Int J Adv Manuf Technol (2002) 19:461–471
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The International Journal of Advanced Manufacturing Technology

Approximate Estimation of the Product Life Cycle Cost Using Artificial Neural Networks in Conceptual Design

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In order to improve the design of products and reduce design changes, cost, and time to market, life cycle engineering has emerged as an effective approach to address these issues in today's competitive global market. As over 70% of the total life cycle cost of a product is committed at the early design stage, designers can substantially reduce the life cycle cost of products by giving due consideration to the life cycle implications of their design decisions. During the early design stages there may be competing requirements. In addition, detailed information is scarce and decisions must be made quickly. Thus, both the overhead in developing parametric life cycle cost (LCC) models for a wide range of concepts or requirements, and the lack of detailed information make the application of traditional LCC models impractical. A different approach is required because a traditional LCC method should be incorporated in the very early design stages. This paper explores an approximate method for providing the preliminary life cycle cost. Learning algorithms trained to use the known characteristics of existing products can perhaps allow the life cycle cost of new products to be approximated quickly during the conceptual design phase without the overhead of defining new LCC models. Artificial neural networks are trained to generalise product attributes and life cycle cost data from pre-existing LCC studies. Then, the product designers query the trained artificial model with new high-level product attribute data to obtain an LCC for a new product concept quickly. Foundations for the learning LCC approach are established, and then an application is provided. This paper has been developed to provide designers with LCC information to guide them in conceptual design.

Keywords: Approximate LCC; Artificial neural networks; Conceptual product design; Learning LCC; Product attributes

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1. Introduction

The ability of a company to compete effectively in the increasingly competitive global market is influenced to a large extent by the cost, as well as the quality, of its products and by the ability to bring products onto the market in a timely manner. It has been recognised that the life cycle, or concurrent, engineering approach to the design of products has a great potential to achieve these goals. People are always concerned about product cost, which encompasses the entire product life from conception to disposal. Manufacturers usually consider only how to reduce the cost of materials acquisition, production, and logistics. In order to survive in the competitive market environment, manufacturers now have to consider reducing the cost of the entire life cycle of a product, called the life cycle cost (LCC). Owing to widespread consciousness of global environmental problems and environmental legislative measures such as take back and recycling laws, manufacturers also have to consider reducing the cost which a user incurs during consumption and which society incurs in disassembling, recycling, and disposal. The costs incurred during production, use, and disposal are mostly committed by early design decisions. Studies reported in Dowlatshahi [1] and by other researchers in design, suggest that the design of the product influences 70%–85% of the total cost. Therefore, designers can reduce substantially the LCC of the product they design by giving due consideration to life cycle cost implications of their design decisions. Design methods for minimising the LCC of the product thus become very important and valuable.

The need for sustainable development has begun to change the way many companies design products. Traditional product designers are being asked to judge the cost of the products they are developing. Not only is this an additional task for designers, but it is something they are not necessarily qualified to do. Therefore, the LCC models created by cost estimators should be integrated with traditional design models, making the parametric LCC results available on demand. However, the use of detailed parametric models is not well suited to early conceptual design, where ideas are diverse and numerous, details are very scarce, and the pace is swift. This is unfortunate

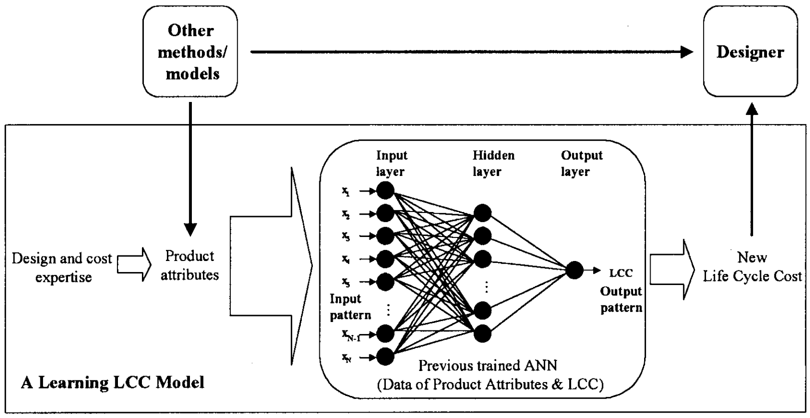

Fig. 1. The learning LCC model in the design environment.

because the early phases of the design process are widely believed to be the most influential in defining the LCC of products.

This paper describes the development of an estimation method for product LCC, called a learning LCC model, for use in conceptual design. This method facilitates an integrated system of the design process, allowing the approximate and rapid estimation of the product LCC based on high-level information, typically known in the conceptual phase. An artificial neural network (ANN) is trained on product attributes and the LCC data from pre-existing detailed LCC studies. The product designers query the trained artificial model with new high-level product attribute data to obtain an approximate LCC quickly for a new product concept. This does not require a new LCC model. The designer can then use the predicted cost performance, along with key performance measures from other models, in a trade-off analysis and concept selection (Fig. 1).

Key ideas that must be developed and tested to validate the learning LCC concept are studied in this paper, which provides a basis for the learning LCC concept, a preliminary application, and a discussion of its limitations. This paper is organised as follows. In Section 2, as the background section, the conceptual design and previous LCC studies are reviewed. In addition, state-of-the-art LCC methods are discussed. The learning LCC concept is described in Section 3. Section 4 elucidates the development of learning LCC models. The four primary elements established in Section 4 are as follows: a meaningful set of product attribute inputs; a useful set of the outputs of LCC factors; a training data set based upon previously analysed products; and an appropriately trained LCC model. The test of the learning LCC models is then presented in Section 5. Finally, some conclusions and suggestions for future research are provided in Section 6.

2. Background

2.1 Conceptual Design

The conceptual design phase defines the basic characteristics of a product, ranging from cost [2] to environmental impact [3]. Decisions that emerge from the conceptual phase are often locked in, owing to the large amount of resources (time, manpower, and money) required to change course as launch deadlines approach. Therefore, it is important that cost considerations are used in the evaluation of concept feasibility along with other requirements. This means that the design team must be able to evaluate the approximate cost performance of many solution concepts, early in the design process (see Fig. 2).

Time is usually scarce during the product development cycle. Development time can mean the difference between leading or following in an industry; therefore, it limits the ability to create detailed models for many different concepts. Additionally, in conceptual design, the lack of information is a significant barrier to the creation of the models required to evaluate different ideas.

Although it is a good idea for product designers to have some knowledge of cost estimation, it is not, and should not be, their area of primary expertise. Ideally, the services of cost estimators should be extended to designers. Communication, although necessary for such an extension, is often a barrier as it takes time to establish and maintain the synchronisation of information between designers and cost estimators.

2.2 Life Cycle Approach to Design

In an attempt to improve the design of products and reduce design changes and time to market, concurrent, or life cycle, engineering has emerged as an effective approach to address these issues in today's competitive global market. The unique aspect of life cycle engineering is that the complete life cycle of the product is kept under consideration in each phase of product development [4]. Life cycle engineering goes beyond the life of the product itself and simultaneously considers the

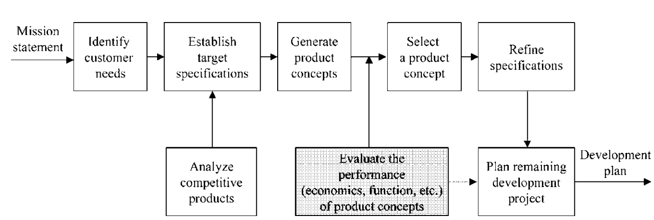

Fig. 2. The concept development process.

issues of the manufacturing process and the product service systems.

The life cycle of the product begins with the identification of needs and extends through design, production, customer use, support, and finally, disposal. Alting [5] distinguishes between six phases in a product's life: need recognition, design development, production, distribution, use, and disposal. However, the life cycle of the product in most other papers is usually divided into only four phases: design development, production, use, and disposal. The process life cycle begins with the definition of the production task by the preliminary product design. This entails production planning, plant layout, equipment selection, process planning and other similar activities. The third life cycle, which deals with logistic support, should also be initiated at the preliminary design phase. This involves the development of support for the design and production stages, consumer support and maintenance during product usage, and support for product recovery.

In suggesting a life cycle engineering approach to design, Alting [5] also identified a number of issues that must be addressed: ease of manufacture, environmental protection, working conditions, resource optimisation, life cycle cost, and product properties. In this paper, we intend to concentrate on the product LCC.

2.3 Life Cycle Cost Analysis

Typically, design and economic justification have been considered as two separate undertakings. Though they both have the common goal of arriving at a competitive product, their goals are diametrically opposed to each other – the goal of designing the best product possible often conflicts with the goal of cost minimisation [6]. As stated earlier, it has been reported that during the design stage, most (70%–85%) of the total LCC of a product is committed. This can be reduced by giving due consideration to LCC issues early in the design. LCC analysis provides the framework for specifying the estimated total incremental costs of developing, producing, using, and disposing of a particular item.

Cost estimation is usually done by professional cost estimators who may have little or no design experience and may or may not be an integral part of the design process. The estimates by designers and professional cost estimators tend to differ. Because cost estimators can put more time and effort into their calculations, their estimates are usually more accurate. Designers do not have the cost estimators' skill and experience. Furthermore, cost estimators will be satisfied if they obtain a reasonable estimate [7]. The cost estimating community rarely focuses on why a system will cost what it does [8]. Designers, the other hand, will not be satisfied with just an estimate; on seeing the estimate they search for an understanding of why the product costs what it does, and for more cost-effective solutions. The most important task for the designers, therefore, is to balance the relationship between cost information and design decisions. Therefore, it is important to develop a method that gives the designers quick and accurate estimates of the financial consequences of their design decisions, and procedures to determine optimal design parameters.

2.3.1 Cost Estimating Approaches

Depending on the stage of the analysis and the level of detail expected, an LCC model may be a simple series of cost estimation relationships (CERs) or a set of computer subroutines. LCC analysis during the conceptual or preliminary design phases may require the use of basic accounting techniques and the model may be simple in construction [9]. On the other hand, LCC analysis done during the detailed design stage may be more elaborate. Just as the design process produces a lower level of functional requirements through functional decomposition to enable design solutions to be developed easily, it is imperative to perform a cost decomposition. Such a cost decomposition is known as a cost breakdown structure (CBS). Cost function/models can then be allocated to the various categories to allow easy calculation of the total cost.

Estimation models used in industry can be broadly classified as parametric models, analogous models, and detailed models. Parametric estimation is the generation and application of equations that describe relationships between cost schedules and measurable attributes of a system that must be developed, sustained, and retired [10]. Cost estimation made by analogy identifies a similar product or component and adjusts its costs for differences between it and the target product [11]. The effectiveness of this method depends heavily on an ability to identify correctly any differences between the case in hand and those deemed to be comparable [12]. A detailed model uses estimates of labour time and rates and also material quantities and prices to estimate the direct costs of a product or activity [11]. An allocation rate is then used to allow for indirect/overhead costs. It is a most time-consuming and costly approach, and requires a detailed knowledge of the product and its processes. However, the most accurate cost estimates can be made using this approach.

2.4 Review of Life Cycle Cost Methods

There are different approaches to develop cost models for LCC analysis. Most LCC models are structured along three general lines: conceptual, analytical, and heuristic [13,14]. Conceptual models consist of a set of hypothesised relationships expressed in a qualitative framework. They are generally very flexible, and can accommodate a wide range of systems. They require a minimum of details and require little ability to quantify a system's cost characteristics. Conceptual models are limited when they come to analyses [14]. Analytical models are usually based on mathematical relationships which are designed to describe a certain aspect of a system/product under certain conditions/assumptions. These assumptions tend to restrict or limit the model's ability to reflect the actual system's performance. Heuristic models are ill-structured analytical models, usually employing an approach which produces a feasible and sufficient solution, but does not guarantee that the solution is optimal [13]. These models are usually developed through the use of computer simulation [14]. Heuristic models are not as general as analytical models, and can normally be used only for the specific situation for which they are intended.

Some authors have focused on presenting frameworks to be used for LCC analysis, whereas others have focused on developing models to be used for the evaluation of cost. For the most part, these models have been developed for use in specific phases of the product life cycle or for specific operations in a particular life cycle phase.

Greenwood and Reeve [15] presented a comprehensive activity-based framework for supporting operational decision-making which allows managers to predict activity and process costs under alternative product design and production. Although the architecture described supports process analysis, product costing, and simulation, the framework presented is not easy to understand. Moreover, though the authors indicated that it is intended to be used for predictive purposes, it does not deal with uncertainties.

Noble and Tanchoco [6] presented a conceptual framework for concurrent design and economic justification of systems. They proposed a design justification environment that allows the decision maker to see the potential economic implications for different design alternatives. The cost of manufacturing the product was divided into fixed and variable components and allocated on a per unit basis. Although the framework is useful, the model is based on traditional accounting concepts which are not very useful for accurate cost tracing.

A multistage integrated decision model, in which decisions on product and process design are simultaneously made and supported by economic evaluation at each stage of the manufacturing process, is presented by Oh and Park [16]. This paper reclassifies the total manufacturing cost into four categories: productivity cost, quality cost, flexibility cost, and inventory cost. For each classified cost element, the cost function for a unit of a product for each significant process in the manufacturing operation is derived for a set of alternatives for that particular process. For a solution procedure, a dynamic programming method is used to obtain the optimal design decision that minimises total product costs.

An object-oriented approach to activity-based cost estimation that is capable of supporting the engineer in the early phases of design is presented in Fischer et al. [17]. This method combines a product model and a resource model, which are both based on STEP structures.

Ong [18] presents the development of an activity-based cost-estimating system to help designers estimate the manufacturing cost of a printed circuit board assembly at the early concept stage of design. Activities are identified and quantified and the cost is allocated based on the number of activities used by the printed circuit board. Though the author claims the model is meant to be used at the conceptual phase of design, the data required for the evaluation will most probably not be available until the preliminary design stage.

As a part of a design for manufacture research program at the University of Rhode Island, a number of computer-based models for estimating the cost of fabricating parts have been developed [19]. The objective of these studies was to provide methods with which the designer or design team can quickly obtain information on costs before detailed design has taken place. Studies have been completed for machine parts, injection-moulded parts, die-cast parts and sheet-metal stampings.

In a series of papers, Boothroyd and Dewhurst [20,21] presented models for calculating the cost of assembly of products using robots, automatic machines, and manual labour. These have been formalised into computer programs.

The concept of service model analysis (SMA) as an evaluation method of design for serviceability was developed by Gershenson and Ishii [22]. SMA focuses on any form of service needs in estimating life cycle ownership cost. A computer software package infers the labour necessary for various service operations, identities cost drivers, and indicates areas for improvement. Service models include regular maintenance, repair of failed components of systems, and service for undesirable side effects.

Technical cost modelling (TCM) is presented in automotive engineering [23]. This is an approach to determine the best ways to recover materials from automobiles. The TCM approach has been implemented using a spreadsheet. The model tracks material flow through the various recycling stages, beginning with the scrapped vehicle, to determine the net cost of recycling. However, TCM focuses only on direct costs.

Navinchandra [24] has developed a CAD tool, ReStar, for disassembly sequence optimisation and environmental recovery analysis. It inputs a description of the product and generates a disassembly plan. The program currently has disassembly schedules and costs in its database. It has some information on energy and emissions; but according to the author, this part of ReStar's databases is not well developed because of a lack of reliable information sources.

Emblemsvag and Bras [25] illustrated how an activity-based deterministic cost model can be used in the decision-making process to obtain an overall cost-efficient design. The recycling of the product at the end of its useful life is specifically considered. The recycling phase is broken down into a hierarchy of activities. Then, for each particular design, a determination is made of the activities required and the calculated cost. Though this model is supposed to help designers make decisions, the model as presented in this paper can be used only to make decisions at the product level.

Bras and Emblemsvag [26] further extend their work in Emblemsvag and Bras [25] to include uncertainties. The objective in developing an activity-based cost model is to identify the activities that will be present in the life cycle of a product and assign reliable cost drivers and associated consumptions to the activities. Uncertainty distributions are assigned to the numbers used in the calculations, representing the inherent uncertainty in the model.

Although these methods are all useful, they are not ideally suited for early conceptual design. Qualitative information is difficult to use in highly dimensional multi-attribute trade-offs, and the analytical techniques are still prohibitive from a modelling viewpoint.

3. The Learning LCC Concept

The learning LCC model is a different approach from other LCC methods. Unlike the others, it does not require any LCC modelling on a product basis. Learning algorithms train artificial neural networks (ANNs) using high-level product attributes and corresponding LCC factors from pre-existing life cycle cost studies. Through this training, the ANN is adapted to emulate existing LCC studies and generalise trends between products. This is illustrated in Fig. 3.

The product designers query this learning model with high-level product attributes to obtain an approximate LCC quickly for a new product concept. Designers provide high-level attributes of new product concepts to obtain LCC predictions based upon trends inferred from real products and LCC studies used as training data.

The learning LCC model learns from detailed LCC studies, yet possesses a high-level interface allowing it to operate with the limited data available in conceptual design. It has the flexibility to learn and grow as new information becomes available, but it does not require the creation of a new model to make an LCC prediction for a new product concept. Also, by supporting the extremely fast comparison of the cost performance of product concepts, it does not delay product development.

However, the learning LCC model is not envisaged as a replacement for traditional detailed LCC models, but as a complement to them. In the early design stages, the learning LCC uses previously conducted detailed LCC studies to provide rapid feedback on a wide variety of concepts. In later design stages, when a smaller range of variations is under consideration, detailed parametric LCC models can be used. Results from the detailed LCC models are then added to the training database as new training material for the learning LCC model.

4. Development of the Learning LCC Model

There are four components of the learning LCC model: a meaningful set of product attribute inputs; a useful set of LCC factor outputs; a training data set based upon previously analysed products; and an appropriately trained LCC model.

The product attribute inputs must be meaningful to designers and consist only of product attributes typically known during conceptual design. The LCC factor outputs should also be in a form useful to cost estimators and designers in different contexts. Therefore, LCC factors would provide the most flexibility as different schemes can be applied subsequently. The

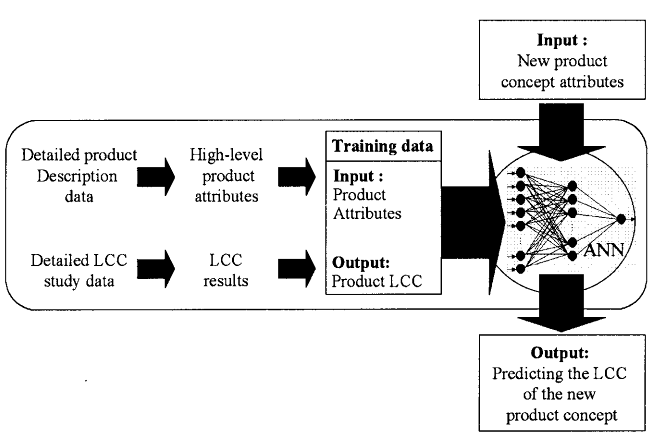

Fig. 3. The training process of the learning LCC model.

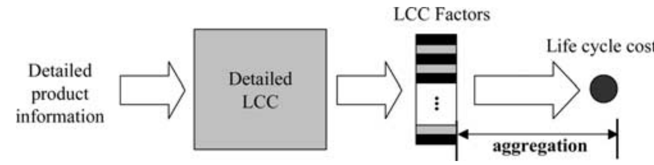

Fig. 4. The aggregation scheme for the LCC.

LCC training data must represent a range of products and contain many complete input samples of product attribute data and corresponding outputs of LCC factors. Data transparency should be maintained with any LCC by fully stating any assumptions, estimations, or uncertainties. Finally, the structure of the learning LCC model must be chosen, trained, and validated. In application, the learning LCC model must be fast and provide reasonable LCC estimates.

Given these observations, there are three key areas that must be investigated in order to evaluate the learning LCC concept. First, the feasible LCC factors to predict the LCC must be established. Secondly, a list of reasonable product attributes must be identified and correlated with LCC data to create a set of meaningful attributes. Thirdly, it must be established that a learning LCC model can be trained to effectively emulate LCC results. The LCC training data will be developed in the course of gathering information to evaluate the three areas.

4.1 Identifying Life Cycle Cost Factors

The first issue is to establish the feasible LCC factors for use in training the learning LCC models. In order to identify the LCC factors, all the costs incurred in the product's life are investigated and enumerated. The LCC of a product is determined by aggregating all the LCC factors, as shown in Fig. 4.

The life cycle cost of a product is the aggregate cost to the manufacturer, the user, and society. This is depicted in Fig. 5.

	Company Cost	Users Cost	Society Cost
Design	Market Recognition Development		
Production	Materials Energy Facilities Wages, Salaries Etc.		Waste Pollution Health Damages
Usage	Transportation Storage Waste Breakage Warranty Service	Transportation Storage Energy Materials Maintenance	Packaging Waste Pollution Health Damages
Disposal/ Recycling		Disposal/ Recycling Dues	Waste Disposal Pollution Health Damages

Fig. 5. Life cycle stages and cost factors [5]. © 1993 Alting. Reprinted by permission of John Wiley & Sons, Inc.

The total cost of any product from its earliest concept through to its retirement will eventually be borne by the user and will have a direct bearing on the marketability of that product [27]. As purchasers, people pay for the resources required to develop and market the product; as owners of the product, people pay for the resources required to deploy, operate, and dispose of the product. The product LCC can be decomposed into cost factors, as shown in Fig. 5. This decomposition is by no means the most comprehensive and representative of all products or any product. The cost factors considered will depend on the stage at which we want to use the model, the kind of information to be extracted from the model, the data available as input to the model, and the product being designed. The life cycle cost is the aggregate of all the costs incurred in the product's life, but it must be pointed out that there are differences between the cost issues that will be of interest to the person designing the product and the firm developing the product in the LCC analysis.

Table 1 gives the cost factors for product life cycles adapted to the feasible LCC factors useful for predicting the product LCC. The cost factors are derived from Fig. 5, proposed by Atling [5].

4.2 Identifying Product Concept Attributes

The second issue is to define product attributes for use in training and querying the learning LCC model. The attributes must be both logically and statistically linked to elements in the LCC factors, and also must be readily available during product concept design. The attributes must be sufficient to discriminate between different concepts and be compact so that the demands on the learning LCC model are reasonable. Finally, they must be understood easily by designers and, as a set, span the scope of the product life cycle. These criteria were used to guide the process of systematically developing a product attribute list.

With these goals in mind, a set of candidate product attributes, based upon the literature and the experience of experts, was formed. Ecodesign checklists and design improvement strategies [28–33] provided a starting point for product attributes. For example, checklist questions such as, "What type of energy is required when using the product?", suggest in-use energy consumption and in-use energy sources as possible attributes characterising the product use phase.

Other workers [34,35] also specifically addressed the problem of defining product attributes. Rombouts [35] derived a list of attributes from the ecodesign checklist defined by Brezet and Hemel [29], whereas Mueller and Besant [34] modelled life cycle parameters as functions of design parameters. For example, mass, material composition, and efficiency are functions of an engine's power. Experts in both product design and cost estimation used candidate attributes derived from the literature. In practice, product attributes at the conceptual stage are few and simple and are expressed in a product-specific language. For example, frequently used product attributes 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 [personal communication, A. Potts, Potts Design, Stoneham, MA, 2000].

The candidate product attributes identified initially are given in Table 2.

After candidate attributes were identified, they were grouped for organisational purposes and reviewed for conceptual linkages to the LCC factors and potential coverage of the entire life cycle. The attributes were grouped according to the method developed by Hubka and Eder [36], which is based on recognised life cycle phases, and the nature and purpose of technical systems. In Fig. 6, the grouped candidate attributes are provided, along with steps to identify qualitatively potentially strong links among attributes and between attributes and the LCC factors. The representation in Fig. 6 is based upon the quality function deployment (QFD) [37].

If the designer was able to specify or estimate an attribute in an appropriate qualitative or quantitative sense, the attribute was deemed specified. If the designer could not specify the attribute, but could typically rank order concepts, the attribute was deemed ranked. If an attribute could not be specified or ranked, but the designer could provide a "yes" or "no" answer, the attribute was deemed to be binary. For example, the designer might know that a concept will contain polymers, but may not be able to specify or rank the amount used. If the designer could typically provide no information about an attribute, it was deemed unknown. Finally, if an attribute did not apply to the class of products designed by the participant, the attribute was categorised as not applicable (N/A). Results assessing attributes based upon end-of-life grouping are shown in Fig. 7.

This study helped us identify attributes that designers could both understand and had knowledge of during the conceptual design. For example, attributes such as in-use energy source and mode of operation were readily specified, whereas modularity and serviceability are more likely to be ranked with respect to other concepts. Furthermore, we were able to assess

Table 1. The list of life cycle cost factors.

Market recognition	Storage
Development	Breakage
Materials	Warranty service
Energy	Maintenance
Facilities	Waste
Wages	Pollution
Packaging	Health damages
Transportation	Disposal/recycling dues

Table 2. Candidate product attribute set.

Durability	Selling price	In use energy source
Strength	Product liability	In use power consumption
Conductivity	Distribution mass	Modularity
Mass	Distribution volume	Upgradeability
Volume	Transport distance	Serviceability
Materials (various)	Transportation means	In use flexibility
Performance	Lifetime	Recycled content
Functionality	Use time	Recyclability
Process	Mode of operation	Reusability
Assemblability	Additional consumable	Disassemblability

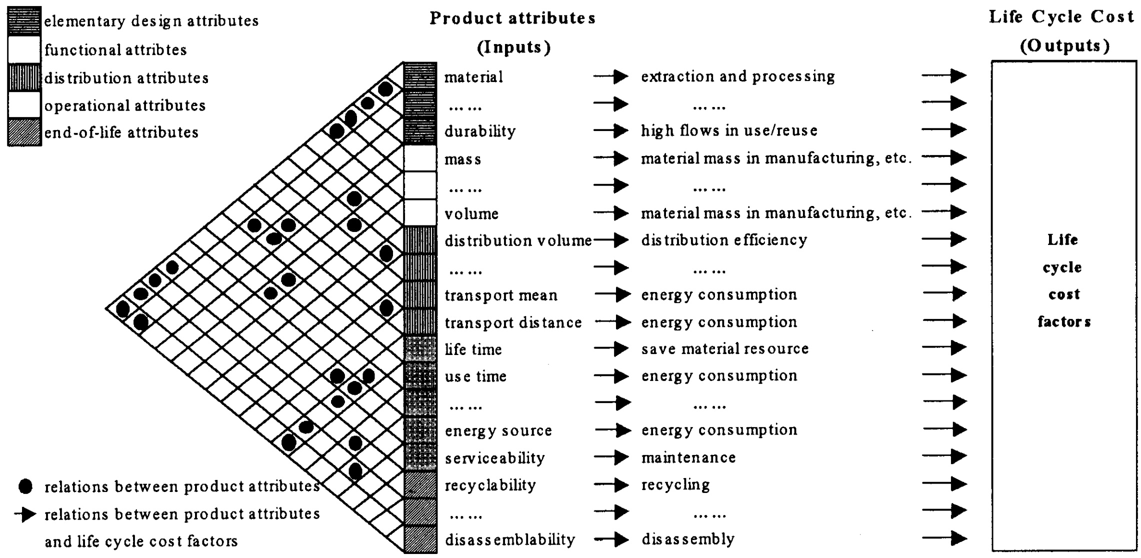

Fig. 6. Conceptual relationships between product attributes and the LCC factors.

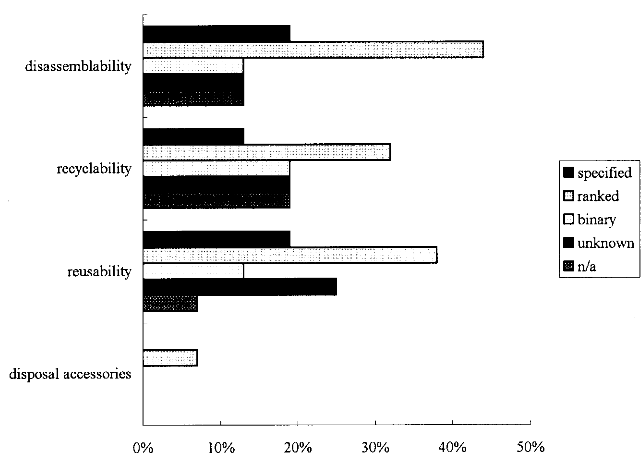

Fig. 7. Survey results for end-of-life properties.

which attributes are likely to vary significantly from concept to concept.

Based upon these data, the candidate attribute set was again refined, and then tested for first-order relationships with the LCC factors. Bivariate correlations were computed and correlation tests to 95% statistical significance were performed between quantitative attributes and the data of LCC factors for various products. Linearity and bivariate normality in the data were assumed when checking for trends.

This first-order examination required careful interpretation and grouping of products. For example, the data in Table 3 suggest that many product attributes are strongly correlated with many of the LCC factors (life cycle energy) as expected. Insight gained about product attributes through the analysis will later be proposed as a structure for specialising the learning LCC models to improve results.

Mass and power consumption were most strongly correlated with the LCC factor (life cycle energy) and disassemblability,

Table 3. An example of correlation coefficients and tests: product attributes vs. LCC factor (life cycle energy).

Product attributes	Coefficient of correlation
Mass	0.9656
Lifetime	–0.1092
Use time	–0.3760
Operation mode	0.2320
Additional consumable	0.6035
Energy source	0.6658
Power consumption	0.9890
Modularity	0.4610
Durability	0.0933
. . . . . .	. . . . . .
Upgradability	–0.0100
Serviceability	0.5807
Flexibility	–0.0295
Post consumable material	–0.0060
Reusability	–0.0455
Recyclability	–0.0325
Disassemblability	0.7730

and additional consumable and energy source were strongly related. The affect of qualitative attributes on the LCC factor was assessed visually through scatter plots. Additionally, it is believed that some correlations were not apparent because of potentially nonlinear relationships between attributes. The product attributes strongly correlated with the LCC factors are used to predict the product LCC in the learning LCC model.

In this study, the cost of life cycle energy consumption, that was the one important element of LCC factors defined previously, was shown, as an example, to predict the LCC. Tables 4 and 5 show the final product attributes chosen for use in the learning LCC model. The analysis provided a basis for the belief that the attribute list could span the elements in the LCC factors.

Table 4. The final product attribute set.

Q	Mass (kg)	Q	Other materials (%mass)
Q	Ceramics (%mass)	Q	Lifetime (h)
Q	Fibres (%mass)	Q	Use time (h)
Q	Ferrous metals (%mass)	D	Mode of operation
Q	Non-ferrous metals (%mass)	B	Additional consumable
Q	Plastics (%mass)	D	In use energy source
Q	Paper/cardboard (%mass)	Q	In use power consumption (W)
Q	Chemicals (%mass)	B	Modularity
Q	Wood (%mass)	B	Serviceability
		B	Disassemblability

(Q: Quantitative, D: Dimensionless, B: Binary)

Table 5. Product attribute list used in training the learning LCC model.

Product attributes	Unit	Level of information
Mass	kg	Quantitative, specified
Ceramics	%mass	Quantitative, specified
Fibres	%mass	Quantitative, specified
Ferrous metals	%mass	Quantitative, specified
Non-ferrous metals	%mass	Quantitative, specified
Plastics	%mass	Quantitative, specified
Paper/cardboard	%mass	Quantitative, specified
Chemicals	%mass	Quantitative, specified
Wood	%mass	Quantitative, specified
Other materials	%mass	Quantitative, specified
Lifetime	h	Quantitative, specified
Use time	h	Quantitative, specified
Operation mode	Dimensionless	Qualitative, specified
Additional consumable	Dimensionless	Qualitative, binary
Energy source	Dimensionless	Qualitative, specified
Power consumption	W	Quantitative, specified
Modularity	Dimensionless	Qualitative, binary
Serviceability	Dimensionless	Qualitative, binary
Disassembleability	Dimensionless	Qualitative, binary

5. Test of the Learning LCC Model

Finally, with product attributes and LCC factors defined, ANN-based learning LCC models were trained in an effort to validate the concept. As also mentioned earlier, a feasibility test was conducted, focusing only on the total life cycle energy consumption component of the LCC factors. Training data with product attributes and corresponding life cycle energy consumption from past studies were collected for 150 different products. The products included were various types of electronic appliance, vehicles, and other goods. These data were obtained from the same sources as the data used in the development of the list of LCC factors and the product attribute list provided by previous studies. The total energy consumption during the life cycle was investigated through the energy unit (MJ), which was converted into electric power units (kWh). Finally, the LCC for life cycle energy consumption was derived by multiplying the electric power unit by the electric power rate ($\$\,\mathrm{kWh})^{-1}$. The examples of learning patterns for testing the learning LCC model are shown in Fig. 8.

A multiple-layer neural network with back propagation training [38,39] was used to predict the product LCC. In order to decide the structure of the back propagation neural network, the error convergence rate was checked by changing the number of hidden layers and the number of nodes in each layer, and by adjusting the learning rate η, and momentum term α. Here, η and α are constants whose values are between 0 and 1. More than 60 experiments were performed to determine the best combination of the learning rates (η), the momentum term (α), the number of hidden layers, the number of neurons in hidden layers, the learning rules, and the transfer functions. The resulting network had a hidden layer with 16 neurons. The most popular learning rules and generalised delta rules and a sigmoid transfer function were used for the output node. Figure 9 shows the structure of the back-propagation neural network, which consists of an input layer with 19 nodes, a hidden layer with 16 nodes, and an output layer with one node.

Inputs : Product attributes									Outputs : Product LCC
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8.17	32.62	5.40	61.58	61320.00	...	...	1.00	3.00	596.21
49.78	67.08	5.06	27.64	0.20	...	...	24.00	3.00	2221.19
35.01	24.24	7.19	51.76	0.29	...	...	24.00	3.00	2190.92
20.97	2.72	1.67	54.14	14.30	...	...	3.20	1.00	653.83
51.04	8.96	2.02	0.44	0.00	...	...	3.20	1.00	2837.60
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Fig. 8. Examples of learning patterns for the learning LCC model.

The artificial neural network for the learning LCC models was implemented in C++. The training of the back-propagation neural network took 2688 s for 150 learning patterns on a 500 MHz Pentium III processor. When $\eta = 0.6$ and $\alpha = 0.1$, the number of iteration was 60 000, and the mean square error was 0.000143. The ANN runs its learning cycle by reading a text file containing the training data. Once the model learns, users can set the model inputs (product attributes) to values corresponding to a product concept. The learning LCC model then immediately provides the predicted LCC output.

The trained neural network was evaluated using products with known LCC results. The learning LCC model was assessed in two different ways: absolute accuracy and the ability to generalise trends. Five different products were used in the assessment.

The results of LCC prediction and accuracy comparisons for the five products are provided in Table 6 and Fig. 10. The absolute errors of LCC predictions were 0.11%–12.02% of the levels given by the true LCC analyses. During the early conceptual design stages of product development, available

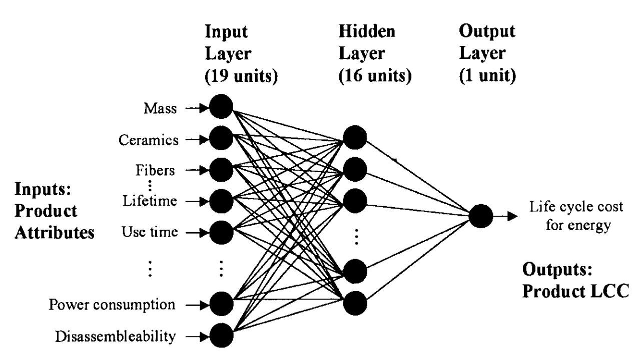

Fig. 9. Structure of the back-propagation neural network for predicting the product LCC.

Table 6. Comparison of the LCC of products as predicted by the learning LCC model with the detailed LCC.

	Detailed LCC ($)	Learning LCC ($)	Absolute error (%)
Vacuum cleaner	595.96	572.03	4.06
Heater	2893.22	3241.38	12.02
Washing machine	6359.30	6365.62	0.11
Refrigerator	2220.72	2193.78	1.23
TV	2935.70	3023.57	3.01

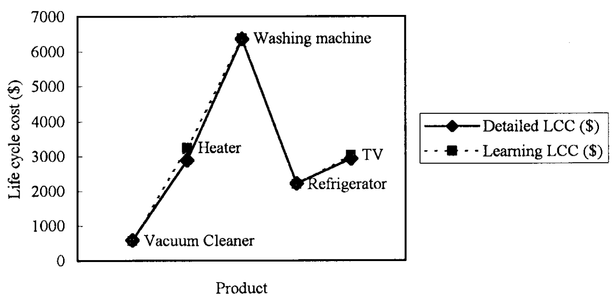

Fig. 10. Comparison results of the LCC of products in Table 6.

data are limited and the cost analyst must depend primarily on the use of various parametric cost estimating techniques for the development of cost data. The accuracy of an LCC model predicted from an actual LCC is typically −30–+50% [40], so these results seem very satisfactory.

The results of LCC prediction would rank the different products in a relative sense. This is important for cases where designers are comparing very different design concepts. Rank order may provide some useful guidance for a designer's decisions at the conceptual product design. In Fig. 11, the five products are compared relative to LCC by the TV.

Secondly, the five products were used to test the learning LCC model's ability to generalise 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 and power consumption.

The mass results for the washing machine, shown in Table 7 and Fig. 12, are representative for illustrating trends as pre-

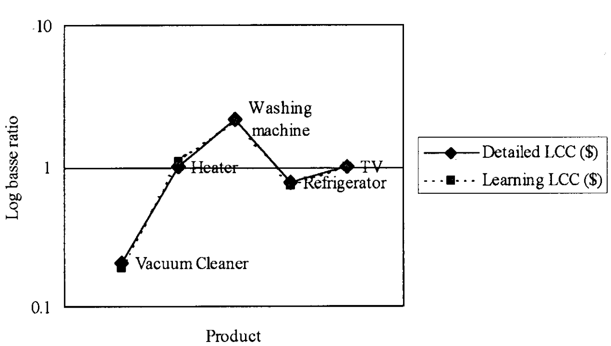

Fig. 11. Ranking different products with the LCC results by the TV as the baseline product.

Table 7. Prediction of the LCC results according to mass trends for the washing machine.

Mass (kg)	Learning LCC	Detailed LCC
30	5923.78	
40	6009.48	
50	6095.17	
60	6180.86	
70	6266.45	
82	6365.62	6359.30
90	6437.32	
100	6522.50	
110	6607.47	
120	6692.12	

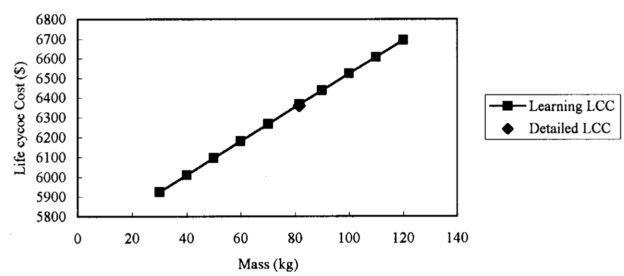

Fig. 12. Results of mass trends for the washing machine.

dicted by the learning LCC model. Results produced in trying to assess trends with respect to mass were generally good.

The trend predicted for power consumption is shown in Table 8 and Fig. 13. The power consumption results were also good, as expected.

The prediction results of trends for the other products were generally good too. The methodology developed in this paper to predict the product LCC is somewhat generalised since the results of the trend experiment were shown to be satisfactory. This generalisation can be extended to the product LCC according to various product attributes and diverse products.

6. Conclusions and Future Research

It has been recognised that the design process requires cost models that:

Table 8. Prediction of the LCC results according to energy consumption trends for the washing machine.

Energy consumption (W)	Learning LCC	Detailed LCC
1000	6337.91	
1100	6343.44	
1200	6348.94	
1300	6354.53	
1400	6360.02	
1500	6365.62	6359.30
1600	6371.11	
1700	6376.60	
1800	6382.09	
1900	6387.69	

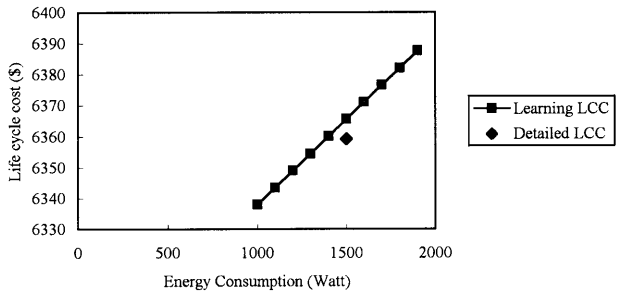

Fig. 13. Results of energy consumption trends for the washing machine.

1. Take into account the complete life cycle of products.
2. Can be used at the very early stages of design.
3. Can provide information to designers in a timely manner and in a form that can be understood and used.

Some efforts have been made toward providing the designer with cost information during the design process. The product LCC is mainly determined by early design decisions. However, at the early conceptual design stage, designers do not know the costs incurred in subsequent life cycle phases. Thus, the estimation method for minimising the product life cycle cost should be able to offer sufficient prediction of the product LCC in response to design decisions and design guidelines for reducing the product LCC.

The lack of analytical methods for early conceptual design motivated the development of a learning LCC concept. This paper described procedures to develop a foundation for the concept. Three areas critical to the preliminary validation of the approach were explored: model outputs in the form of the LCC factors; model inputs in the form of a compact, meaningful, and understandable set of concept attributes; and the ability to predict the product LCC through training an ANN-based learning LCC model.

The LCC factors for a learning LCC model were investigated, and they were able to be used to predict the product LCC. A list of meaningful product concept attributes required for inputs to the learning LCC model was made: utilisation only of product information readily available during conceptual design; conciseness to reduce demands on the learning LCC model; and relationships to elements of the LCC factors. A candidate set of product attributes was identified, and tested for first-order relationships to elements in the list of LCC factors.

Finally, LCC data and product attributes were collected for 150 products, and ANN-based learning LCC models were trained to predict the product LCC, and then tested. The learning LCC models for five products with known LCC results were successfully tested to assess performance in two categories: absolute accuracy, and the ability to predict trends associated with changes for a given product concept.

We believe that the learning LCC concept merits further study. In particular, data availability was found to be a critical element in the development of the concept. In practice, it may be necessary to use proprietary LCC sources. Further tests using more data are required to determine to what extent the learning LCC model can provide reasonable predictions for innovative products and to test for other LCC factors in addition to the cost of life cycle energy.

It is apparent that the learning LCC model should be feasible for estimating the cost incurred in subsequent phases of the product life cycle based on design decisions at early conceptual design stages and for minimising the product LCC by selecting, modifying or optimising those design decisions.

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