

Early Environmental Design of Solar Collector with Consideration for Parameter Variability

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Abstract. This article focuses on assessing the environmental impact during the early stages of design, emphasizing the minimization of negative consequences on the environment. We explore methods for integrating environmental constraints into the design process and underscore the importance of preliminary choices. Considering the variability of design parameters plays a fundamental role in ensuring reliable and stable outcomes. In-depth analysis of behavior models allows quantifying the influence of assumptions on prediction accuracy. Classifying these assumptions based on their level of practical verification sheds light on the reliability of expected results. The introduction of objective and subjective accuracy indicators enhances our ability to evaluate models and identify potential sources of uncertainty. Through the study of a concrete case, that of a Fresnel mirror solar concentration system, we demonstrate the relevance of our approach. The optimal and robust design of the collector support is explored using simulation and optimization tools. The obtained results demonstrate a significant improvement in the environmental indicator, confirming the effectiveness of our approach.

1 Introduction

Minimizing the environmental impact of a product or process has become a major concern for industries, which have undertaken various scientific efforts in the field of eco-design [1] in recent years. In this context, numerous tools have been developed to facilitate the integration of environmental constraints into the design process. These tools can be divided into two main categories [2-5].

The first category comprises improvement tools [6] that direct and guide the designer by providing advice and recommendations to identify potential areas for improvement. These tools include checklists, guidelines, diagrams, and matrices like the M.E.T. matrix [7]. These tools have a predominant qualitative dimension, making them suitable for use in the early stages of design as they do not require a substantial amount of product-specific information.

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The second category encompasses quantitative tools, also referred to as tools for assessing and analyzing environmental impact [8]. These tools aim to measure and evaluate the environmental impact of the product. They require a substantial amount of product-specific information, which limits their use to the detailed phases of design. The Life Cycle Assessment (LCA) method is the most widely recognized evaluation tool on a global scale [9].

It is crucial to consider the environmental criterion during the initial phases of design, as the majority of negative environmental impacts are generated at this stage [10]. However, these phases are characterized by a notable lack of data and information about the product [11], which hinders an early assessment of environmental impact, especially through evaluation and analysis tools of environmental impact such as LCA, considered the most relevant and reliable tool [12].

Most of the research conducted in this direction primarily focuses on reducing the negative environmental impact of products, while a limited number of them emphasize minimizing the variability of these impacts [13-15]. This variability stems from various factors, including intrinsic uncertainties related to random characteristics of the product, such as its physical properties.

At times, these variations can lead to inaccuracies related to the manufacturing equipment used for producing parts, which could result in slight fluctuations in the design parameters of the part and, consequently, in its environmental impact. Accounting for the variability of these parameters has the effect of enhancing the predictability and stability of the product's environmental impact. Among the approaches aimed at incorporating these variabilities, robust design stands out.

2 Literature

2.1 Environmental Impact Assessment during Preliminary Design Phases

The preliminary phases of design play a crucial role in the product development process, whether it's to ensure its performance and reliability or to create an environmentally friendly product. Decisions made at this stage can account for up to 80% of the negative environmental impacts of the product, and nearly 90% of the economic and environmental costs of a system are defined during these stages [16]. This greatly complicates the alteration of environmental performance during the detailed phases.

Numerous research studies have been undertaken to integrate environmental constraints in the early phases of design. Furthermore, new methodologies are being developed to consider the entire product lifecycle with the aim of reducing its environmental impact. In this regard, [18] proposed an approach that allows designers to embrace the principles of Design for Environment (DfE) right from the conceptual phase. This approach is of paramount importance as designers often have limited tools or straightforward quantitative methods to assess their products.

Anticipating the overall environmental impact of a product throughout its entire lifecycle from the early stages of design is undeniably important to ensure the successful development of a product in line with environmental imperatives [19]. Omitting this integration throughout the design process can lead to unfavorable decisions that do not meet required regulations and environmental requirements [20]. However, assessing the environmental impact during these initial phases using analysis tools such as Life Cycle Assessment (LCA) requires an abundance of detailed product data, which is typically not available at this stage. According to [21], evaluating the environmental impacts of any given product necessitates the determination of three essential elements:

- *Materials and Manufacturing Processes*: The choice of materials can generate environmental impacts from raw material extraction to end-of-life. Recyclability/reusability characteristics and the substances used influence toxicity, the effects of regulated substances, and end-of-life impact. This parameter helps determine potential manufacturing processes and the associated energy.
- *Mass*: The mass of the material has a significant effect on energy consumption and CO₂ emissions during usage and transportation phases. Therefore, reducing mass further reduces these emissions and thus leads to overall improvement.

In a similar vein, [22,23] highlights that determining these parameters during the preliminary phases allows the designer to early anticipate the environmental repercussions of products using the Life Cycle Assessment (LCA) evaluation tool.

In reality, as early as the architectural phase, and more precisely during the pre-sizing phase, the fundamental design choices are established, including the materials to be used as well as the main product dimensions, expressed through design parameters. These latter serve as a means through which the product's mass can be determined. However, this step remains intricate, as even though the mass can be estimated at this stage, it is often subject to certain uncertainties.

Indeed, the determination of design parameters, including mass, is carried out based on the use of behavior models suited for these phases [24]. Generally, these models serve to: (i) assess performance parameters that embody design objectives, and (ii) identify design parameters best suited to achieve the design goals envisioned by the company.

However, the results predicted by these models often yield discrepancies compared to the actual behavior of the product, raising questions about their accuracy.

Typically, behavior models encompass all the necessary knowledge for designing the modeled system, forming the basis upon which conclusions are drawn to guide decisions. Consequently, the reliability of the decisions made is closely tied to the quality of the behavior models employed. Therefore, evaluating their effectiveness during implementation is of paramount importance. In this regard, [25] introduce four criteria for characterizing a behavior model, grouped under the acronym PEPS: Parsimony, Accuracy, Precision, and Specialization. In our work, we pay particular attention to the criterion of Accuracy as it directly impacts performance parameters and, by extension, environmental performance. The other criteria (Precision and Specialization) are solely dependent on the choice of the model and do not influence the model's output (the performance variable).

According to [25], model qualification refers to validating the realization assumption step in relation to the inherent model requirement. This entails the need to qualify the model resulting from the realization step, which is itself conditioned by the previously established assumptions. In this regard, it proposes two phases for model qualification: (i) intrinsic qualification, which is primarily based on the assumptions used during model realization, and (ii) qualification with respect to the requirement.

Furthermore, [26] highlights that discrepancies between model results and the actual behavior of the product arise from two main sources: (i) the uncertainty surrounding the assumptions defining the validity domain, and (ii) the uncertainty associated with the identification of parameters feeding the model.

In this work, we propose an approach aimed at accurately determining the design parameters leading to an optimal mass and, consequently, reduced environmental impact. We also take into account their variability to achieve an environmental indicator that is both optimal and robust.

3 Proposed Approach: Selection of Appropriate Design Parameters

Our approach aims to identify optimal design parameters to achieve both an optimal and robust environmental indicator while meeting the design objectives set by the company. To achieve this, our methodology is based on three key steps.

3.1 First Step: Classifying Design Parameters Based on the Level of Validation of Study Assumptions in Real Product Behavior.

The first step involves selecting design parameters that lead to more accurate outcomes. To this end, we evaluate the accuracy of behavior models used during the architectural phase. Design parameters serve as inputs to these models, and as output, we obtain performance parameters that reflect design objectives. Thus, to assess the accuracy of these models, we advocate an approach of classifying the assumptions used in the development of these models, as they are the underlying cause of their inaccuracy.

Therefore, we propose to initiate this evaluation by classifying the assumptions formulated during the creation of behavior models. This classification will help determine when these assumptions are effectively verifiable in the actual behavior of the product and when they are not.

Indeed, this classification relies on delimiting the intervals of design parameters associated with each type of assumption. Our work envisions a classification based on three categories of assumptions:

- Type 1: Assumptions of this type have a high probability of being verified in reality. These assumptions correspond to design parameter intervals that have demonstrated, through multiple physical tests, a closer match to reality. Therefore, we qualify this first type of assumption as "weak assumptions."
- Type 2: These assumptions possess intermediate strength, falling below the level of Type 1 assumptions. They are referred to as "moderate assumptions."
- Type 3: These assumptions remain largely unverified in the actual behavior of the product, and consequently, they are called as "strong assumptions."

The subsequent phase involves assessing the accuracy of these models based on two indicators of distinct natures. The first indicator relies on an objective accuracy assessment, involving a comparison between the outcomes predicted by the behavior models and the results obtained from a reference solution that has been physically prototyped by the company. This first indicator is calculated using formula (1).

$$E_p = \left| \frac{(P_i - P_i^*)}{P_i^*} \right| \quad (1)$$

This first indicator is valid only for a specific solution, and as soon as one deviates from that solution, this measurement loses its validity. Hence, to have an indicator covering the entire design space, we opt for a subjective accuracy assessment. This assessment relies primarily on the expertise accumulated by the designer through the fabrication of multiple physical prototypes within the company. These experiential insights enable us to grasp various physical phenomena, with particular emphasis on discrepancies arising from actual behavior.

Therefore, at this stage, we combine objective assessment with designer feedback. To achieve this, we propose calculating an additional indicator, termed the correction indicator (K_i), which quantifies the level of reliability of the candidate solution in relation to the reference solution. This indicator is obtained by evaluating a confidence indicator specific

to each performance parameter of the candidate solution (IC_i) and the reference solution (IC_i^*). These indicators are computed using formulas (2), (3), and (4).

$$IC_i = W_{ij} * Sh_i \quad (2)$$

$$K_i = \frac{IC_i}{IC_i^*} \quad (3)$$

$$SAI_i = EP_i * K_i \quad (4)$$

Where Sh_i : represents the impact of each assumption on the performance parameters
 W_{ij} : represents the impact of each type of assumption on the performance parameters.

Lastly, in the final sub-step, we suggest assessing the impact of behavior model inaccuracies on mass and, by extension, on the environmental indicator, using the coefficients A_i . These coefficients are obtained through a sensitivity analysis, which determines the influence of each performance parameter on mass. The calculation of these coefficients is done as follows:

$$A_i = \left(\frac{\Delta m_i}{\Delta P_i / P_i} \right). \quad (5)$$

3.2 Second Step: Calculation of the Environmental Indicator based on the Life Cycle Assessment (LCA) tool.

After calculating the mass, determining the environmental indicator becomes more straightforward. Indeed, the Life Cycle Assessment (LCA) tool allows for the calculation of quantitative indicators, such as midpoint (Climate change, depletion of the ozone layer, etc.) and endpoint (Loss of human lives, loss of ecosystems, etc.) indicators, or a single-score indicator resulting from a combination of these two types of indicators. Several LCA calculation methods enable obtaining a single-score indicator, with the Recipe method being the most recent and comprehensive [24]. We also employ the SimaPro software for calculating the environmental indicator, carried out according to the following formula:

$$E_i = m * I_r \quad (6)$$

Where I_r primarily depends on the type of materials used. And (m) represents the mass of the product. We also specify that we neglect the estimation of the impact of manufacturing processes. This neglect is justified by our application domain, which mainly concerns metallurgical products, where the influence of this parameter is marginal compared to the impact of mass and materials used.

3.3 Third Step: Studies of Design Parameter Variability on the Environmental Indicator

At a more advanced stage of the architectural phase, our objective goes beyond achieving an optimal solution in terms of accuracy and environmental impact indicators. We also aim for a solution that remains insensitive to variations in design parameters, thus ensuring robust optimization, especially concerning the environmental indicator. To accomplish this, we propose the use of the ModeFrontier software [27]. This software enables the evaluation of robustness using simulation models, numerical models, and optimization models that incorporate parameter variability.

ModeFrontier considers the probabilistic aspect of the objective function and employs iterative stochastic models within a defined uncertainty zone characterized by two measures: standard deviation and mean of the objective function. The standard deviation assesses the dispersion of values around the mean value. Thus, the solution exhibiting minimal standard deviation for the environmental indicator proves to be the most robust solution.

4 Application Case

The chosen application case for this study is a Fresnel mirror solar concentration system. This concentration mechanism harnesses solar rays to convert them into electrical energy, utilizing reflective panels that redirect the sunlight onto an absorber tube containing a high-temperature heat transfer fluid. This fluid is then used in a thermodynamic cycle to generate electricity. Typically, this system consists of reflective panels, a reflector support, and a fastening device to secure the reflective panels in place (Figure 1).

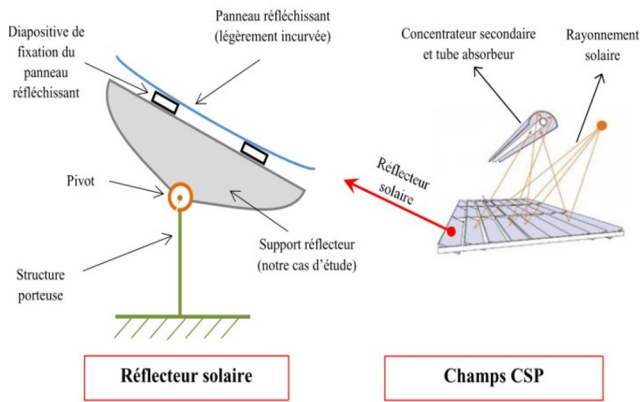


Fig. 1. Structure of the Solar Reflector.

It should be noted that in this application context, our focus is uniquely on the design of the solar collector support, i.e., the truss structure (Figure 2).

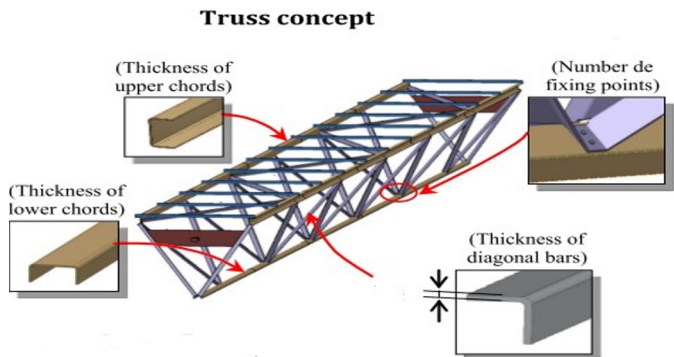


Fig. 2. Truss Structure.

The intended design objectives for this collector are as follows:

- **Ensure high optical performance.** To achieve this goal, we need to evaluate two crucial performance parameters: (p1) maintaining minimal deflection of the structure and (p2) minimizing torsion of the structure.
- **Design a collector capable of withstanding external environmental conditions.** With this in mind, we have considered performance parameter p3, which reflects the support's ability to withstand extreme winds.
- Develop a collector support that is both environmentally optimal and robust.

The design parameters considered for the truss structure are:

- PC_1^{tr} : thickness of diagonal bars.

- PC_2^{tr} : thickness of the upper chord.
- PC_3^{tr} : thickness of the lower chord.
- PC_4^{tr} : height of the structure.

The assumptions studied during the development of behavior models used to evaluate the performance parameters are as follows:

- H1: Neglect the peeling phenomenon.
- H2: Joints between bars are assumed to be perfect.
- H3: Diagonal bars of the structure are assumed to intersect at nodes.

After classifying the assumptions based on the intervals of the defining design parameters, we obtained the results shown in Table (1).

Table 1. Accuracy Evaluation Indicators.

Reference Solution		Subjective Accuracy		Correction Factors			Coefficients (A_i^{tr})		
IC_1^*	0.99	SAI_1^{tr}	0.21	K_1^{tr}	K_2^{tr}	K_3^{tr}	A_1^{tr}	A_2^{tr}	A_3^{tr}
IC_2^*	0.99	SAI_2^{tr}	0.24	1	0.75	1.02	$1.8 \cdot 10^{-2}$	$2 \cdot 10^{-3}$	8.810^{-2}
IC_3^*	0.98	SAI_3^{tr}	0.61						
Truss Solution		Objective Accuracy							
IC_1^{tr}	0.99	Ep_1^{tr}	0.21						
IC_2^{tr}	0.75	Ep_2^{tr}	0.28						
IC_3^{tr}	1	Ep_3^{tr}	0.6						

Thus, the environmental indicators as well as the calculated overall optimal accuracy for the lattice structure are presented in the following table:

Table 2.Overall Accuracy Indicator and Environmental Indicator of Truss Structure.

	E_i^{tr}	OAI^{tr}
Truss Solution	67.5 mPt	41.4(%)

In the final step, our objective is to achieve an optimal and robust concept in terms of the environmental indicator. To accomplish this, we utilized the ModeFrontier software. The obtained results revealed an enhancement of the environmental indicator compared to the initially obtained value. The design parameters leading to this outcome are listed in Table (3).

Table 3. Robustness Optimization Results of the Environmental Indicator for the Truss Concept.

Solution A (Robust Truss Solution)			Initial Truss solution		
PC_i^{tr}		E_i^{tr}	PC_i^{tr}	E_i^{tr}	
PC_1^{tr}	2.45mm	63.8mPt	PC_1	2.5mm	67.65 mPt
PC_2^{tr}	3.23mm		PC_2	3.5mm	
PC_3^{tr}	4.64mm		PC_3	3.5mm	
PC_4^{tr}	921.8mm		PC_4	920 mm	

5 Conclusion

In summary, this study underscores the significance of early-stage consideration of environmental impacts during the design process, while also acknowledging the inherent variability in design parameters and their influence on the product's environmental performance. The integration of accuracy assessment of behavior models, spanning through levels of considered assumptions, various types of accuracy indicators, and optimization tools, has enabled the proposal of a more optimal, robust, and environmentally friendly solution that is better aligned with real-world constraints. This work represents a substantial contribution to sustainable product and system design, providing insights for future advancements in this crucial field.

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