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ORIGINAL PAPER

Multiobjective optimization including design robustness objectives for the embodiment design of a two-stage flash evaporator

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Abstract During the early phases of design processes, designers have to take the best decisions in order to converge quickly toward the most preferred design solution. More precisely, in a preliminary design context, the phase of embodiment design consists in determining the best values for the main dimensioning parameters of the system to improve its performances. In general, these performances must satisfy functional or technical requirements related to design objectives. The balancing act between the satisfaction of constraints and objectives can be treat as a multiobjective optimization problem. Although designers often face to a qualitative evaluation of design solutions, difficulty arises from his ability to express preferences and expectations throughout the objective function of the multiobjective optimization problem. Illustrated through the preliminary design of a two stage flash evaporator, the purpose of this article aims to develop a methodology to formulate both constraints and preferences into the optimization model. Thus design solutions are evaluated with a single global indicator of confidence. Flash evaporators are thermal systems which are mainly used for flash cooling and juice concentration applications. The design of such a system has to respect specific constraints related to these areas of applications and should meet multiple design objectives. Several goal-oriented design solutions are discussed, in particular when low design sensitivity is expected.

Keywords Multiobjective optimization · Desirability · Preference · Robust decision · Genetic algorithm

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1 Introduction

1.1 Embodiment design and optimization

In preliminary design context, the phase of embodiment design aims to determine the main dimensioning and monitoring elements of the system to meet the design requirements. Such an activity is turned toward multiobjective optimization (MO). Indeed, designers have to investigate a design space to find the best combination of design variables which maximizes, or minimizes every objective and satisfies every constraint. With the development of artificial systems, this approach has been proved to be efficient to deal with a large range of design engineering problems [1–4]. In fact, the high computing capacity enables to test many possible solutions in a short period of time, and selection rules, based on expert knowledge, can be automated to sort alternatives. Moreover, specific techniques derived from mathematics can be implemented to improve the efficiency of research algorithms.

However, the classical mathematical formulation of MO problems doesn't success yet in meeting the designer's needs. Obviously, this approach doesn't provide the flexibility inherent in design activities. This flexibility comes from the human judgment and perception. Therefore, difficulty arises from the formulation of subjective knowledge in a suitable way to be used by artificial systems. In particular, preferences between design objectives and trade-off strategies are required to rank design alternatives between them according to their relevancy. Aggregation methods, or scalarization methods, have been widely studied in the literature [5] to deal with multicriteria decision problems. Such an approach is based on a priori articulation of preferences and turns the initial multiobjective problem into a mono-objective problem.

1.2 Robust design approach

In real world applications, nominal configurations are rarely met since systems are always submitted to many outside perturbations disturbing the nominal system behaviour. Therefore, uncertainty is inherent to design problems and must be identify through the whole system's life cycle. Main sources of variability often occur in functioning, manufacturing and modelling phases. In [6] uncertainties are classified in two categories. The Type I concerns the variations caused by noise factors, assimilated to uncontrollable parameters, whereas the Type II refers to the variations inherent to control factors, i.e. design variables. Another classification into aleatory and epistemic uncertainty is proposed in [7].

The purpose of robust design methodologies (RDM) is to produce systems less sensitive to these uncontrollable parameters instead of reducing the overall degree of uncertainty in the design process. A survey of RDM is proposed by Beyer and Sendhoff [8]. Although RDM have received an increasing interest in mechanical design research [9], they haven't succeeded yet in meeting industrial needs. According to [10], explanations can arise from, on one side, a misunderstanding of the concept of robust design, and on the other side, a preference to favored reliable–based design methodologies involving probabilistic and statistic approaches.

1.3 Developed methodology

The general context of the methodology developed in this article is introduced in [11,12]. In this paper we propose a global procedure to support decision in the early phases of design processes, and more precisely in embodiment design. It is mainly based on the development of a global indicator which qualifies design solutions according to their capability to satisfy every constraint and objective expressed in requirement documents. It is mainly derived from the interpretation of the satisfaction of functional and technical criteria, and from the level of fulfillment of each design objective. Interpretation is based on the translation of criteria into levels of desirability by mapping their value onto a function between zero and one. Successive aggregations of desirability functions into design objective indexes lead to the expression of a unique index of desirability which qualifies the design solution.

Two studies are developed in this paper. The first one deals with the classical optimization of the overall performance. A "design to X" approach is used to achieve different optimal designs. In a second time, variability is taken into account. The objective linked to the design sensitivity is thus considered to achieve robust optimal solution. This particular design objective is traded-off with the objective of performance. The two optimization problems are addressed and solved using a genetic algorithm (GA). Obviously, the complexity of objective functions in real life design problems, characterized by numerous local extrema, partly justifies the choice of metaheuristic optimization techniques. Such techniques intend to improve a candidate solution toward the global optimum of an objective function. Actually, simulation models can involved both continuous and discrete variables, linked by numeric and logic relations, causing discontinuities in the observation space. Furthermore, aggregation methods and weighting techniques may create numerous local extrema, making the search of the global optimum very difficult. Therefore, determinist optimization techniques based on the calculations of function derivatives (conjugate gradients, etc.) on particular areas of the research domain have been proved to be inefficient. Moreover, even if metaheuristics results in the effective optimum of the objective function, they are relevant in a preliminary design context, since due to the high degree of imprecision (predictive models are already approximations of the reality) the optimal point cannot definitively be mapped onto the real optimal design solution.

The developed approach is illustrated with the preliminary design of a two-stage flash evaporator. In recent years, flash evaporation processes have been subjected to many improvements in order to face with specific constraints relating to flash-cooling or juice concentration applications. The simulation model of such a system involves design and observation variables, which are respectively the inputs and outputs of the numerical model, linked by thermodynamic, dimensional, environmental and economical relations.

2 Design model of two-stage flash evaporator

2.1 Flash evaporation process

In industry, the process of flash evaporation is often used for cooling, or for concentration applications of biological fluids such as fruit juices. It consists in evaporating a fluid at a lower temperature than its own saturation temperature, through some expansion chambers put under low pressure conditions. The terminology "flash" refers to the quasi-instantaneous evaporation of the fluid as soon as it enters in the high pressure (LP) and very low pressure (VLP) expansion chambers (Fig. 1).

In this research work, specific requirements related to the wine industry have lead to many improvements. In particular, the reduction of the overall dimensions is a major issue since the system must be transportable between different sites. The current design of the two-stage evaporator was developed by Cadiot et al. [13]. Such system is illustrated on Fig. 1. It involves compact condensers and mist eliminators. In functioning phases, the inlet product, composed by grapes and

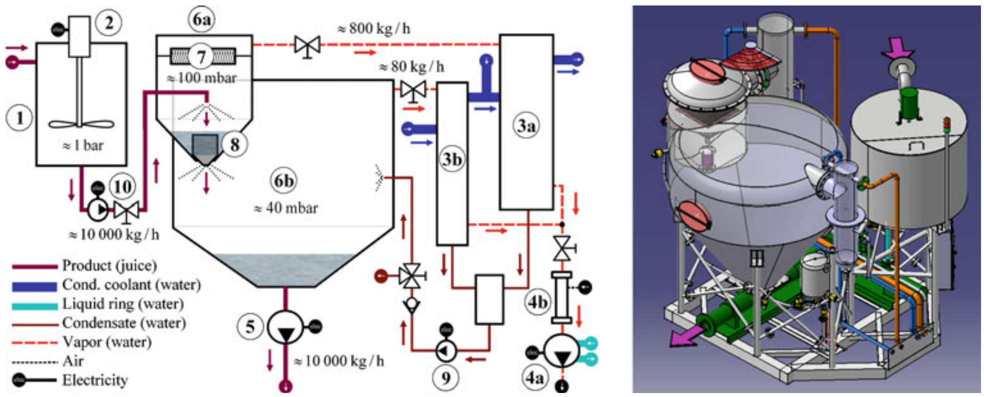


Fig. 1 Principles of the two-stage flash evaporator

juice, is submitted to successive evaporation as soon as it enters in the expansion chambers. Vapours are then condensate through the two condensers, one for each stage. The system is maintained under low pressure conditions by the simultaneous actions of a vacuum pump and an air ejector.

2.2 Behaviour model of two-stage flash evaporator

The behaviour model of the studied two-stage flash evaporator enables to estimate the performances of the system from a set of design variables. The behaviour model of the two-stage flash evaporator has already been presented and experimentally validated in [14,15]. From physical hypothesis and experimental measurements, a physical model of the system behaviour has been developed. Dimensional, environmental and economical models have also been developed to supplement the behaviour model of the system.

The activity of preliminary design implies a characterization of every relevant variable required to support decision. In this paper, they are referred as design and observation variables. They represent respectively the inputs and outputs of the behaviour model. The design of the two-stage flash evaporator involves seven design variables. Their values enable to distinguish different architectures between them. Moreover, we define eight observation variables related to the system's performances. Design and observation variables are linked by the behaviour model as:

$$\begin{aligned} &\mathbf{y} = \mu\,(\mathbf{x}) \\ &\mathbf{x} = \{x_1, x_2, \ldots, x_7\}, \quad \mathbf{x} \in \Omega \\ &\mathbf{y} = \{y_1, y_2, \ldots, y_8\}, \end{aligned} \tag{1}$$

where μ designates the behaviour model, **y** is the vector of observation variables, and **x** is the vector of design variables. The union of the domains of variation of design variables forms the design space Ω reported in Table 1.

Design variables are the main dimensioning and monitoring elements of the flash evaporator. In this study, they concern the inlet temperature (x_1) and flow rate (x_2) of the product, the temperature (x_3) and flow rate (x_4) of the coolant, the flow rate of the coolant added in the LP stage (x_5) and the number of plates in the LP and VLP condensers (x_6 and x_7). From the values of these seven design variables, we derived every other variable involved in the design problem, including the observation variables. These variables refer to relevant characteristics of the flash evaporator, i.e. the overall mass (y_1) and floor area (y_2), the cooling power (y_3), the temperature of the product at the system outlet (y_4), the EcoIndicator (y_5) related to the amount of material used in the manufacturing process, the fluid and electrical consumptions (y_6 and y_7), and the total cost of ownership (y_8). The strict computation of the observation variables **y** associated to a unique set of design variables **x** referred to the nominal design formulation.

Table 1 Design space for the preliminary design of the two-stage flash evaporator

Design. variables	Type	Domain Ω	Units
x_1: Inlet product temperature	Continuous	[70.0 ; 90.0]	°C
x_2: Inlet product flow rate	Continuous	[2.22 ; 3.33]	kg s^{-1}
x_3: Inlet coolant temperature	Continuous	[15.0 ; 20.0]	°C
x_4: Inlet coolant flow rate	Continuous	[2.78 ; 5.56]	kg s^{-1}
x_5: Added coolant flow rate	Continuous	[0.28 ; 6.94]	kg s^{-1}
x_6: Number of plates in the LP condenser	Discrete	{6 ,…, 70}	–
x_7: Number of plates in the VLP condenser	Discrete	{6 ,…, 70}	–

Table 2 Uncertainty on the design variable and physical parameters

	Variable	Type	Domain of uncertainty
Design variables	x_1	Absolute	[−2.00°C; +2.00°C]
	x_2	Absolute	[-0.20 kg s^{-1}; $+0.20$ kg s^{-1}]
	x_3	Absolute	[−2.00°C; +2.00°C]
	x_4	Absolute	[-0.20 kg s^{-1}; $+0.20$ kg s^{-1}]
	x_5	Absolute	[-0.20 kg s^{-1}; $+0.20$ kg s^{-1}]
Physical parameters	k_{HP}	Relative	[−5.00%; +5.00%]
	k_{LP}	Relative	[−5.00%; +5.00%]
	d_{tank}	Absolute	[−0.02 m; +0.02 m]

2.3 Uncertainty and design sensitivity

In the context of the preliminary design of the two-stage flash evaporator, uncertainty is mainly caused by the variability of inlet temperatures (x_1 and x_3) and inlet flow rates (x_2, x_4 and x_5). Moreover, manufacturing processes introduce dispersions in the tanks diameters (d_{tank}). Finally, uncertainty is identified in the modelling phases as imprecision on the two global heat transfer coefficients (k_{LP} and k_{VLP}) since their expressions are derived from experimental correlations. Setting high uncertainties on these two coefficients is particularly relevant in this case since they drive the thermodynamical model through the heat transfer in the condensers. Uncertainties considered in this study are listed in Table 2. It is worth noting that uncertainty is considered both on design variables and on parameters intrinsic to the behaviour model formulation (Table 2).

An efficient way to deal with variability is to randomly disturb the uncertain variables and parameters during the evaluation process of solutions. Thus, we introduce variability as:

$$\mathbf{y}^* = \mu\left(\mathbf{x}^*, \tilde{\boldsymbol{\varepsilon}}\right), \quad \mathbf{x}^* = \mathbf{x} + \tilde{\mathbf{x}} \tag{2}$$

where $\mathbf{y}^*$ and $\mathbf{x}^*$ denote respectively the disturbed sets of observation and design variables, $\tilde{\mathbf{x}}$ is the random variability associated to the design variables and $\tilde{\boldsymbol{\varepsilon}}$ is the perturbation vector associated to the model parameters. The set of tested points around the nominal observation variables is denoted as neighborhood.

We simulate variation in parameters by performing Monte Carlo simulations. Since such a method doesn't provide any guarantees on the extreme values of the observation variables on the variation domain, increasing the number of tested points around the nominal value increases the quality of the observation variable dispersions and thus, the quality of the evaluation performed on the design sensitivity.

In the context of this study, the evaluation of design sensitivity is manly based on the observation of the dispersion of two observation variables: the product temperature (y_4) and the fluid consumption (y_6). Indeed, a constant temperature at the system outlet is expected to ensure the quality of the product. Moreover, a uniform fluid consumption is required to uniformly cool down the product all along the process. According to the design problem requirements, we adopt here a "signal to noise" ratio to observe the robustness of each observation variable. This measurement is expressed as:

$$\mathrm{r} = \frac{\mathrm{Mean}\ (\mathrm{y}, \mathbf{y}^*)}{|\mathrm{Max}\ (\mathrm{y}, \mathbf{y}^*) - \mathrm{Min}\ (\mathrm{y}, \mathbf{y}^*)|} \tag{3}$$

where r is the robustness measure of the observation variable y. Optimizing the design sensitivity consists in this case, in maximising the mean value of the observation variable while minimizing the bandwidth of the variation. The "signal to noise" ratio had been initially introduced by Taguchi [16] to evaluate the robustness in quality engineering. In the following, the measurements r_4 and r_6 refer respectively to the robustness of the outlet product temperature and fluid consumption.

3 Qualification of solutions based on desirability

3.1 Formulation of constraints through desirability functions

Obviously, observation variables have to meet the expectations of designers. Thus, they are submitted to some functional or technical criteria expressed by logical relations and intervals of admissible values specified by design requirements documents and expert rules. Constraints related to the design of the flash evaporator are derived from the requirements of a wine producing company. They are listed in Table 3. This company was interesting in developing a flash evaporator for cooling 10 tons of grape juice per hour from an initial temperature (x_1), ranging between 70 and 90°C, to a lower temperature (y_4), comprised between 30 and 20°C. Criteria related to the cooling power of the system and to the

Table 3 Constraints and design objectives for the design of the two-stage flash evaporator

Design objectives	Observation variable	Criteria
1. Transportability	Overall weight	$y_1 \leq 19$ t
	Floor area	$y_2 \leq 16\ \mathrm{m}^2$
2. Cooling power	Cooling power	$y_3 \geq 243$ kW
3. Product quality	Outlet product temperature	$20°\mathrm{C} \leq y_4 \leq 30°\mathrm{C}$
4. Environmental impact	Environmental impact	$y_5 \leq 50{,}000$
	Fluid consumption	$y_6 \leq 100\ \mathrm{kg\ s}^{-1}$
	Electrical consumption	$y_7 \leq 42$ kW
5. Total cost of ownership	Total cost of ownership	$y_8 \leq 2{,}000$ k€

outlet temperature of the juice have been derived from these specifications.

In general, a design solution is considered as acceptable, or feasible, if every constraint is satisfied. However, in multiobjective optimization problems, difficulties arise from the trade-off between objectives due to antagonist phenomena inherent to complex design architectures. Indeed, multiphysic approaches usually induce strong coupling effects between the variables involved in the behaviour model, in such a way that the individual optimization of one particular property cannot be performed without degrading some others. Moreover, the comparison of properties generally expressed in different units is difficult due to the difference in the scales of measurement. These problems are addressed using desirability functions and indexes.

The purpose of tackling multiobjective optimization problem through the concept of desirability is to translate every constraint into levels of desirability by mapping their value between zero and one. Desirability functions are monotonous or piecewise monotonous functions which express the degree of acceptation of the constraint satisfaction. In this way, a desirability of zero refers to the total non-satisfaction of the criterion whereas a degree of desirability near to one means that the observation variable satisfies the requirement. In [17] Harrington suggests a particular class of desirability function suitable to treat multiobjective optimization problems in quality engineering. These functions are presented in Table 4. While the one-sided function is used for minimization or maximization problems, the two-sided form concerns target problems. At least two parameters are required to specify Harrington's desirability functions. They correspond to the level of desirability associated to the strict respect of the absolute constraints (AC), and then the level of desirability associated to a soft limit (SL) determined a priori in respect with designers' expectations. Harrington desirability functions have already been discussed in [12].

Every constraint related to the design of the two-stage flash evaporator is translated using a Harrington desirability function. Therefore ten desirability functions are defined according to the requirements defined in Table 5. For example, the overall weight of the two-stage flash evaporator is limited by the maximal capacity in charge of a flat bed truck and is expected to be minimized. Such a constraint is represented with the left form of the one-sided Harrington desirability function, specified with an absolute constraint equal to 19 tons. The soft limit is defined such as any design solutions less than 3.8 tons are considered as equally preferred.

Such a formulation of the initial constraint problem is suitable in a preliminary design context where knowledge and data are often incomplete. Instead of expressing vagueness such as membership functions suggested in the fuzzy theory [18], desirability functions enable to model preference and expectations of the designer. Through the specification parameters, the behaviour of the desirability functions can be adjusted to be more or less restrictive on the strict respect of the initial hard constraint. Thus, the initial optimization problem is expressed with a soft constraints formulation which traduces the flexibility required by the design problems.

3.2 Aggregation of design objective indexes

Most of the observation variables, and their related criteria, refer at least to one particular design objective. While constrains are technical or functional requirements that systems must satisfy, design objectives are task specific goals that system should meet. The eight observation variables associated to the behaviour model of the two-stage flash evaporator have been grouped into six suitable design objectives listed in Table 3. For example the transportability objective is linked to the minimization of the overall weight and floor occupation area, whereas the environmental objective is concerned with the reduction of the fluid and electrical consumption. The design objectives related to the cooling power, product quality and cost of ownership are directly link to the satisfaction of the associated criteria. Finally, the objective of robustness consists in the minimization of the design sensitivity. It refers to the robustness measurements of the outlet product temperature and fluid consumption.

The degree of satisfaction of design objectives is quantified by an indicator called Design Objective Index (DOI). This indicator is derived from the desirability index proposed by Derringer [19] to aggregate desirability functions. He suggests to aggregate desirability scores according a weighted geometric mean such as:

$$\mathrm{DOI} = \prod_{i=1}^{k} d_i^{v_i} \quad \text{with} \quad \sum_{i=1}^{k} v_i = 1 \tag{4}$$

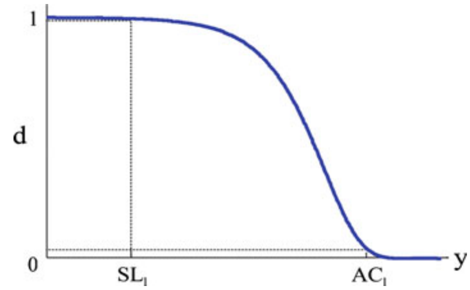
Table 4 Harrington's desirability functions

One-sided (left. form):

$$d(y) = \exp(-\exp(\beta + \alpha \cdot y))$$

$$d(SL_l) = 0.99$$

$$d(AC_l) = 0.01$$



Two-sided (target form):

$$d(y) = \exp\left(-\left|\frac{2 \cdot y - (U + L)}{U - L}\right|^n\right)$$

$$L = (AC_r + SL_r)/2$$

$$U = (SL_l + AC_l)/2$$

$$d(SL_r) = 0.99$$

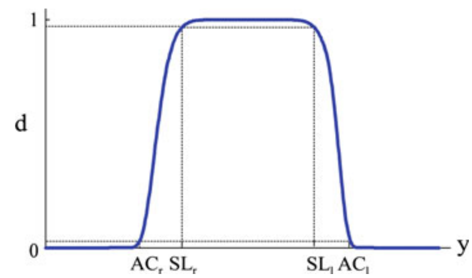


Table 5 Desirability functions specifications

Constraint	Function	Parameters			
		AC_r	SL_r	SL_l	AC_l
$y_1 \leq 19$ t	d_1	–	–	3.2 t	19 t
$y_2 \leq 16$ m^2	d_2	–	–	3.20 m^2	16 m^2
$y_3 \geq 243$ kW	d_3	243 kW	810 kW	–	–
20°C $\leq y_4 \leq$ 30°C	d_4	18°C	20°C	30°C	32°C
$y_5 \leq 50{,}000$	d_5	–	–	10,000	50,000
$y_6 \leq 100$ kg s^{-1}	d_6	–	–	20 kg s^{-1}	100 kg s^{-1}
$y_7 \leq 42$ kW	d_7	–	–	8.40 kW	42 kW
$y_8 \leq 2{,}000$ k€	d_8	–	–	400 k€	2,000 k€
$r_4 \geq 1$	d_9	1	100	–	–
$r_6 \geq 1$	d_{10}	1	100	–	–

where k is the number of aggregated desirability functions. Such an aggregation function is qualified as *design appropriate* by Scott [20]. In fact, the weighted geometric mean verifies a set of mathematical properties which are relevant in a design context. For example, the axiom of annihilation states that the result of the aggregation is equal to zero if at least one the aggregation component is equal to zero. In other word, it means that a design solution becomes undesirable if at least one of the criteria is not satisfied.

The normalized weights v_i are used to adjust the relative importance of the different criteria satisfaction between them, strong weights traducing a high priority level. In this paper, weights assigned in the DOIs formula are supposed to be equal. The six DOIs expressions are given in Table 6.

In the same way, the different DOIs are aggregated into a single global desirability index denoted as GDI. This indicator qualifies the overall capability of a design solution to meet designer's expectations. This GDI is subjected to be maximized and is formulated as:

$$GDI = \prod_{i=1}^{p} DOI_i^{w_i} \quad \text{with} \quad \sum_{i=1}^{p} w_i = 1 \tag{5}$$

where p designates the number of design objectives.

Table 6 Design objective indexes formulation

Design objectives related to performances	
1. Transportability	$DOI_1 = d_1^{1/2}.\ d_2^{1/2}$
2. Cooling power	$DOI_2 = d_3$
3. Product quality	$DOI_3 = d_4$
4. Environmental impact	$DOI_4 = d_5^{1/3}.\ d_6^{1/3}.\ d_7^{1/3}$
5. Total cost of ownership	$DOI_5 = d_8$
6. Design sensitivity	$DOI_6 = d_9^{1/2}.\ d_{10}^{1/2}$

Table 7 Nominal and robust optimization problems formulation

Optimization problem no 1	P_1: max. GDI(X), Sub. to: $GDI(X) = \prod_{i=1}^{5} DOI_i(X)^{w_i}$ $X \in \Omega$
Optimization problem no 2	P_2: max. GDI(X), Sub. to: $GDI(X) = \prod_{i=1}^{6} DOI_i(X)^{w_i}$ $X \in \Omega$

The numerical weights w_i are used to adjust the relative importance of the different objectives in the global design optimization. A strong weight set on a DOI corresponds to a high level of importance. Thus, through these parameters, some major objectives can be defined and, a "design for X" approach can be lead.

However, the non-physical meaning of the weights makes difficult the assignment of numerical values. In the fields of operational research and decision making, methodologies related to analytic hierarchy process (AHP) initiated by Saaty [21], have received increasing interest to deal with multicriteria decision problems. The principle of this approach is based on first, the decomposition of the initial problem into a hierarchy of criteria and sub-criteria and then, the statement of normalized priorities derived from pairwise comparisons.

3.3 Formulation of objective function

The formulation of the global desirability index is built from by the behavior model of the system, the interpretation of constraint satisfaction into levels of desirability and the successive aggregation of desirability scores into indexes. The GDI is a function of the design variables. The objective function of the optimization problem (GDI) is subjected to maximization.

The two optimization problems formulations used in this paper are presented in Table 7. While P_1 is concerned with the optimization the overall nominal performance, P_2 aims to determine an optimal robust solution by taking into account the objective of robustness (DOI_6).

It can be notice that constraints related to the initial design problem are formulated inside the optimization model, through the desirability functions, and consequently, they are not explicit in the formulation of the optimization problem, but intrinsic to its definition. In the following, several weights assignment strategies are proposed to achieve different optimal design solutions.

4 Numerical solving

The numerical solving problem has been addressed by developing a classical genetic algorithm (GA). This evolutionary algorithm [22] considers a finite set of candidate solutions which are evaluated and ranked according to their ability to maximize GDI. The weakest candidates are then eliminated by tournaments between individuals which are randomly selected among the population. The simultaneous actions of three operators, with different occurrence probabilities, ensure the convergence of the set toward the optimal solution. The cross-over operator creates new candidates from combinations candidates already available in the current set. Mutation operator creates new candidates by introducing new information into the population. Climber operator is a mutation operator favouring a local search. In this study, the population of candidate solutions of the GA contains 200 individuals. The crossing probability is of 80%, the mutation probability is of 5% and the climbing probability is of 10%. Moreover an elitist strategy is used to maintain the best individual from one generation to another.

The fitness evaluation process is illustrated on Fig. 2. As mentioned in the last section, two optimization problems are tackled in this study using the same global methodology. While the optimization problem P_1 requires a simple evaluation of the candidate, the optimization problem P_2 requires additional computations to evaluate neighbourhood of the solution. As the evaluation of the design sensitivity criteria requires numerous simulations of the behaviour model (each point of the neighbourhood generates a unique set of observation variables), the whole population evaluation requires high computation resources. Therefore, to ensure solutions with an acceptable level of performance, and to strongly reduce computational times, the evaluation of the robustness criteria is processed if the candidate solution is acceptable according to its nominal performance. In this research work, each desirable solution is randomly tested 1,000 times around its nominal value.

5 Results and discussion

5.1 Optimization of the overall performance

The optimization of the flash evaporator performances consists in looking for solutions that maximize the aggregation

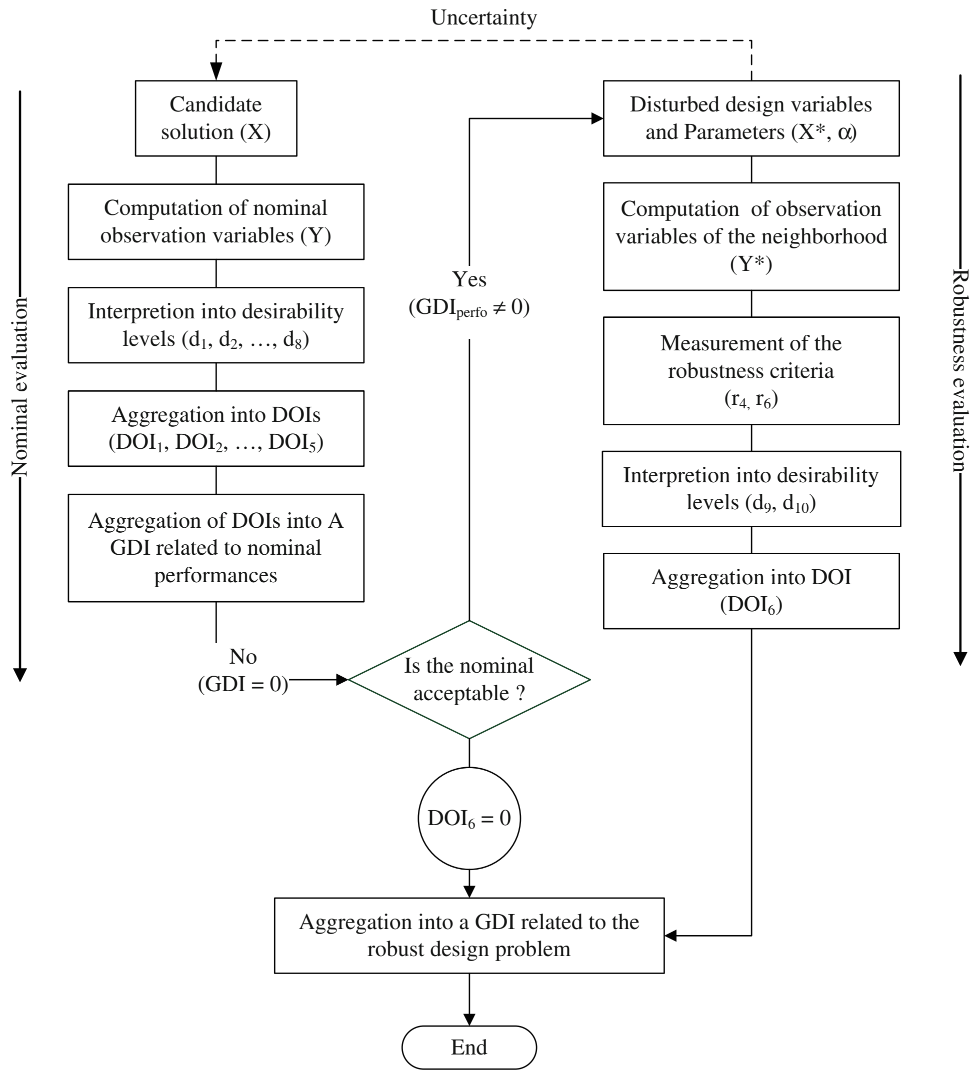


Fig. 2 Fitness evaluation process used in the robust design optimization problem

of the DOIs related to design objectives of transportability, cooling power, product quality, environmental impact and total cost of ownership. The formulation of this optimization problem denoted P_1 in this paper, is given in Table 7. In a first time, weighting parameters involved in the aggregation of the DOIs, are supposed to be taken as equal in such a way that none objective is more important than another. From the numerical solving of this optimization problem by GA, it results a final set of acceptable solutions whose the first one is supposed to represent the most preferred design. In Table 8, we report three admissible design solutions taken respectively at the 1st, 20th and 100th rank in the final population. The GDI values of the three solutions is reported in bold in the left column. Moreover, the highest value of each DOI is underlined. One can notice that all these solutions are acceptable since their fitness score is greater than zero. The optimal design solution achieves a global desirability index of 0.9387 and corresponds to a configuration involving an inlet product temperature of 89.6°C with a 2.34 kg s^{-1} flow rate, a coolant liquid at 15.11°C with a 4.16 kg s^{-1} flow rate, an additional coolant flow rate of 4.25 kg s^{-1}, and a number of plates equal to 70 for the LP condenser and 63 for the VLP condenser. However the three solutions meet in an unequal way every design objectives. For example, the solution ranked at the 20th place has a better value of DOI_2 than the optimal solution. Therefore, trades-off between many design objectives are often expected, and in the case where a high cooling power is expected, the 20th solution should be considered rather than the 1st one (Table 8).

Table 8 Desirability indexes achieved by the 1st, 20th and 100th solutions in final population

Rank	DOI_1	DOI_2	DOI_3	DOI_4	DOI_5	GDI
1st	<u>0.9054</u>	0.9107	0.9984	<u>0.9727</u>	<u>0.9103</u>	**<u>0.9387</u>**
20th	0.9040	<u>0.9135</u>	0.9997	0.9714	0.8943	**0.9357**
100th	0.9019	0.9060	<u>1.0000</u>	0.9686	0.8564	**0.9251**

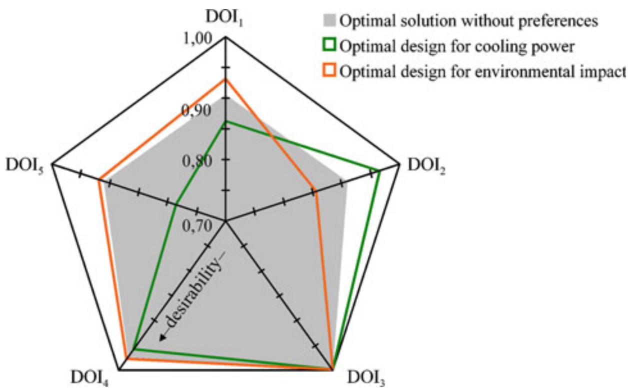


Fig. 3 Design-oriented solutions resulted from different weights assignment strategies

Such an issue can be tackled by allowing the designer to express some priorities orders between the satisfactions of design objectives. These priorities are formulated through the weights assignment in DOIs aggregation into a GDI related to the nominal performances of the system.

For example, by repeating the optimization process assigning successively a weight of ten on the DOI_2 and DOI_4, we can focus either on the cooling power property of the system or on the ecological aspect of the design. The diagram representation, in Fig. 3, illustrates the disparities between the levels of design objective satisfaction achieved by the goal-oriented optimization and the optimal solution obtained without setting any priorities. Moreover, it highlights some design rules for flash evaporators. For example, a system architecture designed to get an important cooling power, tends to increase the overall dimensions of the system and thus, implies a higher environmental impact and cost. Inversely, environment oriented design will obviously improve the environmental impact objective, but this also results in the degradation of the cooling power of the evaporator.

5.2 Trade-off between performance and design sensitivity

As previously explained, the solution of the P_2 optimization problem maximizes GDI. This solution is supposed to present a desirable trade-off between a high level of nominal performance and a low sensitivity to uncertainty. In this application case, none objectives is preferred rather another and thus the weight are taken equal. In Table 9, the optimal solution discussed in 5.1 and the robust optimal design solution are compared. The robustness of the nominal optimal design have also been tested and the resulted DOI_6 and GDI computed. The best value of GDI has been underlined for each optimization problem. Design and observations variables of the two design configurations have also been reported.

Table 9 Optimal design solutions for the nominal and robust optimization problems

Optimization problems	P_1	P_2
Fitness score		
GDI related to nominal performances (without DOI_6)	<u>0.9387</u>	0.9174
GDI related to design robustness (with DOI_6)	0.5500	<u>0.7259</u>
Design variables		
x_1	89.26°C	87.03°C
x_2	2.34 m s^{-1}	2.25 m s^{-1}
x_3	15.11°C	15.88°C
x_4	4.16 m s^{-1}	5.48 m s^{-1}
x_5	4.25 m s^{-1}	5.07 m s^{-1}
x_6	70	58
x_7	63	54
Observation variables		
y_1	3,045 kg	2,898 kg
y_2	9.33 m^2	9.05 m^2
y_3	604 kW	568 kW
y_4	29.65°C	28.45°C
y_5	21,035	20,030
y_6	30.35 kg s^{-1}	38.06 kg s^{-1}
y_7	5.77 kW	5.59 k
y_8	984 k€	1147 k€
Bandwidth of variation		
$\mathrm{Max}(y_4, \mathbf{y}_4^*) - \mathrm{Min}(y_4, \mathbf{y}_4^*)$	38.37 °C	4.94 °C
$\mathrm{Max}(y_6, \mathbf{y}_6^*) - \mathrm{Min}(y_6, \mathbf{y}_6^*)$	5.77 kg s^{-1}	4.38 kg s^{-1}

According to Table 9, the optimal solution of the problem P_1 appears to be more sensitive to uncertainty than the robust optimal solution of the problem P_2, looking at the variations of the observation variables y_4 and y_6. The nominal optimized design fails in being robust for the outlet product temperature since the range of variability for this observation variable is estimated to be about 38°C, whereas the robust optimal design presents a variability of only 5°C. This last solution presents a better ability to maintain the outlet product temperature around its nominal value in the expected range of value, i.e. between 20 and 30°C. The same conclusion can be made for the fluid consumption. This comparison explains the lower score (GDI related to robustness) obtained by the nominal optimized solution compared to the robust optimal design. Although a high level of global performance is achieved, the global desirability of the solution falls down due to the high sensitivity to outsides perturbations. Through the optimization problem P_2, it is shown that the robustness of the nominal design of the two-stage flash evaporator nominal design can be significantly improved performing some compromises on the overall level of performance in order to reduce the sensitivity of the design solution. The performance degradation mainly concerns the cooling power and the cost objectives. In other words, with this approach, the designer can reduce by almost eight times the outlet product temperature sensitivity by decreasing the cooling power of the system of 35 kW and the global cost of 160 k€. In this case, such solution is supposed to represent the best compromise between performance and design sensitivity. However, as it is previously explained, the optimization process developed in this paper provides a set of solutions ranked by their fitness score, and consequently the investigation of solutions ranked just above the optimal solution can support the designer in looking for more suitable alternatives. Therefore, the trade-off problem between increase the global performance and reduce the design sensitivity cannot only rely on the simultaneous optimization of these two criteria. The robustness of a design solution cannot be evaluated only on the architecture sensitivity but also on the sensitivity of the designer decision. Expressing the compromises expected for the design into the objective function of the design problem ensures the designer that further investigations of the design space will not enable to find solutions with a better trade-off.

6 Conclusion

Illustrated on the preliminary design of a two-stage flash evaporator, a global methodology is proposed to tackle multi-objective optimization problems in engineering design. This approach is based on the formulation of a single objective function, involving several objectives derived from the interpretation and aggregation of desirability scores. Preferences and designer's expectations are formulated inside the optimization model formulation through the parameters of desirability functions and weights assignment involved in aggregation formula. Thus several strategies can be established to achieve different kinds of goal-oriented designs. Whereas the optimization of the nominal performances leads to design solutions which are in general highly sensitive to uncertainty, the method is extended to robust design problems by taking into account a design objective related to the minimization of the design sensitivity. This formulation of the optimization problem provides robust optimal solutions which result from compromises on the overall level of performance to reduce the dispersion of the performance variables. Further works must tackle the quantification and formalisation of such trades-off in the early stages of design process to ensure first a low sensitivity of solutions to variability, and then the robustness of the decision in such a way a small increase of performance will not altered the designer's choice. Moreover a future research are turned toward the development of a decision support tool to build suitable objective functions based on an observation-interpretation-aggregation scheme, and solve the resulted optimization problem.

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