
Volume 35, issue 8, 10 August 2011
ISSN 0098-1354
ELSEVIER
Computers & Chemical Engineering
An International Journal of Computer Applications in Chemical Engineering
Editor-in-Chief
R. GANI
Technical University of Denmark, Lyngby, Denmark
Editors
J. LEE
Korea Advanced Institute of Science and Technology, Korea
E.N. PISTIKOPOULOS
Imperial College London, London, UK
V. VENKATASUBRAMANIAN
Purdue University, West Lafayette, Indiana, USA
max
On-line Access via:
www.elsevier.com/locate/compchemeng

Computers and Chemical Engineering 35 (2011) 1478–1487

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

Bi-objective minimization of environmental impact and cost in utility plants

P. Martínez[a], A.M. Eliceche[b,*]

[a] Instituto de Energía y Desarrollo Sustentable, CNEA, CONICET, Av. del Libertador 8250, Ciudad Autónoma de Buenos Aires, Argentina
[b] Chemical Engineering Department, Universidad Nacional del Sur, PLAPIQUI CONICET, Camino La Carrindanga Km 7, (8000) Bahía Blanca, Argentina

ARTICLE INFO

Article history:
Received 2 September 2010
Received in revised form 2 May 2011
Accepted 6 May 2011
Available online 13 May 2011

Keywords:
Bi-objective
Minimisation
Environmental impact
Cost
Utility plant

ABSTRACT

A methodology to minimize potential environmental impact and operating cost in the selection of the operating conditions of a steam and power plant is presented. A bi-objective mixed integer nonlinear programming problem is formulated and solved in GAMS. Different strategies are implemented successfully to generate the Pareto curve such as: minimum distance to the utopia point, ε-constraint, weighted sum and global criterion. An analysis of the Pareto curve allows the identification of two regions where it is cheaper and more expensive respectively, to reduce the potential environmental impact, providing relevant information to support a decision making process. The economical valorisation of greenhouse gases emissions reduction was also carried out, showing the region of the Pareto curve in which the income would compensate the increment in operating cost, leading to a reduction of the potential environmental impact with no extra cost.

1. Introduction

Reduction of environmental impact of process industry is one of the imperative challenges to achieve sustainable development for the current century. Economic objectives as operating and capital cost or net profit value have been extensively used in process system engineering in order to find either the optimal operating conditions of an existing process or flow sheet configurations in the synthesis step. When the operating cost of a process is minimized, the associated environmental impact might rise, conversely an environmental friendly process is often cost intensive. This fact evidences the need of solving problems with more than one objective, that is, to find solutions that satisfy environmental and economic objectives simultaneously. This solutions could be found formulating multi-objective optimization problems in the decision making process.

The multi-objective optimization problem could, in theory, be solved using similar methods as those employed in single objective optimization problems, converting the multiple objectives into a single objective. Authors like Ciric and Huchette (1993) have treated multi-objective optimization applied to environmental and economic objectives minimizing the amount of waste and the capital and operating cost of an ethylene glycol production plant. Dantus and High (1999) proposed a method, called global criterion, to convert a bi objective optimization problem into a single objective optimization problem; the method proposed is a variation of the utopia point distance minimization, including discrete variables to select the type of reactor to be used in the methyl chloride superstructure plant design. Pistikopoulos and Hugo (2005) have treated multi objective optimization with environmental and economic objectives applied to supply chain network design and planning using the ε-constraint method. Azapagic and Clift (1999), have proposed the application of life cycle assessment to aid the decision making process for environmental improvement, with multiple objectives for the mineral boron production. Puigjaner et al. (2008) present a scheduling multi-objective programming problem, solved using genetic algorithms, where environmental life cycle and cash flow balance are used. Recently, Novais, Barbosa-Póvoa, and Duque (2010) present a design and planning problem applied to a pollutant recovery network where the environmental impact due to pollutant discharges and operating cost are including into a multi-objective mixed integer linear problem solved using the ε-constraint method. Gebreslassie, Jimenez, Guilleřn-Gosaĭlbez, Jimeňez, and Boer (2010) present a multi-objective optimization of a solar assisted cooling system using the life cycle environmental assessment and the total cost as objective functions, using the ε-constraint method and solving MINLP problems.

These objectives usually compete with each other, so that it is not possible to find a solution that simultaneously satisfies all of them. Therefore, the concept of Pareto optimal solution is utilized to assess whether a solution is optimal or not. A multi-objective optimization problem requires the simultaneous satisfaction of a number of different and often conflicting objectives. Pareto optimality is the key concept to establish a hierarchy among the solutions of a multi-objective optimization problem, in order to

* Corresponding author. Tel.: +54 291 4861700; fax: +54 291 4861600.
E-mail address: meliceche@plapiqui.edu.ar (A.M. Eliceche).

0098-1354/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.compchemeng.2011.05.003

Nomenclature

C	Utility plant operating cost, \$
e	Emission factor
F	Stream flow rate
g	Inequality model constraint
h	Equality model constraint
PEI	Potential environmental impact
z	Generic single objective function
Z	Generic multi-objective function
W	Imported electricity

Subscripts

ie	Imported electricity
j	Environmental impact category
fw	Fresh water
k	Pollutant
mw	Make up water
ng	Natural gas
p	Purge stream
pe	Pollutant emission
rc	Resource consumption
rg	Residual gas
wt	Water treatment

Superscript

UP	Utility plant

Greek symbols

α	Weighting factors for each environmental impact category j
γ	Environmental Impact category characterization factor
ω	Weighting factors for each single objective function z
Φ	Decision maker's compromise index
ε	Constraint-level parameter for the ε-constraint method

determine whether or not a solution is really one of the best possible trades-off (Sayyaadi, 2009).

In the present work the operating conditions of a steam and power plant are selected to minimize potential environmental impact and operating cost simultaneously solving a bi-objective mixed integer nonlinear optimization problem. The environmental objective is the environmental impact associated with solid wastes, gaseous and liquid emissions of a steam and power plant. The operating cost includes costs of imported electricity, natural gas feed, makeup water and water treatment. The bi-objective mixed integer nonlinear optimization problem is formulated and solved in GAMS (Brooke et al., 2003). The continuous operating variables are temperature and pressure of the high (HPSH), medium (MPSH) and low pressure (LPSH) steam headers and the deareator (DP) pressure. Binary operating variables are introduced to represent discrete decisions such as the selection of: (i) alternative pump drivers such as electrical motors and steam turbines and (ii) boilers which are on or off, and their auxiliary equipment such as feed pumps and air fans.

Different methods to solve the bi-objective optimization problem, like minimum distance to the utopia point, ε-constraint, weighted sum and global criterion, were implemented successfully in GAMS. The Pareto curve is generated and analyzed, finding the more convenient sector of the Pareto curve to reduce potential environmental impact with the least increment in operating cost. The increment in the operating cost is compensated with the Carbon market income that could be generated by the reduction of green house emissions. The analysis of the Pareto curve provides relevant information to support a decision making process in the selection of the operating conditions of a key sector as the numerical results show.

2. Utility plant description

The utility plant provides mainly steam and power to the chemical plant. It consumes fossil fuels, a non-renewable resource burnt in the boilers and also a scarce resource as water. A schematic flow sheet of an ethylene utility plant is presented in Fig. 1.

There are four boilers B_1–B_4 and a waste heat boiler, associated with the quenching sector of the ethane cracking furnace, both kind of boilers produce superheated steam at high pressure (HPS) sending it to the high pressure steam header. The main equipment are: high, medium and low pressure steam headers, steam turbines, pumps, deaerator tank, vents, let-down streams, water treatment plant (WTP), vacuum condenser tank, air fans, electrical motors and heat exchangers. The top product from the demethanizer column of the ethylene plant is recycled as residual gas (RG in Fig. 1) to be mixed with the natural gas (NG in Fig. 1) and burned in boilers and waste heat boiler. There are optional drivers that can be electrical motors (M_1–M_{11}) or steam turbines (T_1–T_{11}) for eleven pumps in Fig. 1. The continuous operating conditions to be selected in utility plant are: temperature and pressures of high, medium and low pressure steam headers and deareator pressure. Their upper and lower bounds are shown in Table 1.

The modelling equations of the main equipment and steam and water enthalpy and entropy property predictions are posed as equality constraints in the optimization problem formulated in GAMS (Brooke et al., 2003). The plant has alternative drivers such as electrical motors and steam turbines for some pumps. Binary variables are used to select the drivers' configuration and on/off equipment selection. Binary variables are associated to the selection of pumps drivers such as water tower pumps, lubricating pumps, condensate pumps, boiler water pumps, cooling water pumps and also the boilers and air fans.

There are twenty-four binary variables shown in Table 2. Twelve of the binary variables are used to select between electrical motors and steam turbines as drivers corresponding to: seven pumps in the ethylene plant (e.g. two water quenching tower, three lubrication and two condensate pumps), one air compressor impeller and four air fan impellers. The rest of the binary variables are used to define if the equipment is ON or OFF as for the four available boilers, three boilers' feeding water pumps and five cooling water pumps.

Those drivers indicated in brackets in Table 2 are fixed and the corresponding binary variable is used to select if the equipment is ON or OFF. In the mathematical model linear relations between binary variables such as logical constraints are considered. These relations are posed as inequalities so as to model an order of priority. This order of priority applies for example to boilers and its auxiliary equipment such as feed water pumps and air fans.

Table 1
Binary variables of the utility plant.

Optimization variables	Lower bound	Upper bound
P1: HPSH pressure, bar	48.00	52.00
P2: MPSH pressure, bar	18.00	26.00
P3: LPSH pressure, bar	3.00	5.00
T1: HPSH temperature, °C	400.00	450.00
T2: MPSH temperature, °C	310.00	370.00
T3: LPSH temperature, °C	150.00	250.00
Pd: Deareator pressure, bar	1.20	3.00

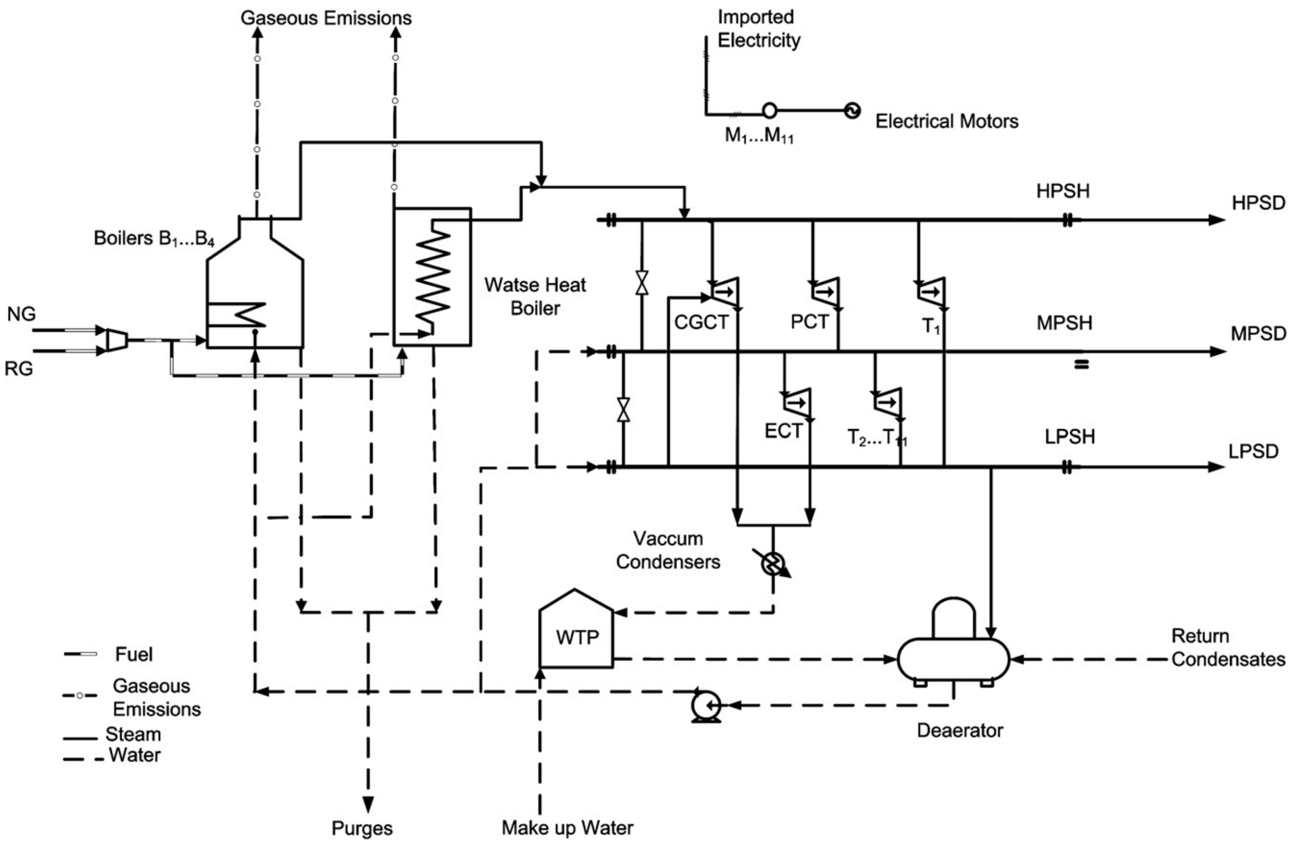

Fig. 1. Utility plant flow sheet.

Condensing and backpressure turbines are the most common types of steam turbines, with the latter having the widest application. Both can be multi stage with more than one steam input or output. The output of condensing turbines commonly goes to a vacuum condenser to increase the power. Turbines take their steam from a header and release the steam to a lower pressure header. In the headers, the steam temperature and pressure is controlled by de-superheating water and by high-pressure steam letdowns. The main power demands of the process plant correspond to three compressors: cracking gas (CGC), propylene gas (PC) and ethylene gas (EC). The condensed steam returning from the chemical process heat exchangers is collected in a tank at atmospheric pressure to be re-used and generate steam. The recycled condensate cannot be re-used without previous water treatment in the water treatment plant (WTP) to prevent corrosion in boilers and turbines. Other power demands posed as equality constraints corresponds to: the energy recovered in the waste heat boiler, energy consumed by the cracking furnace in the ethylene plant, power demands for the condensate pump impellers, air fan impellers, boiler water pumps and cooling water pumps. For further details on the mathematical modelling of the utility sector see Eliceche, Corvalan, and Martinez (2007).

Table 2
Bounds on the continuous operating conditions of the utility plant.

Binary optimization variables	Drivers' selection	
Utility plant units	$y_i = 0$	$y_i = 1$
Water pump no. 1, quenching tower	EM	ST
Water pump no. 2, quenching tower	EM	ST
Lubrication pump no. 1	EM	ST
Lubrication pump no. 2	EM	ST
Lubrication pump no. 3	EM	ST
Condensate pump no. 1	EM	ST
Condensate pump no. 2	EM	ST
Air compressor impeller	EM	ST
Boiler water pump no. 1 (steam turbine)	OFF	ON
Boiler water pump no. 2 (steam turbine)	OFF	ON
Boiler water pump no. 3 (electrical motor)	OFF	ON
Cooling water pump no. 1 (steam turbine)	OFF	ON
Cooling water pump no. 2 (steam turbine)	OFF	ON
Cooling water pump no. 3 (electrical motor)	OFF	ON
Cooling water pump no. 4 (electrical motor)	OFF	ON
Cooling water pump no. 5 (electrical motor)	OFF	ON
Air fan impeller, boiler no. 1	EM	ST
Air fan impeller, boiler no. 2	ST	ST
Air fan impeller, boiler no. 3	EM	ST
Air fan impeller, boiler no. 4	EM	ST
Boiler no. 1	OFF	ON
Boiler no. 2	OFF	ON
Boiler no. 3	OFF	ON
Boiler no. 4	OFF	ON

3. Environmental and economic objective functions

3.1. Potential environmental impact evaluation

The potential environmental impact (PEI) function considered is a multi-objective function itself, since nine environmental impact categories are considered: global warming, acidification, ozone depletion, photo oxidant formation, eutrophication, fresh water ecotoxicity, human toxicity, source depletion and the impact due to ionizing radiation. The potential environmental impact is calculated using the CML 2002 methodology (Guinée et al., 2002). The contribution of the emission of a pollutant k to a given environmental impact category j is evaluated multiplying the pollutant k flow rate F_k emitted into the environment by a characterization factor γ_{kj} published by Guinée et al. (2002). This characterization factor represents the effect that chemical k has on the environmental impact category j. Hence, the potential environmental impact, PEI, is calculated adding the contributions of all the environmental impact categories j as follows:

$$\mathrm{PEI} = \sum_{J}\sum_{k}\alpha_j \times F_k \times \gamma_{k,j} \tag{1}$$

where α_j represent the weighting factors for each environmental impact category j. More information can be found in Eliceche et al. (2007). Eq. (1) transforms the pollutants emissions flow rates into potential environmental impacts. Thus, the simulation of the utility plant provides the emission flow rates F_k to end up calculating the overall environmental impact PEI.

3.1.1. Utility plant environmental impact

The emissions of the steam and power plant are evaluated from the modelling of the main processes formulated in GAMS (Brooke et al., 2003). The emissions come mainly from the combustion in the boilers of a mixture of natural gas, F_{ng} and residual gas recycled from the top of the demethanizer column, F_{rg}. Liquid emissions of purge streams, F_p, in the boilers and cooling system are also considered. The total emission flow rate of a given pollutant k from the utility plant (UP) is calculated as follows:

$$F_k^{\mathrm{UP}} = F_{ng} \times e_{k,ng} + F_{rg} \times e_{k,rg} + F_{rp} \times e_{k,rp} \tag{2}$$

where $e_{k,ng}$ is the emission factor for pollutant k due to the combustion of natural gas, $e_{k,rg}$ is the corresponding emission factor for residual gas combustion and $e_{k,p}$ is the pollutant emission factor for liquid emissions. The emissions factors express the amount of pollutant k emitted by unit mass of natural gas, residual gas and liquid stream, respectively. The CO_2 emission due to natural gas and residual gas combustion are estimated stoichiometrically with the gas composition following the IPCC (2001) recommendations. Nearly 100 gaseous pollutants emissions are estimated from AP-42 report (EPA, 1998). Emissions from liquid discharges were estimated from the Electrical Power Research Institute report (2000).

Thus, the utility plant potential environmental impact due to its pollutants emissions is calculated combining Eq. (2) and Eq. (1):

$$\mathrm{PEI}_{pe}^{\mathrm{UP}} = \sum_{j}\sum_{k}\alpha_j \times F_k^{\mathrm{UP}} \times \gamma_{k,j} \tag{3}$$

The parameters α and γ as well as the subscripts k and j are the same that those explained for Eq. (1). The simulation of the utility plant operation provides the emissions flow rates F_k^{UP} to calculate the overall environmental impact due to utility plant pollutant emissions, $\mathrm{PEI}_{pe}^{\mathrm{UP}}$.

In addition, the resources depletion category was included. This impact category is calculated as a function of the natural gas and fresh water consumption through the following equation:

$$\mathrm{PEI}_{rc}^{\mathrm{UP}} = \frac{F_{ng}}{R_{ng}} + \frac{F_{fw}}{R_{fw}} \tag{4}$$

where R indicates the resource reserve expressed in mass units. Discrepancy on the values for resource reserve to be used has risen. Some authors consider the world reserves for all the resources considered (Guinée et al., 2002). Nevertheless, the global availability of certain resources is not a common practice, especially due to cost and technical constraints. Instead of global values, perhaps it is desirable to use a local reserve reflecting a more realistic situation. This is the case of scarce resources as water. In this work the local reserves of each resource, natural gas and water, are considered.

Finally, the utility plant environmental impact is calculating adding Eqs. (3) and (4):

$$\mathrm{PEI}^{\mathrm{UP}} = \mathrm{PEI}_{pe}^{\mathrm{UP}} + \mathrm{PEI}_{rc}^{\mathrm{UP}} \tag{5}$$

3.1.2. Utility plant operating cost

The operating cost of the utility plant includes costs of imported electricity (ie), natural gas feed (ng), makeup water (mw) and water treatment (wt); where c_{ie}, c_{ng}, c_{mw} and c_{wt} are the corresponding cost coefficients. The operating cost is calculated as follows:

$$C = F_{ng} \times c_{ng} + F_{ie} \times c_{ie} + F_{mw} \times c_{mw} + F_{wt} \times C_{wt} \tag{6}$$

A detailed mathematical model of the utility plant operation is presented in Eliceche et al. (2007).

4. Formulation of bi-objective optimization problems

The multi-objective optimization is a system analysis approach to problems with conflictive objectives. A key factor of multi-objective optimization is that rarely exist a single solution that simultaneously optimizes all the objectives. In its place, there is a set of solutions where one objective cannot be improved except at expense of another objective. This set of compromise solutions is generally referred as non-inferior or Pareto optimal solutions. In a single objective optimization problem the Kuhn–Tucker conditions provide the necessary conditions for optimality. The multi-objective problem can be seen as a vector optimization problem. In this work two objectives are considered, as follows:

$$\begin{aligned}
&\min Z(x) = [z_1(x),\ z_2(x)]\\
&x \in X\\
&s.t.\\
&g_m(x) \le 0, \quad m = 1, 2, \ldots, M\\
&h_s(x) = 0, \quad s = 1, 2, \ldots, S
\end{aligned} \tag{P1}$$

In the bi-objective formulation P1, x is the vector of decision variables being X the feasible region. Z is the vector of objective functions. The solutions of problem P1 minimize the two individual objective functions z_1 and z_2 simultaneously, while satisfying the M inequalities $g_m(x) \le 0$ and the S equalities $h_s(x) = 0$ constraints, which represents the system model equations and operation constraints.

An important characteristic of the multi-objective problems is that rarely exist a solution x^* that minimize all the objective functions while the constraints are fulfilled, then the optimality concept can be defined as:

A solution $x^* \in X$ is efficient or non-dominated for the problem (P) if and only if there is no $x \in X$ such that $z_i(x) \ge z_i(x^*)$ for all $i \in \{1, \ldots, \mathrm{I}\}$ and $z_j(x^*) > z_j(x)$ for at least one j.

In the previous general statement the subscript i is used to indicate each single objective function in the set of single objective functions I. The subscript j is used to denote an objective function different from the i objective function. A set of solutions is said to be Pareto optimal if, when moving from one point to another in the set of solutions, any improvement in one of the objective functions from its current value, would cause at least one of the other objective functions to deteriorate from its current value. The Pareto optimal set is usually an infinite set. The decision maker has to choose from the set of solutions generated.

4.1. Multi-objective solving methods

A wide variety of algorithms for multi-objective optimization has been reported in literature as Hwang and Masud (1979), Zeleny (1982), Goicoechea, Hansen, and Duckstein (1982), Steuer (1986), Zionts and Wallenius (1976, 1980), Hwang, Paidy, Yoon, and Masud (1980), Clark and Westerberg (1983), Ciric and Huchette (1993), Das and Dennis (1997), Dantus and High (1999) and Alves and Clímaco (2007). The general approach converts the multiple objective functions vector into a single objective function, performing then a single objective optimization. Some of these methods are: weighted sum, utopia point distance minimization, ε-constraint method and global criterion method. The general formulation of a bi-objective optimization problem with continuous optimization variables was presented in problem P1. All the solution approaches, except the ε-constraint method, involves a combination of different objective functions into a single one. A brief description of the methods used in this work follows, Bhaskar, Gupta, and Ray (2000).

4.1.1. Weighted sum or parametric approach

The weighted sum of the different objectives has been widely used; the reformulated objective function is a convex combination of the original single objective functions, as follows:

$$Z = \sum_{i=1}^{n} \omega_i \times z_i(x) \tag{7}$$

$$0 \le \omega_i \le 1 \tag{8}$$

$$\sum_{i+1}^{n} \omega_i = 1 \tag{9}$$

The non-inferior points are generated changing the relative weights ω_i. The weighting coefficients are chosen a priori.

4.1.2. Utopia point distance minimization

The utopia point has as coordinates the minimum values of each single objective function z_i^*, and it is the point at which the asymptotes of the Pareto set meet. Each asymptote, $z_i = z_i^* =$ constant, can be obtained by solving the single objective function optimization problem. The best solution minimizes the distance to the utopia point. The single objective for this strategy follows:

$$Z = \left[\sum_{i=1}^{N} [z_i - z_i^*]^2 \right]^{1/2} \tag{10}$$

This objective function represents the distance (Euclidian norm) between the ideal utopia point and the final solution. Some variations of this method use weighting factors as in the weighted sum method.

4.1.3. Trade-off or ε-constraint method

In this method the trade-off among the multiple objectives is specified by the decision maker. This method is also known as the ε-constraint or reduced feasible space method because the technique involves search in a progressively reduced criterion space. The original problem is converted to a new problem in which one objective is minimized while the other objectives are posed as inequality constraints. Mathematically the objective is written as follows:

$$\begin{aligned} &\min z_r(x) \\ &x \in X \\ &s.t. \\ &z_i(x) \le \varepsilon_i, \quad i = 1, \dots, I; \quad i \ne r \\ &g_m(x) \le 0, \quad m = 1, 2, \dots, M \\ &h_s(x) = 0, \quad s = 1, 2, \dots, S \end{aligned} \tag{P2}$$

where ε_i is the desired bound on z_i. By varying the values of ε_i a complete set of Pareto optimal solutions can be found. In this technique, a single objective function is optimized, chosen from among the original ones, while treating all remaining objectives as inequality constraints. This technique does not require the existence of supporting hyper-planes and overcomes duality-gaps in non-convex sets (Haimes & Hall, 1974).

4.1.4. Global criterion method

In this method the decision maker uses an approximate solution z^* or the ideal solution if it is known, to formulate a single objective criterion to determine the optimum decision variables by solving the following single objective optimization problem:

$$Z = \sum_{i=1}^{N} \left[\frac{z_i - z_i^*}{z_i^*} \right]^{\Phi} \tag{11}$$

$$0 \le \Phi \le \infty \tag{12}$$

The decision maker sets the parameter Φ, varying the value of this parameter the Pareto points are obtained. Several adaptations of this method have been developed as presented by Goicoechea et al. (1982), Coello-Coello and Christiansen (1999) and Dantus and High (1999). Basically these methods consider the minimization of deviation of the solution point with respect to a certain point, in this way the search space is reduced to the space limited by the utopia point coordinates. The method proposed by Goicoechea et al. (1982) is implemented in this work, with the following objective function to be minimised:

$$Z = \sum_{i=1}^{N} \omega_i \left[\frac{z_i - z_i^*}{z_i^{**} - z_i^*} \right]^{\Phi} \tag{13}$$

In Eq. (13) ω_i are the weighting factors as in the weighted sum approach; these preference weights are used to represent the relative importance of each objective function z_i. This method also includes constraints over the weighting coefficients ω_i (e.g. Eqs. (8) and (9)) and the compromise index Φ (e.g. Eq. (12)) stated earlier. The decision-maker's preferences are also expressed in the compromise index Φ ($1 \le \Phi \le \infty$), which represents the decision-maker's concern with respect to the maximal deviation from the utopia point. As a result, the non-inferior solutions defined within the range $1 \le \Phi \le \infty$ correspond to the compromise set from which the decision maker still has to make the final choice to identify the best compromise solution (Dantus & High, 1999). The single asterisk as superscript in z_i^* indicates the minimum values of the ith objective function found solving the corresponding single objective optimization problem. Meanwhile double asterisk as superscript in z_i^{**} indicates the maximum allowed value of the ith objective function. For the special case of a bi-objective problem z_i^{**} is the value obtained for z_i when minimizing the alternative objective function. In other words, if $i = 1, 2$ in Eq. (13), then $z_1^* = \min z_1$, $z_2^* = \min z_2$, then the maximum values of each objective function are as follow: z_1^{**} the result for z_1 when z_2 is minimized and z_2^{**} the result for z_2 when z_1 is minimized.

Continuous optimization variables have been considered in the previous description of methods to solve multi-objective optimization problems. The inclusion of binary optimization variables is described next.

4.1.5. Inclusion of binary optimization variables

Multi-objective mixed-integer non-linear problems have been studied much less than multi-objective non-linear problems only with continuous variables. Introduction of discrete variables in the mathematical model turns the problem much more difficult to solve, being the feasible region non-convex. The non-dominance concept in multi-objective mixed-integer programming is defined as for multi-objective mathematical programming with continuous variables only (Alves & Clímaco, 2007). Zionts and Wallenius (1980) studied multi-objective problems with integer variables applied to linear programming problems only. Ciric and Huchette (1993) had dealt with multi-objective nonlinear problems in an ethylene glycol plant. The Pareto curve could be discontinuous due to the presence of discrete variables, where the feasible region is disjointed. Dantus and High (1999) successfully applied the global criterion method (Goicoechea, 1982) to a multi-objective problem including discrete variables to select the type of reactor to be used in the methyl chloride plant design. In the present work all the methods mentioned previously have been implemented to solve a bi-objective mixed integer non-linear problem: weighted sum, utopia point distance minimization and global criterion. In the following section the operating condition of the steam and power plant are selected to minimize the potential environmental impact and operating cost.

5. Minimization of potential environmental impact and operating cost

The objective of this work is to minimise the potential environmental impact and operating cost to select the operating conditions of steam and power plants, leading to a bi-objective mixed integer non-linear optimization problem. The objective functions used are potential environmental impact (PEI) given in Eq. (5) and operating cost (C) given in Eq. (6). Thus, the general formulation of the bi-objective optimization problem considering continuous and discrete variables follows:

$$\begin{aligned} &\min_{x,y} Z = Z[PEI(x,y), C(x,y)] \\ &s.t. \\ &g(x) + A(y) \le 0 \\ &h(x) = 0 \\ &x^L \le x \le x^U \\ &x \in R^N \\ &y \in \{0,1\}^m \end{aligned} \qquad \text{(P3)}$$

where x and y are the continuous and binary optimization variables, respectively. Superscripts U and L, indicate upper and lower bounds on vector x. The equality constraints $h(x) = 0$ are the system of non-linear algebraic equations that represent the steady state modelling of the process plant, including mass and energy balances; enthalpy and entropy predictions. The inequality constraints $g(x) + A(y) \le 0$ represent logical constraints, minimum and maximum equipment capacities, operating and design constraints, etc. The A matrix includes linear relations between binary variables such as logical constraints.

The weighted sum, utopia point distance minimization, ε-constraint and global criterion methods were implemented to solve the bi-objective mixed-integer nonlinear programming problem P3. Their formulation follows:

Weighted sum:

$$Z = \omega_1 \times \mathrm{PEI}(x,y) + \omega_2 \times C(x,y) \qquad (14)$$

Constraints over the weighting factors presented in Eqs. (8) and (9) are also included.

Utopia point distance minimization method, where the distance Z is defined as follows:

$$Z = \{[\mathrm{PEI}(x,y) - \mathrm{PEI}^*]^2 + [C(x,y) - C^*]^2\}^{1/2} \qquad (15)$$

ε-constraint method, minimizing the utility plant environmental impact:

$$\begin{aligned} &\min_{x,y} \mathrm{PEI}(x,y) \\ &s.t. \\ &C(x,y) \le \varepsilon_c \\ &g(x) + A(y) \le 0 \\ &h(x) = 0 \end{aligned} \qquad \text{(P4)}$$

ε-constraint method, minimizing the utility plant operating cost:

$$\begin{aligned} &\min_{x,y} C(x,y) \\ &s.t. \\ &\mathrm{PEI}(x,y) \le \varepsilon_{\mathrm{PEI}} \\ &g(x) + A(y) \le 0 \\ &h(x) = 0 \end{aligned} \qquad \text{(P5)}$$

Table 3
Minimization of utility plant environmental impact.

Objective functions and cont. var.	Solution point
UP env. impact, PEI/h	28,591.307
Operating cost, $/h	515.224
Natural gas, ton/h	6.995
Imported electricity, kWh	3806.508
Make up Water, ton/h	22.000
Drivers	
Electrical motors power/units	3277.13 kWh/13
Steam turbines/units	0 kWh/0

Global criterion:

$$Z = \omega_1 \times \left[\frac{\mathrm{PEI}(x,y) - \mathrm{PEI}^*}{\mathrm{PEI}^{**} - \mathrm{PEI}^*}\right]^{\Phi} + \omega_2 \times \left[\frac{C(x,y) - C^*}{C^{**} - C^*}\right]^{\Phi} \qquad (16)$$

Constraints over the weighting factors given in Eqs. (8) and (9) and over the compromise index given in Eq. (12) are considered. The parameters for Eq. (16) are defined as follows:

PEI^* = min PEI.
C^* = min C.
PEI^{**} = value of PEI at the minimum operating cost point.
C^{**} = value of C at the minimum environmental impact point.

The parameters needed for the global criterion method implementation are obtained in the single objective function optimization step.

6. Selection of the operating conditions

The operating conditions, including continuous and binary variables, are selected to minimise potential environmental impact and operating cost simultaneously, solving problem P3. The discrete decisions are associated with the selection of optional drivers for some pumps, which can be driven by existing electrical motors or steam turbines. Other decisions associated with binary variables are the selection of equipment that can be in operation (ON) or shut down (OFF), like the boilers and their auxiliary equipment. The binary variables were listed in Table 2.

Single objective minimization is carried out before attempting the bi-objective minimization. Results minimising the potential environmental impact are shown in Table 3 and minimizing the operating cost are presented in Table 4.

The weighted sum and ε-constraint methods had a good performance when using only continuous variables. Utopia point distance minimization and global criterion methods had a very good performance when using continuous and binary variables. Numerical results generated with the utopia point distance minimization and the global criterion methods are presented in this section.

6.1. Utopia point distance minimization

This method was stated in Eq. (15) and produces only one Pareto point. The optimal point has the following coordinates:

Table 4
Minimization of utility plant operating cost.

Objective functions and cont. var.	Solution point
UP env. impact, PEI/h	29,335.360
Operating cost, $/h	470.763
Natural gas, ton/h	7.246
Imported electricity, kWh	671.700
Make up water, ton/h	22.000
Drivers	
Electrical motors power/units	570.91 kWh/3
Steam turbines/units	2400.31 kWh/10

Table 5
Single Optimization results including binary variables in the UP model.

Objective function	Min. $C(x)$	Min. $PEI^{UP}(x)$	% variation
Operating cost, $/h	**470.763**	*515.224*	8.629
Pot. env. impact, PEI/h	*29,335.360*	**28,591.307**	2.536

$C = 506.01$ $/h, $PEI^{UP} = 28{,}644.70$ PEI/h. At this point 11 electrical motors and 2 steam turbines were ON.

6.2. Global criterion method

To solve the bi-objective optimization problem with the global criterion method, single optimization results are needed as parameters and both extreme points are shown in Table 5. The minimum values for each single objective function has been highlighted in bold letters and the maximum allowed values for each single objective function are presented in italics letters (this values are used as parameters in the global criterion method, Eq. (16)).

The expected variations, between extreme points, are in the order of 8.63% in operating cost and 2.54% en total potential environmental impact.

Each Pareto optimal point was obtained with GAMS (Brooke et al., 2003) using the following solver options: DICOPT as a MINLP solver, including CONOPT2 to solve the NLP subproblem and CPLEX to solve the MIP subproblem, respectively.

The weighting parameters ω_i vary from 0.1 to 0.9 with a step equal to 0.1. The decision maker's compromise index Φ has been taken equal to: $\Phi = 1$, 2 and 3. Twenty Pareto optimal points are obtained and reported in Table 6, where single objective function values, the specific global criterion method parameters used, solver performance (e.g. CPU time in seconds and number of iterations) and the continuous optimization variables values are included. The continuous variables reported are temperatures (T1, T2, T3) and pressures (P1, P2, P3) of high, medium and low pressure steam headers and deareator pressure (Pd). Pressure are expressed in bar and temperature in °C. The first point (1) corresponds to minimum operating cost and the final point (20) to minimum environmental impact point (both numerical values indicated in bold letter in Table 6). As the decision maker's compromise index rise, for fixed value of the weighting coefficients ω, the computational time to reach a solution is longer.

Temperature (T1) and pressure (P1) of high pressure steam header are at their upper bound value and temperatures of medium

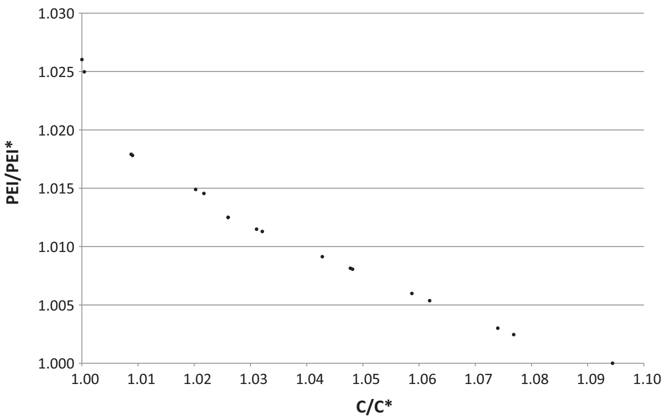

Fig. 2. Pareto curve for bi-objective minimization using continuous and binary optimization variables.

(T2) and low (T3) pressure steam headers are at their lower bound values, as expected to provide maximum steam turbines' power. The Pareto curve is shown in Fig. 2, with the twenty optimal points presented in Table 6.

The number of electrical motors and steam turbines required providing the power demands of the ethylene plant for each point in the Pareto curve are reported in Table 7, to show binary results of each Pareto point.

At point 1 corresponding to the minimum operating cost point, steam turbines are selected because the power generated in the utility plant is cheaper than the electricity power imported, due to

Table 7
Number of electrical motors and steam turbines in operation for different Pareto points.

Pareto points	Electrical motors	Steam turbines
2, 3, 4	2	11
1, 7, 8, 9, 10	3	10
13	4	9
11, 12	5	8
5, 6, 14, 17	6	7
15	7	6
18	9	4
16, 19	10	3
20	13	0

Table 6
Continuous optimization variables for the Pareto optimal points.

Pareto points	Cost, $/h	PEI/h	ω_1	Φ	CPU time, s	It	P1	P2	P3	Pd	T1	T2	T3
1	**470.763**	29,335.360	–	–	3.64	4	52.00	22.98	3.00	3.00	450.00	326.74	150.00
2	470.967	29,305.450	0.1	1	3.91	3	52.00	22.93	3.00	2.98	450.00	310.00	150.00
3	474.886	29,103.120	0.3	1	3.03	2	52.00	23.86	4.08	2.75	450.00	310.00	150.00
4	475.001	29,100.500	0.1	2	5.14	3	52.00	23.86	4.08	2.75	450.00	310.00	150.00
5	480.288	29,017.090	0.2	2	5.45	3	52.00	23.53	4.86	2.39	450.00	310.00	150.00
6	480.981	29,007.310	0.1	3	5.28	3	52.00	23.34	4.89	2.14	450.00	310.00	150.00
7	483.009	28,948.680	0.3	2	3.16	2	52.00	23.30	4.97	2.17	450.00	310.00	150.00
8	483.010	28,948.670	0.2	3	3.44	2	52.00	23.30	4.97	2.17	450.00	310.00	150.00
9	483.014	28,948.590	0.5	1	3.98	3	52.00	23.33	4.98	2.20	450.00	310.00	150.00
10	483.017	28,948.540	0.3	3	4.28	3	52.00	23.35	4.98	2.23	450.00	310.00	150.00
11	485.394	28,919.700	0.5	2	3.44	2	52.00	23.31	4.97	2.21	450.00	310.00	150.00
12	485.879	28,914.150	0.5	3	3.44	2	52.00	23.49	5.00	2.47	450.00	310.00	150.00
13	490.903	28,852.350	0.7	3	7.21	5	52.00	23.34	5.00	2.33	450.00	310.00	150.00
14	493.254	28,824.060	0.7	2	4.67	3	52.00	23.38	5.00	2.42	450.00	310.00	150.00
15	493.439	28,821.840	0.8	3	5.16	3	52.00	23.38	5.00	2.43	450.00	310.00	150.00
16	498.414	28,762.330	0.9	3	4.86	2	52.00	23.46	5.00	2.62	450.00	310.00	150.00
17	499.896	28,744.690	0.8	2	2.77	2	52.00	23.49	5.00	2.67	450.00	310.00	150.00
18	505.609	28,677.110	0.9	2	18.85	4	52.00	23.58	5.00	2.90	450.00	310.00	150.00
19	506.939	28,661.490	0.6	1	8.00	6	52.00	23.60	5.00	2.96	450.00	310.00	150.00
20	515.224	**28,591.307**	–	–	11.82	13	52.00	23.46	5.00	3.00	445.00	310.00	150.00

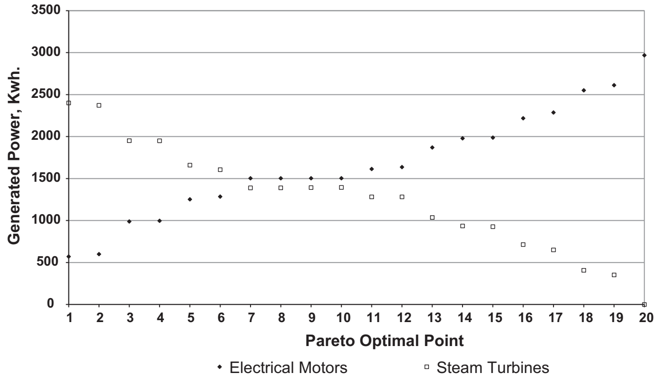

Fig. 3. Power generated by electrical motors and steam turbines for the Pareto optimal points.

the mass and heat integration of the utility sector with the ethylene process plant. The two main reasons are that: (i) a rich hydrogen residual stream coming from the top of the demetanizer column is burned in the boilers to generate high pressure steam as has been analyzed by Martínez and Eliceche (2010) and (ii) high pressure steam is generated to cool down the ethylene cracking furnace. On the other hand, when minimizing potential environmental impact (point 20) the power demand is supplied with electrical motors because there is no impact associated with the imported electricity. For these reasons the power provided by the steam turbines has a monotonic decreasing behaviour and the power delivered by electrical motors has a monotonic increasing behaviour in Fig. 3 along the Pareto curve.

Pareto curve will be analyzed in the following section to identify the more attractive solutions.

7. Analysis of the Pareto curve

Convergence was achieved with the global criterion method using compromise index values up to a value of $\Phi = 10$, generating 95 point of the Pareto curve. No solutions were found with a compromise index $\Phi = 11$. In Fig. 5 these 95 points are included, with the 20 points of Table 6 indicated with (+). These twenty points were calculated with compromise index $\Phi = 1$, 2 and 3.

Two regions of the Pareto curve can be approximated by linear correlations as shown in Fig. 4.

The analytical expressions of the two straight lines were obtained using minimum squares method and the analytical expressions follow:

$$\left[\frac{\mathrm{PEI}}{\mathrm{PEI}^*}\right] = 1.909 - 0.884\left[\frac{C}{C^*}\right] \tag{17}$$

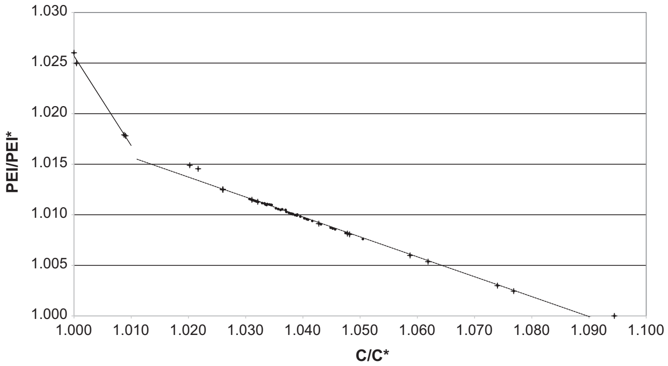

Fig. 4. Linearization of the Pareto curve, for $1 < \Phi < 11$, global criterion method.

Table 8
Ratio of reduction of PEI per increment in op. cost between the extreme points of the two straight lines.

Differences between points of the Pareto curve	(4th–1st) points	(20th–5th) points
Δ PEI reduction, PEI/h	−234.860	−425.783
Δ Operating cost increment, \$/h	4.238	34.936
Δ PEI/Δ operating cost	−55.418	−12.188

$$\left[\frac{\mathrm{PEI}}{\mathrm{PEI}^*}\right] = 1.216 - 0.198\left[\frac{C}{C^*}\right] \tag{18}$$

The reduction in potential environmental impact (PEI) and the corresponding increment in operating cost (C) between the extreme points of the first straight line (4 is the final point and 1 is the first point) are shown in the first column of Table 8; while the reduction in potential environmental impact and increment in operating cost between the extreme points of the second straight line (20 is the final point and 5 is the first point) are shown in the second column of Table 8. These values can be calculated from data presented in Table 6.

The ratios of PEI reduction with respect to increment in operating cost, for the two regions of the Pareto curve, are reported in the third line of Table 8. This ratio for the first straight line is more than four times bigger than the same ratio for the second straight line, indicating that the reduction of potential environmental impact per unit of increment in operating cost is four times more in the region of the first approximation than in the second region. The slope of the first straight line (Eq. (17)) is also more than four times bigger than the slope of the second straight line (Eq. (18)). As a conclusion, it could be said that the cost of reducing the PEI in the region approximated by the first straight line (points 1–4) is four times less than the cost of reducing the PEI in the region approximated by the second straight line (points 5–20).

At a decision making level, this information would indicate that it is more convenient to go from point 1 to 4 than going from point 5 to 20. It would be advisable to work in the region of the Pareto curve approximated by the first straight line, rather than in the region of the Pareto curve approximated by the second straight line. Thus point 4 looks as the best compromise solution.

The economical valorization of the reduction of greenhouse gases emission is studied in the following section to evaluate the possibility of compensating the increment in operating cost.

8. Considering the economical income due to greenhouse gases emissions reduction

It is worth mentioning the fact that under a tradable permit system, an allowable overall level of pollution is established and allocated among sectors in the form of permits. Sectors that keep their emission levels below their fixed level may sell their surplus permits to other sectors or use them to compensate excess emissions in other parts of their facilities; the market is regulated and organized by the Kyoto Protocol Clean Development Mechanism (Hepburn, 2007).

Thus, a potential economic incentive of the greenhouse gases emissions reduction can be estimated, considering the income that could be obtained in the carbon market that has arisen with the Kyoto protocol. The greenhouse gases emissions, measured in CO_2 equivalent kg/h, represent 99.6% of the potential environmental impact in the steam and power plant, as has been shown in Eliceche et al. (2007). The greenhouse gases emissions, measured in CO_2 equivalent kg/h, account for emissions of greenhouse gases such as CO_2, CH_4 and N_2O which are the typical fuel combustion emissions as shown in Martínez and Eliceche (2009). The utility plant does not emit greenhouse gases as CFCs (chlorinated fluorocarbons) and

Table 9
Potential income due to reduction of greenhouse gases emissions.

Pareto points	Operating cost, \$/h	Greenhouse, kg/h	CO_2 income, \$/h
1	470.763	29,218.019	76.746
2	470.967	29,188.228	77.342
3	474.886	28,986.708	81.372
4	475.001	28,984.098	81.424
5	480.288	28,901.022	83.086
6	480.981	28,891.281	83.281
7	483.009	28,832.885	84.449
8	483.010	28,832.875	84.449
9	483.014	28,832.796	84.450
10	483.017	28,832.746	84.451
11	485.394	28,804.021	85.026
12	485.879	28,798.493	85.136
13	490.903	28,736.941	86.368
14	493.254	28,708.764	86.931
15	493.439	28,706.553	86.975
16	498.414	28,647.281	88.161
17	499.896	28,629.711	88.512
18	505.609	28,562.402	89.858
19	506.939	28,546.844	90.169
20	515.224	28,476.942	91.568

HFCs (hydro fluorocarbons). To evaluate a possible economic incentive due to carbon emissions permit sold in the emission trading market, a price of 20 \$/ton is used to quantify the potential income. The greenhouse gases emissions flow rate, the corresponding CO_2 income and the operating cost for each Pareto point are shown in Table 9.

Reductions in greenhouse gases emissions, increments (Δ) in operating cost and CO_2 income between the extreme points of the first and second straight lines approximations of the Pareto curve are reported in the first and second columns respectively of Table 10 and calculated from data in Table 9.

It can be observed that in the region of the Pareto curve approximated by the first straight line, first column of Table 10, the CO_2 income is slightly superior to the operating cost increment, so the reduction in greenhouse gases emissions would generate a CO_2 income that would compensate the increment in operating cost going from point 1 to point 4 of the Pareto curve. Therefore it would be convenient to reduce greenhouse gases emissions with no additional cost and operate in point 4.

On the other hand in the second column, going from point 5 to point 20, the possible CO_2 income by reduction of greenhouse gases emissions represents only 24% of the increment in operating cost, so the net cost increment would still be equal to 26.45 \$/h. Thus at first glance, it would be more expensive to go from point 5 to point 20 and it is less attractive from an economical point of view. The increments in operating cost and CO_2 income are presented in Fig. 5 for the twenty Pareto optimal points.

It can be observed in Fig. 5, that when moving from point 1 to 4 the increment in operating cost is of the same value than the increment of CO_2 income in the carbon market, but when moving from point 5 onwards the operating cost increment is bigger than the increment of CO_2 income. Therefore considering the economical assessment of CO_2 income in the carbon market, due to reduction of greenhouse gases emissions, would indicate that the reduction

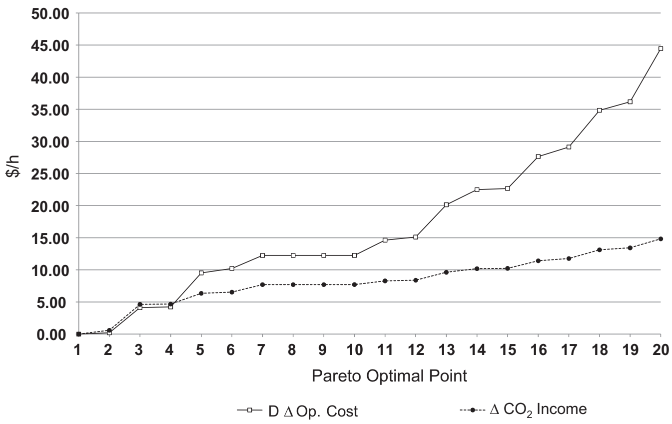

Fig. 5. Increments in CO_2 income and operating cost.

of potential environmental impact between points 1 and 4 of the Pareto curve would be done with no extra cost. These results reinforce the conclusions obtained in the Pareto curve analysis of the previous section.

Thus, it is very important to generate the Pareto curve and more so, to analyze its behaviour in order to gain insight of the trade offs, providing relevant information to support a decision making process, as it has been shown in this work.

9. Conclusions

A methodology has been presented to select the operating conditions (continuous and binary) of a steam and power plant minimizing simultaneously the potential environmental impact and operating cost. Different methods to solve a bi-objective mixed integer nonlinear optimization problem such as: minimum distance to the utopia point, ε-constraint, weighted sum and global criterion were implemented successfully in GAMS. With the global criterion method 95 points of the Pareto curve were generated.

It is relevant not only to generate the Pareto curve, but also to analyze the behaviour of the different compromise solutions of the Pareto curve to gain insight that would support a decision making process. In the Pareto curve of the steam and power sector of an ethylene plant, two regions can be identified that were approximated with two straight lines. In the first region it is much cheaper to reduce potential environmental impact than in the second region, therefore it would be advisable to reduce potential environmental impact in the first region of the Pareto curve as shown in Table 8 and Fig. 4. Furthermore, the assessment of CO_2 income in the carbon market due to greenhouse gases emission reduction compensates, in the first region of the Pareto curve, the increment in operating cost, as shown in Table 10 and Fig. 5. The possibility of reducing the potential environmental impact with no additional cost makes more attractive the first region of the Pareto curve, and in particular the neighbourhood of point 4, that would have the minimum potential environmental impact.

Table 10
Ratios of potential greenhouse gases emissions income and increment in operating cost.

Differences between points of the Pareto curve	(4th–1st) points	(20th–5th) points
Δ Operating cost increment, \$/h	4.238	34.936
Δ Greenhouse emissions reduction, kg/h	233.921	424.080
Δ CO_2 income increment, \$/h	4.678	8.482
Δ CO_2 income/Δ Operating Cost	110.382%	24.279%

References

Alves, M. J., & Clímaco, J. (2007). A review of interactive methods for multiobjective integer and mixed-integer programming. *European Journal of Operational Research*, *180*, 99–115.
Azapagic, A., & Clift, R. (1999). Life cycle assessment and multiobjective optimization. *Journal of Cleaner Production*, *7*(2), 135–143.
Bhaskar, V., Gupta, S., & Ray, A. (2000). Applications of multiobjective optimization in chemical engineering. *Reviews in Chemical Engineering*, *16*, 1–54.
Brooke, A., Kendrick, D., Meeraus, A., & Raman, R. (2003). *GAMS development corporation. A user guide.*

Clark, P. A., & Westerberg, A. W. (1983). Optimization for design problems having more than one objective. *Computers and Chemical Engineering*, *7*, 259–278.
Ciric, A., & Huchette, S. (1993). Multiobjective optimization approach to sensitivity analysis: waste treatment costs in discrete process synthesis and optimization problems. *Industrial & Engineering Chemistry Research*, *32*, 2636–2646.
Coello-Coello, C., & Christiansen, A. (1999). MOSES: a multiobjective optimization tool for engineering design. *Engineering Optimization*, *31*(3), 337–368.
Dantus, M., & High, K. (1999). Evaluation of waste minimization alternatives under uncertainty: A multiobjective optimization approach. *Computers and Chemical Engineering*, *23*, 1493–1508.
Das, I., & Dennis, J. E. (1997). Normal-boundary intersection: a new method for generating the Pareto surface in multicriteria optimization problems. *SIAM Journal on Optimization*, *8*, 631–657.
Eliceche, A., Corvalan, S., & Martinez, P. (2007). Environmental life cycle impact as a tool for process optimization of a utility plant. *Computers and Chemical Engineering*, *31*, 648–656.
Electrical Power Research Institute. (2000). Aqueous discharges from steam electric power plants, data evaluation. Updated report http://www.epri.com
EPA, U.S. Environmental Protection Agency (1998). *AP-42 Compilation of air pollutant emission factors*.
Gebreslassie, B., Jimenez, M., Guilleǐn-Gosaǐlbez, G., Jimeǐnez, L., & Boer, D. (2010). Multi-objective optimization of solar assisted absorption cooling system. In S. Pierucci, & G. Buzzi Ferraris (Eds.), *20th European symposium on computer aided process engineering – ESCAPE20*.
Guinée, J., Heijungs, R., Huppes, G., Kleijn, R., Koning, A., van Oers, L., Sleeswijk, A., Suh, S., & Udo de Haes, H. (Eds.). (2002). *Handbook on life cycle assessment. Operational guide to the ISO standards*. Dordrecht: Kluwer Academic Publishers.
Goicoechea, A., Hansen, D. R., & Duckstein, L. (1982). *Multiobjective decision analysis with engineering and business applications*. New York: Wiley.
Haimes, Y., & Hall, A. (1974). Multiobjectives in water resources system analysis: The surrogate worth trade-off method. *Water Resources Research*, *10*, 615–624.
Hepburn, C. (2007). Carbon trading: A review of the kyoto mechanisms. *Annual Review of Environmental Resources*, *32*, 375–393.
Hwang, C. L., & Masud, A. S. (1979). *Multiple objective decision making – Methods and applications*. *Lecture notes in economics and mathematical systems* Berlin: Springer.
Hwang, C. L., Paidy, S. R., Yoon, K., & Masud, M. (1980). Mathematical programming with multiple objectives: A tutorial. *Computers & Operations Research*, *7*, 5–31.
IPCC. (2001). *Climate change 2001: The scientific basis. Intergovernmental panel on climate change*. Cambridge University Press., 2002.
Martínez, P., & Eliceche, A. (2010). Recycling a hydrogen rich residual stream to the power and steam plant. *International Journal of Hydrogen Energy*, *35*, 5882–5889.
Martínez, P., & Eliceche, A. (2009). Minimization of life cycle CO_2 emissions in steam and power plants. *Clean Technology and Environmental Policy*, *11*, 49–57.
Novais, A. Q., Barbosa-Póvoa, A. P., & Duque, J. (2010). Design and planning of sustainable industrial networks: Application to a recovery network of residual products. *Industrial & Engineering Chemistry Research*, *49*(9), 4230–4248.
Pistikopoulos, P., & Hugo, A. (2005). Environmentally conscious long-range planning and design of supply chain networks. *Journal of Cleaner Production*, *13*, 1471–1491.
Puigjaner, L., Arbiza, M. J., Bonfill, A., Guillen, G., Mele, F., & Espuña, A. (2008). Metaheuristic multiobjective optimisation approach for the scheduling of multiproduct batch chemical plants. *Journal of Cleaner Production*, *16*, 233–244.
Sayyaadi, H. (2009). Multi-objective approach in thermoenvironomic optimization of a benchmark cogeneration system. *Applied Energy*, *86*, 867–879.
Steuer, R. E. (1986). *Multiple criteria optimization: Theory, computation and application*. New York: Wiley.
Zeleny, M. (1982). *Multiple criteria decision making*. New York: McGraw Hill.
Zionts, S., & Wallenius, J. (1976). An interactive programming method for solving the multiple criteria problem. *Management Science*, *22*, 652–653.
Zionts, S., & Wallenius, J. (1980). Identifying efficient vectors: some theory and computational results. *Operational Research*, *28*(3), 788–793.