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# The application of life cycle assessment to process optimisation

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**Abstract**

One of the main potential uses of life cycle assessment (LCA) in environmental management is for identifying options for environmental improvements of a system in which complete supply chains are considered. The main problem, however, lies in finding the optimum improvement strategies and choosing the best alternative in a decision environment with multiple, and often conflicting, objectives. To aid the decision-making process, this paper proposes the use of multiobjective optimisation (MO), whereby the system is simultaneously optimised on a number of environmental objective functions, defined and quantified through the LCA approach. This results in a Pareto or noninferior surface, with a range of environmental optima, from which the best compromise solution for improving the environmental performance of the system can be chosen. However, system improvements cannot be based solely on environmental considerations and other factors, including socio-economic, must be considered in parallel. This paper also shows that MO coupled with LCA provides a powerful tool for balancing environmental and economic performance, thus enabling the choice of best practicable environmental option (BPEO) and best available technique not entailing excessive cost (BATNEEC). The value of this approach in environmental system analysis lies in providing a set of alternative optimal options for system improvements rather than a single prescriptive solution, which may be optimal but not necessarily appropriate for a particular situation. A decision–aid tool–optimum LCA performance (OLCAP)–has been developed for these purposes. OLCAP is tested and demonstrated by application to a case study of an existing mineral-processing system producing boron products. It is shown that LCA can successfully be combined with optimisation techniques to satisfy both economic and environmental criteria for more sustainable performance of the product system over the whole life cycle. 

*Keywords:* BPEO; BATNEEC; Boron; LCA; Multicriteria decision analysis; Multiobjective optimisation; System analysis

## 1. Introduction

Life cycle assessment (LCA) represents an application of system analysis to problems of environmental management. Its embodiment of systems thinking is, at root, no different from the approaches normally used in selecting and designing processes. Yet, despite the fact that, compared to the technical effort required in designing and optimising a process, incorporation of LCA represents only slight incremental effort, the adoption of life cycle approaches by the process industries has been relatively slow. However, recent literature suggests that this attitude is changing and that LCA is gaining wider acceptance in many industrial sectors (Lee, O'Callaghan & Allen, 1995; Baumann, 1996; Curran, 1997; Wright, Allen, Clift & Sas, 1997; Clift, 1998), particularly in the process industries (Franke, Kluppel, Kirchert & Olschewski, 1995; Dobson, 1996; Ophus & Digernes, 1996; Yoda, 1996; Aresta & Tommasi, 1997; Bretz & Fankhauser, 1997). Some other examples of using LCA in corporate decision making include energy (Audus, 1996; Matsuhashi, Hikita & Ishitani, 1996; Tahara, Kojima & Inaba, 1997; Dones & Frischknecht, 1998), nuclear (Griffin, 1997; Solberg-Johansen, 1998), water (Roeleveld, Klapwijk, Eggels, Rulkens & van Starkenburg, 1997; Dennison, Azapagic, Clift & Colbourne, 1998), electronic (de Langhe, Criel & Ceuterick, 1998; Miyamoto & Tekawa, 1998) and other industries.

There are reasons in addition to disciplinary compatibility to expect the use of LCA in the process industries to expand rapidly. In the European Union, the

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Directive on Integrated Pollution Prevention and Control (IPPC) (EU, 1996) represents a significant shift in the basis of environmental regulation (Emmott & Haigh, 1996; Nicholas, 1998). IPPC incorporates the principle of integrated pollution control (IPC), introduced in the UK by the 1990 Environmental Protection Act to regulate processes which give rise to different emissions, particularly into different environmental media. However, IPPC goes beyond IPC to embrace the life cycle both of the process (including construction and decommissioning) and of materials and energy (including resource usage and waste) (Nicholas, 1998; RCEP, 1998). IPPC is planned to be implemented by EU member states by October 1999. If applied strictly, IPPC will mandate the use of LCA in identifying the best practicable environmental option (BPEO).

Although the use of LCA has traditionally been oriented towards improving the environmental performance of products (Fava et al., 1991; Tillman, Baumann, Eriksson & Rydberg, 1991; Boustead, 1992; Heijungs et al., 1992; Pedersen & Christiansen, 1992; Fava, Consoli, Dennison, Dickson, Mohin & Vigon, 1993; Guinée, Heijungs, Udo de Haes & Huppes, 1993; Keoleian, 1993; Pedersen, 1993; Vigon et al., 1993; Weidema & Krüger, 1993; Azapagic, 1997; Fleischer & Schmidt, 1997), several authors have recently demonstrated the previously unexplored potential of LCA as a tool for process selection and BPEO (Golonka & Brennan, 1996; Rice, 1997; Clift & Azapagic, 1998; Yates, 1998), process design (Pesso, 1993; Stefanis, Livingston & Pistikopoulos, 1995; Kniel, Delmarco & Petrie, 1996; Pistikopoulos, Stefanis & Livingston, 1996; Stewart & Petrie, 1996; Stefanis, Livingston & Pistikopoulos, 1997) and optimisation (Azapagic & Clift, 1995a,b; Azapagic, 1996; Azapagic & Clift, 1997; Azapagic & Clift, 1999a,b; Azapagic, Clift & Lamb, 1996a,b). A more detailed exposition of the application of LCA to process selection and design is given elsewhere (Azapagic, 1999). Here, the focus is on the use of LCA for process optimisation. The aim is to show how the kind of analysis adapted from operations research and welfare economics can be combined with system analysis in the context of LCA to provide a powerful decision-making tool for more sustainable performance of process industries. The potential of this approach is illustrated by the example of an industrial case study of a mineral-processing system.

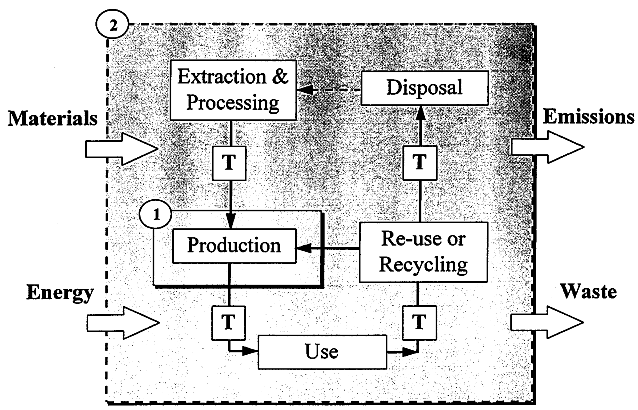


Fig. 1. Stages in the life cycle of a product (system boundary: 1, process analysis; 2, life cycle assessment; T, transport.

## 2. Life cycle assessment

LCA is a quantitative environmental performance tool, essentially based around mass and energy balances but applied to a complete economic system rather than a single process. In terms of the system boundary definition, this represents an extension to the conventional system analysis, in which the system boundary is drawn around the process of interest only. Fig. 1 illustrates the way in which LCA can complement conventional process analysis. While chemical or process engineering is normally concerned with the operations within system boundary 1, LCA considers the whole material and energy supply chains, so that the system of concern becomes everything within system boundary 2. The material and energy flows that enter, exist in or leave the system include material and energy resources and emissions to air, water and land. These are often referred to as environmental burdens and they arise from activities encompassing extraction and refining of raw materials, transportation, production, use and waste disposal of a product or process. The potential effects of the burdens on the environment, i.e. environmental impacts, normally include global warming potential (GWP), acidification, ozone depletion (OD), eutrophication etc. (see Appendix A).

The LCA methodology is still under development. At present, the methodological framework comprises four phases (ISO, 1997):

1. Goal and scope definition: selecting the system boundaries (see Fig. 1) to ensure that no relevant parts of the system are omitted;
2. Inventory analysis: performing mass and energy balances to quantify all the material and energy inputs, wastes and emissions from the system, i.e. the environmental burdens;
3. Impact assessment: aggregating the environmental burdens quantified in the Inventory Analysis into a limited set of recognised environmental impact categories, such as global warming, acidification, Ozone Depletion, etc.;
4. Interpretation: using the results to reduce the environmental impacts associated with the product or process.

Applied to process analysis, LCA can have two main objectives. The first is to quantify and evaluate the

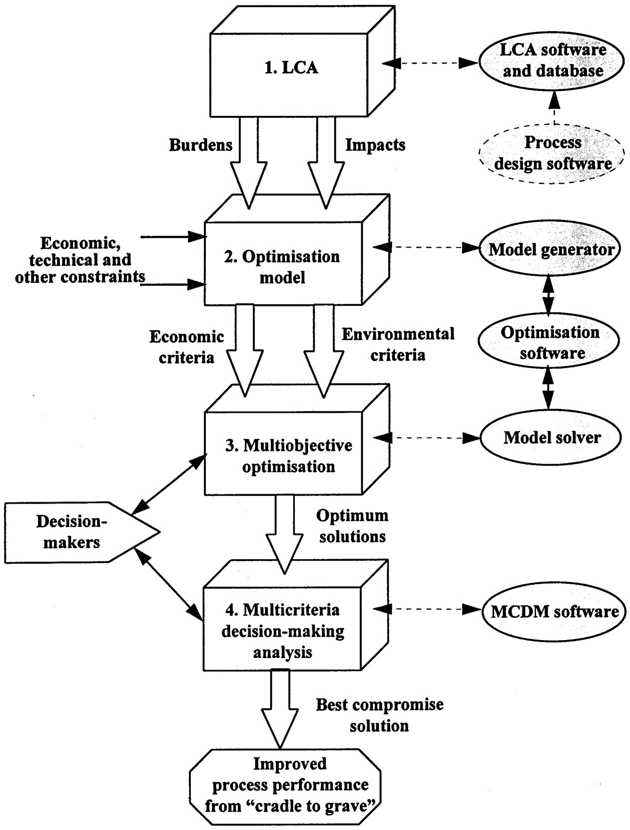


Fig. 2. The methodological framework for Optimum LCA Performance (OLCAP).

environmental performance of a process from 'cradle to grave' and so help decision-makers to choose between alternative processes and processing routes. In this context, LCA provides a useful tool for identifying BPEO. Another objective of LCA is to help identify options for improving the environmental performance of a system. This objective can be of particular importance to process designers and engineers, because it can inform them on how to modify a system to decrease its environmental impacts. To assist in identification of the optimal options for improved system operation from 'cradle to grave', LCA can be coupled with optimisation techniques as discussed in the next section.

## 3. LCA and system optimisation

To describe and predict the behaviour of complex industrial systems, it is often necessary to use elaborate mathematical modelling. In the same manner, identification of the optimum operating conditions that will ensure improved process performance usually renders the use of an optimisation technique essential. Historically, system optimisation in chemical and process engineering applications has focused on maximising the economic performance, subject to the certain constraints in the system. Over the past decade, optimisation of environmental performance has started to be incorporated into system optimisation, alongside traditional economic criteria. These approaches have mainly been focused on various waste minimisation techniques (El-Halwagi & Manousiouthakis, 1990; Ciric & Jia, 1994; Wang & Smith, 1994; Linninger, Stephanopoulos, Ali, Han & Stephanopoulos, 1995). The attempts to incorporate environmental considerations into the design and optimisation procedures represent the beginning of the paradigm shift in the process industry traditionally oriented towards the economic performance of the process. However, the main disadvantage of these approaches is that they concentrate on the emissions from the plant only, without considering other stages in the life cycle. Thus, it is possible for waste minimisation approaches to reduce the emissions from the plant but to increase the burdens elsewhere in the life cycle, so that overall environmental impacts are increased (e.g. RCEP, 1998).

Consequently, the need to integrate life cycle thinking into process design and optimisation procedures has been recognised by a number of researchers (Azapagic, 1996; Pistikopoulos et al., 1996; Stewart & Petrie, 1996). One such approach that establishes a link between the environmental and economic performance of a process from 'cradle to grave' has been developed by Azapagic and co-workers (Azapagic & Clift, 1995a,b; Azapagic, 1996; Azapagic et al., 1996a,b; Azapagic, 1997; Bell, Azapagic, Faraday & Schulz, 1998; Azapagic, 1999; Azapagic & Clift, 1999a,b). This method, here referred to as 'Optimum LCA Performance', is presented and discussed in the following sections.

### 3.1. Optimum LCA performance (OLCAP)

A general framework for the optimun LCA performance (OLCAP) methodology comprises four steps:
1. Completion of the LCA study;
2. Formulation of the optimisation problem in the context of LCA;
3. Multiobjective optimisation (MO) on environmental and economic criteria;
4. Multicriteria decision analysis and choice of the best compromise solution.

The diagramatic representation of the OLCAP approach is given in Fig. 2. The first step in this procedure involves carrying out an LCA study of the system, by following the ISO (1997) methodology. As indicated in Fig. 2, appropriate LCA software, e.g. PEMS (PIRA International, 1998) or TEAM (Ecobalance, 1998), can be used to carry out material and energy balances and to quantify the burdens and impacts along the life cycle. The material and energy balances for the process itself (boundary 1 in Fig. 1) can also be carried out within existing design operation software and these data can then be fed into the LCA software. The data for the other parts of the system (boundary 2 in Fig. 1) can be sourced from a database which is normally an integral part of the LCA software. A more detailed exposition of the LCA methodology is given elsewhere (ISO, 1997) and is not discussed further here. Instead, the focus of this paper is on steps 2–4 of the OLCAP procedure.

The environmental burdens and impacts quantified in step 1, represent an input into the optimisation model, which is formulated in step 2. In addition to environmental criteria, the model includes economic, technical, legislative and other constraints within which the system must operate. In step 3, the system is optimised on environmental and socio–economic objectives of interest to the decision-makers, to yield a number of optimum solutions. A suitable optimisation technique and software must be used to generate and solve the optimisation problem. A more detailed account of these two steps of OLCAP is given in Sections 3.1.1 and 3.1.2. Finally, step 4 enables the decision-makers to choose the best compromise alternative from a range of optimum solutions. Any of the multi-criteria decision making techniques, some of which have been formalised in various software packages, can be used to facilitate the decision-making process. This is discussed in Section 3.1.3.

*3.1.1. Step 2: Formulation of the optimisation problem*

Because of the nature of LCA, where there are a number of distinct environmental burdens or impacts to be considered, optimisation problems in this context are inevitably multiobjective. Thus, conventional single-optimisation problems, involving one (usually economic) function are transformed into multiobjective problems, to include the environmental objectives. A Multi-Objective (MO) problem in the context of LCA can take the following form:

$$\min \boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) = [f_1\, f_2 \ldots f_p] \tag{1}$$

s.t.

$$h(\boldsymbol{x},\ \boldsymbol{y}) = 0$$

$$\boldsymbol{g}(\boldsymbol{x},\ \boldsymbol{y}) \le 0$$

$$\boldsymbol{x} \in \boldsymbol{X} \subseteq R^n$$

$$\boldsymbol{y} \in \boldsymbol{Y} \subseteq Z^q \tag{2}$$

where $\boldsymbol{f}$ is a vector of economic and environmental objective functions; $h(\boldsymbol{x},\boldsymbol{y}) = 0$ and $g(\boldsymbol{x},\boldsymbol{y}) \le 0$ are equality and inequality constraints, and $x$ and $y$ are the vectors of continuous and integer (discrete) variables, respectively. For instance, the equality constraints may be defined by energy and material balances; the inequality constraints may describe material availabilities, heat requirements, capacities etc. A vector of $n$ continuous variables may include material and energy flows, pressures, compositions, sizes of units etc., while a vector of $q$ integer variables may be represented by alternative materials or processing routes in the system. If the integer set $Z$ is empty and the constraints and objective functions are linear, then Eqs. (1) and (2) represent a Linear Programming (LP) problem; if the set of integer variables is nonempty and nonlinear terms exist in the objective functions and constraints, Eqs. (1) and (2) is a Mixed-Integer Nonlinear Programming (MINLP) problem. Mixed Integer Linear Programming (MILP) problems incorporate integer and linear variables only.

An economic objective typically involves a cost or profit function as defined by:

$$\min\ F = c^T \boldsymbol{y} + f(\boldsymbol{x}) \tag{3}$$

where $c$ is a vector of cost or profit coefficients for integer variables and $f(x)$ is a linear or nonlinear function described by continuous variables. The environmental objectives in this context represent the burdens $B_j$ or impacts $E_k$:

$$\min\ B_j = \sum_{n=1}^{N} b_{j,n} x_n \tag{4}$$

$$\min\ E_k = \sum_{j=1}^{J} e_{k,j} B_j \tag{5}$$

where $b_{j,n}$ represents emission coefficients associated with continuous variables $x_n$. In Eq. (5), $e_{k,j}$ represents the relative contribution of burden $B_j$ to impact $E_k$, as defined by the 'problem oriented' approach to Impact Assessment (Heijungs et al., 1992). In this approach, for example, GWP factors, $e_{k,j}$, for different greenhouse gases are expressed relative to the GWP of $CO_2$, which is therefore defined to be unity. If a different impact assessment approach is used, then Eq. (5) may be redefined accordingly. Note that at present the LCA approach assumes that environmental burdens and impacts functions are linear, i.e. they are directly proportional to the output of functional unit(s) and there are no synergistic or antagonistic effects.

Depending on the characteristics of the system, the problem (1)-(2) can be formulated as LP, MILP or MINLP. The theory for solving such problems is well established (Dantzig, 1963; Floudas, 1995) and a number of commercial software packages are available for large scale problems, of which XPRESS-MP (Dash Associates, 1993) and GAMS (1998) are often used in process and chemical engineering applications.

*3.1.2. Step 3: Multiobjective optimisation*

The system is then optimised simultaneously on a number of environmental and economic objective functions to locate the multidimensional noninferior or Pareto surface which maps the optimal solutions. By definition, the noninferior state is achieved if no objective can be improved without worsening the value of some other objective. If examined more closely, it is obvious that this definition is identical to the Pareto optimality concept (Pareto, 1971) which marked the beginning of new welfare economics and has been influencing decision-making process ever since. Welfare economics, although historically divided into several periods, focuses on the general problem: how should resources be allocated for the production and consumption of goods so as to maximise social welfare? Although this predates the sustainability concept of today, the question asked remains the same; what changed over time, however, was the definition of 'social welfare' and the approaches to solving this problem.

The choice of environmental objectives for optimisation depends on the Goal and Scope of the study. Thus, optimisation can be performed either at the inventory or impact assessment levels, in which case the environmental objectives are defined as either burdens or impacts, respectively (Azapagic & Clift, 1999a,b). In optimisation, local and global system improvements are found by first moving the system to conditions on the Pareto surface, and then 'surfing' on it. As already pointed out, all objectives on the surface are optimal in the Pareto sense and trade-offs between the objectives are necessary to identify the best compromise solution. For example, if the system is optimised simultaneously on two objectives-one economic and one environmental-the resulting Pareto optimum does not necessarily mean that these functions are at their respective optima achieved when the system is optimised on each of them separately (see Fig. 3). The Pareto optimum, however, does mean that the set of best possible options has been identified for a system in which both objectives should be improved. This can be of particular relevance to the chemical and process industries, which face problems of having to keep total costs down while at the same time complying with ever tightening environmental legislation and other socio–economic requirements.

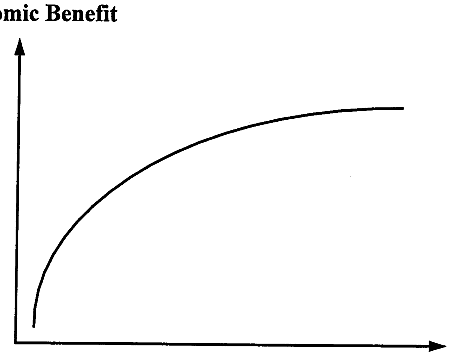


Fig. 3. Noninferior curve obtained in multiobjective optimisation.

One possible approach to optimisation in the context of LCA would be to aggregate environmental and economic objectives into a single function by attaching weights to indicate their significance, so that the problem reduces to single objective optimisation. However, one of the main advantages of MO is that it does not require a priori articulation of preferences, so that the whole noninferior set of solutions can be explored. The emphasis is then on the range of choices from the set of noninferior solutions, rather than explicit definition of preferences before analysing all the trade-offs among objectives. Trade-offs between the noninferior solutions show explicitly what can be gained and what lost by choosing each alternative. Where there are multiple decision-makers with conflicting interests, this technique can help to resolve disputes by generating different alternative solutions. Decision makers who understand the trade-offs and the alternatives are more likely to understand the interests of other parties and, therefore, to compromise. Although the evaluation of trade-offs between the objectives to choose the best compromise solution will still imply certain preferences and value judgements, at least the choice will be made from all possible noninferior solutions.

Furthermore, by being able to trade-off incommensurable objectives, e.g. environmental impacts and economic requirements, this approach avoids the well known problems encountered, for instance, in cost–benefit analysis (Pearce, Markandya & Barbier, 1989), i.e. reducing individual preferences to a market value or trying to express quality of the environment in financial terms. Cost-benefit analysis (CBA) is probably the tool most exploited by neoclassical[1] economists in the decision-making process, particularly in the area of public investments. CBA is based on the idea of maximum net gain: it reduces aggregate social welfare to the monetary unit of net economic benefit. So for example, given several alternatives, the CBA approach would favour the one in which the difference between monetarised benefits and costs is the greatest. More recently, CBA has been applied in environmental decision-making. The most widely applied, and even more criticised, technique is 'contingent valuation' (CV). In CV, participants are asked to say how much they would be prepared to pay to protect an environmental asset ('willingness to pay') or how much they would be willing to accept for loss of that asset ('willingness to accept') (Pearce et al., 1989).

Limitations and difficulties of this approach have been recognised both by its proponents and critics. The latter (Jacobs, 1991; Adams, 1993; Clift, 1994) have

[1] The common feature of neoclassical economics is that it reduces many broad categories of market phenomena to considerations of individual choice, subject to the constraints of technical knowledge, social practice, and scarcity of resources.

pointed out that CBA has serious difficulties in dealing with problems of intergenerational equity and sustainability and in valuing the natural environment. They have also shown that CV is based on individual preferences which may not provide firm foundations for environmental decision-making. Furthermore, the results of the analysis largely depend on the way the questions are asked, and whether the participants are familiar with the asset in question. It is more likely that people who know nothing about the asset will place a nil value on it, although the life of others may depend on it. Also, the values that people place on things strongly depend on self-interest, which does not help resolving conflict between opposing parties.

To summarise, CBA and related economic approaches to decision-making face at least three problems: the measurement of individual preferences, the interpersonal comparison of these preferences, and their aggregation into a social preference function. All these operations imply ethical value judgements, probably the least acceptable being the expression of individual preferences and values in monetary terms. Indeed, the controversial techniques of pricing nonmonetary objectives, such as environmental quality, and aggregating non-commensurables into a single 'utility' function provide a strong motivation for using multiobjective analysis in environmental decision-making.

Furthermore, these approaches cannot provide information for decision-making on a 'local' level: for example, they cannot advise engineers on how to modify a process in order to improve its environmental performance. MO, on the other hand, does exactly this: it can optimise the operation of a system with environmental, technical, economic and other aspects taken into account. If applied in the LCA context, it can optimise the whole life cycle of a process or product and so provide a more effective approach to environmental management of a system.

#### *3.1.3. Step 4: Choice of the best compromise solution*

The noninferior solutions, obtained in step 3, provide input into the decision-making process in step 4 of OLCAP. To choose the best compromise solution out of a number of optimum alternatives, some articulation of preferences is necessary. However, these preferences are at least articulated by decision-makers in the post-optimal analysis of all noninferior solutions and their trade-offs, as distinct from expressing preferences and aggregating the objectives prior to identifying all noninferior solutions. One of the possible ways to choose the 'best' solution is to consider a graphical representation of the noninferior set and then choose the best compromise solution on the basis of the trade-offs. However, this approach is limited to two or three objective functions at most; beyond that, graphical representation becomes too complex. Alternatively, the noninferior values of the objectives may be expressed in terms of the difference from the value at their individual optima. If all objectives are considered to be of the same importance, than the best compromise solution might be that which equalises the percentage by which all objectives differ from their optimum values. However, should any of the objectives be considered more important than the others, then other methods that allow ordering and quantifying of preferences, usually referred to as multicriteria decision-making (MCDM) techniques, can be used to identify the best compromise solution.

MCDM techniques provide a structured approach to a decision making process. They enable systematic analysis and modelling of preferences with the aim of providing help and guidance to decision-makers in identifying their most desired solution. The major advantages of these techniques are that they are transparent, non-ambiguous and easy to use by non-experts. Furthermore, the quantitative nature of these numerical methods may particularly be appealing to quantitatively oriented managers and engineers.

A number of methods for ordering and quantifying preferences have been developed over the past years and some of them include simple additive weighting, weighted product, median ranking method (Hwang, Paidy & Yoon, 1980), the analytic hierarchy process (Saaty, 1980), multiattribute utility theory (Keeney & Raiffa, 1976), simple multi-attribute rating technique (von Winterfeldt & Edwards, 1987). Extensive reviews of MCDM techniques can be found in Stewart (1992) and Yoon and Ching (1995). User friendly software with various MCDM methods to aid the decision making process are also available (Hämäläinen & Lauri, 1995).

The choice of a suitable MCDM technique will depend on a given decision-making situation and the sophistication of the decision-makers. Most of these techniques are based on a definition of a multiattribute or utility function, which associates a number with each alternative to reflect the importance of the attribute in the opinion of the decision-maker, so that all alternatives may be ordered. For example, if there are five noninferior solutions identified in step 3, each with different values for the three objectives (attributes), i.e. GWP OD and costs, the decision-makers are then asked to articulate their preferences for each of the attributes on scale 1–10. The mathematical analysis or ordering of the preferences, for instance by a pair-wise comparison of attributes (Saaty, 1980), returns the best compromise solution for this particular example. It is important to note that the attributes and the preferences are always identified on a case by case basis within a bounded decision space, and that they only apply in that particular decision-making context. This avoids the criticism often voiced, in both LCA and

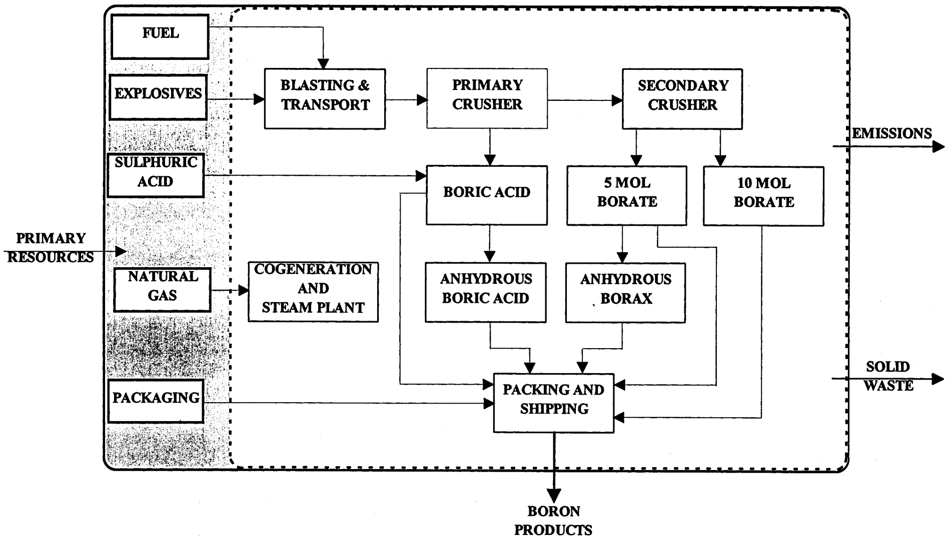


Fig. 4. Simplified LCA diagram of the boron system.

CBA, of trying to use general weights or costs to indicate the importance of distinct criteria in different decision-making situations.

The OLCAP procedure is now illustrated on an industrial case study of the boron products system.

## 4. Application of OLCAP — a case study

The process chosen for illustration of the OLCAP approach is an existing mining and mineral processing operation, producing several boron products from two mineral ores. The environmental and economic performance of the life cycle of the system can be optimised, subject to market constraints, by varying the product spectrum and some of the on-site operations, including generation of electrical energy and steam.

### *4.1. Step 1: LCA of the boron system*

A simplified LCA diagram of the boron system, from extraction of primary resources through mining and processing, is shown in Fig. 4. Two boron minerals, borax ($Na_2B_4O_7 \cdot 10H_2O$) and kernite ($Na_2B_4O_7 \cdot 4H_2O$), are extracted in the mine, crushed and transported to the adjacent plant. Five products are produced on site. 5 mol ($Na_2B_4O_7 \cdot 4.67H_2O$) and 10 mol ($Na_2B_4O_7 \cdot 10H_2O$) borates are produced by dissolving borax and kernite in water. Na-borates are then separated from insolubles, crystallised and dried to produce powder products. Boric acid ($H_3BO_3$) is made by reacting kernite ore with sulphuric acid and by drying the crystallised borates. Anhydrous borax ($Na_2B_4O_7$) and anhydrous boric acid ($B_2O_3$) are produced in high-temperature furnaces from 5 mol borate and BA, respectively. All products are then either packed or shipped in bulk. Electric energy and the steam for the system are provided by the on-site natural gas cogeneration facility, which meets most of the electricity and steam demand. If necessary, additional steam is provided by the steam plant which is also fired by natural gas. The waste water from the refinery is discharged into contained ponds. All activities, from extraction of raw materials to the production and packing of the boron products, are included in the system. However, the use and disposal phases of the products are not considered in this study, making this a ‘cradle to gate’ study. The functional unit, defined as the ‘operation of the system for 1 year’, is related to the annual output of the boron products.

One of the aims of this LCA study is to identify the ‘hot spots’ in the system and evaluate possibilities for improving its environmental performance. Hence, the first step in the OLCAP procedure includes identification of the most significant burdens and impacts and subsystems that contribute most to these impacts. The efforts to improve the performance are then aimed at these subsystems to achieve the maximum decrease in the total impacts on the environment. The results of the inventory and impact assessment stages (Figs. 5 and 6) show the most significant burdens and impacts and reveal that several subsystems contribute to most of these burdens and impacts. They include mining, 5 and 10 mol plant, steam production, boric acid plant, and packing and shipping. For instance, in the inventory stage, it has been found that 5 and 10 mol plant and steam production contribute 80% to nuclear electricity[2] and gas consumption and to most of the emissions to air. The boric acid plant accounts for around 60% of

[2] Nuclear electricity and coal are mainly used in the life cycles of gas and sulphuric acid, respectively.

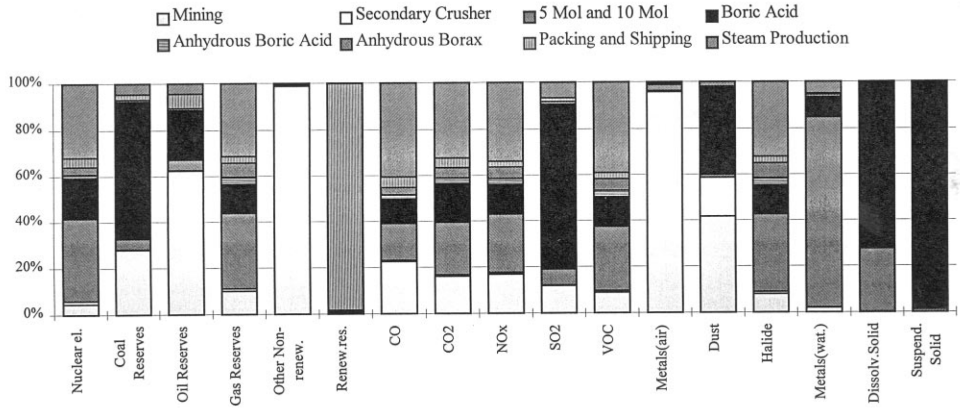


Fig. 5. The results of inventory analysis: selected burdens (expressed as a percentage of total burden from the system).

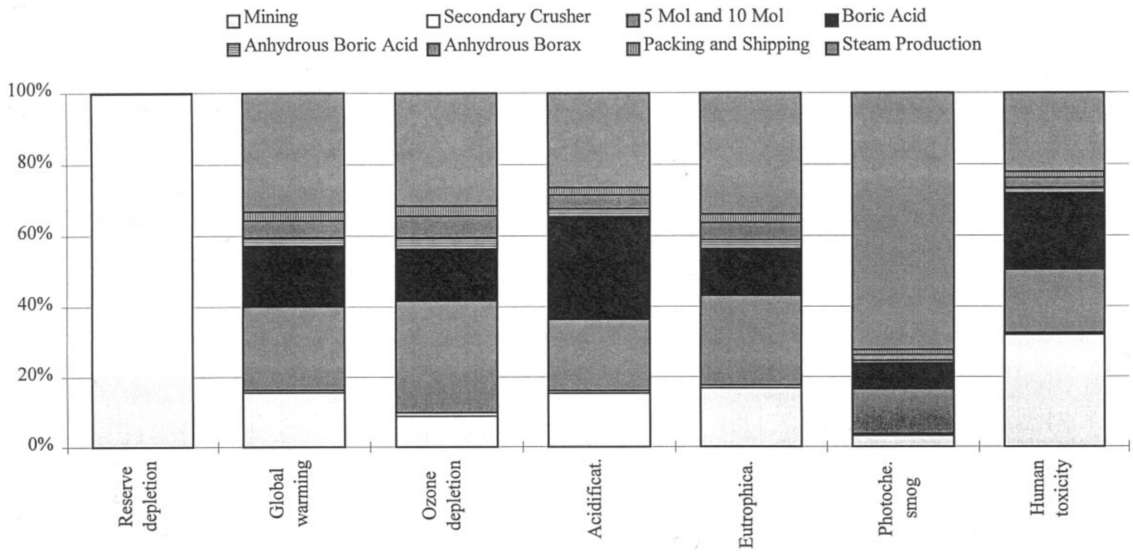


Fig. 6. The results of Impact Assessment (expressed as a percentage of total impact from the system).

the coal usage, 70% of $SO_2$ emissions and most of the total suspended and dissolved solids in water. Packing and shipping are the main users of renewable resources (paper bags), while oil reserves and other non-renewables (i.e. borax and kernite ore) are used in the mining operations. Furthermore, the mining activities are the main source of emissions of metals and dust to air.

The corresponding contributions of these processes to the impacts are found in the impact assessment phase (see Fig. 6). The subsystems with the greatest impacts are the first to be considered for targeted system improvements. The analysis of the results indicates there are a number of possibilities for bringing about environmental improvements to these subsystems; to illustrate the potential of MO in LCA, some of the alternatives are considered here. In the mining subsystem, a significant part of the burdens and impacts is attributed to transport within the mine. Therefore, one of the options to reduce the burdens from this subsystem is to consider conveyors as an alternative means for transport of the ore. Another possibility considered for reducing the burdens from the mining system is to identify the optimum kernite to borax ratio for production of 5 and 10 mol borates, subject to the process constraints.

Further analysis of the disaggregated LCA results shows that the burdens from 5 and 10 mol production are mainly energy related, and a significant proportion is attributed to the dryers. There are a number of possibilities to reduce the burdens from this area; however, in this work only two of them are considered. Since 5 mol can be produced in both rotary and fluid bed dryers, the most immediate option is to optimise their use so that only dryers with the least environmental impacts in the system are in operation. This option is also easy to implement because it does not require any major changes in the process. The second option for improvements in the primary process concerns plans to install low-$NO_x$ burners in the dryers.

Furthermore, steam production, which includes the steam cogeneration and steam plant subsystems, has been identified as one of the significant contributors to the burdens from the boron system. Since the steam can be produced in both cogeneration and steam plants, one of the possibilities to reduce the burdens is to identify the best options for generating steam. The final improvement option taken into consideration here is related to packing and shipping. Since most of the burdens from this subsystem arise from the life cycle of different packaging, the system is optimised to identify the type of packaging that causes the lowest environmental burdens.

### 4.2. Step 2: Optimisation model of the boron system

Following the OLCAP procedure, the next step is to formulate the boron system as an optimisation problem in the context of LCA. The model incorporates the alternative operations and technologies for environmental improvements identified in step 1. In this case, the system model is formulated as a linear programming problem and includes the following constraints:

(i) Mass balance constraints:

$$\sum_{n=1}^{N} a_{i,n}^{(\kappa)} m_n^{(\kappa)} = 0 \quad \forall n \tag{6}$$

(ii) Market demand constraints:

$$P_l \le D_l \quad \forall l \tag{7}$$

(iii) Primary and raw material availability:

$$R_\gamma^{(\kappa)} \le S_\gamma^{(\kappa)} \tag{8}$$

(iv) Productive capacity constraints:

$$\sum_{n=1}^{N} m_n^{(\kappa)} \le C_u^{(\kappa)} \quad \forall u \tag{9}$$

(v) Heat requirements:

$$\sum_{n=1}^{N} H_n^{(\kappa)} \le Q_z^{(\kappa)} \quad \forall z \tag{10}$$

The optimisation variables in this case study describe material and energy flows only; however, depending on the goal of the study, they could also include operating pressures, stream compositions, unit sizes etc. The mass balance constraints include mass flows $m_n$ in each subsystem $\kappa$ from ‘cradle to gate’. Production of each product $P_l$ is limited by the market demand $D_l$. Since the discussion in this paper is related to the functional unit defined as the operation of the system for 1 year, the product demand $D_l$ is taken to be equal to the total output of each product for 1 year. Primary and raw materials consumption $R_\gamma$ is constrained by their supply $S_\gamma$; mass flows $m_n$ in each subsystem are subject to the capacity limit $C_u$ of a process or operation unit and the heat production $H_n$ is determined by the heat demand $Q_z$. The alternative operations and technologies are defined by Eqs. (7), (9) and (10) and are optimised for the material and energy flows.

The objective functions are defined by the environmental burdens or impacts; the economic objectives are taken to be total annual production and life cycle operating costs, respectively:

(vi) Minimise burdens or impacts:

$$\min B_j = \sum_{n=1}^{N} b_{j,n}^{(\kappa)} m_n^{(\kappa)} \tag{11}$$

$$\min E_k = \sum_{j=1}^{J} e_{k,j} B_j \tag{12}$$

(vii) Maximise production:

$$\max P = \sum_{L=1}^{L} P_l \tag{13}$$

(viii) Minimise life cycle operating costs:

$$\min C = \sum_{n=1}^{N} c_n^{(\kappa)} m_n^{(\kappa)} \tag{14}$$

The model consists of around 1500 constraints and 3500 variables. The total number of environmental objectives at the inventory level (burdens) is 17, as defined by Eq. (11) and shown in Fig. 5. For the analysis at the impact assessment level, the number of objective functions (impacts) of interest is seven; they are given by Eq. (12) and listed in Fig. 6. Finally, there are two economic objectives, defined by Eqs. (13) and (14). A large scale LP software XPRESSMP (Dash Associates, 1993) has been used to formulate and solve this optimisation problem. MO was tackled by the constraint method (Cohon, 1978), in which a series of single-objective optimisations is performed to identify the lower and upper feasible bounds for each objective. All objectives but one are then converted into constraints and optimisations repeated with the parameters of the objectives-constraints ranging from the lower to upper bounds to generate a Pareto surface.

### 4.3. Step 3: Multiobjective environmental optimisation

MO on environmental and economic performance criteria is the next step in the OLCAP methodology. Although the objective functions have been defined in step 2, the choice of the objectives for optimisation is deferred to step 3. The objectives for optimisation are chosen by the decision-makers, depending on the goal of the study. The goal of this study was to identify the optimum options for improvements in both environmental and economic performance. However, to illustrate the approach, the system is initially optimised on the environmental objective functions, first at the inventory then the impact assessment level, to identify the BPEO in the system; these results are compared with

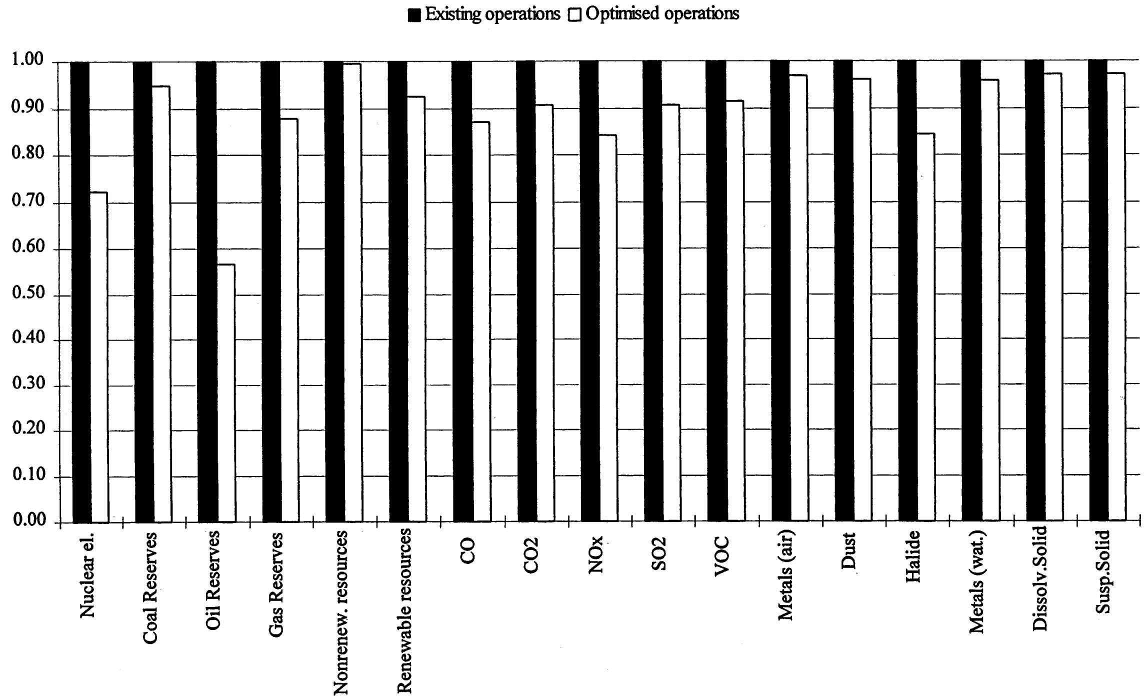


Fig. 7. Single-objective optimisation on environmental burdens.

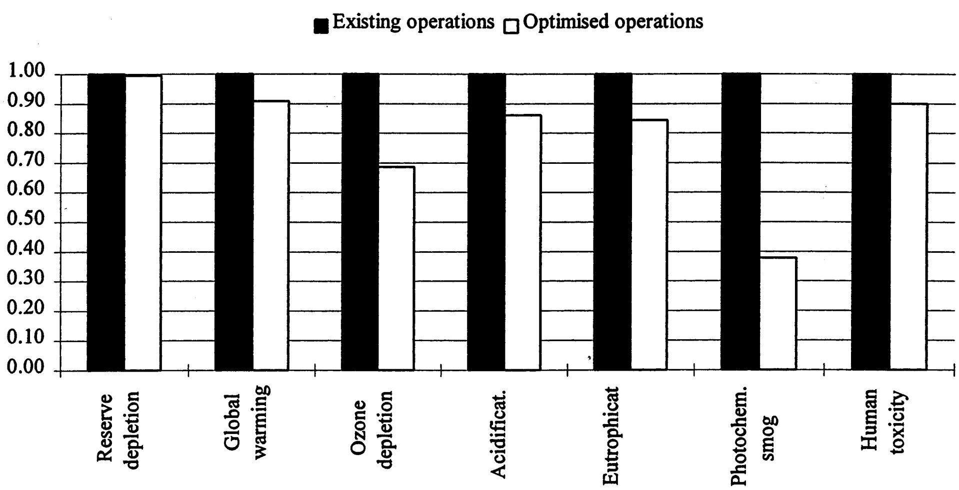


Fig. 8. Single-objective optimisation on environmental impacts.

the existing operations. In these optimisations, the economic objectives are ignored. The system is then simultaneously optimised on environmental impacts and economic objective functions to yield the whole set of optimum solutions as an input into the decision-making process in step 4 of OLCAP.

#### 4.3.1. Single-objective optimisation of environmental performance

Prior to MO, it is interesting to compare the results of single-objective optimisations on the environmental burdens and impacts with the existing operations. This comparison is depicted in Figs. 7 and 8 and indicates that environmental optimisation offers a potential for an average reduction of the burdens of 12%, with the highest reduction of 44% for oil reserves. The environmental impacts follow similar trends: the average reduction in the optimised system is 20%, while photochemical oxidants creation potential can be decreased by 62%. At the same time, the total production is reduced by only 0.5% in comparison to the current operations. On closer inspection of the optimisation results, the reason for these significant improvements becomes apparent. Firstly, the ratio of kernite to borax ore is increased from the current value of 0.2 to the optimum value of 0.4. Since increasing the kernite to borax ratio increases $B_2O_3$ content, the total amount of ore required in the production process is reduced thus reducing the extent of the mining operations and the related environmental burdens from the mine. Moreover, the increased kernite to borax ratio also causes a decrease of the insolubles to borates ratio in the dissolvers and thickeners. This, in turn, results in reduced gangue, energy requirements, and other related environmental burdens from the 5 and 10 mol process.

Reductions of the environmental burdens are also achieved in the 5 and 10 mol plant by using the rotary instead of fluid bed dryer for production of 5 mol product. The main reason for choosing the rotary dryer as a better environmental option lies in its lower energy requirements. A reduction in the burdens and impacts from the dryers due to this change amounts to 60% per unit of 5 mol. A further reduction of up to 85% per unit of product in the $NO_x$ emissions (and the corresponding impacts) is also achievable by installing low $NO_x$ burners in the dryers.

A decrease in the burdens and impacts in the optimised operations is also attained through different transportation means in the mine. However, unlike the other improvement options discussed so far, it is more difficult to decide which type of transport is a better choice. In minimising gas consumption, for example, transport by trucks is a more environmentally acceptable solution, because the electricity used to drive the conveyors is generated by gas. Optimisation on oil usage, on the other hand, favours the use of conveyors because of the reduced need for diesel fuel.

Single-objective optimisation, as shown in Figs. 7 and 8, identifies an optimum solution for a particular objective for which the optimisation has been performed. However, in many cases it may so happen that, while optimising that objective, the other objectives will in fact be sub-optimised. For instance, analysis of the single-objective optimisation results shows that minimisation of the nuclear electricity objective maximises gas, oil and some other objectives. Similarly, minimisation of GWP maximises photochemical oxidant creation potential[3] (POCP). These two examples reinforce the importance of optimising all relevant objectives simultaneously, so that trade-offs between the burdens or impact are made explicit. MO on environmental objectives is illustrated in the next section.

#### *4.3.2. Multiobjective optimisation of environmental performance*

As already mentioned, MO can be performed on objective functions representing either environmental burdens or impacts. In this study, the interest is in identifying possibilities for reducing the impacts, so that the analysis is at the impact assessment level. Prior to optimisation, it is useful to analyse the results of the single-objective optimisation to identify if optimisation on one of the objectives simultaneously optimises some of the others. This may reduce the number of the functions in MO and hence decrease the computational burden. It may be noted that, in theory, the number of the objectives can be as large as necessary. However, on a practical level, it is better to optimise on a smaller number of objectives, not only because of the computational burden but because the number of optimum solutions increases exponentially with the number of objectives, which can make the decision-making process more complex.

The single-objective optimisations on the impacts show that minimisation of GWP also minimises acidification, nutrification and human toxicity, while optimisation on POCP gives the optimum value of OD. The value of the resource depletion objective, which is dominated mainly by depletion of the boron mineral, does not change in the optimisations, so that it can be disregarded. Therefore, to identify and explore the noninferior solutions, it suffices to optimise the system on two objectives only, for instance GWP and POCP, and the other objectives will be optimised accordingly. The constraint method (Cohon, 1978), in which one of the functions is arbitrarily chosen for the optimisation and all other objectives are converted to constraints, has been used for generating the optimum solutions. In a number of optimisations, the parameters of the objectives-constraints are varied between their lower and upper feasible limits, obtained in single objective optimisations, to yield a number of noninferior solutions. These results are then fed into the decision-making process to identify BPEO.

### *4.4. Step 4: Choosing the BPEO*

As introduced in Section 3.1.3, there are a number of techniques to facilitate the decision-making process. One of the possible ways to choose the ‘best’ solution is to consider a graphical representation of the noninferior set and then choose the best compromise solution on the basis of the trade-offs. The noninferior curve, showing the trade-offs between GWP and POCP for the boron system, is shown in Fig. 9. The values of the impact objective functions have been normalised by dividing them by their respective optimum values, GWP* and POCP*, obtained in the single-objective optimisations. Several noninferior solutions are shown to illustrate how much of one objective has to be given up to gain in another. At point A, for instance, GWP is at its optimum; moving along the curve increases its value to reach its maximum at point E, where POCP is at its minimum. Shifting from point A to B yields a ‘gain’ (improvement) of 33% in POCP and a ‘loss’

[3] Also known as Photochemical smog.

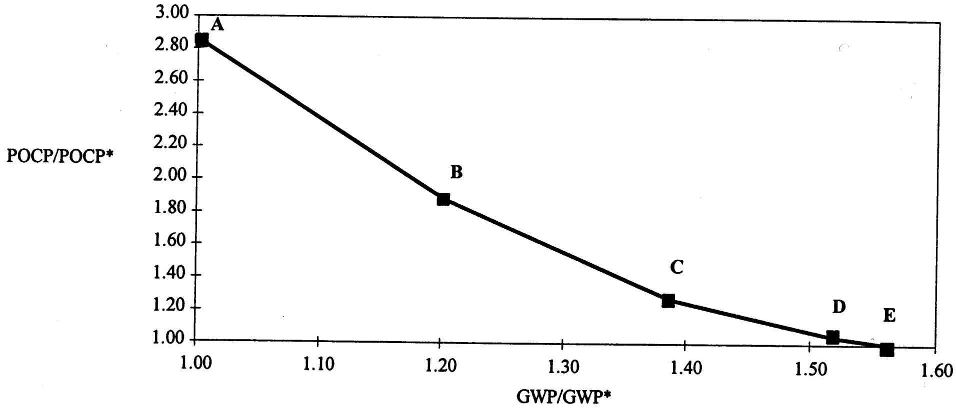


Fig. 9. Noninferior curve for multiobjective optimisation on GWP and POCP.

(deterioration) in the GWP objective of 17%. Point D brings an improvement in POCP of 19% for a loss of GWP of 10%, relative to the point C. These changes in the optimum solutions are mainly related to a change in the transportation means and to the source of steam. So for instance, at solution A, transport by the conveyors with steam produced in the cogeneration plant are chosen as the better environmental options, while the best environmental options at point E are transport by the trucks with steam produced in the steam plant. The environmental options are discussed in more detail in conjunction with economic optimisation in Section 4.5.

Another way to facilitate the decision-making process, as shown in Fig. 10, is to express the values of the objectives in terms of the percentage that they differ from their individual optima. So for instance, GWP and other related functions are at the minimum at point A; however, POCP and OD are 65 and 7% above their respective optima. At solution C, all objectives are between 20 and 30% away from their optima, except for OD, which is barely 3% above its minimum, and so on. As already discussed, if all objectives are considered to be of the same importance, then the best compromise solution could be that at which all objectives differ from their optimum values by the same percentage. However, if the objectives are not considered to be equally important, then a MCDM technique can be used to identify the best environmental solution.

In the preceding discussion, the system has not been optimised on any objective related to economic performance. In reality, few decisions are made on the basis of environmental performance only and a number of other criteria, usually technical and economic, are considered in parallel. The remaining sections of this paper show for the boron case study how optimisation on both environmental and economic performance can help identify options for a more sustainable system operation. For that, it is necessary to return to step 3 of the OLCAP procedure, i.e. MO. To avoid unnecessary repetition, steps 3 and 4 are presented together in the following section.

### *4.5. Steps 3 and 4: Improving the economic and environmental performance*

In this section, MO on environmental and economic performance is carried out to identify possibilities for minimising total environmental burdens and impacts from the boron system, while maximising production subject to total product demand and keeping the production costs at the minimum. This will also enable the identification and choice of BPEO and best available technique not entailing excessive cost (BATNEEC). Thus, in addition to environmental impacts (Eq. (12)), the objective functions include total production and operating costs, as defined by Eqs. (13) and (14).

In order to explain the approach on a simpler example, the system is first optimised on three objectives only, i.e. GWP, production (P) and costs (C), and other functions are ignored. In the second part of this section, in addition to these three objectives, the system is also simultaneously optimised on OD, to generate a range of noninferior solutions which map a four-dimensional Pareto surface. The results of both 3- and 4-objective optimisation are presented on the noninferior surfaces showing the trade-offs among the objectives as an input into the decision making-process.

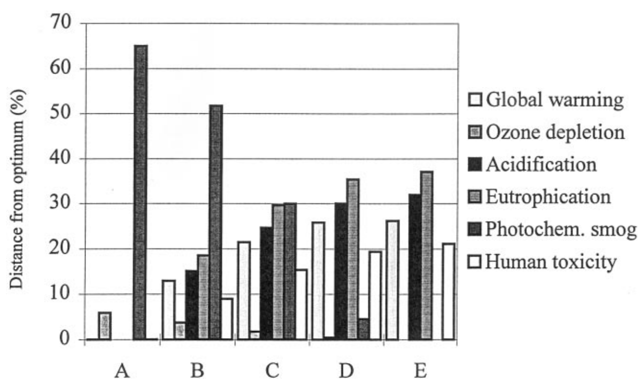


Fig. 10. Selected noninferior solutions of multiobjective optimisation on Global Warming Potential (GWP) and Photochemical smog (POCP).

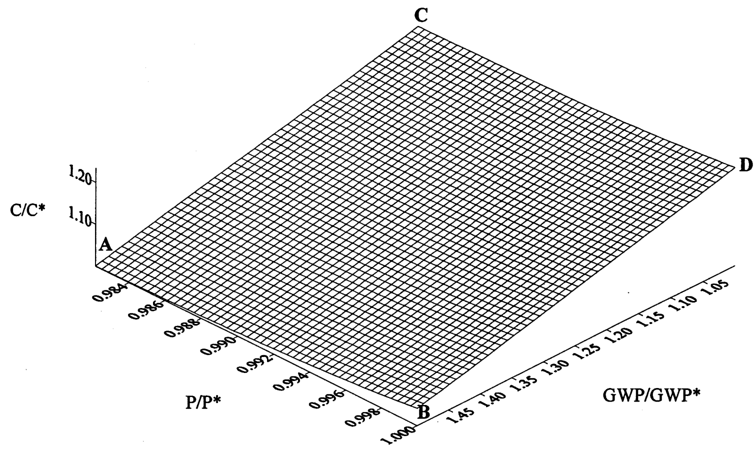


Fig. 11. Noninferior surface for optimisation on GWP, P and C objective functions.

#### *4.5.1. Three-objective optimisation*

The 3-dimensional objective space ABCD, representing the noninferior surface obtained in optimisations on the GWP, P and C objectives, is shown in Fig. 11.

Point A in Fig. 11 represents the minimum costs; however the production is at the minimum and GWP is 31% above its optimum. The Kuhn–Tucker multipliers[4], equal to $-140$ and 51 for GWP and production, respectively, indicate that at this solution, the effect of GWP on costs is larger than that of the production; the marginal cost of reducing GWP by 1 tonne is $140 while, if the production were to increase by 1 tonne, the resulting increase in the costs would be equal to $51. The BPEO and BATNEEC at point A are represented by transport in the mine by the trucks and steam produced in the steam plant. The whole output of 5 mol is produced in the rotary dryer and polypropylene bags are preferred to paper packaging. The latter two options remain the BPEO and BATNEEC in all subsequent optimisations.

By moving from point A along the noninferior curve for constant GWP, both costs and production increase, to reach their maximum feasible values at point B. Here, the Costs function is 4% above its optimum value. The effects of the GWP and production objectives on costs have now reversed order, so that P influences changes in the costs much more than GWP. If production is increased by 1 tonne, $450 of the cost objective have to be given up. Similarly, 1 tonne change in the GWP is associated with a cost change of $170. At this solution, steam is generated by both steam and cogeneration plants; however, the contribution of the latter to the total steam production is only 6%. As opposed to the solution at point A, the preferred transportation means in the mine are the conveyors.

Furthermore, if for instance the system were to be operated at point C, GWP would be 3.3% above its optimum value obtained in the single-objective optimisation. The production would be at its minimum, and the costs would increase by 14%. The effect of GWP and production on costs is similar to that found at point A, except that an improvement in GWP of 1 tonne would worsen the values of the costs objective by $170, while a tonne increase in P would result in $54 increase in the costs. These changes in the system are due to the different environmental options chosen at this solution. Here, the BPEO and BATNEEC are represented by generation of 93% of the steam in the cogeneration plant and the rest in the steam plant. The conveyors still remain the best transport option in the mine.

However, if for example, point D were to be chosen as the best compromise solution, then for the same value of GWP as at point C, the production would reach the maximum; however, costs would have to increase by 17%. It may be noticed here that both GWP and production affect the cost similarly: a decrease in GWP by one tonne increases the Cost objective by $5240 while, if the production is increased by 1 tonne, the costs increase by $5400. At this solution, the BPEO and BATNEEC are defined by truck transport in the mine and steam production in the cogeneration plant.

It is now interesting to find out what improvement options exist if the system is simultaneously optimised on OD, GWP, P and C objective functions.

#### *4.5.2. Four-objective optimisation*

MO on GWP, OD, P and C generates a whole plethora of noninferior solutions on a four dimensional surface. For graphical analysis, these results are shown in Fig. 12a–d in the 3-dimensional OD-GWP-C space for constant values of the P objective. The surface delineated by points $A_1B_1C_1D_1$ in Fig. 12a represents the noninferior solutions for a constant production of

[4] Kuhn-Tucker multipliers show trade-offs between the objective functions; they are equivalent to marginal or Lagrange values.

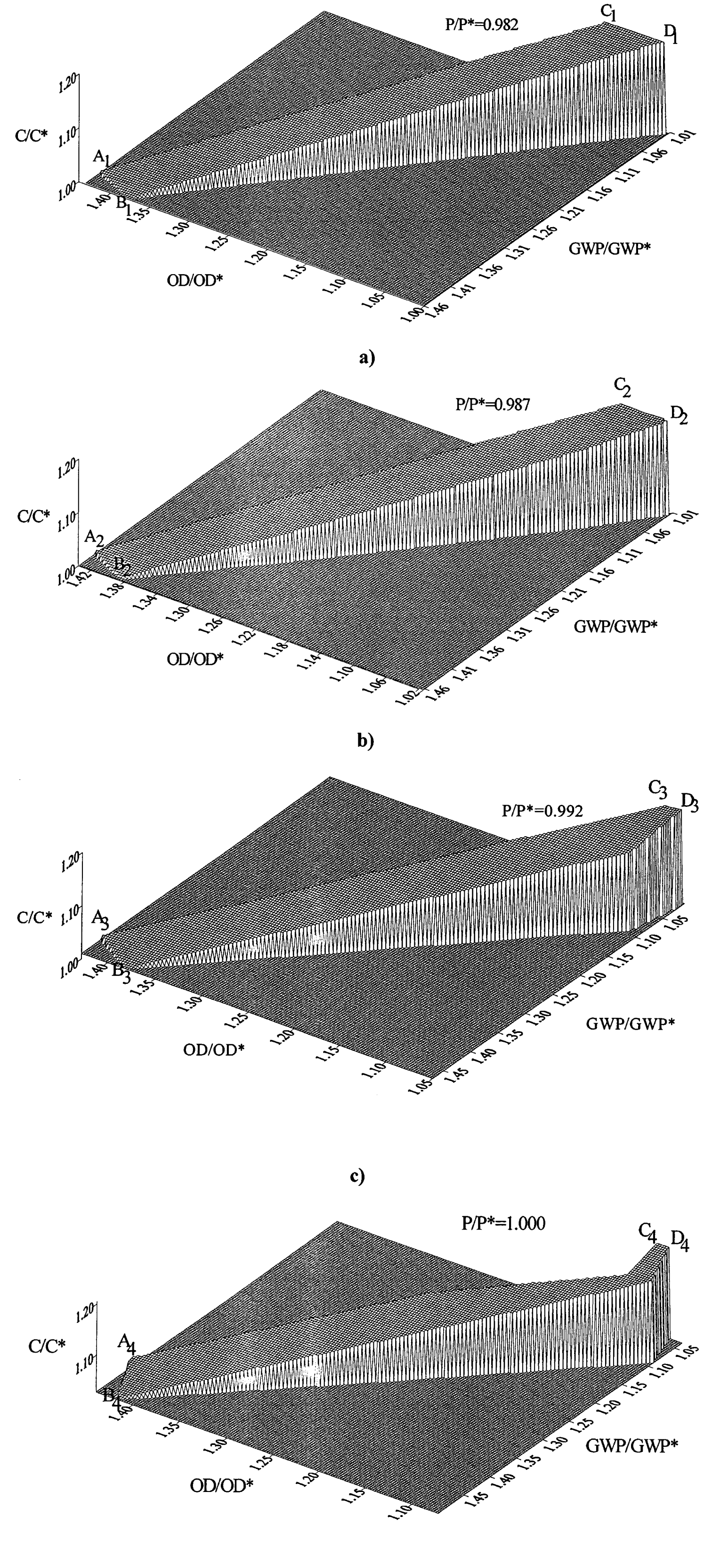


Fig. 12. Noninferior surface for optimisation on OD, GWP, P and C: (a) P/P* = 0.982; (b) P/P* = 0.987; (c) P/P* = 0.992; (d) P/P* = 1.00.

1.8% below the optimum. At solution $B_1$, for instance, the costs are at the minimum; however, GWP and OD are 31 and 27% above their optimum values. This solution corresponds to point A in Fig. 11, obtained in the three-objective optimisation. There, GWP and C are, respectively 0.7 and 0.3% lower than at point $B_1$; however, OD is 3.4% higher. As at point A, transport by trucks and steam production in the steam plant are also identified as the best environmental options at solution $B_1$. Furthermore, it is noticeable that the effect of OD on the costs is much higher than the effect of the other two objectives: 1 kg decrease in OD causes costs to increase by \$974. For the same change in GWP and P, the costs increase by, respectively \$0.134 and \$0.054.

If the operating state of the system moves, for example from point $B_1$ to $A_1$, it is possible to reduce the value of GWP by 1%. However, this improvement is carried out at the expense of OD and C, which increase by 3 and 0.8%, respectively. Trucks and steam plant are still the best environmental options in the system.

A more extreme change occurs if the system is operated around solution $C_1$ in Fig. 12a. There, the costs are 14.5% above the minimum and OD and GWP are, respectively 6.9 and 1.3% higher than their optimum values. The ore is transported by the conveyors and 97% of the steam is generated in the cogeneration plant. Furthermore, for the same GWP, a 0.1% increase in the costs brings the value of OD down to the minimum at point $D_1$. The steam is again produced in the cogeneration plant and trucks are the best environmental option for transport in the mine. If compared to the 3-objective optimisation, the operating state at point C in Fig. 11 falls in between points $C_1$ and $D_1$ in Fig. 12a.

Similar trade-offs among C, OD and GWP are noticed for $P/P^* = 0.987$, i.e. for production 1.3% below the optimum (Fig. 12b). At points $A_2$, $B_2$ and $C_2$, OD and GWP remain almost the same as at solutions $A_1$, $B_1$ and $C_1$ in Fig. 12a, while costs increase by on average 0.5%. However, at point $D_2$, OD is 1.9% above its minimum and Costs increase by 1% in relation to the values obtained for solution $D_1$. At the same time, GWP is 1.2% higher than the optimum. These changes are a result of the combined transport of ore by conveyors and trucks, as opposed to transport by trucks only which was the best environmental option at point $D_1$. Moreover, the effect of OD on the cost objective function at point $D_2$ reaches its maximum of 23 241 \$/kg, while the effect of the same change in GWP or P is only \$4.40 and \$0.75, respectively.

As production increases to reach the maximum and the requirements on the other objectives become stricter, thereby limiting the range of options for the process operations, the noninferior space becomes progressively more narrow and hence offers a more limited choice of noninferior solutions (Fig. 12c and d). For instance, if the system is operated anywhere on the boundary between points $C_1$ and $D_1$ (Fig. 12a), the noninferior solutions with respect to OD range from 0 to 6.9% above the minimum. Compared to this, the choice of the noninferior solutions between points $C_4$ and $D_4$ (Fig. 12d) is significantly more limited and ranges from 0 to 1.2% above the optimum.

These examples illustrate the value of MO in not being prescriptive; it offers a set of alternative options for system improvements, rather than a single optimum solution. Single-objective models dictate the use of a single measure of efficiency and provide only one solution for decision makers. Decision-makers like to decide and MO allows them to do so. The elicitation of preferences and identification of the best compromise solution by the decision-makers can then be carried out with the aid of graphical presentation, as shown in Figs. 11 and 12, or by using any of the MCDM techniques, as discussed in Section 3.1.3.

## 5. Concluding remarks

As an environmental tool for process management, LCA has two main objectives. The first is to quantify and evaluate the environmental performance of a process from 'cradle to grave' and so help decision-makers to choose a more sustainable option among alternatives. Another objective is to provide a basis for assessing potential improvements in the environmental performance of a system. Two main problems are associated with these objectives of LCA. First, in many cases there will be a number of options and possibilities for improvements and it may not always be obvious which of them represents the optimum solution. Therefore, some kind of system optimisation will be necessary. Secondly, there may exist more than one optimum solution for improving the system's performance, in which case the issue becomes that of choosing the best compromise option from a number of optimum solutions.

The optimisation problem in the LCA context is inevitably multiobjective, and that is one of the reasons that MO has been chosen for this work. The paper has attempted to demonstrate that MO can be combined with LCA to assist in the decision-making process for improving both environmental and economic performance of a process from cradle to grave. The main advantage of MO over other methods which have been used in LCA is that generating optimum solutions does not require a priori articulation of preferences, so that the whole noninferior set of solutions can be explored. The emphasis is then on the range of choices from the set of noninferior solutions, rather than explicit definition of preferences before analysing all the trade-offs among objectives. By being able to trade-off incommensurable objectives, e.g. environmental impacts and economic requirements, this approach avoids the well known problems encountered, for instance, in cost-benefit analysis, i.e. reducing individual preferences to a market value or trying to express quality of the environment in financial terms.

Furthermore, MO can be applied in a wide range of decision-making contexts. In the case of single decision-makers, it provides information on the trade-offs between different objectives, to show explicitly what can be gained and what lost by choosing each alternative. Where there are multiple decision-makers with conflicting interests, this technique can help to resolve disputes by generating different alternative solutions. Decision makers who understand the trade-offs and the alternatives are more likely to understand the interests of other parties and, therefore, to compromise.

A decision-support tool — OLCAP — has been developed for these purposes. Multiobjective optimisation used in this approach provides a more effective approach to environmental system management by offering a number of alternative optimal solutions and enabling decision-makers to identify and choose the BPEO and BATNEEC.

## Appendix A. Nomenclature

All units are expressed per functional unit of the system.

| | |
|---|---|
| $a_{i,n}^{(\kappa)}$ | input/output coefficients of a process or activity $n$ (kg/kg) |
| $b_{j,n}$ | environmental burden coefficients (kg/kg) |
| $B_j$ | Environmental burden (kg) |
| $C$ | cost objective function ($) |
| $C_u^{(\kappa)}$ | capacity of a process or an operation unit (kg) |
| $c_n$ | cost coefficients in the cost objective function ($/kg) |
| $D_l$ | market demand on the output of the products (kg) |
| $e_{k,j}$ | environmental impact coefficients (kg/kg)[5] |
| $E_k$ | environmental impact (kg) |
| $F$ | economic objective function ($) |
| $f_p$ | objective function (kg); ($) |
| $g$ | inequality constraints |
| $h$ | equality constraints |
| $H_n$ | heat production in the system (MJ) |
| $m_n^{(\kappa)}$ | mass flow $n$ in a subsystem $\kappa$ (kg) |
| $P_l$ | product output (kg) |
| $Q_z$ | heat demand (MJ) |
| $R_\gamma^{(\kappa)}$ | primary or raw material availability (kg) |
| $R^n$ | set of $n$ continuous variables (kg); (MJ) |
| $S_\gamma^{(\kappa)}$ | supply of primary or raw material (kg) |
| $Z^q$ | set of $q$ integer variables (−) |
| *Vectors* | |
| c | cost or profit coefficients for integer variables |
| f | environmental and economic objective functions |
| x | continuous variables |
| y | integer variables |

[5] kg/year for Abiotic resource depletion.

## Appendix B. Environmental impacts

This section lists definitions of environmental impacts which are referred to in the paper. A more detailed description can be found in Heijungs et al. (1992). It may be noted that these impact categories are starting to be used in reporting the environmental performance of multinational companies (e.g. Wright et al., 1997).

1. Resource depletion (RD) describes depletion of non-renewable resources, i.e. fossil fuels, metals and minerals related to the world's estimated reserves.
2. GWP is believed to be caused by emissions of the greenhouse gases, e.g. $CO_2$, $N_2O$, $CH_4$ and other VOCs. GWP factors for different greenhouse gases are expressed relative to the GWP of $CO_2$, which is therefore defined to be unity. The values of GWP depend on the time horizon over which the global warming effect is assessed. GWP factors for shorter times (20 and 50 years) provide an indication of the short-term effects of greenhouse gases on the climate, while GWP for longer periods (100 and 500 years) are used to predict the cumulative effects of these gases on the global climate.
3. The OD category indicates the potential of chlorofluorocarbons (CFCs) and chlorinated HCs for depleting the ozone layer. The ODP factors of each of the ozone-depleting substance is expressed relative to the ozone depletion potential of CFC-11.
4. Acidification potential (AP) is based on the contributions of $SO_2$, $NO_x$, HCl, $NH_3$, and HF to the potential acid deposition, i.e. on their potential to form $H^+$ ions.
5. Eutrophication (or nutrification) potential (EP) is defined as the potential to cause over-fertilisation of water and soil, which can result in increased growth of biomass. Emissions of species such as $NO_x$, $NH_4^+$, N, $PO_4^{3-}$, P, and COD are considered to be responsible for eutrophication. EP is expressed relative to $PO_4^{3-}$.
6. Photochemical oxidants creation potential (POCP), or photochemical smog, is thought to be caused primarily by VOCs, including: alkanes, halogenated HCs, alcohols, ketones, esters, ethers, olefins, acetylenes, aromatics and aldehydes. POCPs of these species are expressed relative to the POCP of ethylene.
7. Human toxicity potential (HTP) is related to releases to air, water and soil which are toxic to

humans. The toxicological factors are calculated using the acceptable daily intake or the tolerable daily intake of the toxic substances. The human toxicological factors are still at an early stage of development so that HTP can only be taken as an indication and not as an absolute measure of the toxicity potential.

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