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Optimized development: defining design rules through product optimization techniques

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ABSTRACT

In recent years, parametric optimization has become an important part of product development, allowing the designer to explore an unprecedented number of product configurations. However, optimization is often thought of as the last step of the design process; the product has already been defined and the designer aim is toward the optimization of its performance. At this stage, the main performance trade-offs have been set and cannot be solved by the optimization.

We propose an early application of optimization techniques during the product embodiment phase; aimed not at finding the optimal configuration of an existing product, but at highlighting trade-offs and the effect of design variables on the product performance. The output of the proposed procedure is a set of design guidelines that describe the design challenges at an early stage, when there is still time to address trade-offs, and, possibly, resolve them before the final, and more classical, product optimization.

The procedure has been tested on two exemplary case studies pertaining to food product refrigeration: a refrigerated display unit and a cabinet shelf.

KEYWORDS

Optimization; design guidelines; Embodiment design

1. Introduction

The importance of automation and optimization in the design and the production processes of an industrial product is increasing, especially with regards to resources consumption and product quality. Optimization strategies can play a fundamental role in the product design, by allowing the designer to study a greater number of product configurations and reach an optimal result with an automated process. Parametric optimization [3], [12] is currently used mainly as the last step of the product development. Once the embodiment [11] of the product has been defined, the optimization algorithms can enhance its performance by finding the most favorable product configuration. By modifying detailed parameters without changing the general embodiment, the optimization can provide trade-offs, like energy saving vs. costs, without ever solving them. In fact, such trade-offs are frequently highlighted by the final product optimization [5], when it is sadly too late to tackle them in the product development.

The proposed methodology, called *Optimized Development*, provides an early application of optimization techniques during the product embodiment phase; aimed not at finding the optimal configuration of an existing product, but at highlighting trade-offs and the effect of design variables on product performance. In [13] the authors used multi objective optimization as an approach to support the early stages of the design of a two level flash evaporator. The embodiment phase consists in determining the value of a set of parameters, to obtain a first dimensioning of the system. Multi-objective optimization is here treated as a way to determine the proper dimensioning in accordance with the product constraints and objectives. The results of the classic approach are limited to the ability of the designer to express preferences and expectations throughout the objective functions. In [11] constraints and preferences are defined during the embodiment design into an optimization model, by means of indicators called Design Objective Index (DOI) and Global Desirability Index (GDI). In [1], the authors obtain a set of optimal design principles involved in the performance of micro channels by analyzing the results of a multi-objective optimization.

Furthermore, optimization results must be analyzed to gain useful insights to be applied during the following stages of product development. In [9] the authors use clustering analysis to determine modular reconfigurable manufacturing systems with the help of average linkage

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clustering algorithm in order to define the most adequate modular system architecture and the modular definition of the reconfiguration variables that are needed to reach the required flexibility. In [10] MCDM have been used to select the most appropriate Pareto solution among a set of optimized configuration in construction problems assigning objective weights with the Shannon entropy technique.

The proposed methodology guides the user during the first steps of product development. Four phases have been defined (Fig. 1). A pre-processing phase, where the designer parameterizes the product and defines product performance and constraints, through a set of analytical or numerical equations [4]. A processing phase, where the design space of possible product configurations is populated with both optimization and factorial algorithms. A post processing phase, where clustering analysis and scalarization algorithms are applied in order to highlight trends and product families. And finally, a results evaluation phase, where trends and trade-offs are defined through a set of product specific guidelines. The aim of the proposed procedure is to describe the characteristics of a product, which has yet to be thoroughly defined, through a finite set of optimal and factorial configurations. To achieve such a result, we study the cluster of designs with statistical, clustering, and multi-criteria tools. The output of the proposed procedure is a set of design guidelines that describe the design challenges at an early stage, when there is still time to address trade-offs, and, possibly, resolve them before the final, and more classical, product optimization.

2. Proposed methodology

The proposed methodology aims at defining a set of product-specific design rules that will guide the designer during the early stages of product development. In order to achieve such a goal, we aim at describing the product design space through the integration of a set of design evaluation and analysis tools: parametric optimization, DoE (Design of Experiment) analysis [6], clustering analysis [7], and MCDM (Multi Criteria Decision Making) or scalarization algorithms [8]. Design rules are then formulated based on the response of the product mathematical model to each design variable.

The proposed procedure comprises four main steps (Fig. 1): (a) pre-processing, the parameterization of the product and its performance criteria; (b) processing, the appraisal of the design space through both optimization and factorial algorithms; (c) post-processing, a set of analysis tools aimed at refining the results of the processing phase, and (d) results evaluation, a critical review of the previous outputs to determine a set of design guidelines. Each phase is described in the following subsections.

2.1. Pre-processing

Pre-processing is an essential step in any product simulation. Its goal is to describe mathematically the product performance and constraints, through a set of analytical or numerical equations [4]. It can entail a numerical model such as FEA, CFD, and any other form of

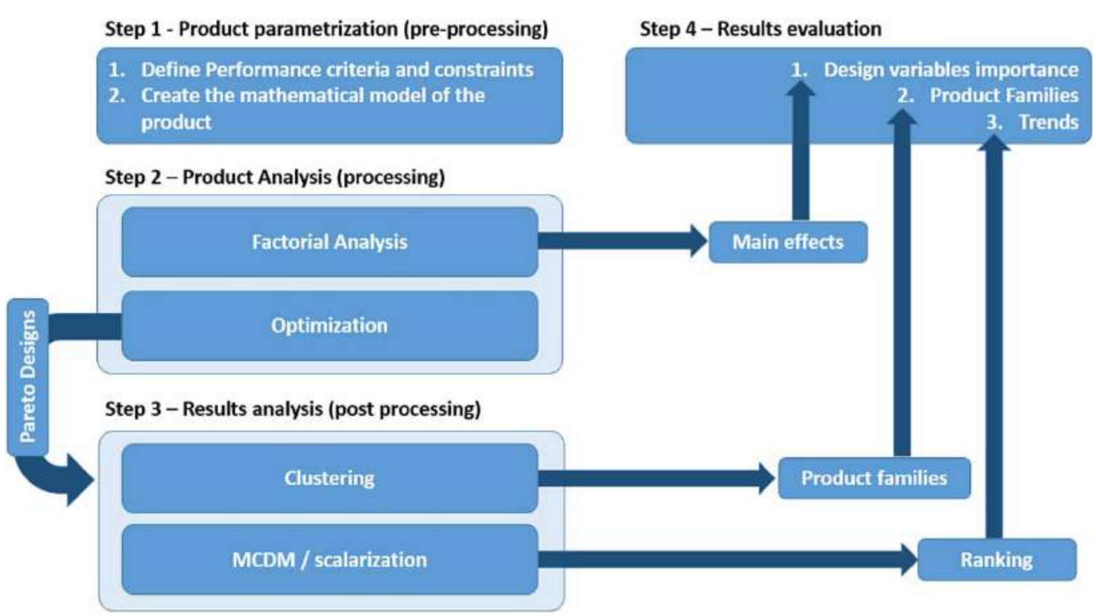

Figure 1. Steps of the optimization methodology

CAE required to determine the product characteristics. However, the model should be repeatable and consistent across the entire design space.

When defining performance criteria and performance constraints, the designer should list all the parameters required to model the product, and identify which of these should be studied through the proposed optimization methodology. We will call these chosen parameters: *optimization variables*. If the product to be modeled is a refrigerated cabinet (as in the upcoming case studies), the number of modelling parameters includes both geometric, structural, and thermal parameters. None of these is less important per se; it all depends on what the designer wishes to study, and on what parameters have a range of possible values. For instance, the product under analysis might have stringent geometric requirements that make it impossible to study variations in its shape. Thus, geometric parameters will be set to predefined values and won't be part of the optimization process. On the other hand, any relevant parameter which can range in value, can become an optimization variable.

The product performance criteria and constraints are a function of a set of optimization variables of finite range. For instance, the compliance of a beam is a function of its length, which may vary between a lower and a higher boundary. Whether the compliance is a product performance criterion to be optimized, or a product performance constraint that must meet a certain value range, is up to the designer. A product performance criterion is a product characteristic that should be either maximized or minimized. On the contrary, a performance constraint is a product characteristic that must meet certain standards; either a higher boundary, a lower boundary, or both. A performance constraint is either active, when the specified boundary is exceeded; in which case the resulting combination of optimization variables is inacceptable; or it is inactive, when the specified boundary condition is met. No difference results from the constraint being more or less close to the boundary, when the constraint condition is met.

Defining product performance, constraints, and design variables is a key step of the methodology [16], [15]. Only key variables should be included in the analysis, as best results are achieved with a low number of design parameters. However, the next step will help the designer in reducing the number of optimization variables, whenever possible.

2.2. Processing

The processing phase is the most automated step of the procedure. Its aim is to produce a consistent number of factorial and optimal designs, through the use of standard factorial and optimization algorithms, to populate the product design space.

In order to study how each design variable affects product performance, it is essential to have a good number of product designs. Product designs, whether optimal or factorial in origin, are strings of optimization variables that in turn describe a single product version. A common comparison is with DNA strings. Each design has the same number of optimization variables, but with different values. Thus, each design is a slightly different product of the same family, each with a set of performance criteria resulting from its string of optimization variables. This family of product designs can be created in two ways: with an optimization of the product, or with a DoE approach [6]. The optimization of the product produces a set of optimal designs that is focused on finding the best product performance (or performance trade-off, in case of a multi-criteria optimization). Regardless of the optimization algorithm chosen, the approach leads to a very narrow scatter of product designs that includes the product versions that maximize performance criteria. This sub-family of best designs, also known as *pareto designs*, will be the core data for the post-processing phase described in the next step.

A second approach to creating a core of product designs is the DoE approach. The DoE approach is a set of algorithms, originally created to plan experiments were only a finite set of measurements was possible, that define rules to populate the family of product designs regardless of the resulting performance. While the optimization algorithm is constantly active and dynamic, choosing the next string of optimization variables based on the performance achieved by the last, a DoE algorithm plans each variable string before evaluating each design performance. Thus, the designer can choose the desired distribution of product designs, in order to study not just a narrow portion of the design space, but its entirety. However, being limited to a finite number of designs, a DoE distribution will be far less dense than an optimization distribution of equivalent design number, and it will populate both regions of high performance products and regions of low performance products.

Clearly the two approaches are very different, and the DoE approach might seem redundant, if not counterproductive. However, the reader should keep in mind that a big enough family of product configurations is essential in order to draw meaningful results, but the overall quantity of designs is a function of the number of chosen optimization variables. A small enough set of optimization variables can be studied well with a small number of product designs, but the growth is exponential with respect to the number of variables. It is then very important to identify key parameters that should be treated as optimization variables, and discard the unimportant ones. Yet this step is often not trivial, and relies heavily on the designer understanding of the product. Being the proposed methodology aimed at the first steps of product design, it is better to not rely too much on what could turn out to be misconception. A DoE distribution can help the designer in discarding non relevant variables through the use of DoE Main Effects, applied to a factorial distribution. Variables main effects are determined by dividing a 2 level factorial DoE into two subgroups, one for the chosen variable higher value, and one for the lower value. By comparing the objective values within the two groups, it is possible to gauge the influence of the chosen variable on the performance of the product. Main Effects quantify the relative influence of each design variable (Fig. 2). Their main function is to provide the means to focus on the important variables, and eliminate ineffective variables, thus reducing the number of optimization variables. Main Effects are determined on the results of a factorial DoE algorithm. A factorial DoE guarantees no correlation between input variables (basically a perfectly spaced grid), which is essential for reliable statistical results.

In the example of Fig. 2, the Evaporator Diameter is an unimportant variable across both performance criteria: the total cost of the product and its power consumption. This parameter can then be safely removed from the optimization variables. On the contrary, the Evaporator Height has little to no effect on one of the performance criteria, but is a relevant variable for the product power consumption. This parameter should not be removed from the optimization variables. Clearly then, all variables which have a relevant effect on at least one performance criteria should be included in the optimization variables.

2.3. Post-processing

Post-processing is a further enhancement of the previous step results, to highlight possible trends that may provide useful design guidelines. All post-processing analysis is applied to a selected group of best designs from the optimization results. Best designs are selected through the Pareto concept: *pareto designs* are product configurations which are equally good and cannot therefore be ranked. A set of Pareto designs arises whenever there are multiple conflicting performance criteria. It is therefore impossible to maximize all criteria with a single product configuration and the optimization algorithm will find multiple trade-off designs that can only be ranked by weighing the set of performance criteria. These designs are called *pareto designs*, and they represent the product configurations where none of the performance criteria can be improved without deteriorating at least one of the other criteria.

The main tools of the post-processing phase are Clustering analysis (Fig. 3) and MCDM/scalarization ranking. Clustering analysis [2] is applied to the *pareto designs* of the optimization results. Its main function is to determine product families of similar performance. This grants the designer a first qualitative assessment of the correlation between design variables and performance criteria.

To identify clusters of similar designs, our methodology uses a partitive cluster algorithm. Cluster analysis can be considered as one of the most important approaches to unsupervised learning. The goal of clustering is to find clusters from unlabeled data, which means that data belonging to the same cluster are as similar as possible, whereas data belonging to different clusters are as dissimilar as possible [14]. Most clustering software allows the user to define what variables should be accounted for

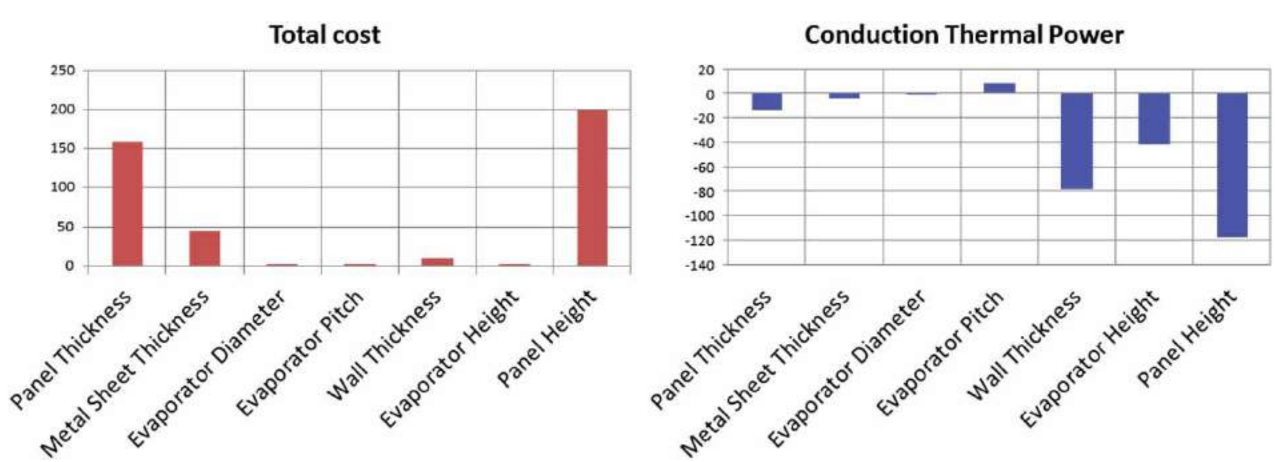

Figure 2. Influence chart of Input vs. Output

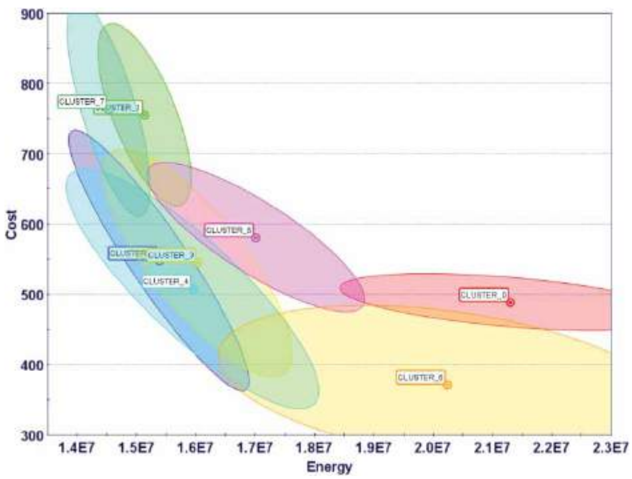

Figure 3. Cluster analysis of the optimization results

during the clustering analysis. While performance criteria are the key parameters on which to base the clustering study, the designer might find useful to study different sets of input variables to gain a better idea of the distribution of optimal designs. Regardless, the proposed methodology requires a partitive cluster based on the performance criteria. The result is a grouping of different product configurations that share a common performance profile. For instance, one cluster will include designs that have a high performance on one criterion, and a very low performance on other criteria; another cluster might comprise well-rounded designs that do not excel in any performance criteria, and so on. In any case, the clustering algorithm disregards any similarity in input variables and partitions designs solely based on their performance.

The results of the optimization are further refined with an MCDM/scalarization approach. As aforementioned, Pareto designs are equally good and cannot be ranked. This is due to the fact that each performance criteria is equally important for the optimization algorithm. Thus, a product configuration that excels in one criteria, while being exceedingly bad in all other aspects, is just as good as a well-rounded product. Clearly, this is not true in reality, where extreme configurations are unlikely to outperform more rounded designs.

In order to identify trends for product development, the proposed methodology needs a ranking of all Pareto designs across the range of performance criteria. In order to achieve this, the designer can use either an MCDM algorithm, or reduce the number of optimization objectives to one. An MCDM algorithm allows the user to weight each performance criteria and build a ranking, based on a single resulting indicator. The weighting system is, however, subjective and hard to define. When applicable, the user should aim at reducing the number of optimization objectives to one. This can be done by converting all the objectives to a common indicator, through scalarization. This can usually be applied to cost, by converting each performance criteria to its corresponding cost. For example, energy consumption can be converted to its relative energy cost, and market research can help correlating a cost to any other product performance. This allows a ranking of the optimal designs, from best to worst, with a single common performance indicator.

2.4. Results evaluation

Design guidelines are defined by studying the previous steps results. Trends are extracted by choosing a subset of the highest-ranking designs from the previous MCDM/scalarization analysis; we recommend studying the top 100 ranking designs. These top ranking designs are then plotted with respect to each optimization variable (Fig. 7). By studying the graphical results and regression lines, the designer can determine the correlation between each optimization variable and the product performance, find trends, and compare the effect of different variables against a common indicator.

Trends take the form of a direct relationship between the product performance indicator (ranking) and each design variable: e.g., *increasing variable (a) results in a higher performance*; *variable (b) has an optimal value around 50% of its range*. These might seem trivial results, but they are not so intuitive when combining multiple objectives in a single performance indicator. Trends can also take the form of a comparison between variables: e.g., *variable (b) has the most beneficial effect on product performance*. This might seem a similar result to the Main Effect analysis, but the latter has only a statistical value and assesses both beneficial and harmful effects.

Further trends can be determined on multiple performance criteria by studying the Pareto designs of the optimization and the clustering results. By analyzing the clusters composition, the designer can obtain valuable information on how each optimization variable was optimized. Results might show that a single, or a set of clusters share common values across a range of optimization variables. For instance, the designer might learn that well rounded products all stem from a precise combination of variables, or, on the contrary, he might learn that a certain variable has no correlation with the clustering results. Trends identified through the study of clusters composition take the form of a direct relationship between all performance criteria and each design variable: e.g. *increasing variable (a) increases performance (x), but decreases performance (y)*.

Trends are then combined to create guidelines for further product development. Guidelines describe the characteristics of the optimal product and highlight important trade-offs that the designer will have to optimize or resolve. This is by no means the final step of product development, but rather the starting point. With the guidelines is possible to identify direction of design in terms certain layout of insulation, for example identification of wall thickness range with a condenser that covers all the refrigerator surface, or the location of insulation panels with respect to the location of the heat exchangers. These guidelines will guide the designer during the development process, by highlighting the hotspots of the design effort, and removing any previous misconception that might have led the designer astray.

3. Case studies

The proposed methodology was tested during a research program on commercial food refrigeration cabinets: a closed refrigerated display unit and a cabinet shelf. The research project aims at studying a limited set of product configurations in order to define the most promising areas of further development. Additionally, the project aims at: studying the influence of a limited set of product specific parameters on the overall performance, defining regions of overlapping technology, and detailing a set of design rules based on the results of a product optimization.

Both studies entailed the development of a dedicated mathematical model, to simulate the thermal exchange and determine power consumption and operational cost. This article, however, will not go in detail of the modeling phase, preferring to focus on the methodology. Furthermore, only the closed refrigerated display unit will be described in detail, while results and conclusions will be outlined for both.

3.1. Performance criteria and constraints (Step 1.1)

The cabinet performance has been assessed through four objectives: the energy consumption of the cabinet, the material cost of the cabinet, the Total Display Area (TDA) of the cabinet, and the Total Display Volume (TDV) of the cabinet. Performance constraints concern food products temperatures, which may not rise over a certain value across the entire cabinet. Four critical areas inside the cabinet were mapped and studied, to ensure the preservation of the stored products integrity.

Performance criteria were determined as follows:

- The energy consumption of the cabinet has been evaluated as the Heat Extraction Rate (H.E.R.) of the evaporator over a 24 hours cycle. The H.E.R. accounts for every positive thermal flow within the cabinet: conductive heat from the walls and the glass, radiating heat through the glass, heat from the vents, the internal lights, and the resistors inside the doorframe.
- The material cost is representative of the overall cabinet cost, and is determined as the sum of each component materials and manufacturing costs.
- The TDA was determined from a fixed outer cabinet dimension and aspect ratio. TDA is defined as the sum of vertical and horizontal projected areas of visible products.
- The TDV is defined as the cabinet internal capacity to hold refrigerated food.

3.2. Mathematical model and product parameterization (Step 1.2)

We will not go into the details of the mathematical model and focus on the choice of parameters and optimization variables. In order to study the cabinet performance over a variety of configurations, a small set of optimization variables was chosen, among the many parameters required to model the product. As aforementioned, there is no definite way to choose optimization variables. For the present study, the selected parameters represent the main areas of development focus, and have been chosen with the intent of gaining insights on their influence on the overall performance. A list of all the optimization variables and performance criteria can be seen in Tab. 1.

The optimization variables are:

- *Insulating element thickness*. The cabinet back, top and bottom walls are lined with insulating material. The insulation thickness is constant along each wall, but each insulated wall is independent of the rest, thus allowing for different distributions of insulation thickness.
- *Insulating element material*. The insulating material can be either polyurethane foam or Vacuum Insulated Panels (VIP), the latter being the most

Table 1. Optimization variables and performance criteria.

Optimization variables	Performance criteria
Insulation thickness on lower wall	Heat Extraction Rate
Insulation thickness on upper wall	Material cost
Insulation thickness on back wall	Total Display Area (TDA)
Air flow	Total Display Volume (TDV)
VIP ratio on lower wall	
VIP ratio on upper wall	
VIP ratio on back wall	
Glass Transmittance	
Evaporator position	

advanced and costly technology. In order to work with continuous variables, the material type has been parameterized as a percentage of VIP on the overall thickness.

- *Internal airflow*. The studied cabinet is of a forced ventilation type. Airflow is therefore a critical parameter, which has been the focus of many scientific articles, and experimental and analytical studies. Airflow directly determines the evaporator power consumption, its dimension, and the internal temperature of the cabinet and refrigerated products.
- *Glass transmittance*. The cabinet glass is the only see-through wall and the most conductive side of the cabinet. Its transmittance can be lowered at great technological and economical expense. Two main technologies are available; an economic, but high transmittance glass, and a costly, low emissivity glass. Since a discreet variable of only two levels would be less than ideal for a parametric optimization, the range of glass transmittance was parameterized as a continuous variable.
- *Evaporator position*. The evaporator can be positioned along the three inner walls of the cabinet. Its position has a great effect on the distribution of temperature inside the cabinet, as well as the overall energy consumption. Depending on its position, the circulating air coolest and warmest point shift along the inner edge of the cabinet, creating a different thermal system each time.

3.3. Factorial analysis (Step 2.1)

A factorial DoE analysis allows studying the design space boundaries with a limited number of simulations. Through a statistical DoE, which guarantees a zero correlation between input variables, it was also possible to study the relative influence of each parameter on the performance of the product, by determining each variable Main effects. Main effects analysis (Fig. 4) shows the prominent effect of airflow on energy consumption (27%), material cost (9%), TDA (41%), and TDV (48%) (the last three are a product of the evaporator dimensioning). VIP ratio and insulation thickness are also important factors, accounting together for much of the material cost, energy consumption, TDA, and TDV. The glass transmittance has a great impact on the overall cost, but its influence on energy consumption, TDA, and TDV is limited. It seems that glass insulation is a costly technology with little benefit on the cabinet performance. Finally, the evaporator position has a very limited effect on energy consumption and overall cost ($<$ 1%), but plays a big role in determining the cabinet TDA and TDV.

All the chosen variables have a quantifiable effect on at least one performance criteria, and all variables form a trade-off between at least two performance criteria (i.e. there is no variable that can be maximized or minimized without any negative effect on product performance). Therefore, the number of optimization variables cannot be reduced without losing an important aspect of the analysis.

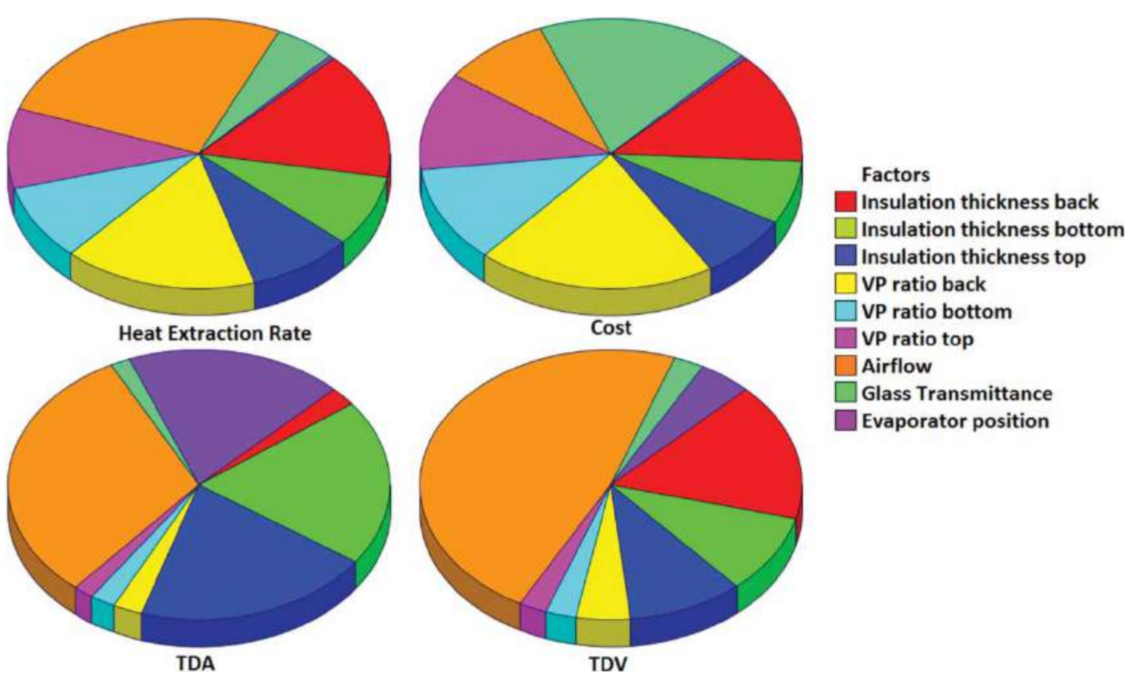

Figure 4. Optimization variables main effects

3.4. Optimization (Step 2.2)

A set of genetic algorithms was employed to generate the core of optimal product configurations with respect to the objectives defined in step 1.1. From this set of designs, the *paret*o configurations were extracted (Fig. 5). The hyperbole trend of the graph reveals the intrinsic dependency of energy and cost. Energy efficiency is mainly achieved through technologically superior materials and components, leading to a higher material cost of the cabinet. The *pareto* scatter chart of Fig. 5 does not show a clear *pareto* frontier on account of there being four objectives, which make it impossible to represent a *pareto* frontier in two dimensions. Plots for TDA and TDV are not showed.

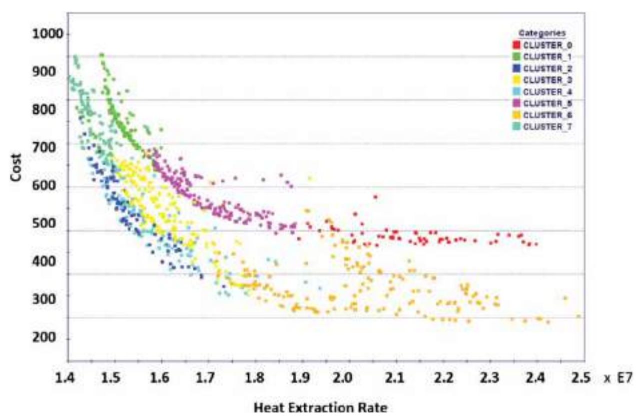

Figure 5. Pareto designs scatter chart, with applied clustering results

3.5. Cluster analysis (Step 3.1)

A partitive clustering algorithm was employed for a cluster analysis of the Pareto designs. The aim of such analysis is to find regions of overlapping technology, were different configurations may achieve similar performance in all or some of the performance criteria, and to define product families based on performance criteria rather than configuration. The partitive clustering algorithm found 8 clusters, shown in Fig. 5.

Clusters are labeled (Fig. 6) based on their mean performance across the range of performance criteria. Their composition can then be studied for each optimization variable. Continuous variables should be divided in high and low ranges, or any number of sub-divisions. For instance, the glass transmittance was split in high values (from the highest value to the mean value) and low values (from the lowest value to the mean value). Thus, it is possible to determine the composition of each cluster. For instance, results for the glass transmittance (Fig. 6) show that low values of transmittance are mainly associated with high materials costs (clusters 1 and 7), while high values of transmittance are mainly associated with high energy consumption (clusters 0, 5, and 6). Finally, clusters 2,3, and 4 show a more homogeneous distribution of low and high values of transmittance. This means that a similar performance can be achieved with different product configurations: some that work better with a high transmittance glass, and some that tailor the remaining optimization variables in order to accommodate a low transmittance. Clearly, we can increase the definition by defining a higher number of sub-divisions for each variable; for instance: low, medium low, medium, medium high, and high.

3.6. MCDM/Single objective (Step 3.2)

In order to identify trends for product development, the proposed methodology needs a ranking of all Pareto designs across the range of performance criteria. In order to achieve this, the four performance criteria were reduced to a single objective: operational cost. The operational cost was defined as the cost of running the cabinet for a period of three years (material cost and energy consumption), minus the economic benefit of a higher TDA and TDV. It was then possible to rank the Pareto designs and select the top 100.

As aforementioned, determining the conversion factors that allow the reduction to a single objective is in itself a daunting task, but it will not be treated in the present article.

3.7. Results evaluation (Step 4)

The best 100 designs in operational cost have been studied in detail to define a set of design rules, based on the results of the product optimization. The following graphs (Fig. 7) display the 100 top designs ranked by operational cost (*y axis*) with respect to the main model variables (*x axis*).

By studying the best results, it was possible to define a set of twelve design guidelines and rules that enable the minimization of the operational cost over a three-year running period. These design guidelines target each optimization variable, as well as the overall product. For example, two values of optimal airflow can be found in Fig. 7 (left): a very low airflow of about 0.05 kg/s, and a mid-range value of 0.11 kg/s. Regression lines don't show a clear benefit for either value, which indicates that it should be possible to build two different product configurations of similar performance. Choosing either airflow value, in fact, will result in a different set of values for the

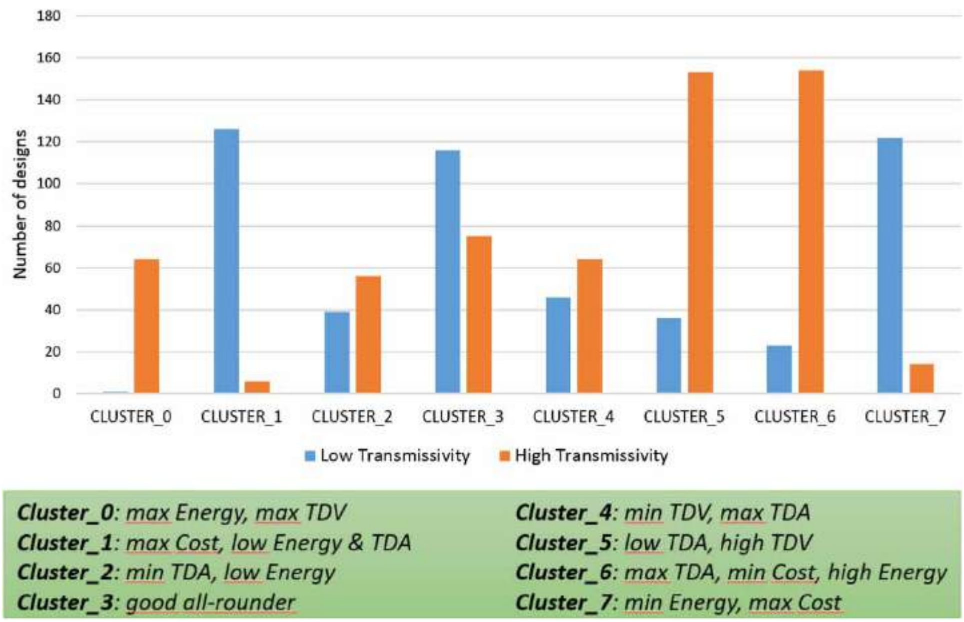

Figure 6. Clusters composition analysis

Figure 7. Scatter graphs of optimization variables vs the ranking of the best 100 designs.

remaining optimization variables. The resulting guideline is: *Two distinct airflow values were found to be optimal. Each configuration should be studied in detail before choosing the nominal airflow rate.*

In a similar way, a set of guidelines was defined for the second case study, the refrigerated cabinet shelf, providing trends and design rules in terms of the layout of the insulating material, and the use of special insulation panels. The analysis also highlighted the relation between the height of the evaporator and the shape of the condenser, allowed identifying a correct universal thickness for the special insulating panels, and provided important clues for the shape of the condenser.

These guidelines can help the designer during the embodiment phase of product design, by focusing the development effort on critical areas, and highlighting possible trade-offs and unexplored configurations.

4. Conclusions

The proposed methodology, called *Optimized Development*, aims at using optimization techniques as one of the first tools of product development, applicable during the embodiment phase. By describing the design space through a finite set of optimal and factorial configurations, and by using statistical, clustering, and multi-criteria tools, the proposed procedure can describe the characteristics of a product, which has yet to be thoroughly defined. The output is a set of design guidelines that describe the design challenges at an early stage, when there is still time to address trade-offs, and, possibly, resolve them before the final, and more classical, product optimization. The methodology should not be viewed as an alternative to the standard step of product optimization, but rather as a complementary phase, with a broader scope, aimed at studying the relationship between product performance and design variables.

The approach has been tested on two kinds of refrigerators for commercial exposition. Results show the feasibility and benefit of applying *Optimized Development* from the early stages of product development. On the other hand, the main limit of the methodology is the need of parameterizing the product, which binds the analysis to the choice of parameters.

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