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Multi-objective optimization of the design of two-stage flash evaporators: Part 2. Multi-objective optimization

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ABSTRACT

Flash evaporation process is currently developing in the wine industry where it is used for flash-cooling or concentration. The design of flash evaporators is faced with specific constraints and must take into account multiple design objectives. In this paper, the development of a multi-objective optimization method is investigated for the joint optimization of design objectives such as process transportability, environmental efficiency, operative cost or cooling power. The optimization method is based on the aggregation of design objectives through desirability functions and indexes. Desirability functions are suitable for formulating design constraints more precisely than inequality relations and, moreover, the global design model results in an unconstrained optimization problem. However, aggregation methods do make it difficult to compute the global optimum of the design problem. This difficulty has been addressed by developing a distributed genetic algorithm which is not so sensitive to this type of numerical solving difficulty. Another difficulty arises from the weighting method for the aggregation of desirability functions since weight parameters have no physical meaning. This weighting problem is approached through a sensitivity analysis of the weight parameters and by observing their relative influence.

1. Introduction

This paper presents a methodology of multi-objective optimization for designing applications and is applied to a two-stage flash evaporation process for cooling and concentration applications. The first part of the paper was focused on modeling the design problem of flash evaporators, taking into account the thermodynamical modeling of the coupling between heat and mass transfer phenomena inside the system, mainly the evaporation chambers and the condensers. It also considers the industrial requirements relating to the flash evaporation process, such as the dimensional, economical or environmental constraints of the problem.

The present part of the paper deals with the multi-objective optimization method of the design problem. Optimization is performed by considering five global performance criteria relating to the system and the product. System criteria concern the cooling power, eco-performances, transportability and costs of the system. The product criterion concerns the cooling temperature of the product at the system outlet. Multi-objective optimization is performed by defining desirability functions for every design objective of the problem and by aggregating them as desirability indexes. Two levels of desirability indexes are distinguished, which concern design objectives or the objective function of the optimization process. Optimal design solutions are computed using a distributed genetic algorithm. In the fourth chapter, the aggregation method is investigated through the flash evaporator design application. We mainly perform a sensitivity analysis of weighting parameters and we study the ability of the method to support design decision. This analysis is carried out by computing several optimal design configurations relating to different weight parameters.

2. Desirability and global optimization

Process optimization is faced with the difficulty of defining design objectives for complex processes. Optimization must take into account many different objectives relating to the entire life cycle of the process, which includes constraints relating to its use (product quality, maintainability, etc.) but also to its ability to be manufactured, transported, sold, recycled, etc. Global optimization must take into consideration every constraint of the design problem. However, the life cycle of a system such as a flash evaporator is complex and its global optimization entails selecting and modeling the most relevant objectives of the system design. This paragraph aims at presenting the approach, based on the concept of desirability, developed for modeling the design objectives and optimizing the design problem.

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2.1. Variable characterization

In design optimization some of the variables of the design problem must be characterized. Here, we consider two main types of variables to characterize candidate solutions to the design problem and qualify their performance. Design variables (decision variables) typify the main characteristics of a flash evaporator regarded as a candidate solution and its functioning environment (fluids). These variables are:

- inlet flow rate (q_{pi}) and inlet temperature (T_{pi}) of the product,
- flow rate ($q_{cl\ LP}$) and temperature of the ($T_{cl\ LP}$) of the coolant,
- flow rate (q_{cl+HP}) of the coolant added in the HP stage,
- number of plates of the HP condenser (N_{HP}) and the LP condenser (N_{BP}).

Every variable value of the design problem model is derived from the values of these seven variables, including the performance variables (response variables). Performance variables are observed to qualify any candidate solution determined from a set of values related to the design variables. Design variables and performance variables are denoted X and Y respectively. We consider seven design variables and eight performance variables, therefore:

$$X = \{x_1, x_2, \ldots, x_7\}, Y = \{y_1(X), y_2(X), \ldots, y_8(X)\} \quad (1)$$

where,

$$X \in \Omega \quad (2)$$

Ω is the value domain of the design variables and is defined in Table 1.

2.2. Desirability functions and performance variables

In the following, every design objective has been related to one or several performance variables. For instance, the transportability of the process is linked to the mass (M_{sys}) or floor occupation area (S_{sys}) of the system. These two performance variables determine the ability of the flash evaporator to be transported on a flat bed truck. Standard dimensions and maximal carrying capacities of trucks constrain the admissible maximal values of the mass and occupation area. As a general rule, every performance variable can be linked to admissible values related to constraints in the system life cycle. Transportability is related to system utilization since flash evaporators must be transported between several production sites during the grape harvesting period (see Section 1), but also to its manufacturing and recycling phases. In this paper, admissible values are formulated through Harrington's desirability functions [1]. These are mapped onto performance variables to define the most desirable values expected for these variables. These functions are non-dimensional, monotonous or piecewise monotonous and take their values between zero and one. Desirability functions can be interpreted as a degree of satisfaction of the constraint; zero value corresponds to minimal satisfaction and 1 to maximal satisfaction.

Harrington defined two types of desirability functions (see Fig. 1) to formulate the constraint satisfaction in multicriteria optimization problems: one-sided and two-sided functions. One-sided functions aim at maximizing or minimizing performance variables and require two (one-sided functions) or four (two-sided functions) limit specification parameters, namely, the Absolute Lower Cutoff (ALC), Lower Soft Limit (LSL), Upper Soft Limit (USL) and Absolute Upper Cutoff (AUC). These limits correspond to desirability values close to one (0.99) or zero (0.01). Typically, one-sided functions are used to express design specifications relating to threshold values. For instance, the transportability of a flash evaporator is limited by the maximal mass and dimensions of flat bed trucks, which correspond to threshold values of mass and floor occupation area of the system. Maximal threshold values must not be exceeded and, the lower the mass and overall dimensions of the system, the more desirable they are. Desirability functions relating to these performance variables are used for modeling such preferences or design specifications. Limit specification parameters are mainly derived from human expert knowledge on the part designers, manufacturers, customers, and so on, which is often based on practical knowledge of the process life cycle and its environment. Desirability functions often encompass complex technical know-how and intricate physical phenomena and may be regarded as knowledge-based models.

The eight performance variables of the two-stage flash evaporator observed in this paper are the cooling power ($\mathcal{P}_{cool}$), eco-indicator (EI), fluid consumption (C_f), electrical energy consumption (C_e), mass (M_{sys}), floor occupation area (S_{sys}), total cost of ownership ($\overline{C}_{tot}$) of the system and the outlet temperature of the product (T_{po}). Every performance variable is linked to a desirability function and their corresponding limit specification parameters are presented in Table 2. Some limit specification parameters have been based on the design requirements of a wine producing company in the Bordeaux area (France). This company was interested in developing a flash evaporator capable of cooling ten tons of grape juice per hour from an initial temperature ranging from 70 °C to 90 °C to a temperature lower than 30 °C. The limit specification parameters of the cooling power and outlet product temperature have been derived from these data. The parameter ALC corresponds to a product mass flow rate of 7 tons per hour cooled from 70 °C to 30 °C (330 kW) and the parameter SLS to a product mass flow rate of 10 tons per hour cooled from 90 °C to 20 °C (820 kW) (Table 3).

2.3. Desirability index and optimization problem formulation

Every performance variable, and therefore every desirability function, may be related to particular design objectives (see Fig. 2). The eight desirability functions of the flash evaporator design model have been linked to five design objectives. In the same way, the global objective of the optimization process has been aggregated into a single Objective Function. The same method has been used to aggregate desirability functions into design objectives and design objectives into an objective function. This method is based on the concept of desirability index introduced by Derringer [2] and

Table 1
Design variables and their corresponding value domains.

	Design variables $X = \{x_1, x_2, \ldots, x_7\}$		Value domain $\Omega(X)$		
	Name	Unit	x_-	x_+	Type
Product	T_{pi}	(°C)	70	90	Interval: $[x_-; x_+]$
	q_{pi}	(kg s^{-1})	2.22	3.33	Interval: $[x_-; x_+]$
Condenser coolant	$T_{cl\ LP}$	(°C)	15	20	Interval: $[x_-; x_+]$
	$q_{cl\ LP}$	(kg s^{-1})	2.78	5.56	Interval: $[x_-; x_+]$
	q_{cl+Hp}	(kg s^{-1})	0.28	6.94	Interval: $[x_-; x_+]$
Condenser plates	N_{HP}	(−)	6	70	Sequence: $\{x_-; x_+\}$
	N_{BP}	(−)	6	70	Sequence: $\{x_-; x_+\}$

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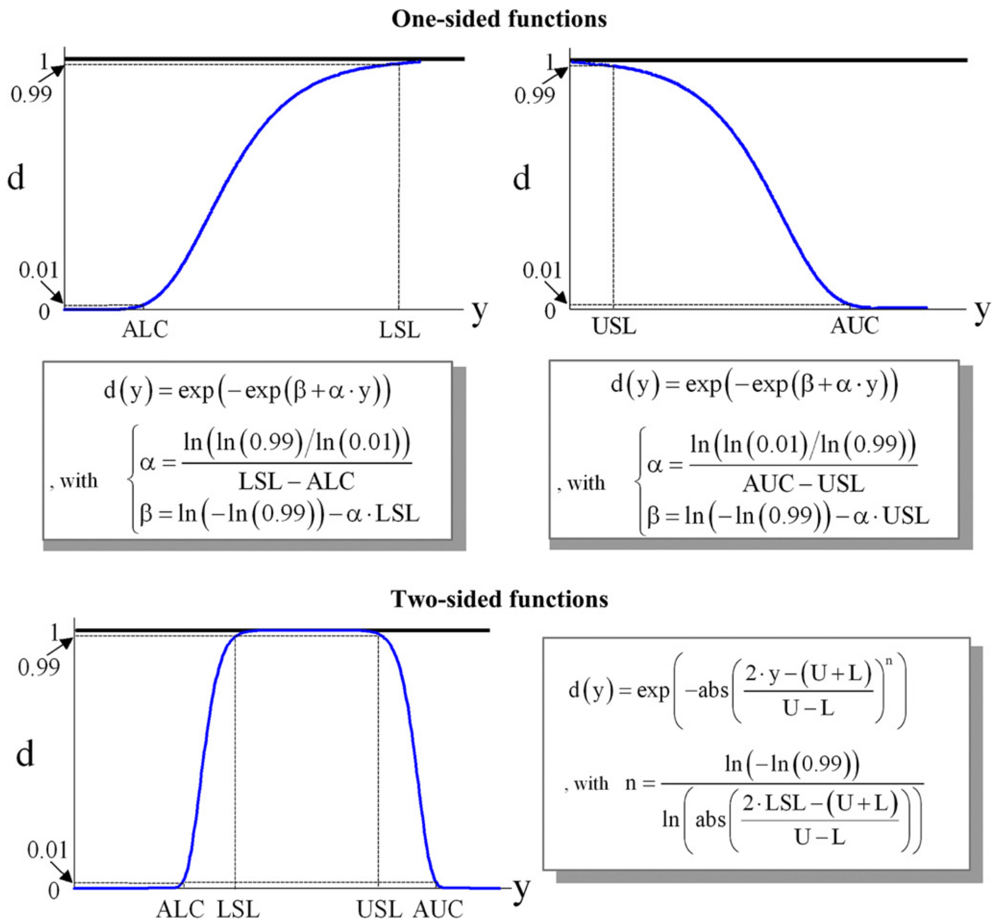

Fig. 1. Desirability functions.

recently developed in multi-response optimization [3,4]. Any system design becomes unacceptable as soon as at least one of the values of the performance variables is non-desirable. From this principle, Derringer proposed to aggregate every value of individual desirability into a global desirability index through a weighted geometric mean. This principle has been used to aggregate desirability functions into design objectives (DOI standing for Design Objective Index) and design objectives into an objective function (OF):

$$\mathrm{DOI_i}(X) = \prod_{j=1}^{n_i} d_j\left(y_j(X)\right)^{v_j/\sum v_j} \tag{3}$$

Where v_j is the weight corresponding to the jth desirability function of the design objective and n_i the number of desirability functions taken into account in the definition of the ith Design Objective Index $\mathrm{DOI_i}$ (see Table 2).

$$\mathrm{OF}(X) = \prod_{i=1}^{5} \mathrm{DOI}_i(X)^{w_i/\sum w_i} \tag{4}$$

Where w_i is the weight corresponding to the ith design objective.

The weights are used to adjust the relative influence of the different design objectives in the global optimization objective. The global optimization problem relating to the flash evaporator design is formulated as:

$$\text{Find } X/\ X \in \Omega \quad \max.\ \mathrm{OF}(X) \tag{5}$$

Constraints of the design problem (relating to cost, mass and so on) are formulated inside the model through desirability functions; consequently the constraints are not explicit in the formulation of the optimization problem, but are intrinsic to its definition.

Table 2
Design objectives, performance variables and limit specification parameters of the desirability functions.

Design obj. and perf. variables $Y = \{y_1(X), y_2(X), \ldots, y_8(X)\}$				Desirability function definition $D = \{d_1(y_1), d_2(y_2), \ldots, d_8(y_8)\}$			
Des. Objective	D.O. Index	Perf. Var.	Unit	ALC	LSL	USL	AUC
Transportability	$\mathrm{DOI_1}$	M_{sys}	(kg)	–	–	3800	19 000
		S_{sys}	(m^2)	–	–	3.20	16
Cooling power	$\mathrm{DOI_2}$	$\mathcal{P}_{cool}$	(kW)	330	820	–	–
Product quality	$\mathrm{DOI_3}$	T_{po}	(°C)	18	20	30	32
Environmental efficiency	$\mathrm{DOI_4}$	EI	(–)	–	–	10 000	50 000
		C_f	(kg s^{-1})	–	–	20	100
		C_e	(kW)	–	–	8.40	42
Objective cost	$\mathrm{DOI_5}$	$\overline{C}_{tot}$	(k€)	–	–	400	2000

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Table 3
Scenarios and optimal values.

Scenarios and order of preference	Design Variables	Performance Variables	Desirability	Design Obj. Index	Weights	Objective Function
Transportability Optimization: $\begin{cases} DO_2 \sim DO_3 \sim DO_4 \sim DO_5 < DO_1 \\ w_2 = w_3 = w_4 = w_5 < w_1 \end{cases}$	$T_{pi} = 82\ °C$	$M_{sys} = 2297$ kg	$d_1 = 0.995$	$DOI_1 = 0.982$	$w_1 = 10/14$	OF = 0.954
	$q_{pi} = 2.30$ kg s^{-1}	$S_{sys} = 5.58$ m^2	$d_2 = 0.969$			
	$T_{cl\ LP} = 15\ °C$	$P_{cool} = 512$ kW	$d_3 = 0.776$	$DOI_2 = 0.776$	$w_2 = 1/14$	
	$q_{cl\ LP} = 4.13$ kg s^{-1}	$T_{po} = 30\ °C$	$d_4 = 0.973$	$DOI_3 = 0.973$	$w_3 = 1$	
	$q_{cl+HP} = 6.79$ kg s^{-1}	EI = 14010	$d_5 = 0.982$	$DOI_4 = 0.969$	$w_4 = 1/14$	
	$N_{HP} = 70$	$C_f = 39.41$ kg s^{-1}	$d_6 = 0.957$			
	$N_{LP} = 22$	$C_e = 8.90$ kW	$d_7 = 0.968$			
		$C_{tot} = 1129$ k€	$d_8 = 0.849$	$DOI_5 = 0.849$	$w_5 = 1/14$	
Cooling Power Optimization: $\begin{cases} DO_1 \sim DO_3 \sim DO_4 \sim DO_5 < DO_2 \\ w_1 = w_3 = w_4 = w_5 < w_2 \end{cases}$	$T_{pi} = 88\ °C$	$M_{sys} = 3232$ kg	$d_1 = 0.992$	$DOI_1 = 0.859$	$w_1 = 1/14$	OF = 0.946
	$q_{pi} = 2.92$ kg s^{-1}	$S_{sys} = 10.26$ m^2	$d_2 = 0.744$			
	$T_{cl\ LP} = 15\ °C$	$P_{cool} = 728$ kW	$d_3 = 0.976$	$DOI_2 = 0.976$	$w_2 = 10/14$	
	$q_{cl\ LP} = 5.27$ kg s^{-1}	$T_{po} = 31\ °C$	$d_4 = 0.954$	$DOI_3 = 0.954$	$w_3 = 1/14$	
	$q_{cl+HP} = 5.79$ kg s^{-1}	EI = 23610	$d_5 = 0.922$	$DOI_4 = 0.954$	$w_4 = 1/14$	
	$N_{HP} = 69$	$C_f = 39.92$ kg s^{-1}	$d_6 = 0.955$			
	$N_{LP} = 59$	$C_e = 8.90$ kW	$d_7 = 0.985$			
		$C_{tot} = 1272$ k€	$d_8 = 0.753$	$DOI_5 = 0.753$	$w_5 = 1/14$	
Environmental Impact Optimization: $\begin{cases} DO_1 \sim DO_2 \sim DO_3 \sim DO_5 < DO_4 \\ w_1 = w_2 = w_3 = w_5 < w_4 \end{cases}$	$T_{pi} = 88\ °C$	$M_{sys} = 2802$ kg	$d_1 = 0.993$	$DOI_1 = 0.931$	$w_1 = 1/14$	OF = 0.959
	$q_{pi} = 2.26$ kg s^{-1}	$S_{sys} = 8.64$ m^2	$d_2 = 0.873$			
	$T_{cl\ LP} = 15\ °C$	$P_{cool} = 567$ kW	$d_3 = 0.870$	$DOI_2 = 0.870$	$w_2 = 1/14$	
	$q_{cl\ LP} = 4.79$ kg s^{-1}	$T_{po} = 30\ °C$	$d_4 = 0.980$	$DOI_3 = 0.980$	$w_3 = 1/14$	
	$q_{cl+HP} = 3.27$ kg s^{-1}	EI = 19071	$d_5 = 0.960$	$DOI_4 = 0.972$	$w_4 = 10/14$	
	$N_{HP} = 69$	$C_f = 29.10$ kg s^{-1}	$d_6 = 0.980$			
	$N_{LP} = 42$	$C_e = 8.90$ kW	$d_7 = 0.975$			
		$C_{tot} = 927$ k€	$d_8 = 0.927$	$DOI_5 = 0.927$	$w_5 = 1/14$	
Objective Cost Optimization: $\begin{cases} DO_1 \sim DO_2 \sim DO_3 \sim DO_4 < DO_5 \\ w_1 = w_2 = w_3 = w_4 < w_5 \end{cases}$	$T_{pi} = 82\ °C$	$M_{sys} = 2941$ kg	$d_1 = 0.993$	$DOI_1 = 0.910$	$w_1 = 1/14$	OF = 0.943
	$q_{pi} = 2.22$ kg s^{-1}	$S_{sys} = 9.25$ m^2	$d_2 = 0.833$			
	$T_{cl\ LP} = 15\ °C$	$P_{cool} = 496$ kW	$d_3 = 0.740$	$DOI_2 = 0.740$	$w_2 = 1/14$	
	$q_{cl\ LP} = 4.83$ kg s^{-1}	$T_{po} = 30\ °C$	$d_4 = 0.983$	$DOI_3 = 0.983$	$w_3 = 1/14$	
	$q_{cl+HP} = 0.85$ kg s^{-1}	EI = 20409	$d_5 = 0.952$	$DOI_4 = 0.969$	$w_4 = 1/14$	
	$N_{HP} = 69$	$C_f = 20.53$ kg s^{-1}	$d_6 = 0.990$			
	$N_{LP} = 51$	$C_e = 8.90$ kW	$d_7 = 0.965$			
		$C_{tot} = 747$ k€	$d_8 = 0.963$	$DOI_5 = 0.963$	$w_5 = 10/14$	

3. Numerical solving

Aggregation methods based on weighting techniques tend to increase the complexity of the shape of the response surface OF(X); weighting may create numerous local minima, which makes the search for the global optimum of OF(X) more difficult. More to the point, the design variable domain Ω is mixed since some variable domains are discrete and sequential (number of condenser plates) whereas others are continuous and real (mass flow rates and temperatures). Therefore, optimization techniques based on the

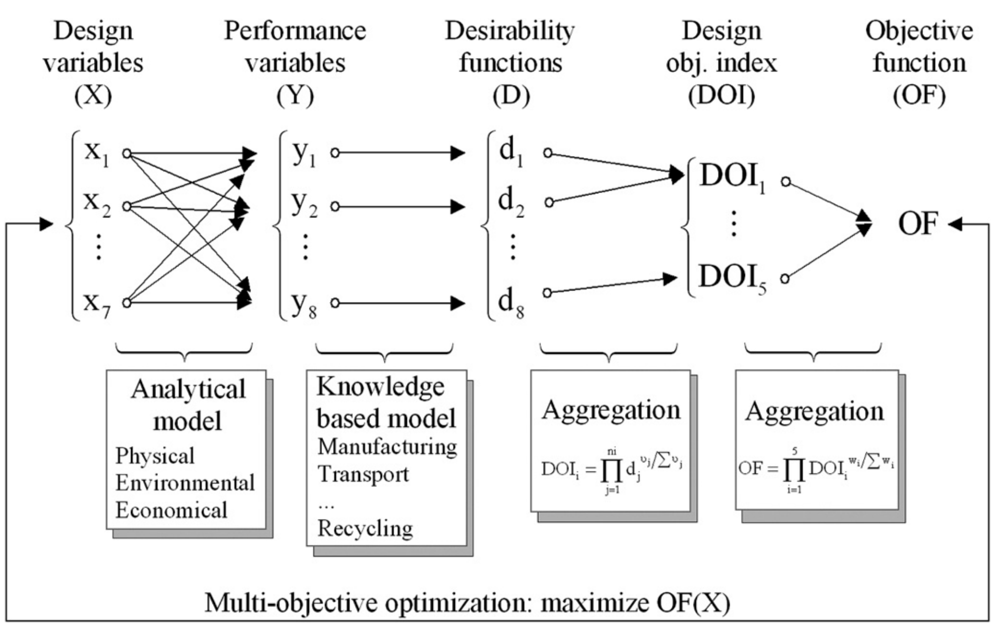

Fig. 2. From design variables to the objective function of multi-objective optimization.

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analysis of the neighborhood of candidate solutions iteratively improved from derivate calculations (conjugate gradients, etc.) are difficult to implement and prove to be inefficient.

This problem has been addressed by developing a distributed Genetic Algorithm [5] to perform the global optimization of the flash evaporator. Genetic algorithms are nature-inspired algorithms [6], which are receiving increasing interest in energy engineering and sciences from heat transfer optimization [7–9] to energy system synthesis [10–12]. These iterative algorithms enhance the performances of populations of candidate solutions (individuals) based on simulated competition between the individuals of the population. Individuals are coded as a set of values corresponding to the design variables. In other words, every individual is assigned to a particular value of X. Optimization is performed by assessing the Objective Function for every individual and individuals are competing for their own survival in the population according to this desirability. Each design variable x_i is regarded as a gene of the individual and the sequence $\{x_i,\ldots, x_{i+k}\}$ as a gene sequence.

Competition is organized by means of four operators, namely selection/reproduction, crossing, mutation and climbing operators. Selection/reproduction is based on tournaments intended for randomly selecting pairs of individuals and eliminating the less desirable individual of the pair. This operator tends to favor desirable individuals according to the Objective Function. Genetic algorithms carry out a global exploration of the design search space Ω through the mutation operator. Mutation is performed by randomly selecting genes in the population and assigning new random values to them inside the design search space Ω. Finally, the climbing operator generates new genes by randomly selecting genes in the population and converting them into a neighbor gene, namely by transforming the value of the selected gene into a close value. This last operator supports the global optimization process in the search for local optima. Crossing, mutation and climbing operators are linked to three probabilities defining the proportion of individuals treated by these operators. Crossing probability (p_{cr}), mutation probability (p_{mu}) and climbing probability (p_{cl}) have been evaluated through a sensitivity analysis:

$$p_{cr} = 0.8 \quad p_{mu} = 0.05 \quad p_{cl} = 0.15 \tag{6}$$

Distributed genetic algorithms rely on the handling of population subsets that evolve in a semi-isolated manner by regularly exchanging individuals (migrations). We developed an algorithm with 4 populations migrating when the best individuals of each of the isolated populations are no longer improved by the algorithm. Migration is equivalent to a global combination of the population and is activated as soon as the best individuals are not improved during at least six iterations of the algorithm. Each of the isolated populations contains 150 individuals. Iterations of the algorithm consist of applying the four genetic operators to the isolated populations (create new generations) and combining isolated populations provided that they no longer improve the Desirability Index. Iterations are stopped when DI optimization fails after ten generations. Due to their stochastic nature, Genetic algorithms cannot guarantee the optimality of the design solutions resulting from the optimization process. For this reason, as we note later in this paper, different optimization calculations may result in different optimal solutions.

Weight parameters (υ_i and w_i) of the desirability indexes (DOI_i and OF) involved in the aggregation process have no physical meaning. For this reason, even for specialists in the domain of flash evaporator design, it seems very difficult to evaluate them, namely to properly balance their values. Weighting parameters are related to expert knowledge which is difficult to formulate since it is somewhat correlated to the context of the design project and is dependent on the optimization solutions. Faced with this difficulty, we propose to start the optimization from one particular configuration of weight parameters and improve this solution step by step. For simplicity's sake, every weight parameter υ_i relating to each of the Design Objective Indexes was fixed to one in the following paragraphs. However, design solutions will be improved by changing weighting parameters w_i.

4. Sensitivity analysis and numerical results

4.1. Aggregation scenarios

Designing complex processes deals with antagonist phenomena induced by both a high degree of complexity and combining variables. Improvement in one particular performance generally causes deterioration in one or several others. Improving the transportability of flash evaporators, for instance, leads to powerless systems since this downsizing process tends to decrease the exchange surfaces of the condensers. Therefore, a feasible solution is generally a compromise between all of the design objectives (see [13] and [14]). In design processes human judgment is required to select the most relevant solutions by taking into account cognitive aspects which come from outside the application domain of mathematical models.

Aggregation methods and weight assignment allow designers to classify solutions according to the satisfaction of design objectives. A stronger weight on a particular DOI means that the associated design objective is more relevant than the others in the whole product life cycle. Introducing the notion of preference, we propose a systematic weight assignment in this paper. Given a set of design objectives$\{DO_1, DO_2, DO_3, DO_4, DO_5\}$ and that each DO_i is associated to a single index DOI_i, which is linked to a unique weightw_i, the preference and indifference relations are defined as,

$$\begin{cases} DO_j \text{ is preferable to } DO_i \Leftrightarrow DO_i \prec DO_j \Leftrightarrow w_i < w_j \quad \text{(preference relation)} \\ DO_j \text{ is as preferable as } DO_i \Leftrightarrow DO_i \sim DO_j \Leftrightarrow w_i = w_j \quad \text{(indifference relation)} \end{cases} \tag{7}$$

Using both the reflexivity and the transitivity of such relations, it becomes possible to sort design objectives by setting orders of preferences. Several levels of preference can then be identified from level 0, an initial state consisting of only indifference relations and homogeneous weights. Although the value of weights associated to this level has no physical meaning, it will be set to 1 by default in this paper. The maximum number of different preference levels which can be found is equal to the number of design objectives. Weight assignment is finally established according to the level of preference of each design objective through an arbitrary scheme $w = f(n)$, where w is the weight associated to the level n. Therefore, identical weights will be assigned to two design objectives at the same preference level. Consider, for instance, a two-stage flash evaporator designed with transportability as the primary objective. Cooling power and the cost of the process are also considered as quite relevant objectives for the users. This scenario can be expressed in terms of preference relations as,

$$\begin{cases} DO_3 \sim DO_4 \prec DO_5 \prec DO_2 \prec DO_1 \\ w_3 = w_4 < w_5 < w_2 < w_1 \end{cases} \text{with a scheme } w_i = \begin{cases} 1/\sum w_i & \text{if } n = 0 \\ 10 \times 2^{n-1}/\sum w_i & \text{otherwise} \end{cases} \quad (8)$$

The solution found using this particular aggregation scenario presents properties which are required to satisfy both the design objectives and their preferences. This is the topic of the following chapter.

4.2. Results and discussion

This part deals with different feasible design solutions for the two-stage flash evaporator. Each one translates a desire to orient the design of the solution towards satisfying one of the design objectives. Different orders of preference are combined, starting from an initial configuration with a homogeneous weighting. The initial solution, called iso-solution, is improved step by step, assigning different weights to the DOIs. The iso-solution will be used as an element of comparison. Using this process we are able to determine the most salient characteristics for each scenario, and define at least an Eco solution, for example, or a Low Cost solution. Seven aggregation scenarios are performed:

- iso-scenario: initial configuration with homogeneous weighting
- α-scenario: optimization of the transportability objective
- β-scenario: optimization of the cooling power objective
- γ-scenario: optimization of the product quality objective
- δ-scenario: optimization of the environmental efficiency objective
- ε-scenario: optimization of the cost objective
- mix-scenario: configuration of the example in Section 4.1

For computing the design objective indexes and objective functions, the weights υ_i are set to 1, whereas the w_i are computed with the formula given in Section 4.1. Fig. 3 shows some results from optimizing the two-stage flash evaporator design. It displays the properties expected from each optimal solution. The bars of the design objective indexes are plotted on the desirability scale, which corresponds to levels of satisfaction of the design objectives. The figure reveals that any improvement in the DOI index of one particular design objective tends to degrade the other indexes. Whatever the value of the DOI, the aggregation formula property makes the solution still acceptable, even if the result is near 0. For example, some improvement in the transportability of the iso-solution (α-scenario), i.e. both its size and mass, tend to decrease the desirability of the cooling power and objective cost. In fact, if the size is reduced, the condenser exchange surface decreases and a higher fluid consumption is required to cool down the product. Thus, the resulting solution will be smaller and lighter than the iso-solution, but powerless and more expensive. In the same way, a rigorous comparison between all scenarios identifies some antagonistic design objectives such as:

- Transportability and cooling power objectives cannot be satisfied simultaneously,
- Fluid consumption increases while the system dimensions decrease,
- Operation costs decrease as the system becomes powerless.

Using preference relations leads to some balance between two antagonistic phenomena, reaching solutions which are trade-offs among the design objectives. Starting from the α-scenario solution, cooling power and cost objectives can be improved according to the mix-scenario. The resulting solution is not as good as the α-solution for the transportability objective, but its cooling power and cost objectives are considerably better. Whatever the weighting applied, the environmental efficiency objective seems to keep a constant value. The DOI relating to environmental efficiency is computed from the desirability of the eco-indicator and the consumption of fluids or electrical energy. Desirability on the eco-indicator increases while the mass of the system decreases, and fluid consumption increases while the size of the system decreases. Moreover, electrical energy consumption does not vary significantly. Therefore, the balance of the aggregation formula remains

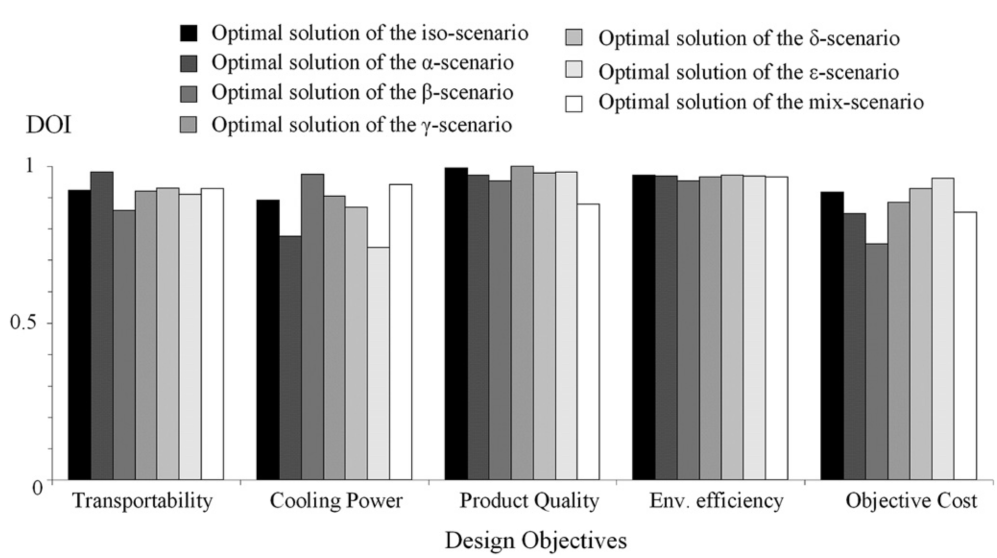

Fig. 3. Comparative analysis of the Design Objective Indexes.

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constant. From the design and performance variable given in Table 2, the most salient characteristic for scenarios α, β, δ and ε can be determined:

- A compact system is obtained by reducing both size and mass. The number of plates in the LP condenser and the tank dimensions are reduced and such a system therefore allows a lower inlet product treatment, at a lower temperature. As the cooling power of the system is less, more coolant liquid is required, which increases the operative costs. However, the eco-indicator is very high since it is determined from the mass of the system.
- Conversely, a powerful solution (cooling power) is obtained by increasing the exchange surface of the condensers and the tank dimensions. Consequently, more inlet product can be treated at a higher inlet temperature.
- Designing an "eco-solution" consists of finding a compact system with the lowest possible fluid consumption, since the eco-indicator is linked to the mass and we have seen that the electrical energy consumption has little influence. Basing the "eco-solutions" design on the eco-indicator criteria does not seem appropriate. The fluid consumption is the most significant variable able to qualify an "eco-solution" and this variable is improved by optimizing the system size.
- Low cost solutions (total cost of ownership) correspond to evaporators as tall as possible, and requiring the minimum cooling power. This is therefore able to treat the same quantity of inlet product as a compact system but using less coolant.

Through this study, we have shown that using strategy aggregation based on preference relations leads to an oriented solution, satisfying some design objectives chosen by the designer. This solution is optimal for the scenario applied, and thus strongly dependent on the values of the weighting parameters. This difficulty results from the lack of physical sense of these parameters. We must therefore wonder if there is an optimal set of weights which produce a global optimal solution instead of a local optimum. In the following section, a sensitivity analysis is performed in order to consider this problem and observe the influence of weighting parameters on solutions.

4.3. Sensitivity analysis

The sensitivity analysis has been performed by assigning variable weights to particular design objectives while keeping the others constant. In this case we focus on the transportability and cooling power DOI indexes. Starting form the iso-scenario, these DOI indexes (respectively DOI_1 and DOI_2) have been assigned to increasing values of the weight parameters. Two different optimizations are performed corresponding to weight values of w_1 or w_2 ranging between 0.2 and 0.95. The evolutions of DOI_1, DOI_2, d_1 and d_2 with the weight value, are shown in Fig. 4. DOI_1 and DOI_2 correspond to optimal solutions computed by the genetic algorithm and are mapped onto a desirability scale. Several computations have been performed for every value of the weighting parameters and, as the genetic algorithm did not reach the global optimum and is based on the generation of random numbers, this results in different optimal solutions. It is worth remembering here that the transportability objective (DOI_1) results from the aggregation of the desirability functions of the size and mass (d_1 and d_2) of the system.

Fig. 4 highlights the fact that increasing w_1 (respectively w_2) makes DOI_1 (respectively DOI_2) increase until a limit value is reached. It would therefore appear that above a certain weight value, DOI values no longer vary significantly. The same observation can be made for the associated antagonist design objective. The larger the weight, the more the antagonist DOI decreases, until it also reaches a limit value. However, for w equals 2, optimization of the transportability and cooling power objectives can lead to the same solution. Assigning greater and greater weights (from 10 for example) ensures that radically different solutions are obtained. More to the point, this figure shows that when the transportability objective of the system is optimized, only the size of the system is actually improved. The mass keeps a constant value close to 1 and the criterion set on the mass are easily satisfied. The mass is not a restrictive element for optimization. If we set more restrictive criteria on the mass, changing the maximal capacity of the truck to 6500 kg, feasible solutions are still found. Solutions for flash evaporators are very compact (2053 kg for 2.89 m^2) but their cooling power is at the limit of the minimum required (412 kW). Thus, we are no longer able to increase compactness without any deterioration in the cooling power.

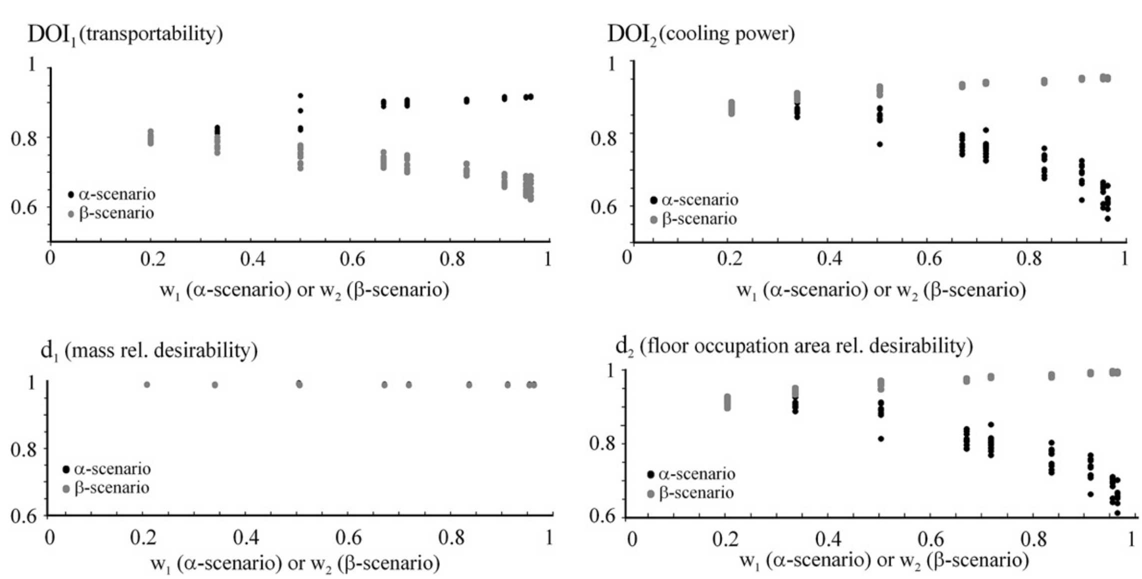

Fig. 4. Weighting parameters and sensitivity analysis.

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5. Conclusion

Multi-objective optimization of complex processes remains a challenging research topic. Faced with the rapid development of some innovative energy processes, more and more constraints relating to their life cycle (manufacturability, transportability, etc.) must be taken into account in the early phases of the design process in order to improve the reliability of design decisions. This difficulty entails the development of novel approaches to the optimization of design applications. In this paper, a modeling method based on the aggregation of physical, environmental, economical models with design objectives through desirability functions and indexes has been proposed. This method has proved to be effective to some extent since it is able to reach efficient solutions from a design analysis point of view. Numerical solving difficulties may be overcome by using distributed genetic algorithms, and design objectives may be satisfied by controlling a set of weighting parameters, however, weighting parameters must be adjusted through a sensitivity analysis, which remains the bottleneck of this kind of approach.

According to our model and regarding the particular design problem discussed in this paper, this study proves that it is no longer possible to drastically improve one of the design objectives of the two-stage evaporator without deterioration in one or several of the other design objectives. Any major improvements in this technology will have to rely on novel adaptations of the concept. Such adaptations may concern the droplet filtration system, which remains problematic since, due to the flash phenomenon, the diameter ranges of the droplets are difficult to predict. Other improvements may concern the pumps in the system which are expensive and prevent any increase in investment cost. Current developments in the optimization method concern robustness optimization.

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