *driver_factor* is a fuel consumption scaling factor that represents how good (positive %), indifferent (zero) or bad (negative %) a driver performance can be in relation to fuel consumption. Although simplistic, I envision this type of approach and/or others to be further explored by the company based, for example, on their recently developed Fleet Analysis System that can monitor in real time driver's performance and transport network structure and availability.

A production costs model of past development projects could also be included in the system model. Spreadsheet-based technical cost models such as the ones developed by the Materials Systems Laboratory at the Massachusetts Institute of Technology for vehicles' body-in-white (BIW) could be used to predict trends in manufacturing and assembly operation costs, based on the door's weight and material composition. These models account for not only design specifications and material properties, but also use as inputs production-specific information and economic parameters (e.g. labor wage rates and energy, material and capital costs).

Product concept descriptors such as door weight and material composition are envisioned in this example as services provided by technical models developed by the company specialized in door systems that worked in collaboration with Scania in the door pre-development project.

In a first step of building an integration simulation within the second-generation DOME framework, model owners use simple DOME publishing programs to define parametric interfaces to their simulations. The publishing programs allow model owners to transparently create metadata defining service interfaces for their models and the types of DOME objects that will embody those services (Abrahamson et al., 2000). For example, in Excel® a wizard-like publishing macro is used to select cells and define model inputs and simulation outputs. Then, model owners use a web browser to log into a DOME model server and use wrapper objects (software plug-in to DOME for third-party applications) to make their published services available over the Internet (see Figure 5.6). Through this publishing process, each model owner brings in expertise and formal representations in the form of data and models, and selectively exposes model parameters while protecting inner workings developed in their own modeling tools of choice. Their model services can now be accessed and operated through a web-browser.

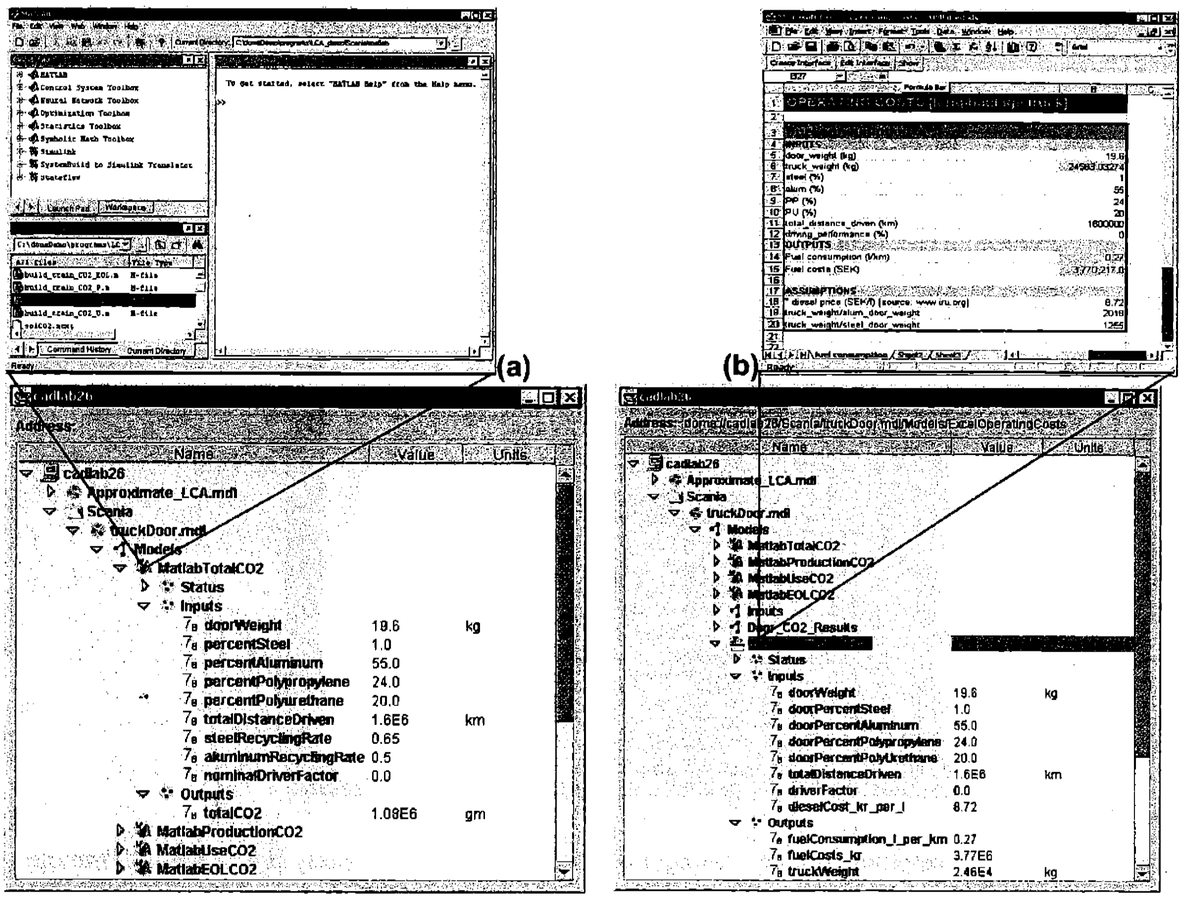


Figure 5.6. DOME interfaces to the published (a) learning surrogate LCA models (b) and the operation cost model (mapped wrapper objects for Excel® and Matlab®).

Interfaces to environmental and cost simulations are now remotely accessible and operable over the Internet. A second step is to provide each individual participant with the ability to define systems interactions locally and build system models. Suppose that the project manager (system integrator) is now interested in studying the effect of system changes concerning the new design concept. He will then log into a DOME server, subscribe to the environmental expert model and the cost model services, and use the DOME synthesis environment to define an overall door simulation model by relating these services and create new services. In Figure 5.7 the project manager has completed the system model by mapping parameters from the subscribed remote simulations to appropriate parameters and using mathematical relationships he introduced to perform a consistent integration.

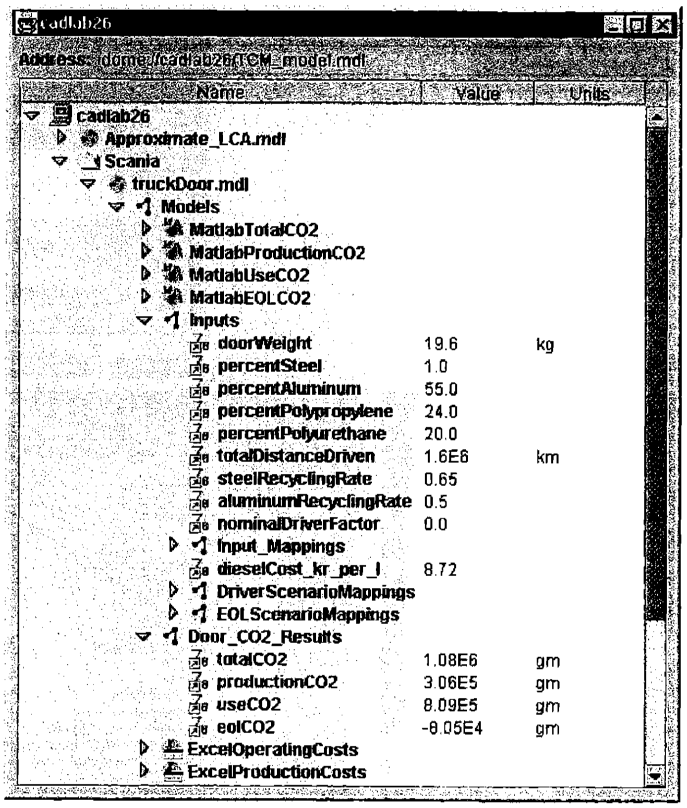


Figure 5.7 The pre-development project manager built an integrated door study simulation with remote parameters mapped to relationship parameters.

The project manager was not required to have any special programming knowledge to coordinate the services of these distributed multiple-platform product design models. In addition, he is not supposed to have a centralized control over the distributed system model. Through federated parametric solving capabilities, the simulation network can solve itself in an appropriate manner.

The project manager is now ready to further explore the integrated simulation services he just specified for the overall door system model. He first added catalog objects to easily switch between different driving performance and end-of-life scenarios (see Figure 5.8). The catalog interfaces manage the back-side mappings to the chosen scenario so that he can swap scenarios without redefining model relationships.

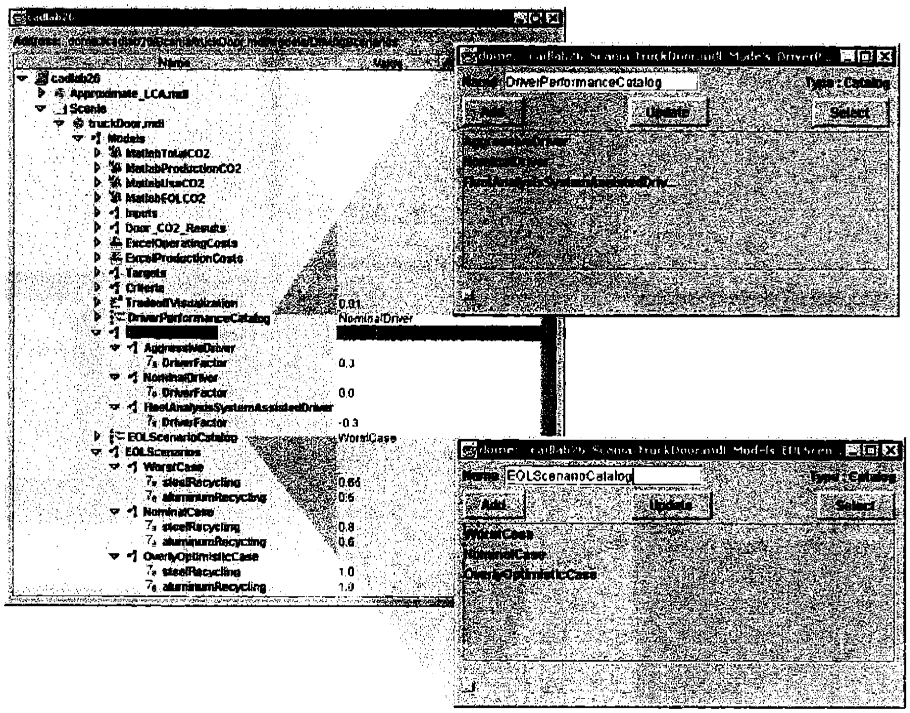


Figure 5.8 The project manager added catalog objects to easily explore different driving performances and end-of-life scenarios.

To grasp a real-time view of system-wide tradeoffs when making changes, the project manager added a decision support object to the system model. Figure 5.9 shows the services provided by the DOME decision support object.

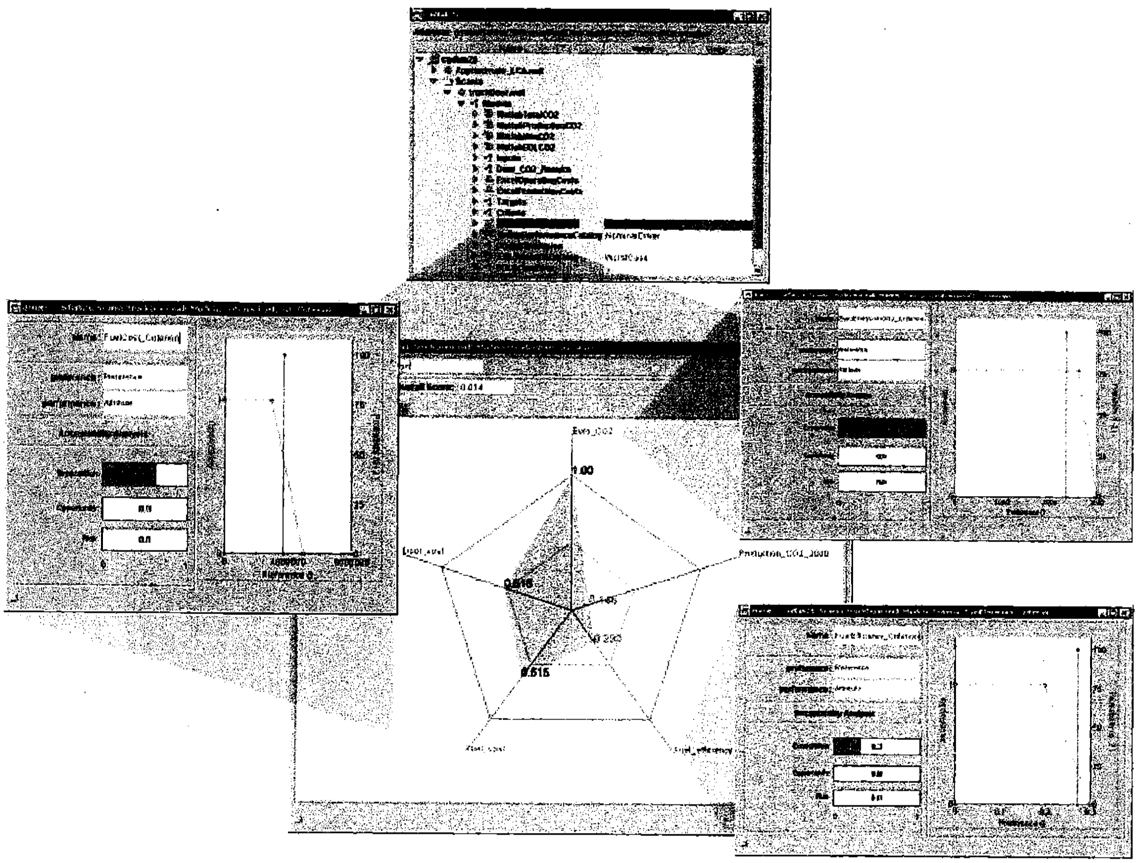


Figure 5.9 The services of a decision support object are added to visualize system-wide tradeoffs.

A spider diagram visualizes performance assessments on five axes, while expanded detail windows show the predictions relative to their design specifications:

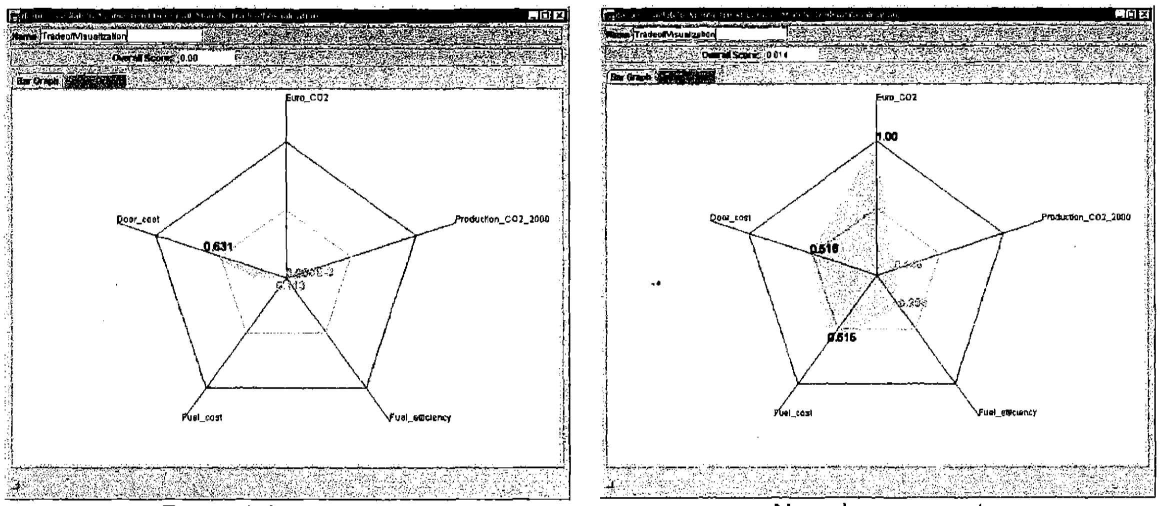
- *EuroEmissionCO_2*. The acceptability function and its extreme points are defined based on CO_2 emission factors estimated for Scania engines. These factors specify the quantity of emissions released in relation to the amount of fuel consumed, in grams per liter of fuel. They are not definitive though. For example, they do not take into account inadequate maintenance such as blocked air filters or tuned engines. The specification as it is now defined drives a complete acceptance of Scania Euro 3 engines. Scania Euro 3 engines are approved in accordance with current European Union legislative requirements for NO_x, PM, HC and CO (CO_2 is not regulated).
- *ProductionCO_2*. The acceptability function is defined such that the production emissions of CO_2 are to be reduced to approximately 30% of the current production values. As an extremely ambitious goal, in practice this acceptability function will drive a constant need to surpass current performance.
- *FuelEfficiency*. The specification is defined such that fuel efficiency of up to 0.2 l/km is completely accepted. A fuel efficiency of 0.3 l/km is not acceptable.
- *FuelCost*. The acceptability function is defined such that operation fuel costs up to 3000000 SEK are completely accepted. Fuel costs of 5000000 are not acceptable.

- *DoorCost.* Design and performance specifications of this axle are shown only for illustration purposes. A technical cost model of doors was not available to incorporate in the demonstration.

The project manager can now simulate different scenarios and explore various tradeoffs by changing parameter values and/or design specifications. For illustration purposes, some examples are presented in the following section.

Simulating present and new door systems

Figure 5.10 shows the spider graphs corresponding to the simulations of the present and the new door systems. Under present design specifications, the new door concept performs best.



Present door concept New door concept

Figure 5.10 Spider graphs for the present and the new door concepts.

Changing EuroCO_2 specification

Figure 5.11 shows the spider graphs corresponding to the simulations of the new door system under the previously defined EuroCO_2 specification (extreme points drive complete acceptance of Scania Euro 3 engines) and using a more stringent specification. Performance decreased under this new target as expected, although it did not affect significantly the overall acceptance of the concept.

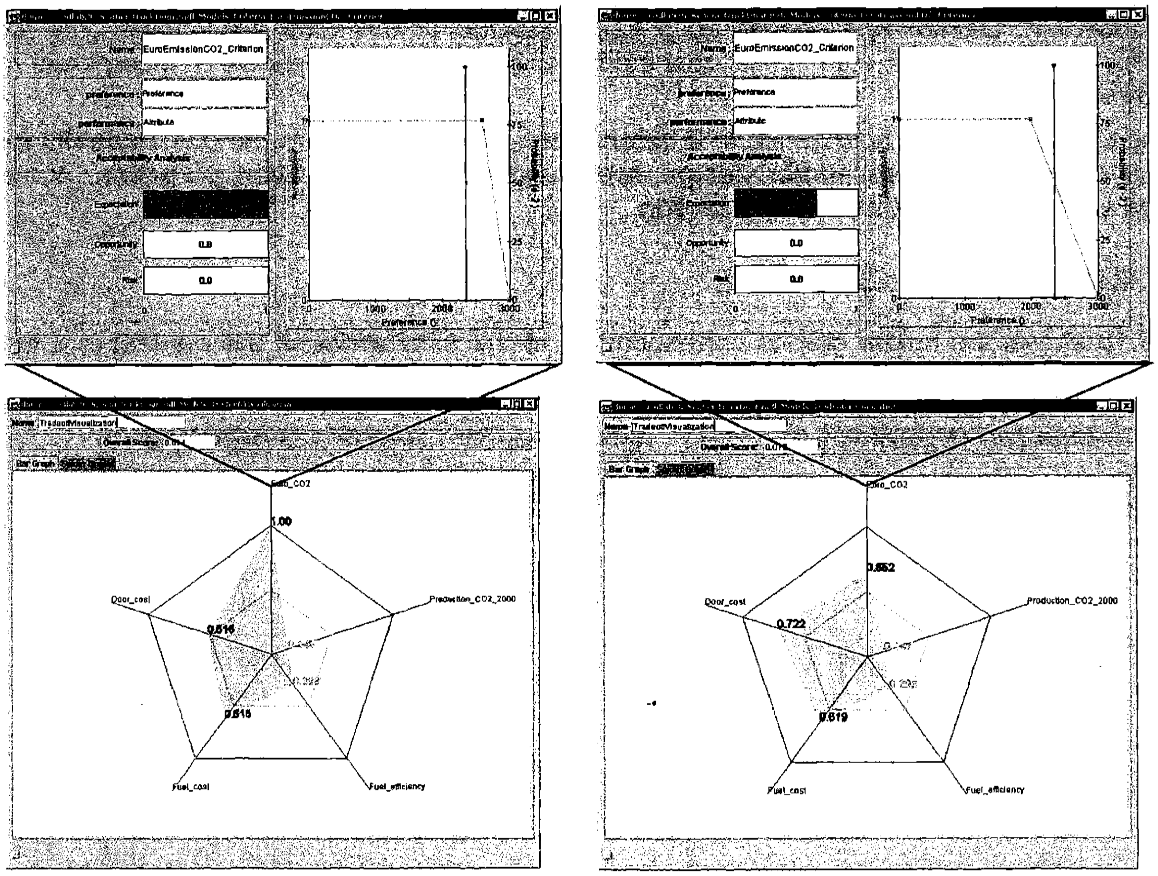
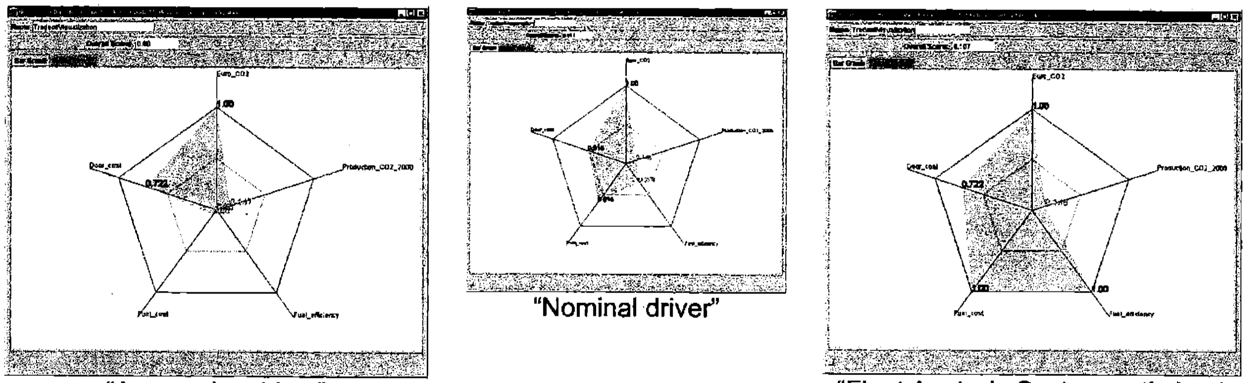


Figure 5.11 Changing the EuroCO2 specifications and visualizing results for the new door concept

Simulating different driving behaviors

Figure 5.12 shows results for the new door concept for simulations with different driving performances. This analysis scenario could occur, for example, if the company wanted to explore the impact of introducing new IT equipment in the truck for driving optimization The overall acceptance of the new door concept changes significantly. Driving performance is therefore an important factor to consider in early stages of design, even at the sub-system level of a cab door in a heavy truck.



"Aggressive driver" "Nominal driver" "Fleet Analysis System optimized driving performance"

Figure 5.12 Changing the EuroCO_2 specifications and visualizing results for the new door concept.

5.5 Discussion on the Application Study

The application study provided a valuable experience in the process of customizing and using the learning surrogate LCA method in a specific product development context. The case study research facilitated the incorporation of experts' knowledge and heuristics in the design of the surrogate model simulation interface. However, one might argue:

- Why not just simply use existing empirical data on automotive products to roughly define (e.g. Equation 5.6) or estimate (e.g. using linear regression) relationships between key automotive characteristics and environmental performance?

These product data and empirical knowledge are useful to capture key conceptual linkages between product characteristics and environmental burdens that are specific to a certain type of products. However, they are "pieces of puzzle" that, in order to be able to describe the "whole puzzle system," require further modeling tasks and assumptions involving often unknown non-linear interactions. The effort involved is time and resources consuming and cannot be justified at early stages of development when only high-level knowledge of the concept is defined. In contrast, the product descriptor set for the door concept system put together a number of different key characteristics in a high-level parameterized input structure that is also useful for the pre-development team members to interface with other simulation models. The ANNs can rapidly learn from different sources of data, such as existing empirical data or simulation results and information from literature, to approximately emulate key environmental burdens without having to spend time and resources in explicitly model the whole system. The structure of the simulation interfaces – the product descriptor set and predicted set of environmental burdens – can be redefined as needed at the expense of re-training the learning system redefined training data vectors, however without having to invest in reformulating an explicit model of the whole system.

- The existing detailed TEAM® LCI model only required a small redefinition of its external variable structure in order to be at a level to cope with identified interface simulation needs. This redefinition task however originally only took place to allow random generation of appropriate training data. So why not just incorporate this detailed model in the system model (using the TEAM® DOME plug-in) and use it to perform integration simulations with the other models?

That could have been done for this particular study where a detailed LCI model already existed. However, the purpose of the study was to explore the applicability of the learning surrogate LCA method in the company's pre-development projects using existing data and resources. It happened that the detailed model had been already developed, and it was made available to help on generating training data for door concepts. Training data could also have been extended to incorporate existing data (empirical, simulation, or provided by experts) on other vehicle-type concepts (e.g., whole truck, cabs, chassis), and for those there were no detailed LCI models, most likely there were isolated empirical studies and expertise. Still, these "knowledge pieces" could have been included in the learning cycles of the ANNs, unlike the door detailed LCI that is highly specified to only incorporate door concepts. Unfortunately, the extension of the training data was not possible under the circumstances of this particular application study (e.g. restricted timing, nature of communication channels, logistic issues). An "over-specialization" of the trained ANNs was actually confirmed with some tests, previously presented, using other automotive parts and/or sub-systems.

Although not addressed by this research, it is likely that such flexible, high level, "multi-language" simulation interfaces of learning surrogate models, when integrated with other design models using a framework such as DOME, will have a greater, real impact in the early decision-making process of the company than that of isolated LCA studies, highly specialized in each one of the pre-development projects. Integrated learning surrogate LCA models can provide "visible" scenarios with what-if integration simulations, which can be highly effective in getting the commitment of all involved stakeholders early on and increasing the overall awareness of the company. The real need at these early stages is to perform representative, rather than precise, integrated simulations and high-level tradeoff analysis. These need to be credible though. For that, proof-of-concept testing showed already that learning LCA models at their general level are capable to predict trends correctly, and make predictions sufficiently accurate for the purpose of their use.

6 CONCLUSIONS AND FUTURE WORK

6.1 SUMMARY AND CONTRIBUTIONS

The learning surrogate LCA concept

Early conceptual design stages are an opportunity and a challenge for environmentally-conscious design. While widely recognized as the critical stage for shaping the life-cycle environmental performance of a product, these early stages lack detailed information needed for thoroughly assessments and require quick decisions on diverse and numerous product concepts.

The lack of analytically-based methods capable of tackling these issues at early design stages motivated the development of an approximate life-cycle assessment (LCA) concept based on learning algorithms. The learning surrogate LCA method facilitates an integrated system design process at early conceptual stages, allowing the approximate and rapid assessment of environmental impact based on high-level information typically known in the conceptual phase.

An artificial neural network (ANN) is trained on product attributes and environmental performance data from pre-existing full life-cycle assessment studies and/or other available simulation or empirical data. The product design team queries the trained artificial model with high-level product attribute data to quickly obtain an approximate environmental impact assessment for a new product concept. This is done without requiring a new LCA model and under the guidance of environmental experts who train, validate and maintain the ANN-based LCA models. The product design team can then use the predicted environmental performance, along with key performance measures from other models, in trade-off analysis and concept selection.

A method that works

Foundations for the learning system approach were established. Two critical areas were investigated: (1) model inputs in the form of a compact, meaningful, and understandable set of product concept descriptors; (2) the ability to gather LCA data and appropriately train an ANN-based surrogate LCA model.

First, the feasibility of establishing a compact Life-Cycle Inventory (LCI) that can represent key environmental impact categories and be used to assess the environmental significance of product descriptors was tested. An abbreviated LCI list of suitable size for outputs of a surrogate LCA model was proposed, and tested for its ability to predict impact categories. It was concluded that the abbreviated LCI list could possibly be used to predict life-cycle energy consumption, solid material waste, greenhouse effect, ozone layer depletion, acidification, eutrophication, winter smog, and summer smog levels. The abridged LCI list cannot be used to predict impact categories related to carcinogens, heavy metals, and pesticides.

Then, a list of meaningful product concept descriptors, needed as inputs to the surrogate LCA model, was defined. The descriptors should: utilize only product information readily available during conceptual design; be compact to reduce demands on the surrogate model, and; be related to elements of the abridged LCI list. A candidate set of product descriptors was identified, and tested for first order relationships with elements in the abbreviated LCI list.

Finally, LCA data and descriptors were collected for 175 products or variations, and ANN-based learning surrogate LCA models were trained to predict life-cycle energy consumption and tested within DOME (Distributed Object-based Modeling Environment), a software infrastructure that facilitates integrated, emergent simulations over the Internet. These proof-of-concept tests showed that the ANN-based learning surrogate LCA models were able to: (a) match detailed LCA results within the accuracy of typical LCA studies; (b) predict relative differences of distinct product concepts; (c) correctly predict and generalize trends associated with changes for a given product concept.

Product classification to enhance learning performance of surrogate LCA models

Insight gained with previous testing motivated further research to develop a product classification system enabling systematic support to specialized learning surrogate LCA models of different categories of products. Hierarchical analysis of 61 products was carried out with the product descriptors as the clustering variables. The results of this exploratory clustering analysis guided the definition of environmentally driven categories of products: (1) durable, high-mass, efficiently active household appliances; (2) durable, active, household appliances durable; (3) durable, active electronic consumer products; (4) low-mass, passive products; (5) low-mass, fiber-based, active (external energy based) products; (6) durable, mobile, active (external energy based) products; (7) durable, low-mass, active (external energy based) products. Using these product categories and the concept descriptors as classification criteria, C4.5 decision tree algorithms generated classification systems with different structures and error estimations by varying algorithm parameters and product descriptors.

Although data were not sufficient to induce good generalization, such product classification systems were considered to be a viable strategy to make ANNs learn faster and more effectively, as it narrows down the "learning space", into general product categories, prior to the prediction phase. The learning architecture will then be a combination of a tree-based classifier based upon the product concept descriptors, to perform the initial product categorization, with "category-based" neural networks, to approximately predict environmental performance in the subsequent step.

Application study explored method customization

An application study was conducted in a large Swedish heavy truck manufacturing company and targeted a pre-development project concerning a new door concept. A simple example was presented to illustrate how a product design team could apply the learning surrogate LCA method to make integrated assessments and tradeoffs in the context of a pre-development project at the company.

The study showed that it is possible to customize the learning surrogate LCA approach to a particular specific product development context:

- Case study research supported definition of door product concept systems by incorporating expert's knowledge and heuristics.

- Product descriptors incorporated system and sub-system features in a simple, high-level parameterized input structure, suitable for designers to interface with other models in simulation and tradeoff analysis.

The ANNs were further tested with data points corresponding to other vehicle-type parts or sub-systems – cab, chassis, car fenders – and did not perform sufficiently well. They were perceived as highly specialized and biased towards truck door concepts. To make a more efficient use of the model in other truck parts and/or sub-systems assessments, it was considered that the training data set should be updated to include a broader range of automotive products.

The examples showed to illustrate application scenarios for tradeoff analysis using DOME integrated simulation environment suggested that such flexible, high level, "multi-language" simulation interfaces of the learning surrogate models, when integrated with other design models, can have a greater, real impact in the early decision-making process of the company than that of isolated LCA studies, highly specialized in each one of the pre-development projects.

Contributions

If one desires to position the learning surrogate LCA concept in the existing structure of simplified LCAs, this new approach can be considered a form of streamlined LCA that covers the whole life-cycle to identify hot spots from a systems perspective, at early conceptual design stages. However, the strategy that it uses to address the methodological challenges of early design stages does not follow the standardized LCA framework.

As streamlined LCAs, learning surrogate models only predict selected key life-cycle environmental issues or screening indicators (e.g. energy consumption and CO_2 emissions) and reduce the requirements for data quality by learning from life-cycle data that can be primary, secondary or other existing empirical data or simulation results. The simplification process is based on life-cycle concepts but occurs implicitly, based on algorithms that learn from high-level product characteristics, rather than explicitly through engineering process analysis and mass balance equations as in the standardized LCA framework.

This strategy agrees with the purpose of the learning surrogate LCA method. It is not to explore environmental causalities in the product concept system. Instead, the goal is that designers use it to better relate design changes with approximate environmental performances, internalizing environmental effects of their decision making in a holistic sense and under the guidance of an environmental expert, who trains, validate and maintain the learning system. Designers follow the design path, not the environmental path. By being able to quickly explore a greater variety of scenarios using high-level parameterization in what-if analysis, the quality of preliminary analysis can be improved and innovation can actually be stimulated with the degrees of freedom provided by the various simulations.

The learning surrogate LCA concept is then a powerful alternative to existing approximate LCA approaches. It simultaneously supports:

- Life-cycle thinking with lack of detailed information of ill-defined, complex product concept systems. System outcomes of early conceptual design decisions should be considered. For example, design changes can easily transfer unintended environmental burdens from one life-cycle stage to another. Scarce details on the concepts should not be a barrier to integrate life-cycle environmental assessment early on. The learning surrogate concept overcomes this barrier by bringing into early stages life-cycle knowledge of pre-existing products from which it learns and averages life-cycle performances.

- Analysis of substantially different concepts, without the need for building new models. The implicitly modeled LCAs and their generalization power imply no modeling effort in contrast with the standard LCA approach and its streamlined forms.
- Analytically-based simulation for use in high-dimensional systems and problem specific, multi-attribute trade off-analysis. On one hand, the approach relies on approximated models that consequently bring down the large amount of resources, typically needed for detailed assessments. On the other hand, surrogate LCA models perform and interface on a quantitative, analytical basis. This is a key element of the method that simplifies detailed approaches and still incorporates the inherent complexity of environmental systems early on in the design process. Qualitative approaches such as DFE guidelines, abridged LCA matrices, rules of thumb or simple intuition fail in grasping the multi-dimensional, highly contextual and often contradicting environmental effects originated by design changes. The simplicity of the learning surrogate method is distinct from the one of ad-hoc rules, which cannot generalize. Even at early design stages, general environmental guidelines can be misleading when designing and assessing a particular system.
- Simulation interface between environmental experts and other members of the product design team, in a systems' modeling context. Environmental issues can be successfully incorporated into early stages of product design only if balanced with the existing traditional design criteria. The simulation capabilities highlighted in the previous point are extended to support integration simulation with other design models traditionally considered in product design. Product concept descriptors are a flexible simulation interface between environmental experts and designers for this new approach. They can be viewed as a set of keywords that simultaneously are part of a designer's language in relation to preliminary product concepts (e.g., materials, mass, form) and meaningful in shaping the environmental performance of product concept systems. They are also customizable to different high-level parameterized structures that are more helpful in some product design contexts than others, without the need for investing in new explicit modeling tasks. In supporting a team-oriented, multidisciplinary design process at early conceptual stages, this new learning surrogate LCA method assumes that environmental experts and design engineers are specialists in their own fields. They can exchange their simulation-based services and perform tradeoff analysis through an integration framework such as DOME.

In addition, this research contributed significantly with the development of a fairly large database that includes both product and environmental data. It is a very useful data source for future research work.

6.2 APPLICATIONS OF THE LEARNING SURROGATE LCA METHOD

The learning surrogate LCA method is appropriate to inform system design decision making in early conceptual stages of product development. It is most useful when members of the product design team, including environmental experts, participate in the design process using their own expertise, and negotiate and perform integrated, high-level simulation in a modeling environment for tradeoff analysis.

Different types of product development organizations can benefit from the internal use of this approach. They can range from consulting firms, such as product design or environmental consulting firms, to large manufacturing companies, such as automotive original equipment manufacturers. The general level of the learning surrogate concept with the classification step to feed category-based ANNs is more appropriate for consulting firms that work with different types of products. A customized approach fits better in companies specialized in a certain type of products.

Still, for each of these types of application, this method will vary in practice in terms of when, how and by whom it is used. For instance, there were various answers, which in general did not agree with the "theory" found in the literature, to the question "When does the early conceptual design stage take place in the product development process?" and "What is the early conceptual design stage?". In the automobile development process, for example, learning surrogate LCA models could be more useful in the *concept stage* rather than on the *design studio* stage as generally defined for the automobile industry by U.S. Congress (1992). Or perhaps in both stages, or in different organization units (e.g. overall strategy groups, sub-systems research units), within the company or outside, depending on which OEM we are talking about.

This range of applicability could eventually 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 this approach can be aimed beyond traditional consumer product design, at being able to, through an appropriate customization process, handle services systems, construction projects, policy issues, and other developmental ventures.

6.3 IMPLICATIONS OF THIS RESEARCH

There is a general consensus that LCA, if used appropriately and consciously regarding methodological limitations, can play an important role in systematically fueling a holistic thought process that guides the selection of design options and provides a spectrum of useful insights on a system. However, a continuing concern has been the cost and time required to conduct LCAs, which are beyond the reach and practical usefulness of most potential users. The various methodological techniques that have been proposed for simplifying analytically-based LCAs are still costly and do not yield timely information for the product development cycle. Streamlined LCAs are currently often performed only after a specific product embodiment had been already decided. They become even more prohibitive to use in early stages of the cycle, where they are of most value.

The innovation of this research focuses on rethinking the LCA framework. It proposes a method that requires simple, high-level and readily accessible product information to provide approximate yet powerful results – these are the realistic analytical information channels through which environmental assessments can be timely and effectively incorporated into early, critical steps of the decision-making process. In addition, the cost of decreased accuracy can easily breakeven by acknowledging in the first place the rather arbitrary quality of LCA data, which still carries high levels of uncertainty and depends on judgmental factors. Estimated data with sufficient accuracy is better than no data at all, and very often not much worse than "real" LCA data. Current alternatives being used in practice are qualitative, ad-hoc approaches, such as matrices, guidelines, rules of thumb, that alone do not match the complex, ill-defined, high-dimensional and contextual nature of environmental systems.

Therefore, key implications of this research are:

- The assimilation of LCA by the product development cycles becomes feasible, as environmental assessments supported by learning surrogate modeling can be timely incorporated into short time intervals between decision-making gates. The time frames required for producing data and training cycles are still very different from the ones needed to use the method. All the potential LCA users, in particular the industry, who have been wondering about cheap methods that can provide sufficiently precise, credible environmental information for decision-making within the time, data and cost constraints of real-world product development may now rethink the possibility of using life-cycle approaches in product development and start to explore the potentials of the learning surrogate LCA method to do so.
- The current paradigm of believing that the feasible way to incorporate environmental issues early on in the design process is to only rely on DFE guidelines and ad-hoc general rules can now be argued against with the proposal of a credible and feasible alternative. The learning surrogate LCA method is a better alternative that allows easy, problem specific incorporation of life-cycle thinking into the mainstream design activities of multi-disciplinary teams. It can give product design teams the ability to consider environmental issues in a handy, assertive and integrated way at a stage of the product development process where decisions are not yet locked-in.

6.4 FUTURE WORK

The learning surrogate LCA concept developed by this research suggests interesting avenues to pursue in future investigations. They all are relevant if the learning surrogate method is to be improved for its actual application in the real world.

Method improvements

There are important issues worthwhile to further investigate in order to enhance the performance and usability of the learning surrogate method. Relevant questions to be answered are:

- *How faster and better could the ANNs become if other network architectures, learning algorithms and methods for improving generalization had been used?* In this thesis, only feedforward, two-layer ANNs with backpropagation training cycles were tested. It would be useful to conduct a benchmarking, systematic comparative study using different network architectures coupled with various training algorithms and regularization methods. Radial-basis function networks, another class of layered neural networks, could also be explored. This way a more systematic knowledge of learning networks appropriate to be used in learning surrogate models could be developed. And this could be a starting point to evolve current available network techniques to fulfill the specific needs of a new field of application created by the learning surrogate LCA concept.

- *How sensitive is the learning surrogate LCA method to different levels of data quality and system boundaries?* Although proof-of-concept testing showed a significant robustness to different sources of data collected and/or estimated to train the models, the subsequent variability in the input parameters, system boundaries, data quality and assumptions made should be more thoroughly investigated. For example, it could be useful to search for different levels of desired performance that would correspond to distinct degrees of training data quality and agreement on system boundaries and assumptions involved. This way the developer and/or user can better evaluate what level of performance to expect, given the available data and information resources.
- *What are suitable decision tree structures that can better support specialized learning surrogate LCA models?* This thesis found this type of classifiers as appropriate for this task. Still the different trees obtained in this work were not further explored to test the level of performance enhancement they were able to provide. By using more data, further studies should be conducted to assess the performance of hybrid learning systems for different classification schemes and select the best ones for implementation.
- *To what extent can the learning surrogate method provide reasonable predictions to innovative products?* Major technological shifts, for instance, might disrupt models' prediction performance given that they learn by example. An important future investigation is to try to define a validity range of their learning capabilities, which can be limited by thresholds that make data usable for training cycles corresponding to different levels of re-thinking product concepts.

Improvement of model reusability

Learning surrogate LCA models, general or category-specialized, can be made more reusable. Key benefits are costs in model development, timing in expertise to be readily available, and reliability due to accumulation of knowledge of system, interactions and user problems (Magee, 2001). Reusable learning surrogate LCA models should be: (1) able to efficiently incorporate new training data as needed; (2) usable in different contexts of product development projects at the organization; (3) maintainable by a range modelers (environmental experts) in different times and development teams.

For this purpose further research should be done in particular areas, namely:

- Development of environmental information systems – or adaptation of existing ones – capable of supporting a systematic data collection and quality control by the environmental experts and automatic data retrieval by the learning models.
- Development of mechanisms that allow the ANNs undergo continual training with time-ordered examples. A dynamic approach to learning could be based on procedures such as the one proposed by Haykin (1999), based on selecting time windows short enough for the input data to be considered pseudostationary.
- Development of a friendly graphical user interface that help environmental experts in building, training, validating and maintaining the learning models.

Research on implementation

The application study presented in chapter 4 already gave a flavor of how important is to consider organizational issues when trying to implement a new approach and make it usable in a given "real world" product development context. The work of this thesis can only be extended to be actually used in practice if further studies are conducted aiming at investigating organizational structures that better accommodate the introduction of this new approach in the product development cycle. Qualitative research on industry's experience of integrating environmental considerations into the design process such as the one described in McAloone (2000) is appropriate to identify key organizational and behavioral factors to consider when implementing the method.

Investigation of new application areas

An interesting avenue to pursue is to broaden the method's range of applicability by exploring a possible extension to areas of development beyond traditional product design and life-cycle analysis. 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 "super-classes" of products that will require two separate learning surrogate modeling frameworks to be developed. Service systems design can be another possible area of application that will require its own adjustments to use the method. Finally, technology policy design is a potential area of application worthwhile to be explored. What are technology and/or socio-economic descriptors that best emulate different environmental policy strategies, based on past experience? This can be a question that policy makers might want to answer to filter out irrelevant strategies early on, before thoroughly moving forward to a more detailed policy design.

REFERENCES

Abrahamson, S., Wallace, D. R., Senin, N., & Sferro, P. (2000). Integrated Design in a Service Marketplace. *Computer-Aided Design. 32*(2), 97-107.

Abrahamson, S. Wallace, D. R., Senin, N. & Borland, N. (1999). Integrated Engineering, Geometric, and Customer Modeling: LCD Projector Design Case Study, *Proceedings of the ASME DT Conferences*, DETC/DFM-9084, Las Vegas, NV.

Allenby, B. R. (1992). *Design for Environment: Implementing Industrial Ecology*. Doctoral Dissertation, Rutgers University.

Alting, L.& Legarth, J. (1993). Life-Cycle Engineering and Design. *Annals of the CIRP. 44*, 569-580.

Arnold, F. (1993). Life Cycle Assessment Doesn't Work. *The Environmental Forum 10*(5), 19-23.

Barron, A. R. (1993). Universal approximation bounds for superposition of a sigmoidal function. *IEEE Transactions on Information Theory 39*(3), 930-945.

Baumann, H., Boons, F., & Bragd, A. (2000). *Mapping the Green Product Development Field: Engineering, Policy and Business Perspectives*, AFR Report 301, Swedish Waste Research Council (at the Swedish EPA), Stockholm.

Baumann, H. (2000). Personal communication. Assistant professor in the Environmental Systems Analysis Group, Chalmers University of Technology, Sweden.

Beasley, D., Bull, D., & Martin, R. (1993). An Overview of Genetic Algorithms: Part 1, Fundamentals. *University Computing, 15*(2), 58-69.

Berg, E. and Lindgren, E. (2001). *Environmental Assessment of Two Door Concepts for Trucks*. Master thesis at the Linköping Institute of Technology in cooperation with Scania CV AB. Södertälje.

Berkel, R., Willems, E., Lafleur, M. (1997). The relationships between cleaner production and industrial ecology. *Journal of Industrial Ecology 1*(1), 51-65.

Bhamra, T. A., Evans, S., McAloone, T. C., Simon, M., Poole, S., & Sweatman, A. (1999) Integrating Environmental Decisions into the Product Development Process: Part 1 The Early Stages. *Proceedings of the First International Symposium on Environmentally Conscious Design and Inverse Manufacturing,* IEEE, Tokyo, 1999, p.329-333.

Bishop, C. (1995). Neural Networks for Pattern Recognition. Clarendon Press. Oxford, UK.

Borland, N., & Wallace, D. (2000). Environmentally Conscious Product Design: A Collaborative Internet-based Modeling Approach, *Journal of Industrial Ecology, 3*(3), 33-46.

Borland, N., Wallace, D. R. & Kaufmann, H. P. (1998). Integrating Environmental Impact Assessment Into Product Design. *Proceedings of the 1998 ASME Design Engineering Technical Conference*, DETC98/DFM-5730, Georgia Institute of Technology, Atlanta, GA.

Bose, N.K. & Liang, P. (1996). *Neural Network Fundamentals with Graphs, Algorithms and Applications.* New York: McGraw-Hill, Inc.

Boustead, I., Yaros, B., & Papasavva, S. (2000). Eco-labels and Eco-Indices. Do They Make Sense? *Proceedings of the SAE Total Life Cycle Conference and Exposition*. Detroit, MI. SAE Technical Paper Series 2000-01-1473

Bras, B. (1997). Incorporating Environmental Issues in Product Design and Realization. *UNEP Industry and Environment 20* (1-2), 7-13.

Brezet, H. & van Hemel, C. (1997). *Ecodesign, a Promising Approach to Sustainable Production and Consumption.* Paris, France: United Nations Environmental Program (UNEP) Industry and Environment.

Cagan, J., & Vogel C. (2002). *Creating Breakthrough Products – Innovation from Product Planning to Program Approval.* New York: Prentice Hall.

Canter, K. G., Kennedy, D. J., Montgomery, D. C., Keats, J. B., Carlyle, W. M. (2002). Screening Stochastic Life Cycle Assessment Inventory Models. *International Journal of Life-Cycle Assessment,* 7(1), 18-26.

Clark, T., & Charter, M. (1999) *Eco-design Checklists for Electronic Manufacturers, Systems Integrators, and Suppliers of Components and Sub-assemblies*, The Centre for Sustainable Design . URL: http://www.cfsd.org.uk/etmuel

Clausing, D. (1995). *Total Quality Development – A Step-by-Step Guide to World Class Engineering.* New York: ASME Press.

Cox, E. (1994). *The Fuzzy Systems Handbook – A Practitioners Guide to Building, Using, and Maintaining Fuzzy Systems.* Academic Press Professional, Cambridge, MA.

Crawley, E., de Weck, O. (2001, September/December). "System Architecture", Course Notes from 16.882/ESD.34J, Massachusetts Institute of Technology, Cambridge, MA.

Curran, M. A. (1999). The Status of LCA in the USA. *International Journal of Life-Cycle Assessment 4*(3), 123-124.

Deniz, J. C. (2000). *Learning Theory Applications to Product Design Modeling, Master of Science in Mechanical Engineering.* Cambridge, MA: Massachusetts Institute of Technology.

De Schepper, M. (1999). *An LCA-datamodel for use in conceptual integrated product design*, course 450, Research Project conducted at MIT. Delft, the Netherlands Industrial Design Engineering, Delft University of Technology.

Design for Sustainability Group (DfS). (1994-1997). TU Delft: Various student LCA research reports on consumer products.

Duda, R., Hart, P., and Stork, D. (1997). Pattern Classification and Scene Analysis: Part I Pattern Classification. Pre-publication.

Eagan, P. and Weinberg, L. (1997). Development of a streamlined, life-cycle, design for environment (DFE) tool for manufacturing process modification: a Boeing Defense & Space Group case study. *Proceedings of IEEE International Symposium on Electronics and the Environment*, San Francisco, California, 188-191.

EcoBilan. (1996). *TEAM®, 2.0 Users Manual.*

Economic Classification Policy Committee (ECPC). (1993) Conceptual Issues, North American Industry Classification System (NAICS) supporting documents.

URL: http://www.census.gov/epcd/www/naics.html

Eherenfeld, J.(1997). The Importance of LCAs – Warts and All. *Journal of Industrial Ecology 1*(2), 41-49.

Eisenhard, J. (2000). *Product Descriptors for Early Product Development: an Interface Between Environmental Expert and Designers.* Master of Science in Mechanical Engineering. Cambridge, MA: Massachusetts Institute of Technology.

Eisenhard, J., Wallace, D., Sousa, I., De Schepper, M., & Rombouts, J.(2000). Approximate Life-Cycle Assessment in Conceptual Product Design, *Proceedings of the 2000 ASME Design Engineering Technical Conference,* DETC2000/DFM-14026, Baltimore, MD.

Eisenhardt K. (1989) Building Theories from Case Study Research. *The Academy of Management Review,4*(4), 532-550.

Eriksson, M., & Izar, M. (2000). *Life-Cycle Assessment on Saucepans,* KTH Project, Stockholm, Sweden.

Evans, S., Bhamra, T., & McAloone, T. (1999). An Ecodesign Model Based on Industry Experience. *Proceedings of the 6th International Seminar on Life-cycle Engineering.* CIRP, Kingston, Ontario, 122-130.

Fava, J. (1997). LCA: concept, methodology, or strategy? *Journal of Industrial Ecolog, 1*(2), 8-10.

Fiksel, J. (1996). *Design for Environment: Creating Eco-efficient Products and Processes.* McGraw-Hill, New York, 1996.

Fleischer, G., Kunst, H. and Rebitzer, G. (1998). Life Cycle Assessment of Complex Products – Introducing an Efficient and Reliable Method. *Proceedings of the SAE Total Life Cycle Conference and Exposition.* Graz, Austria. SAE Technical Paper Series 982208.

Franklin Associates, Ltd. (1990). *Energy and Environmental Profile Analysis of Children's Disposable and Cloth Diapers.* Prairie Village, KS: Franklin Associates, Ltd (FAL).

Franklin Associates, Ltd. (1994). *Life-Cycle Assessment of Ethylene Glycol and Propylene Glycol Based Antifreeze,* Prairie Village, KS: Franklin Associates, Ltd (FAL).

Goldberg, D.E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning. Reading,* MA: Addison Wesley.

Graedel, T. (1998). *Streamlined Life-Cycle Assessment.* New York: Prentice Hall.

Graedel, T., Allenby, B., & Combrie, P. (1995). Matrix Approaches to Abridged Life-Cycle Assessment. Environmental. *Science and Technology, 29*(3), 134-139.

Grüner, C., Dannheim, F., & Birkhofer, H. (1999). Integration of EMS and DFE: Current Practice and Future Trends. *Proceedings of the 6th International Seminar on Life-cycle Engineering.* CIRP, Kingston, Ontario, 131-140.

Gupta, A. & Lam, M. S. (1996). Estimating missing values using neural networks. *Journal of the Operational Research Society 47*, 229-238.

Guinée, J. B., et al. (2001). *The New LCA Guide.* Ministry of housing, Spatial Planning and the Environment (VROM) and Centre of Environmental Science – leiden University (CML). Kluwer Academic Publishers.

URL: http://www.leidenuniv.nl/cml/lca2/index.html

Hand, D., Mannila, H., & Smyth, P. (2001). *Principles of Data Mining,* Cambridge, MA: The MIT Press.

Hanssen, O. J. (1999). Sustainable Product Systems – Experiences Based on Case Projects in Sustainable Product Development. *Journal of Cleaner Production 7,* 27-41.

Hanssen, O. J. (1996). *Sustainable Industrial Product Systems: Integration of Life Cycle Assessment in Product Development and Optimization of Product System,* Doctoral Dissertation, Trondheim: Norwegian University of Science and Technology.

Hauser, J. R. & Clausing, D. P. (1988). The House of Quality. *Harvard Business Review, 66*(3): 63-73.

Haykin, S. (1999). *Neural Networks – A Comprehensive Foundation.* New York: Macmillan College Publishing Co.

Henderson, R. & Clark, K. (1990). Architectural Innovation, *Administrative Science Quarterly* 35, 9-30.

Hoffman III, W. (1997). Recent Advances in Design for Environment at Motorola. *Journal of Industrial Ecology 1* (1),131-140.

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks* 2(5), 359-366.

Hubka, V. & Eder, W. E. (1992). *Engineering Design: General Procedural Model of Engineering Design.* Zürich, Switzerland: Heurista.

Innovest (2001). *Uncovering hidden value potential for strategic investors – the automotive industry.* Innovest Strategic Value Advisors. INNOVEST R-AUT001.

ISO, International Organization of Standardization. (1997). Environmental Management - Life Cycle Assessment - Principles and Framework (ISO/FDIS 14040). ISO TC 207.

Jackson, P. (1998). *Introduction to Expert Systems.* Boston, MA:Addison Wesley Longman.

Jackson, P., & Wallace, D. (1997a). An analytical method for integrating environmental and traditional design considerations. *Annals of CIRP 46* (1), 335-360.

Jackson, P. & Wallace, D. (1997b). A modular method for representing product life-cycles. *Proceedings of ASME Design Engineering Technical Conferences.* Sacramento, California.

Kaebernick, H., & Soriano, V. (2000). An Approach to Simplified Environmental Assessment by Classification of Products. *Proceedings of the 7th International Seminar on Life Cycle Engineering*, The University of Tokyo.

Keoleian, G., Kar, K, Manion, M., & Bulkley, J. (1997). *Industrial Ecology of the Automobile; A Life Cycle Perspective.* Society of Automotive Engineers, Inc.

Keoleian, G. (1998). Is Environmental Improvement in Automotive Component Design Highly Constrained? – An Instrument Panel Case Study. *Journal of Industrial Ecology, 2*(2): 103-117.

Kim, J. & Wallace, D. R. (1997). A Goal-oriented Design Evaluation Model, *Proceedings of the ASME DT Conferences.* 97-DETC/DTM-3878, Sacramento, CA.

Kljajin, M. (2000). Design for Environment Using Life Cycle Assessment. *Proceedings of the 6th International Design Conference - Design 2000*, 175-180.

Kolodner, J. (1993) *Case-Based Reasoning,.* San Mateo, CA: Morgan Kaufmann.

Kraines, S. B., Wallace, D. R., Iwafune, Y., Yoshida, Y., Aramaki, T., Kato, K., Hanaki, K., Ishitani, H., Matsuo, T., Takahashi, H., Yamada, K., Yamaji, K., Yanagisawa, Y., Komiyama, H. (2001). An Integrated Computational Infrastructure for a Virtual Tokyo: Concepts and Examples, to appear in *The Journal of Industrial Ecology.*

Krishnan, V., and Ulrich, K. (2001). Product Development Decisions: A Review of the Literature. *Management of Science 47*(1), Special Issue on Design and Development, 1-21.

Kuipers, B. (1994). *Qualitative Reasoning – Modeling and Simulation with Incomplete Knowledge.* Cambridge, MA: The MIT Press.

Kuo, C. & Reitsch, A. (1995). Neural networks vs. conventional methods of forecasting. *The Journal of Business Forecasting Methods and Systems, 14*(4), 17-22.

Lagerstedt, J., Sousa, I., Luttrop, C., Wallace, D. (2002, April). Functional and environmental product attributes – an automotive industry case study. *Proceedings of the 2002 CIRP Life-Cycle Engineering Seminar*. Erlengen, Germany.

Lave, L., MacLean, H., Hendrickson, C., & Lankey, R. (2000). Life-Cycle Analysis of Alternative Fuel/Propulsion Technologies. *Environmental Science & Technology, 34*(17), 3598-3605.

Lave, L., Hendrickson, C., & McMichael, F. (1995). Environmental Implications of Electric Cars. *Science vol. 268*, 993-995.

Lewis, H., Gertsakis, J., Grant, T., Morelli, N.,& Sweatman, A. (2001). *Design + Environment – a Global Guide to Designing Greener Goods.* New York: Greenleaf Publishing.

Magee, C. (2001, September/December). "System Architecture", Course Notes from 16.882/ESD.34J, Massachusetts Institute of Technology, Cambridge, MA.

Masters, T. (1993). *Practical Neural Network Recipes in C++*. San Diego, CA: Academic Press.

McAloone T C. (2000), *Industrial Application of Environmentally Conscious Design, Engineering Research Series*. London: Professional Engineering Publishing Limited.

McCollum, P. (1998). An Introduction to Back-Propagation Neural Networks. *Encoder.* The Newsletter of the Seattle Robotics Society.

URL: http://www.seattlerobotics.org/encoder/nov98/index.html

McLean, H. L. & Lave, L. B. (2000). Environmental Implications of Alternative-Fueled Automobiles: Air Quality and Greenhouse Gas Tradeoffs. *Environmental Science & Technology*. 34(2), 225-231.

Mitchell, M. (1996). *An Introduction to Genetic Algorithms.* Boston, MA: MIT Press.

Mizuki, C., Sandborn, P., & Pitts, G. (1996). Design for Environment – a Survey of Current Practices and Tools. *Proceedings of the IEEE International Symposium on Electronics and the Environment*. Dallas, TX, 1-6.

Mueller, K.G. & Besant, C.B.(1999). Streamlining Life Cycle Analysis: a Method .*Proceedings of the First International Symposium on Environmentally Conscious Design and Inverse Manufacturing,* IEEE, Tokyo, 114-119.

Newell, S. (1998). *Strategic Evaluation of Environmental Metrics: Making Use of Life-Cycle Inventories.* Doctoral Dissertation, Cambridge, MA: MIT.

O'Connor, F. & Blythe, D. (1997, May). Designing environmental considerations in to products – a novel qualitative life-cycle approach. *Proceedings of IEEE International Symposium on Electronics and the Environment,* San Francisco, California, 192-197.

Owens, J. (1997). Life-cycle assessment – constraints in moving from inventory to impact assessment. *Journal of Industrial Ecology 1(*1), 37-49.

Pahl, G. & Beitz, W. (1999). *Engineering Design – a Systematic Approach*. Second Edition. London: Springer-Verlag.

Pahng, K. F., Senin, N., & Wallace, D. R. (1998). Distributed Modeling and Evaluation of Product Design Problems. *Computer-Aided Design, 30* (6): 411-423.

Park, J.H., Seo, K.K., & Jang, D.S. (1999). Recycling Cell Formation using Group Technology for Disposal Products. *Proceedings of the First International Symposium on Environmentally Conscious Design and Inverse Manufacturing,* IEEE, Tokyo, 830-835.

Potts, A. (2000). Personal communication. Principal Designer, Potts Design, Stoneham, MA.

PRé Consultants. (1999). *SimaPro 4 User's Manual.* The Netherlands: PRé Consultants BV. URL: http://www.pre.nl

Pugh, S. (1996). *Creating Innovative Products Using Total Design.* Edited by Don Clausing and Ron Andrade. Boston, MA: Addison Wesley.

Quinlan, J.R. (1993). *C4.5 Programs for Machine Learning.* San Mateo, CA: Morgan Kaufmann.

Rebitzer, G. & Fleischer, G. (2000). Identifying the Environmental Imopact Drivers and Tradeoff Options in the Life Cycle of Automobiles – A Software Based Methodology for the Sound Restriction of System Boundaries. *Proceedings of the Total Life Cycle Conference and Exposition.* Detroit, MI. SAE Technical Paper Series 2000-01-1493.

Reuleaux, F. (1904). *The Constructor: A Hand-book of Machine Design.* New York: The Engineering Magazine.

Ripley, B. D. (1996). *Pattern Recognition and Neural Networks.* Cambridge University Press.

Ripley, B. D. (1997). Can Statistical Theory Help Us Use Neural Networks Better? *Proceedings of Interface 97. 29th Symposium on the Interface: Computing Science and Statistics.*

Rivard, H., Fenves, S. J., & Gomez, N. (1998). Case-Based Reasoning for Conceptual Building Design. *Proceedings of the 1st International Conference on New Information Technologies for Decision Making in Civil Engineering,* Edmond T. Miresco (Editor), École de Technologie Supérieure, Université du Québec, Montreal, 355-366.

Rombouts, J.P. (1998). LEADS-II. A Knowledge-based System for Ranking DfE-Options. *Proceedings of the 1998 IEEE International Symposium on Electronics and the Environment.* IEEE (Institute of Electrical and Electronic Engineers), 287-291.

Romesburg, H.C.(1984). *Cluster Analysis for Researchers.* Belmont, CA: Lifetime Learning Publications.

Rose, C., Beiter, K., & Ishii, K. (1999). Determining End-of-Life Strategies as a Part of Product Definition. *Proceedings of the 1999 IEEE International Symposium on Electronics and the Environment.* IEEE (Institute of Electrical and Electronic Engineers), 219-224.

Rose, C., Masui, K., & Ishii, K.(1998). How Product Characteristics Determine End-of-Life Strategies. *Proceedings IEEE International Symposium for Electronics and the Environment Conference,* Oak Brook, Illinois, 322-327.

Rose, C., Stevels, A., & Ishii, A. (2000) A New Approach to End-of-Life design Advisor (ELDA). *Proceedings of the 2000 IEEE International Symposium on Electronics and the Environment,* IEEE (Institute of Electrical and Electronic Engineers), 99-104.

Rydh, C D. (2001). Environmental Assessment of Battery Systems in Life Cycle Management. Doctoral Dissertation. Gothenburg, Sweden: Chalmers University of Technology.

Saur, K., Rüdiger, H., Stichling, J., & Piwowarzcyk, D. (2000). System Performance Simulation Based on Life Cycle Considerations. *Proceedings of the Total Life Cycle Conference and Exposition.* Detroit, MI. SAE Technical Paper Series 2000-01-1501.

Senin, N., Wallace, D. R., & Borland, N. (2000). Distributed Object-based Modeling in Design Simulation Marketplace, accepted for publication, *ASME Journal of Mechanical Design.*

Senin, N., Wallace, D. R., & Borland, N. (1999). Mixed Continuous and Discrete Catalog-based Design Modeling and Optimization. *Proceedings of the 1999 CIRP International Design Seminar,* Enschede, The Netherlands, University of Twente, 209-218.

Senin, N., Borland, N., Wallace, D. R. (1997). Distributed modeling of product design problems in a collaborative design environment. *Proceedings of the CIRP 1997 International*

Design Seminar: Multimedia Technologies for Collaborative Design and Manufacturing, Los Angeles, California.

SETAC, Society of Environmental Toxicology and Chemistry. (1999). *Streamlined Life-Cycle Assessment: A Final Report from the SETAC North America Streamlined LCA Workgroup*. J. A Todd and M. A. Curran, eds., Society of Environmental Toxicology and Chemistry and SETAC Foundation for Environmental Education, Pensacola, FL. URL: http://www.setac.org/

Schuckert, K., Saur, K., Florin, H., Eyerer, P., Beddies, H., Sullivan, J., & Hu, J. (1996). Life cycle analysis: getting the total picture on vehicle engineering alternatives. *Automotive Engineering*, 49-52.

Schlüter, F. (2001). On the Integration of Environmental Aspects into Early Product Development – Life Cycle design Structure Matrix. Licentiate Thesis. Department of Machine Design. Royal Institute of Technology. Stockholm, Sweden.

Sfantsikopoulos, M., & Pantelis, D.(1997). *Concurrent Product Design and Environmentally Conscious Manufacturing..* Edited by Samir Bilatos and Hong Zhang. 1997 ASME International Mechanical Engineering Congress and Exposition. Dallas, Texas. DE-Vol.94, MED-Vol.5. 207-213.

Sharma, A., Weitz, K., Peters, A., & Baskir, J. (1996a). Streamlining LCA Case Study Report: Disposable Versus Reusable Shop Towels, Draft report,. Research Triangle Park, NC: RTI, 1996.

Sharma, A., Weitz, K., Peters, A., & Baskir, J. (1996b). Streamlining LCA Case Study Report: Recycled and Virgin Newsprint, draft report. Research Triangle Park, NC: RTI.

Smith, A. E. & Mason, A. K. (1997). Cost Estimation Predictive Modeling: Regression versus Neural Network. *The Engineering Economist 42*(2), 137-161.

Soibelman, L. (1998). *The exploration of an integrated representation for the conceptual phase of structural design for tall buildings through distributed multi-reasoning algorithms.* Doctoral Dissertation, MIT CE 1998.

Sousa, I., Eisenhard, J., & Wallace, D. (2000). Approximate Life-Cycle Assessment of Product Concepts using Learning Systems. *Journal of Industrial Ecology 4* (4), 61-81.

Sousa, I., Wallace, D. R., Borland, N., & Deniz, J. (1999). A Learning Surrogate LCA Model for Integrated Product Design. *Proceedings of the 6th International Seminar on Life Cycle Engineering*, Kingston, Ontario, Canada, Queen's University, 209-219.

Sousa, I., & Wallace D. (2002). Product Classification to Support Approximate Life-Cycle Assessment of Design Concepts. To be published in a special issue of the journal *Technological Forecasting and Social Change.*

Srinivas, M. and Patnaik,L. (1994). Genetic Algorithms: a Survey. *Computer.*

Sullivan, J. (2001). Personal communication. Scientific Research Laboratories. Ford Motor Company.

Sullivan, J. and Cobas-Flores, E. (2001). Full Vehicle LCAs: A Review. SAE Technical Paper Series 2001-01-3725.

Sullivan, J., Costic, M., & Han, W. (1998). Automotive Life-Cycle Assessment: Overview, Metrics and Examples. *Proceedings of the SAE International Congress and Exposition.* Detroit, MI. SAE Technical Paper Series 980467.

Sullivan, J. and Hu, J. (1995). Life Cycle Energy Analysis for Automobiles. Proceedings of the SAE Total Life Cycle Conference and Exposition. Vienna, Austria. SAE Technical Paper Series 951829.

Swingler, K. (1996). Applying Neural Networks – A Practical Guide. Morgan Kaufman Publishers.

Thomas, L.M. & Weinberg, L. (1999). Using a streamlined life-cycle analysis matrix to structure a design for the environment program for a complex defense system. *Proceedings of the First International Symposium on Environmentally Conscious Design and Inverse Manufacturing*, Tokyo. IEEE, Tokyo, 128-133.

UK Ecolabeling Board. (1992). Ecolabeling Criteria for Washing Machines, PA Consulting Group.

Ullman, D. (1992). *The Mechanical Design Process*. New York: McGraw-Hill .

Ulrich, K., & Eppinger, S. (2000). *Product Design and Development*. Second Edition, New York:McGraw-Hill.

U.S. Congress, Office of Technology Assessment. (1992). *Green Products by Design: Choices for a Cleaner Environment*, OTA-E-541, Washington, DC: US Government Printing Office.

U.S. EPA, Environmental Protection Agency and Science Applications International Corporation. (2001). LCAccess – LCA 101.

URL: http://www.epa.gov/ORD/NRML/lcaccess/lca101.htm

Wallace, D. (1994). A Probabilistic Specification-based Design Model: application to search and environmental computer-aided design. Doctoral Dissertation, Cambridge, MA: MIT.

Wallace, D., Yang, E. & Senin, N. (2002). Integrated Simulation and Design Synthesis. Manuscript under review. MIT CADlab.

Wenzel, H. & Alting, L. (1999). Danish Experience with the EDIP Tool for Environmental Design of Industrial Products. *Proceedings of the First International Symposium on Environmentally Conscious Design and Inverse Manufacturing*, IEEE, Tokyo, 370-379.

Winston, P. (1993). *Artificial Intelligence*. Boston, MA:Addison-Wesley.

WRI, World Resources Institute (2002). Tomorrow's Markets: Global Trends and Their Implications for Business.

URL: http://www.wri.org/business/tomorrows_markets.html

Zaknich, A. (1998). *Artificial Neural Networks: An Introductory Course*.

URL: http://www.maths.uwa.edu.au/~rkealley/ann_all/ann_all.html

APPENDIX A

PRODUCT CONCEPT DESCRIPTOR SET DEFINITIONS

Descriptor name	Definition (example of value, ranking, and binary levels of information)
Additional consumables	Product requires additional consumables during use (e.g., 200 coffee filters, more-same-less amount used, product [does not] needs consumables during the use phase)
Biodegradability	Product contains biodegradable materials (e.g., %, more-same-less amount used, [no] biodegradable materials used) (e.g., pen made of biodegradable material that degrades when disposed in a composting site)
Ceramics	Product contains ceramics (e.g., %, more-same-less amount used, [no] ceramics used) (e.g., oxides, porcelain, stoneware)
Concrete	Product contains concrete (e.g., %, more-same-less amount used, [no] concrete used)
Disassemblability	Ease of disassembly to recover/separate parts and materials (e.g., # of parts or fasteners, high-mid-low level of disassemblability, disassembly [not] applicable)
Distribution volume	Total product volume including packaging (e.g., 60 m^3, more-same-less volume, [no] volume)
Durability	Endurance for wear or decay (e.g., time to failure, tougher-same-more fragile, n/a)
Ferrous metals	Product contains ferrous metals (e.g., %, more-same-less amount used, [no] ferrous metals used) (e.g., steel, cast iron)
Fibers	Product contains fibers (e.g., %, more-same-less amount used, [no] fibers used) (e.g., cotton, nylon, cloth, wool, polyester)
Glass	Product contains glass (e.g., %, more-same-less amount used, [no] glass used) (e.g., decor glass, toughened glass)
In use energy source	Type of energy source when in use (e.g., batteries vs. Solar vs. wall outlet, n/a, does [not] need an energy source during use)
In use flexibility	Product can be configured by the user to exhibit different capabilities (e.g., # of configurations, high-mid-low level of in use flexibility, single or multi-functional) (e.g., 35mm cameras can be used with different lenses and flash options)
In use power consumption	Power consumption when in use (e.g., 60 W, high-mid-low wattage, [no] power consumed while in use)
Lifetime	Life period of product once it is produced until it is disposed of (e.g., 5 years, long-mid-short lifetime, n/a)
Mass	Total product mass (e.g., 8 kg, more-same-less mass, [no] mass) (e.g., a service or data file has no mass)
Mode of operation	Main mode of operation (e.g., manual on/off vs. standby vs. sensor control, n/a, does [not] require power)
Modularity	Product integrates a combination of distinct building blocks or modules (e.g., # of modular components, more-average-less components, is [not] modular) (e.g., electric motor systems)
Nonferrous metals	Product contains nonferrous metals (e.g., %, more-same-less amount used, [no] nonferrous metals used) (e.g., aluminum, copper, zinc)

Descriptor name	Definition (example of value, ranking, and binary levels of information)
Other materials	Product contains other materials (e.g., %, more-same-less amount used, [no] other materials used)
Paper	Product contains of paper (e.g., %, more-same-less amount used, [no] paper used) (e.g. a label)
Polymers	Product contains polymers (e.g., %, more-same-less amount used, [no] polymers used) (e.g., PET, PC, PVC, ABS)
Recyclability	Product is easily recycled after use (e.g., % product that can be recycled, high-mid-low level of recyclability, can[not] be recycled)
Recycled content	Product contains post-consumer material (e.g., %, more-same-less amount used, [no] post-consumer material used) (e.g., recycled paperboard)
Reusability	Able to be reused (e.g., # of times reused, more-same-less reuse, can[not] be reused)
Serviceability	Ease of maintenance when needed (e.g., time required by technician, high-mid-low level of servicability, does [not] require service)
Transport distance	Total transport distance in product's life-cycle (e.g., 5000 km, farther-same-shorter, transport [un]necessary)
Transport means	Means of transportation (e.g., train vs. vehicle vs. airplane, n/a, transport [un]necessary)
Upgradability	Product accommodates evolutionary technological or user needs through upgrades (e.g., n/a, high-mid-low level of upgradability, can[not] accommodate upgrades)
Use time	Total time (or frequency) the product is expected to be used (e.g. for frequency 24 hr, continuous-some-limited use, does [not] require power)
Volume	Product volume (e.g., 42 m^3, more-same-less volume, [no] volume)
Wood	Product contains wood (e.g., %, more-same-less amount used, [no] wood used) (e.g., pine, linden, chestnut)

APPENDIX B

ON-LINE SURVEY

This survey was organized in an effort to identify what designers know about their products during the ***conceptual phase*** of design. Your responses will help advance our research at MIT in the Center for Innovation in Product Development (CIPD). Thank you in advance! - Ines Sousa (iss@mit.edu) and Julie Eisenhard (liberty@mit.edu)

Please enter your name and company information.

Last name: First name:

Company:

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1 Please mark the type of information you know (or can easily find out) about the following product attributes while in the ***conceptual phase*** of design. Attribute definitions can be found by clicking on their appropriate names (a second browser window will pop up). Use the following examples as 'definitions' for the levels of information:

- if you are able to specify or estimate an attribute in a qualitative or quantitative sense, select ***value.***
- if you cannot specify the attribute, but would be able to rank concepts with respect to the attribute, select ***ranking***.
- if you know whether or not your product will contain (e.g.) polymers, but cannot estimate the percentage or rank a concept among others with respect to polymers, select ***binary***.
- if the attribute is not able to be known in conceptual design, select ***unknown***.
- if the attribute does not at all apply to the types of products you design, select ***N/A***.

Product Attribute Name	known: at what level?			unknown	N/A
	value	ranking	binary		
manufacturing cost					
product price					
lifetime					
in use energy source					
manufacturing process					
in use power consumed					
in use operation					
in use hours of operation					

Product Attribute Name	known: at what level?			unknown	N/A
	value	ranking	binary		
durability					
modularity					
serviceability					
upgradability					
assemblability					
disassemblability					
in use flexibility					
recyclability					
reusability					
strength					
mass					
product volume					
conductivity					
biodegradability					
polymers					
paper					
wood					
ferrous metals					
nonferrous metals					
ceramics					
glass					
fibers					
fluids/lubricants					
concrete					
post-consumer material					
other materials					
distribution volume					
transport distance					
means of transportation					

Product Attribute Name	known: at what level?			unknown	N/A
	value	ranking	binary		
Other (please indicate):					

2 How you would characterize the products you design? (Check all that apply.)

aerospace/defense	housewares	toys
automotive	industrial equipment	Other (please indicate)
buildings/building materials	medical	
chemical	packaging	
consumer electronics	shoes	
exhibits	soft goods (textiles)	
furniture	sporting goods	

3 If you feel you have absolutely no experience in environmentally conscious design, you may skip to section 4 now.

A Which do you think are the most important attributes from an environmental standpoint from the attributes listed below? (Check all that apply.)

manufacturing cost	serviceability	conductivity	fluids/lubricants
product price	upgradability	biodegradability	concrete
lifetime	assemblability	polymers	post-consumer material
in use energy source	disassemblability	paper	other materials
manufacturing process	in use flexibility	wood	distribution volume
in use power consumed	recyclability	ferrous metals	transport distance
in use operation	reusability	nonferrous metals	means of transportation
in use hours of operation	strength	ceramics	
durability	mass	glass	
modularity	product volume	fibers	

B Background: You are designing a product. Suppose all else remains equal; the following 5 decisions will affect *only* the environmental performance of the product. The boxes below represent stages of the thought process, or a chain of logic, you would go through when making a decision in each of the 5 presented cases with respect to the product you are designing. Please let us know the product you are designing:

Instructions: In each case:

1. make a realistic decision;
2. then select the impact category for which you feel your decision will have the most impact (positive or negative). Try to select a different impact category to think about for each decision.
3. Fill in as many or as few of the boxes in between to try to help us understand how you link these two selections. If you run out of boxes, simply insert a comma between your thoughts within a box.

Example (see below): If I am making a decision with regard to the attribute means of transport, perhaps I would select [cargo truck] from the drop menu as the means for transporting my product. Then, I might choose [particulates] as my impact category from that drop menu. I chose this category because I associate cargo trucks with [low fuel economy], therefore [more diesel fuel consumption], therefore a [greater amount of particulate emissions], where the brackets represent the boxes below. Feel free to edit the example if you don't agree with our decision or our logic!

Decision Example: Means of Transport	**Decision 1: Material choice**	**Decision 2: Reusability**
airplane ship cargo truck train	plastic paper glass aluminum	disposable reusable once reusable multiple times
low fuel economy		
more diesel consump		
more particulate emis		

Choose the category below, on which your decision above will have the most impact.

CO2	CO2	CO2
life-cycle energy	life-cycle energy	life-cycle energy
CFC	CFC	CFC
solid mateial	solid mateial	solid mateial
particulates	particulates	particulates
NOx	NOx	NOx
SO2	SO2	SO2

Decision 3: In use energy source	Decision 4: Manufact. process	Decision 5: In use operation
batteries	rapid prototyping	constant use
public electricity	casting metals	manual on/off
gasoline	plastic molding	stand-by mode
diesel	shaping powder	sensor (e.g. thermostat, motion)

Choose the category below, on which your decision above will have the most impact.

CO2	CO2	CO2
life-cycle energy	life-cycle energy	life-cycle energy
CFC	CFC	CFC
solid mateial	solid mateial	solid mateial
particulates	particulates	particulates
NOx	NOx	NOx
SO2	SO2	SO2

4 Please let us know anything else you think might be helpful.

Submit Reset

APPENDIX C

EVALUATION OF ERROR FUNCTION DERIVATIVES IN BACK-PROPAGATION TRAINING OF THE ANN

Change in error due to output layer weights

The partial derivative of the error with respect to the output layer weights is:

$$\frac{\partial E_X}{\partial u_{kj}} = \frac{\partial E_X}{\partial y_k} \cdot \frac{\partial y_k}{\partial u_{kj}} = \partial y_k \cdot h_j$$ **Equation C.1**

where:

$$E_X = \frac{1}{2}\sum_{k=1}^{K}(d_k - y_k)^2$$ error function for input vector X, $K = 1$ output nodes **Equa**

d =desired output, y =ANN output
hj = j th hidden layer node, y_k = k th output layer node
u_{kj} = weight between j th hidden layer node and k th output layer node

$$\partial y_k = (y_k - d_k) \cdot f_k'(\sum_{b=0}^{M} u_{kb} \cdot h_b)$$, $f(.)$ = activation function, M = 15 hidden nodes **Equation C.3**

Change in error due to hidden layer weights

The partial derivative of the error with respect to the hidden layer weights is:

$$\frac{\partial E_X}{\partial w_{ji}} = \partial h_j \cdot x_i$$ **Equation C.4**

where:
hj = j th hidden layer node, x_i = i th input layer node
w_{ji} = weight between i th input layer node and j th hidden layer node

$$\partial h_j = \left[\sum_{a=1}^{K}(y_a - d_a) \cdot f_k'(\sum_{b=0}^{M} u_{kb} \cdot h_b) \cdot u_{aj}\right] \cdot f_j'(\sum_{j=0}^{P} w_{jb} \cdot x_b)$$ **Equation C.5**

Weight adjustments

$$\Delta u_{kj} = -\eta \cdot \frac{\partial E_X}{\partial u_{kj}} = -\eta \cdot \partial y_k \cdot h_j$$ and $u_{kj}^{new} = u_{kj}^{old} + \partial u_{kj}$, η is learning rate cte > 0 **Equation C.6**

$$\Delta w_{ji} = -\mu \cdot \frac{\partial E_X}{\partial w_{ji}} = -\mu \cdot \partial h_j \cdot x_i$$ and $w_{ji}^{new} = w_{ji}^{old} + \partial w_{ji}$, μ is learning rate cte > 0 **Equation C.7**

Additional momentum factor

$$W(k+1) = W(k) - \mu \frac{\partial E_X}{\partial W} + \alpha(W(k) - W(k-1))$$

$$U(k+1) = U(k) - \eta \frac{\partial E_X}{\partial U} + \beta(U(k) - U(k-1))$$

Equation C.8 and **Equation C.9**

where μ, η, α, β are positive learning rate constants, all less than 1.

Note: The above formulas are for a single presentation of an input vector. To compute for an entire training epoch, the gradients for each sample are summed.

APPENDIX D

MAIN STEPS IN CASE STUDY RESEARCH, BASED ON FRAMEWORK BY EISENHARDT (1989)

Step	Activity	Output
Getting started	Definition of research question	What is a general-specific approach, based on product attributes, which can support environmentally conscious early design for automotive-type products?
	Specification of *a priori* construct	Functional-environmental characterization framework
Selecting cases	Selection of population	Automotive industry
	Theoretical sampling	Two sub-cases were selected as polar types: door (sub-system) and truck (system)
Crafting instruments and protocols	Multiple data collection methods	Visit to case study site; meetings with environmental expert, environmental coordinator, project manager; questionnaires; interviews; observations; documentation.
	Qualitative, quantitative data combined	Collection of data on target values, ranges of values and prioritisation both at the truck and the door levels.
	Multiple investigators	Two investigators
Entering the field	Overlap data collection and analysis	Field notes, observations and iterative creation of two questionnaires: 1st on organizational framework of design for environment at the company; second on functional-environmental product attributes and environmental performance – to adjust data collection on product specific attributes within company's design context.
		Meeting on-site, use of phone and email while answering second questionnaire – to capture emergent issues. Reviews and clarification of biases by consulting project manager and environmental expert (key informants)
	Flexible, opportunistic data collection methods	

Step	Activity	Output
Analysing data	Within-case analysis	Analysis of 2nd questionnaire; use of tabular displays and graphs of information to evaluate and rank attributes and environmental burdens, for each sub-case. Clarification of biases with project manager.
	Cross-case pattern search	Iterative creation and analysis of 3rd and 4th questionnaires to evaluate and rank attributes uncovered in the 2nd; selection of dimensions (functional vs. environmental, material vs. energy) followed by search of within-sub-case similarities and between-sub-case differences. Reviews and clarification of biases with project manager and environmental expert .
Shaping hypotheses	Measuring constructs and verifying relationships	Iterative development and analysis of qualitative matrices on system and sub-system attributes – functional and environmental; definition of customized lists of attributes.
Enfolding literature	Comparison with conflicting and similar literature	Support from literature on environmentally relevant vehicle attributes, e.g. Sullivan and Cobas-Flores (2001).
Reaching closure	Theoretical saturation	Stopped iterating between theory and data when incremental learning was minimal. Outlined candidate product descriptor set and environmental outputs.