**Article ID:** 1003-6326(2005)01-0119-06

# ANN valuation model of material LCIA profile①

CHEN Wei-ping(陈维平), LIU Hua(刘 华), ZHAO Hai-dong(赵海东),
ZHU Quan-li(朱权利), LI Yuan-yuan (李元元)
(College of Mechanical Engineering, South China University of Technology,
Guangzhou 510640, China)

**Abstract:** Weighting model is the only valuation model of life cycle impact assessment(LCIA) profile now. It simplifies evaluation function into linear function, and makes the determination of weighting factor complicated. Therefore the valuation of LCIA profile is the most critical and controversial step in life cycle assessment(LCA). Development on valuation models, which are understood easily and accepted widely, is urgently needed in the field of LCA. The modeling approaches for the linear evaluation function were summed up. The modeling approaches for the nonlinear evaluation function were set up by function approximation theory, which include choosing preference products, forming preference data, establishing artificial neural network(ANN) and training ANN by preference data. By selecting 7 material products as preference product, experience was done with modeling approaches of the nonlinear evaluation function. The results show that the modeling approaches and valuation model of the nonlinear evaluation function are more practical than the weighting model.

**Key words:** material life cycle assessment; life cycle impact assessment; valuation model; weight model; function approximation; artificial neural network; preference product

**CLC number:** TB39; X38 **Document code:** A

## 1 INTRODUCTION

Life cycle assessment(LCA) is a technique for systematically analyzing a target from cradle-to-grave, that is, from resource extraction through manufacture and use to disposal. It is an effective tool that not only gives detailed information of environmental profile of material, product or a process, but also gives results that are significantly useful for the purpose to improve the utilization efficiency of resource and energy and decrease environmental impact, as the basis of design for environment(DFE)[1-7].

The methodology for conducting material LCA consists of four phases: goal and scope definition, inventory analysis, impact assessment and interpretation. Life cycle impact assessment(LCIA) is the most incomplete one in the four phases. Especially valuation about LCIA profile is the most critical and controversial step in LCIA[8]. It is an optional element in ISO 14042. In some main LCIA methodologies, some give weighting factors such as Eco-indicator99 and other only recommend approaches on the determination of weighting factor as CML2001[9, 10]. In order to have a simply additive expression, weighting methods simplify the evaluation function into linear function, so that the determination on appropriate weighting factors becomes very difficult and complicated for society or a group of stakeholders.

The valuation model of LCIA profile is involved in social, political and ethical value choice[11]. Different value choices reflect on the temporal and regional character of valuation model. Because of the simple linear evaluation function of weighting model, the determination of right weighting factors must include more than one value choice. As a result it restricts the usage scope of LCA. Related to the above point, the model of valuation about material LCIA profile, which is easier to be understood and accepted, has been developed.

## 2 VALUATION MODEL OF LCIA PROFILE

LCIA is the third phase of life cycle assessment described in ISO 14042. The purpose of LCIA is to assess a product system's life cycle inventory to better understand its environmental significance. It also provides information for the interpretation phase.

LCIA consists of three phases, as presented in Fig. 1: classification, characterization and valuation. Before running LCIA, practitioners must

① **Foundation item:** Project(50135020) supported by the National Natural Science Foundation of China; Project(2001AA337010) supported by the Hi-tech Research and Development Program of China; Project(0203) supported by the Key Grant Project of Ministry of Education of China

**Received date:** 2004-09-29; **Accepted date:** 2004-11-15

**Correspondence:** LIU Hua; Tel: +86-20-87112948; E-mail: liuhua@gzsums.edu.cn

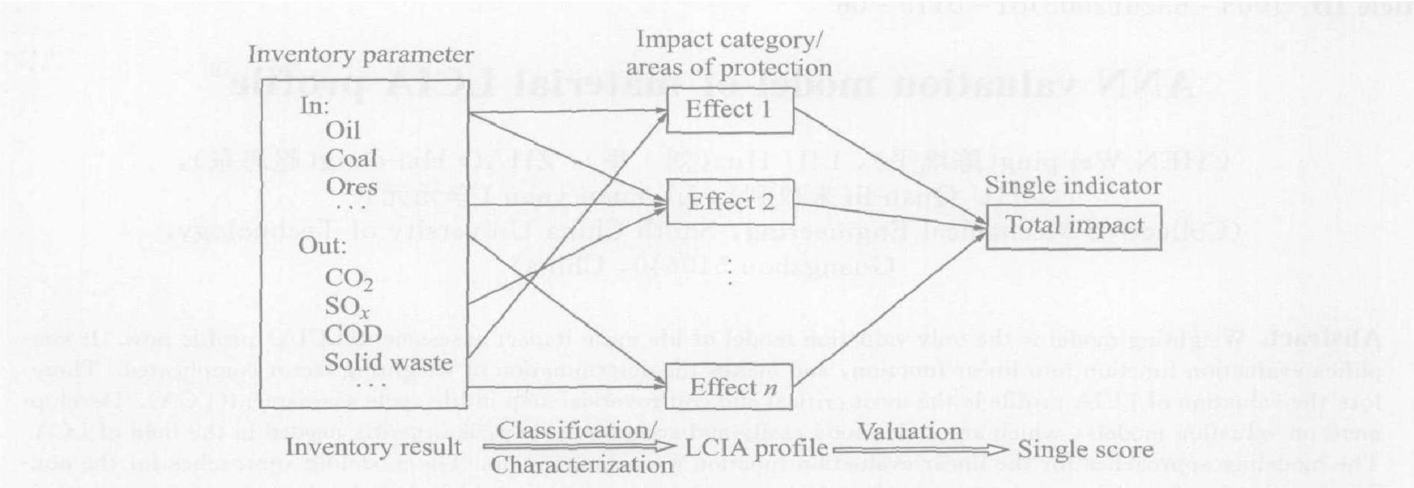


**Fig. 1** Life cycle impact assessment

choose LCIA approaches, which are sorted into the midpoint and endpoint approach. At the same time, the relevant impact categories, the indicators for each relevant impact category and characterization models are selected.

Classification is the assignment of LCI results to the impact category, that is, the data from the inventory table are grouped together into a number of impact categories. Characterization is the calculation of category indicator results(LCIA profile), and the analysis and estimation of the magnitude of the impacts for each of the impact categories, such as depletion of abiotic resources, climate change, and acidification in the midpoint approaches, or ecological health, human health in the endpoint approaches.

Valuation is the expression of the total environmental impact of product system in a single indicator, which is a kind of mapping to establish the correspondences between a given category-indicator set and a given single indicator. The mapping function is also called the evaluation function, which should represent the views of society or a group of stakeholders. The evaluation function is used to convert LCIA profile to a single score:

$$Y = f(X, K(t, p)) \tag{1}$$

In this function, the dependent variable $Y$ is the above-mentioned single indicator, accordingly its value is single score. The independent variables $X$ are the category indicators, and their values are category indicator results. The function parameter $K(t, p)$ is relative to the views of society or a group of stakeholders, where $t$ denotes time and $p$ denotes area.

Because there is usually more than one impact category in life cycle impact assessment, the evaluation function consequentially is a multi-independent-variable function. In general, the evaluation function is divided into linear function and nonlinear function.

### 2.1 Model of linear evaluation function

Valuation using linear evaluation function is referred to weighting in LCA circles, as shown in Fig. 2, which is often applied in the form of weighting additive method:

$$TI = \sum V_k N_k \text{ or } TI = \sum V_k S_k \tag{2}$$

where $TI$ is the total environmental impact indicator, $V_k$ is the weighting factor for impact category $k$, $N$ is the normalized indicator results and $S$ is the category indicator results from the characterization phase.

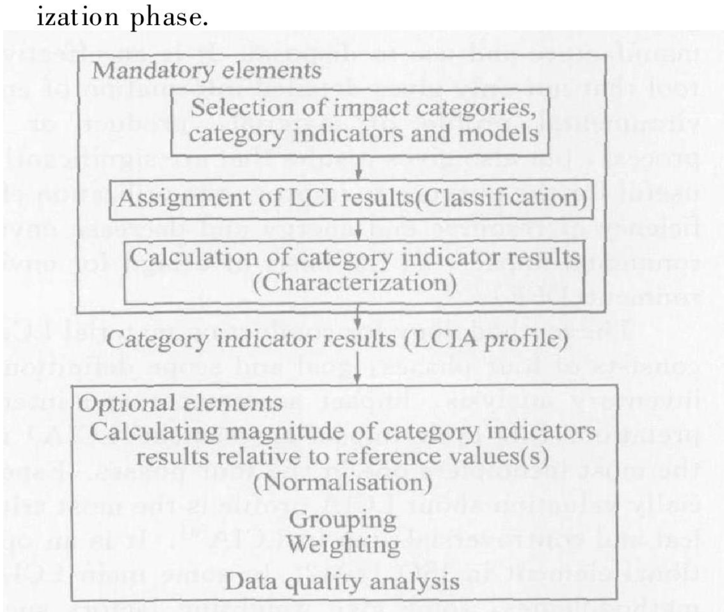


**Fig. 2** Mandatory and optional elements of LCIA according to ISO14042

Methods for weighting can be classified in different ways[12, 13]:

1) A distinction can be made between methods based on impact indicators defined early (at midpoints) or late (e. g. at endpoints or for areas of protection), in the impact chain, as described in Fig. 1.

2) A second distinction is among three major groups of methods: monetisation, panel and dis-

tance to target.

3) A third distinction exists between the expressed preference methods and the revealed preference methods.

Table 1 illustrates the characteristics of some of LCIA methods that predefined or recommended weighting approaches. This table distinguishes between the depth of modeling (to midpoints yielding indicators such as GWPs versus to indicators at the level of AoPs) and the type of subsequent weighting approaching.

The valuation model with weighting linear evaluation function has some assumptions and simplifications. Through comparing Eqn. (2) with Eqn. (1), the evaluation function is simplified to the linear function on the base of the assumption that there exist an independent relation and mutual compensation among the category indicators acting as the independent variables $X$. The function parameters $K(t, p)$ are named as weighting factor for impact category. The modeling approaches are shown in Fig. 3.

The methodologies in Fig. 3 are problem-oriented methods. The significance of problems on impact category being caused in product life is gained with the expressed preference or the revealed preference methods. The relative importance of the different impact categories is weighted against each other in the quantitative step (distance to target, panel or monetisation), which forms the preference data and educes the weighting factors.

### 2.2 Model of nonlinear evaluation function

Because a nonlinear evaluation function is more complicated than a linear evaluation function, it is very difficult to set up a model of nonlinear evaluation function by above-mentioned traditional

**Table 1** Characteristic elements to some LCIA methodologies

| Method (Versions available) | Geographical scope | Indicator basis (impact modeling depth) | | Weighting basis | | |
|---|---|---|---|---|---|---|
| | | To midpoint | To AoP | Distance to target | Expert panel | Monetization |
| Eco-scarcity(1991, 1997) | Switzerland | Partly | | + | | |
| IMPACT(2002+) | Switzerland | + | + | – | – | – |
| CML(2001) | Europe/Netherlands | + | | | – | |
| EPS(1992, 1996, 2000) | World | | + | | | + |
| Eco-indicator(1995) | Europe/Netherlands | + | | + | | |
| Eco-indicator(1999) | Europe/Netherlands | | + | | + | |
| EDIP(1997, 2003) | Denmark | + | | + | | |
| LIME(2003) | Japan | | + | | | + |

\+ Predefined approach; – Recommended approach

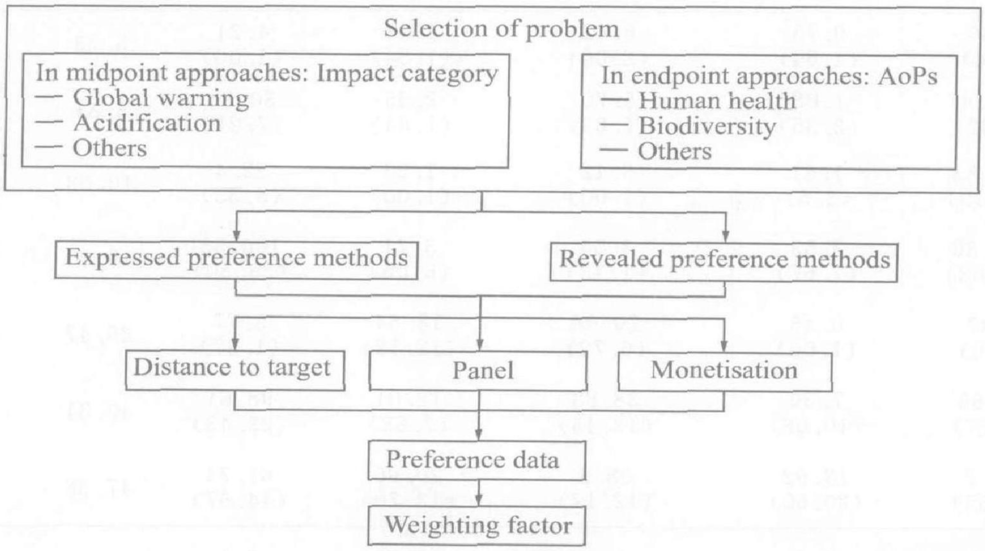


**Fig. 3** Modeling approaches for linear evaluation function

methods. The function approximation method is fit for approximating any linear and nonlinear function. Artificial neural network (ANN) is widely applied to function approximation, and has a self-regulation feature[14, 15]. Through collecting relevant data on some time horizon and geographical scope, and training ANN, the valuation model of nonlinear evaluation function can be gotten in the shape of ANN.

A theme-oriented method is developed as shown in Fig. 4. First a set of preference products is selected, which should be easy to be evaluated on total environmental impact. Second, preferences on different products are disclosed through choosing the expressed preference or the revealed preference methods. The relative priorities of the different products are weighted against each other in the quantitative step (distance to target, panel or monetization), which forms the preference product priority. The preference product priority is changed into the form of total impact score according to the specified rules, forms the total impact of preference product, $Y'$. Third, LCIA profiles on preference products through LCA tool are gotten and denoted to $X'$. $X'$ and $Y'$ make up of preference data $S = [X' \ Y']$. Finally the model of nonlinear evaluation function is obtained by taking preference data as studying samples and training ANN. The above method can denote a mathematical programming:

$$\begin{cases} Y' = f'(X', K(t, p)) \\ [X' \ Y'] = S(t, p) \end{cases} \quad (3)$$

where $S$ is preference data which reveal the value

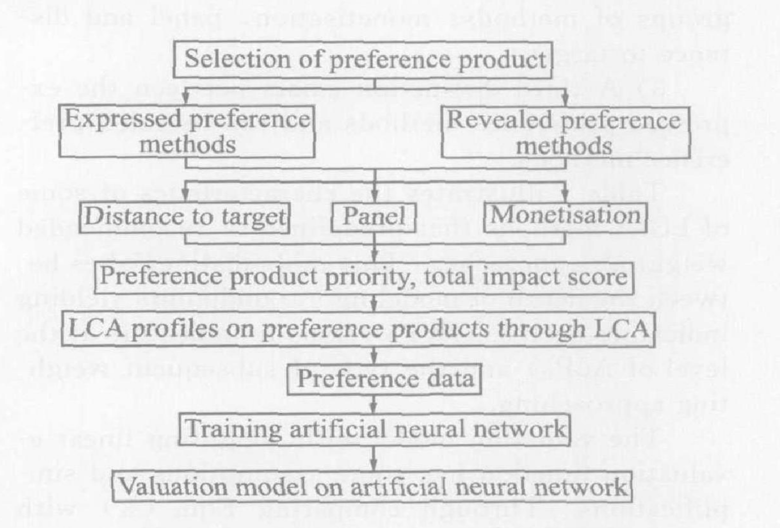


**Fig. 4** Modeling approaches for nonlinear evaluation function

choice of society or a group of stakeholders related to the time horizon $t$ and geographical scope $p$. $f'$ is ANN network function. $K(t, p)$ is ANN parameters, which are gained by solving mathematical programming, i. e. training ANN. Therefore the above modeling process is to acquire preference data and train ANN in nature. This method belongs to the bottom-up method from preference data to model.

## 3 EXPERIMENTAL

According to the modeling approach in Fig. 4, first the preference products are selected as listed in Table 2, which are very popular materials in the

**Table 2** Total environmental impact scores of preference products computed by weighting, preference and BP ANN methods

| Material product | Resource factor/ $(t \cdot t^{-1})$ | Energy factor (standard coal)/ $(t \cdot t^{-1})$ | Gas emission $(SiO_2)$/ $(kg \cdot t^{-1})$ | Liquid emission $(Cr^{+6})$/ $(kg \cdot t^{-1})$ | Land occupation index | Total environmental impact score | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Preference method | Weighting method | BP ANN method |
| Mn13 | 10.86 (1.04) | 0.75 (1.64) | 6.42 (2.06) | 2.33 (1.54) | 4.21 (1.00) | 5.73 | 5.73 | 5.73 |
| 1Cr18Ni9 | 176.14 (16.82) | 1.08 (2.35) | 5.70 (1.83) | 2.35 (1.54) | 30.34 (7.21) | 5.81 | 6.36 | 6.03 |
| W6Mo5Cr4V2 | 9487.83 (906.19) | 1.61 (3.5) | 3.12 (1.00) | 1.53 (1.00) | 22.4 (5.33) | 10.03 | 13.24 | 10.08 |
| Vanadium iron | 3790.36 (360.02) | 3.53 (7.67) | 3.54 (1.13) | 3.21 (6.06) | 106.53 (25.30) | 19.10 | 19.43 | 18.98 |
| GCr15 | 10.47 (1.00) | 0.46 (1.00) | 20.98 (6.72) | 18.54 (12.12) | 5.77 (1.37) | 25.47 | 20.69 | 25.42 |
| Titanium iron | 777.63 (74.27) | 7.39 (10.06) | 38.83 (12.45) | 12.01 (7.85) | 98.61 (23.43) | 40.31 | 34.63 | 40.24 |
| Tungsten iron | 928.2 (88.65) | 13.62 (29.60) | 38.3 (12.17) | 20.96 (13.70) | 61.74 (14.67) | 47.38 | 47.38 | 47.38 |
| Weighting factor | 0.01 | 0.2 | 1.3 | 1.7 | 0.1 | | | |

Normalized data in bracket

market through questionnaire. Then a panel method, which is based on the expressed preference, has been used in giving the relative significance among the different preference products in total environmental impact. The analytical hierarchy process(AHP) determines the relative significance factors of preference products, which are proportionally converted into preference score $Y'$ in the range of total impact score corresponding to the weighting method. Third, LCIA profiles $X'$ of the preference products through LCA tool are gotten in Table 2.

Depending on the number of impact categories in LCIA profile, a three-layer BP network is set up as shown in Fig. 5, which has a five-neuron input layer, five-neuron hidden layer and one-neuron output layer.

The Neural Network Toolbox 3.0 in MATLAB is used as computing tool. Taking preference data $S = [X' \ Y']$ as studying samples, Powell-Beale algorithm trains ANN. Transfer functions of all layers are the logsig function ( $y = (1 + e^{-x})^{-1}$ ). The mean squared error (MSE) performance function is selected as the performance function of the network. Goal is $1 \times 10^{-5}$. After the network is trained for 34 epochs. the performance is $9.340\,66 \times 10^{-6}$. The model of nonlinear evaluation function is obtained. Taking preference data $S = [X' \ Y']$ as simulating samples, the results are listed in Table 2.

## 4 RESULTS AND DISCUSSION

Fig. 6 shows the results of the above experiment. The orders of the preference product rank on total environmental impact scores by three methods are the same. The magnitudes of the preference product's scores are almost equal between the preference method and the BP ANN method, but are unequal except for Mn13, vanadium iron and tungsten iron between the weighting method and other methods. The curves of total environmental impact scores of the preference products have many differences between the weighting method and other methods, but no differences exist between the preference method and the BP ANN method. The curves of preference method and BP ANN method show an S shape relative to the curve of weighting method.

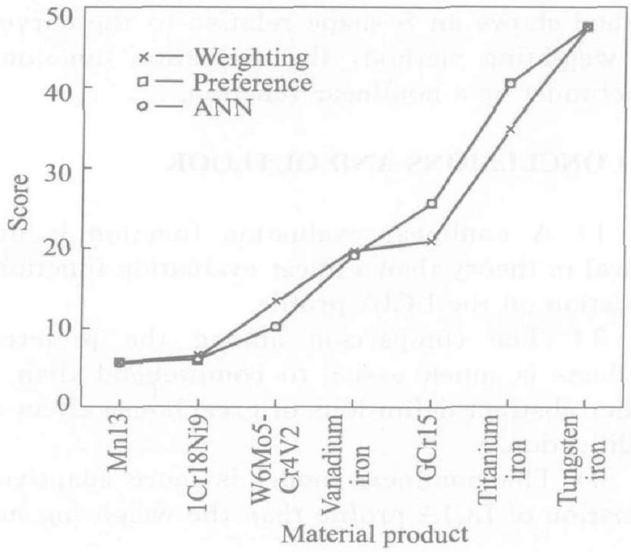


**Fig. 6** Line graph on total environmental impact scores computed by weighting, preference and BP ANN methods

In the three methods, the situation on uniform order of preference product rank indicates that the weighting method and the BP ANN method are identical with the views of panel in ordinal evaluation on preference products.

Little difference, on the magnitude of the preference product's total environmental impact scores between the BP ANN method and the preference method, shows that the BP ANN model has fully approximate the evaluation function. Much difference, on that between the weighting method and other methods except for Mn13, vanadium iron and tungsten iron, demonstrates that a linear evaluation function differs from a nonlinear function in

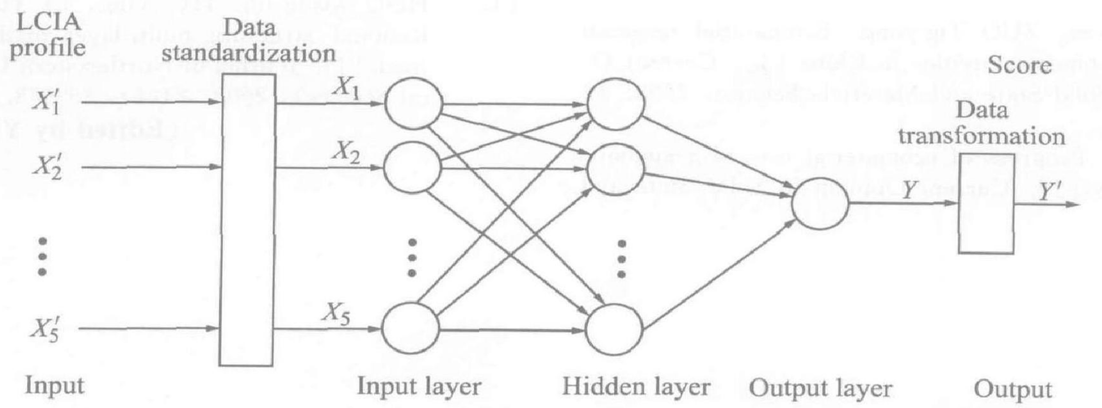


**Fig. 5** Structure of BP neural network evaluation model

the result. Because preference scores are proportionally converted from the relative significance factors of preference products in the range of total impact score corresponding to the weighting method, the same total impact scores of Mn13, vanadium iron and tungsten iron in three methods, turn up.

On the condition that the curve of preference method shows an S shape relative to the curve of the weighting method, the evaluation function of panel must be a nonlinear function.

## 5 CONCLUSIONS AND OUTLOOK

1) A nonlinear evaluation function is more logical in theory than a linear evaluation function in valuation on the LCIA profile.

2) The comparison among the preference products is much easier to comprehend than the rather abstract definitions of greenhouse effect and acidification.

3) The nonlinear model is more adaptive in valuation of LCIA profile than the weighting model.

4) The modeling approaches for the nonlinear evaluation function are applicable in practice. The BP ANN model can approximate the evaluation function of society or a group of stakeholders.

5) The selection of preference products is not only the key issue on the modeling approaches for the nonlinear evaluation function model but also the bottleneck in implementing the nonlinear evaluation function model.

6) The identical preference data are the foundation for comparisons among different nonlinear evaluation function models.

7) The uniform methods on educing preference data and the database of preference products are the condition of the application for the nonlinear evaluation function model, and are the key topic in future LCA research field.

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**(Edited by YUAN Sai-qian)**