Early Environmental Assessment of Products Using Behavior Models and the Impact of their Inaccuracy on Environmental Product Performance

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The decisions made during the preliminary design phases considerably impact the development of a product's lifecycle, acting on its environmental performance, cost, and duration of its realization. However, the lack of relevant information during these phases does not allow for the accurate evaluation of design solutions. In addition, it generates schedule delays and overruns in the budget allocated to developing a given solution. In this perspective, the present work aims to assess the accuracy of the behavior models used for exploring solutions during the embodiment phase. This was based on two measures of different nature, namely objective accuracy, which is evaluated by referring to real prototyping of a given solution, and the subjective accuracy measure, which allows to the expression of the degradation of the first measure in relation to the reference point. This combination will lead to a measure that can be generalized on all the design space. In a second step, the current work suggests an estimation of the effect of these models' accuracy on the proposed solutions' environmental impact. To this end, a sensitivity study was carried out on the input data of the model (design parameters) in order to deduce the effect of the results obtained (performance parameters) on the mass and, consequently, the environmental impact of the solution. In order to highlight the approach adopted in the present study, it was applied to a real industrial case, ultimately leading to the most optimized solution in terms of accuracy and environmental impact.

Keywords: *Model behavior, objective accuracy, subjective accuracy, environmental impact, embodiment design.*

1. INTRODUCTION

Nowadays, the main concern of manufacturers is oriented toward the design of eco-friendly products with the lowest cost and the lowest lead time. Indeed, it turned out that all these elements must be taken into account from the first phases of the design process [1], especially since 80% of environmental decisions are made in this stage [2] and have an impact of 70% on the overall cost of the product, notably during the embodiment design phase [3]. However, several problems can confront the designer during these phases due to the need for more necessary information and the unavailability of data, including the data that allows for evaluating the environmental impacts of a given solution, mainly the mass. Nevertheless, in order to determine this parameter (mass), the designer must go through the pre-dimensioning stage. This stage is often carried out using behavior models, mostly based on approximate assumptions that question their accuracy, resulting in uncertain solutions [4]. In this regard, taking into account these uncertainties from the beginning of the design process remains a crucial decisive step, especially since the proposed design solutions in this phase are partially designed.

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2. LITERATURE REVIEW

Several multi-criteria decision support approaches have been proposed in the literature using various methods, including inter alia the fuzzy set method, which is frequently used in the treatment of inherent imprecision and uncertainties in the preliminary phases [5, 6, 7] including the choice of alternatives in terms of environmental performance.

In this regard, Alemam, A. et al. [8] proposed an approach to estimate concepts' environmental impacts, taking into account the uncertainty of design information based on the Fuzzy interval arithmetic method. This latter is used to specify and identify imprecise information. In the same vein, the fuzzy group method is applied to Eco-QFD for product development plan–ning to reduce the imprecision and uncertainty in a group decision-making process. One of the primary objectives of the fuzzy model is to encourage companies to produce environmentally friendly products[9]. It was also utilized to choose the best alternative of the compromises in a stage where the consideration of environmental performance is a decisive factor for developing an ecological product [10].

Moreover, the fuzzy set method is often applied at the beginning of the design process, especially the con–ceptual phase, where most of the information is imprecise, in contrast to the embodiment phase, in which the designer receives more detailed information. Therefore given their relevance in the field of decision-making, it is important to develop objective-type met–hods. In this sense, several works have been proposed which have developed numerical indicators allowing us to evaluate and quantify the uncertainties during the preliminary phases, such as the confidence indicators proposed by Sylla, A. et al. [11], which are mainly based on subjective and factual indicators.

For a long time, the tools adopted by designers for decision-making are mainly based on their experience and know-how [12]. However, today most companies invest their efforts in the development of tools that rely on numerical calculations using behavior models. These models are based on assumptions and approximations, which often lead to less representative (invalid or unre–liable) findings compared to the real product behavior [13], including environmental performance. For this reason, the verification of the confidence level of the candidate solution is an unavoidable step. This can be achieved through the sequencing of iteration cycles and the fabrication of numerous verification prototypes. Yet, this process remains very long and usually leads to over–runs in time and budget allocated for product development. This, consequently, evokes the need to develop tools aiming at the evaluation of the accuracy of these models in order to have products with the best cost, in the shortest possible time, and with good environmental performance.

In fact, there have been very few attempts to address the evaluation of behavior models in the literature, prominent among which are as follows:

- Collignan, A. et al. [14] proposed a method called OIA (observation-interpretation-aggregation), which allows one to explore the global design space and to qualify at the same time the explored solutions by comparing them with the reference solution. This requires the use of functions, namely confidence functions, granted by the designer. However, one of its limitations is that it proposes functions encompassing any uncertainty. Yet, it is important to determine the exact source of the inaccuracy of the behavior models in order to be able to reduce it.

- Malak, R. J. et al. [15] suggested in a conceptual framework a new approach that goes through three complementary processes for the validation of a model, including the characterization of the validity, compati–bility assessment, and suitability assessment. This de–composition is informed by a formal representation of relevant knowledge for the validation, which allows acquiring, transferring, and effectively using this knowledge and validating the reusable behavior models. In the same perspective, Mocko, G. et al. [16] developed an interface that facilitates the reuse of behavior models. It allows for the reduction of the knowledge gap between the technical design and the analysis. Nevertheless, this process requires the availability of knowledge and specific information to reusable models. Therefore, the application of this type of procedure is only valid for reusable models and cannot be applied to new models.

-Vernat,Y et al. [17] proposed a tool to evaluate the accuracy of behavior models using the acronym PEPS (Parsimony, Exactness, Precision, and Specialization). In addition, the author proposes to measure the accuracy by determining the distance between the envisaged solution and a reference solution. This measure has been implemented in the study of El amine, M et al. [18], along with other subjective indicators called "confi–dence indicators," in which the author takes into consideration the degradation of the measure proposed by Vernat, Y when the proposed solution moves away from the reference solution.

Given the findings obtained in the aforestated re–search studies, the present study is an attempt to address three issues : (i) the use of behavior models as a means of identifying the necessary parameters for an early environmental assessment, (ii) the estimation of the impact of inaccuracies of these behavior models on the environmental performance of the product, and (iii) evaluation of the accuracy of these models based on the notion of hypothesis, in particular the notion of classi–fication of hypotheses.

The current work adopts behavior models for a number of reasons. First, to explore possible solutions during the embodiment phase, on the other hand, to have the necessary dimensions for estimating the mass, which remains a key factor in assessing the product's environmental impact. Second, an approach is proposed to evaluate their accuracy: subjective and objective indicators. Finally, it shows the effect of these models' uncertainty on the product's environmental impact thro–ugh an overall accuracy indicator. The application case chosen for the proposed approach is the supporting structure of a Fresnel solar collector.

3. PROPOSED APPROACH

The embodiment design defines the choices to be made in relation to the form, the components, the materials, and the structural/architectural dimensions [17]. These choices are usually made using behavior models, which allow prediction and evaluation of design solutions' performance. However, most of the time, these models generate deviations from the real behavior of the product because of two main factors: the hypotheses used during the construction of the model and the imprecision of the model's input variables [19]. The study proposes the treatment of the problem of the accuracy of behavior models following four steps: The identification and classification of the hypotheses used during the development of these models, according to three levels (strong, weak, mode–rate). The second step consists of objectively assessing the model's accuracy using a numerical indicator. It is a measure that determines the distance between the performance parameters of a candidate solution (solution predicted by behavior model) and a reference solution (solution tested and physically prototyped by the company). The third step, it consists in integrating the designer's experience developed through the manufacturing of several prototypes, a subjective element but considered very important in assessing the accuracy of these models. The final step stipulates the use of an overall indicator that measures the effect of inaccuracy on the product's environmental impact. Figure 1 shows all the steps followed in evaluating behavior models, going from the classification of hypotheses to having the overall accuracy indicator.

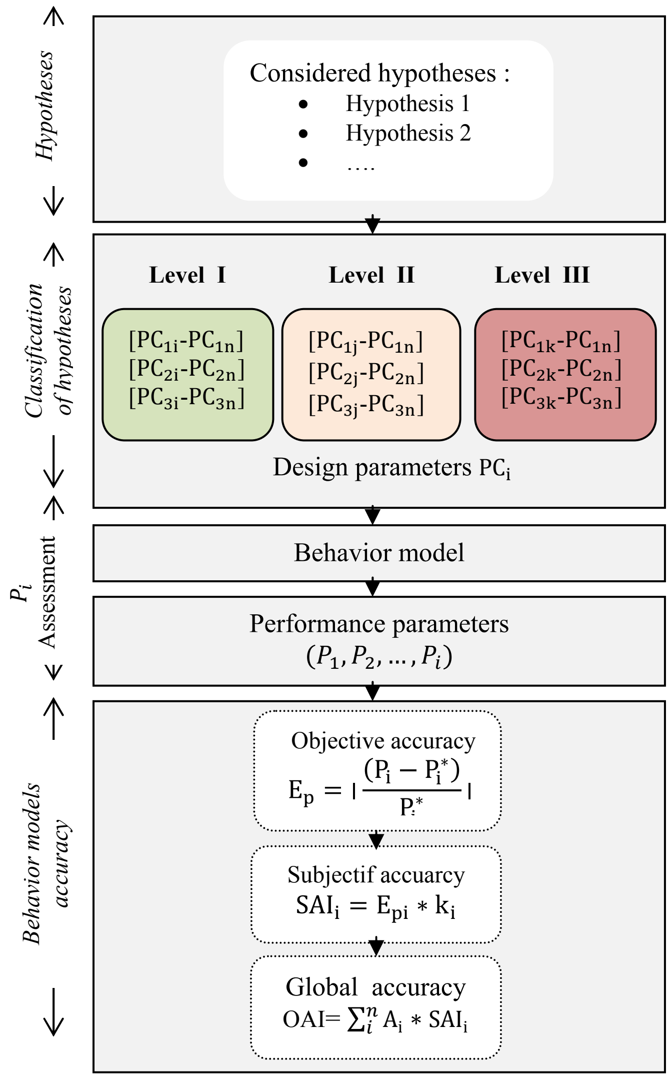

Figure 1. Procedure for assessing the accuracy of behavior models

3.1 Classification of hypotheses

The development of a behavior model requires a multiplicity of hypotheses and approximations that can be subsequently verified in the real behavior of the product. The verification is carried out according to three levels: a complete verification of the hypotheses used, a moderate verification, and another weak verification distinguished as follows:

- **Level 1** (L_1) : **weak hypothesis**; these hypotheses have a high chance of being verified in reality, at this level, the designer defined the interval of the design parameters, which proved during certain prototyping results very close to the real behavior of the product.
- **Level 2** (L_2)**: moderate hypothesis**; these hypotheses are more or less strong, but with a lower level, the design parameters that define this type of hypothesis lead to results that can approach the product's real behavior.
- **Level 3** (L_3) **: strong hypothesis,** these are hypotheses that are far from being verified in real behavior; this level is characterized by the design parameters leading to results that have a low chance of being verified.

Each hypothesis corresponds to a well defined interval of design parameters constituting the input variables of the model Figure 1.These are used to find possible design alternatives. The behavior model is also influenced by control variables that correspond to fixed data related to the hypotheses and are used to define the models and their framework. At the model's output, we obtain the performance parameters representing the design objectives to be achieved. Figure 2 highlights the three types of variables constituting the behavior model:

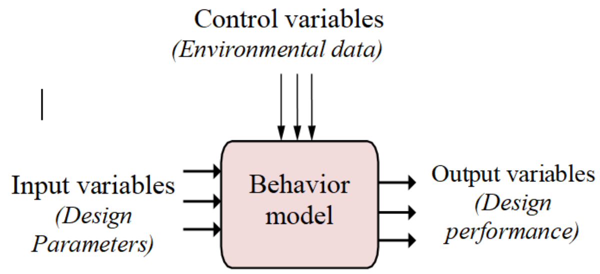

Figure 2. Formalization of a behavior model for product

In reality, the impact of hypotheses on performance parameters varies from one level to another according to the interval of design parameters that define them. To this end, we proceed to use a method frequently used in decision-making [20, 21], the AHP method [22]. This method is mainly based on a pairwise comparison of the criteria which correspond to the suggested levels of hypotheses. Generally, this comparison is carried out using a semantic scale ranging from 1 to 9. This pairwise comparison process permits constructing a judgment matrix to estimate the weights associated with each level of the hypothesis. A consistency coefficient that varies between 0 and 1 was proposed by Saaty [23] in order to check for inconsistencies in pairwise comparisons. This mode of expression is characterized by its simplicity and allows for a cardinal type of weighting [24].

In fact, the weights associated with each level of hypotheses serve to classify them according to their degree of importance and their impact on the performance parameters. For example the weak hypothesis level is the most important level, as it represents the interval of the design parameters allowing to have more exact results. This suggests the reason why a designer must assign the highest score at this level. The scores (*shi*) assigned to each level (L_i) are based on the designer's opinion and their experiences with prototyping and tests already carried out. A significant color was assigned for each level (L_i) as shown in Table1.

Table 1. Hypotheses levels considered

	L_i	Type of hypothesis	sh_i
Hypothesis (H_i)	L_1	Weak hypothesis	1
	L_2	Moderate hypothesis	0.6
	L_3	Strong hypothesis	0.4

3.2 Objective accuracy

The objective evaluation of the behavior models accuracy consists of comparing the performance of the candidate solution predicted by the behavioral model along with those of the reference solution. This evalu–ation was in the form of a numerical indicator, which measures the distance between the performance value of the behavior model and the performance value mea–sured on the reference solution [17, 25]. Indeed, the objective accuracy indicator is a normalized value that is obtained by the relative difference between the performance parameter of the candidate solution and that of the reference solution Eq. (1) :

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

- P_i: the performance parameters of the candidate solution.
- P_i^*: the performance parameters of the reference solution.

However, this measure is only valid for a particular solution (prototype solution), and the accuracy measure degrades as soon as the proposed solution moves away from the prototyped solution. Therefore, a subjective accuracy evaluation of these models has been proposed in order to generalize this measure to the whole design space.

3.3 Subjective accuracy

The knowledge of the designer developed over years of experience and the manufacture of several prototypes in the company, particularly the current product, are im–portant points in evaluating the accuracy of behavior models. Given this, an indicator that combines the objective evaluation and the experience feedback of the designer in relation to the performance parameters envisaged has been proposed.

3.3.1 Confidence indicators for performance para–meters

The performance parameters are strongly influenced by the hypotheses addressed in the present study as well as the levels to which they belong.That is, the stronger the hypothesis, the less the performance parameters will be affected. For this reason, confidence indicators have been proposed for each performance parameter for which the designer must assign scores to each of them using the AHP method. These scores reflect the desig–ner's opinion regarding the effect of each level of hypotheses on the performance parameters. Indeed, the designer's opinion is based mainly on feedback from experiences with prototypes already made for the deve–lopment of a given solution. This helps to compare the degree of influence of the hypothesis on the per–formance considered. Each confidence indicator (IC_i) is defined as the sum of the multiplication of the weights of the performance parameters (w_{ij}) obtained according to the studied hypothesis and the weight (sh_i) of each hypothesis level (L_i) (weak, moderate, strong). These indicators are presented in a matrix format.

$$[IC] = \begin{bmatrix} IC_1 \\ IC_2 \\ \cdots \\ IC_n \end{bmatrix} = \begin{bmatrix} W_{11} * sh_1 + W_{12} * sh_2 + \ldots + W_{1n} * sh_n \\ W_{21} * sh_1 + W_{22} * sh_2 + \ldots + W_{2n} * sh_n \\ \cdots \\ W_{n1} * sh_1 + W_{n2} * sh_2 + \ldots + W_{nn} * sh_n \end{bmatrix} \tag{2}$$

3.3.2 Subjective indicator of behavior models accuracy

In order to generalize the objective measurement over the entire design space, each objective indicator is mul–tiplied by a corrector factor. This latter represents the level of reliability of the performance parameters of the candidate solution compared to the performance para–meters of the reference solution.

$$\begin{bmatrix} SAI_1 \\ SAI_2 \\ \cdots \\ SAI_n \end{bmatrix} = \begin{bmatrix} E_{p1} \\ E_{p2} \\ \cdots \\ E_{pn} \end{bmatrix} \cdot \begin{bmatrix} k_1 \\ k_2 \\ \cdots \\ k_n \end{bmatrix} \tag{3}$$

$$k_i = \frac{IC_i}{IC_i^*} \tag{4}$$

- IC_i: the confidence indicator for the performance parameter P_i of the candidate solution.
- IC_i^*: the confidence indicator for the performance parameter $P^*_i$of the reference solution.

If: $k_i = 1$, the candidate and the reference solutions have the same reliability.

$k_i > 1$, the reliability of the candidate solution is greater than that of the reference solution.

$k_i < 1$, the reliability of the reference solution is greater than that of the candidate solution.

3.4 Overall assessment of the behavior model's accuracy

The behavior models used during the embodiment phase allow not only to explore of possible design solutions but also to determine important parameters, namely (thickness, width, length, etc.), which will subsequently enable to determine the mass, which is an essential ele–ment for the assessment of the environmental impact of the solutions explored, in particular for the calculation of several environmental indicators, such as midpoint, endpoint and single score [26].

The main objective of evaluating the behavior mo–dels was to find the effect of the accuracy of these mo–dels on the mass and, consequently, on the product's environmental impact. Moreover, it may be that a performance parameter with a high level of accuracy but with a low effect on the mass. It is also possible to have a performance parameter with a low level of accuracy however its impact on the mass was considerable. In this case the performance parameter induces a risk on the environmental performance compared to the first possibility, which may require more attention from the designer. For this reason, we propose an overall accu–racy indicator (*OAI*), that represents the effect of each performance parameter (P_i) on the mass using the coef–ficients (A_i) Eq. (5) multiplied by the subjective accu–racy indicators of each performance parameter Eq. (6).

$$OAI = \sum_i^n A_i * SAI_i \quad (5)$$

$$A_i = \frac{\Delta m_i}{\Delta p_i \,/\, p_i} \quad (6)$$

Indeed, in order to optimize the environmental im–pact of the considered alternative, it is necessary to op–timize its mass. To this end, optimizing the design parameters used in the proposed behavior model is important to have the most optimized mass value. This optimization should have a direct impact on the per–formance parameters. Therefore, the current step helps to determine the variation of the mass as a function of the design parameters and to show its effect on the performance parameters.

3.5 Estimation of the environmental impact using LCA

Through this step, we seek to estimate the environ–mental impact of the solutions proposed using the Life Cycle Analysis Method (LCA) [27, 28], using quanti–tative indicators such as midpoint (global warming, ozone depletion, etc.), endpoint (loss of human life, loss of ecosystems, etc.) or even single score which is a combination of midpoint and endpoint indicators) [29]. The main purpose of these eco-indicators is to convert the design properties of a given solution, including the mass and materials used into environmental indicators.

Several LCA assessment methods can estimate these indicators, including the Recipe method, which is a complete assessment method [30]. This latter proposes constantly updated models and suggests exhaustive in–dicators at the midpoint and endpoint levels.

The estimation of the environmental impact of a product requires three main parameters: mass, materials used, and manufacturing processes. In this study the third parameter is not included because only the assem–bly processes are treated (bolting, riveting, clinching... etc) which are not treated by LCA except for "wel–ding"[31].

In fact, the environmental impact induced by the materials remains easy to estimate during the preli–minary phases. Nevertheless, the estimation of the mass is more complicated [26]. Due to this the behavior models are used to determine the dimensions needed to estimate the mass.

The estimation of the product's environmental impact was calculated using Eq. (7), where (*M)* is the estimated mass and (I_r) is the RECIPE indicator which is taken from the database Ecoinvent 2013.

$$Ei = M * I_r \quad (7)$$

4. APPLICATION CASE

The chosen application case is the support of a solar collector (CSP). Its main function is to concentrate and redirect sunlight onto absorber tubes to heat up the working fluid. The recovered heat is then used to generate high pressure steam which drives a turbine in order to produce electricity. The solar collector is composed of a reflecting surface and a metal structure, whose function is to give and maintain reflecting glass shape Figure 3. In our study, only the design of the supporting structure is treated.

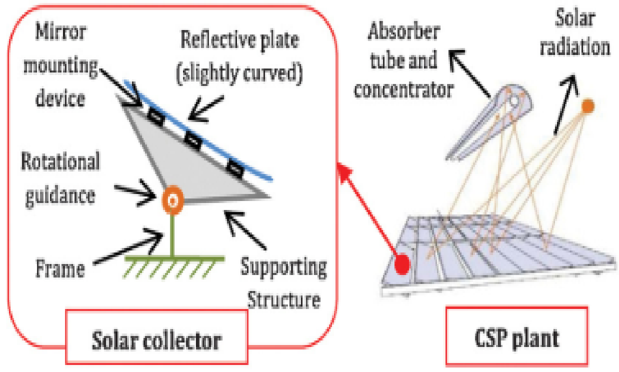

Figure 3. Schematization of solar collector

Given the company's requirements, the supporting structure to be designed must achieve two primary ob–jectives: (i) have high optical performance, (ii) withstand the external environment.

In fact, optical performance refers to the ability of the reflector to concentrate and reflect the sun's rays correctly on the absorber tubes. These tubes directly influence the thermal efficiency of the plant. In order to limit the percentage of rays deviating from their target, it is necessary to limit the deformations of the reflecting mirrors as much as possible and, therefore, specifically of the reflecting support.

The objective of optical performance is then decomposed into two sub-objectives which are: "having a low torsion of structure" and "having a low deflection of structure".

Furthermore, the reflective support must withstand the climatic conditions that characterize the installation site. The more resistant the reflector support is, the more varied the possibilities of implantation sites will be. In our case, the objective of "resisting the external envi–ronment" is mainly linked to resistance to extreme wind.

A performance parameter was associated with each design objective, which will be evaluated subsequently on the solution of the reflective support considered. These variables are noted as follows:

- P_1 : Torsion angle
- P_2 : Deflection
- P_3 : Wind resistance

Continuing the previous study on three concepts during the conceptual phase led to keeping two con–cepts, including the truss concept, and eliminating anot–her concept deemed less relevant [32]. The present work continues the study of the truss concept and, this time, verifies its behavior during the embodiment phase.

- **Concept A: truss concept**

The truss structure presented in Figure 4 is composed of upper and lower diagonal bars, upper chords, and the lower chord. The assembly process used to assemble all these components is "clinching", it is usually fixed at the beginning of the project, and this is also the case for the width (l) and length (L) of the reflector.

4.1 Assessment of behavior model accuracy

The behavior model used for the truss concept is based on three main hypotheses (H_i):
- 1st hypothesis (H_1): neglect the peeling phenomenon which is due to the assembly process used "clinching".
- 2nd hypothesis (H_2): assume that the joints between the truss bars are perfect.
- 3rd hypothesis (H_3): admit that the diagonal bars of the structure are concurrent with the nodes.

These hypotheses are classified into three levels (L_1: strong, L_2: moderate, L_3: weak), according to the interval to which each design parameter belongs Table 2. We indicate that it is enough that a single design parameter belongs to a moderate (orange) or a weak (red) level for the hypothesis to be considered from one of these levels. In fact, certain (L_i) were not considered for the case of the truss structure as well as the

(PC_i) parameters because they do not have a direct effect on the studied hypothesis.

Table 2.The hypotheses considered for the TRUSS struc–ture, their classification, and their weights

H_i	L_i	sh_i	PC_1	PC_2	PC_3	PC_4
H_1	L_1	1	[2,5-5]	[3-5,2]	[3-5,2]	**
	L_2	0.6	[2-2,5]	[2-3]	[2-3]	**
	L_3	0.4	**	**	**	**
H_2	L_1	1	[2-3,5]	**	**	**
	L_2	0.6	[3,5-4]	**	**	**
	L_3	0.4	[4-5]	**	**	**
H_3	L_1	1	**	[3-5,2]	[3-5,2]	[900-1200]
	L_2	0.6	**	[2-3]	[2-3]	[1200-1500]
	L_3	0.4	**	**	**	**

The design parameters that were considered for this application case are: the thickness of the diagonal bars (PC_1), the thickness of the upper and lower chords (PC_2, PC_3) and the height of the structure (PC_4) Figure 4.

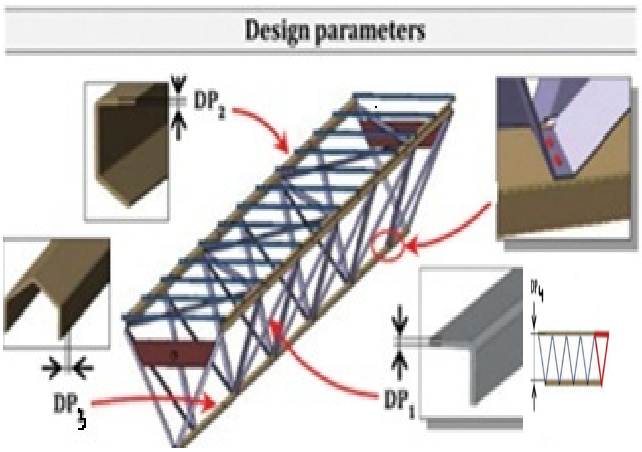

Figure 4. The supporting structure of CSP and the design parameters considered for the truss structure

Design parameters (PC_i) were used in the chosen behavior model in order to estimate the performance already mentioned: angular deformation of structure (P_1), elastic deflection of structure (P_2) and maximum wind pressure supported (P_3). These performances are evaluated using a 'materials resistance' behavior model, which is subsequently programmed in Matlab to auto–mate the calculations.

Optimization by the design expe–riment method was made to have the most optimized design parameters in terms of mass; this method has been used in several works, including the work of Edo–uard, R et al. [33], who used this method to study the influence of geometrical parameters on mechanical res–ponses. In addition, the results obtained concerning the performance parameters (P_i) were compared with the performance parameters of a reference solution (P^*_i) in order to assess the objective accuracy of the behavior model used Table 3.

Table 3. The design and performance parameters of solution A and the reference solution

Solution A				Reference solution				Objective accuracy	
PC_i (mm)		P_i		PC^*_i (mm)		P^*_i		E_{pi}	
PC_1	2.5	P_1 (°)	0.02	PC^*_1	3	P^*_1 (°)	0.03	E_{p1}	0.21
PC_2	3.5	P_2 (mm)	2.51	PC^*_2	4	P_2 (mm)	2.54	E_{p2}	0,28
PC_3	3.5	P_3	0.27	PC^*_3	4	P^*_3	0.72	E_{p3}	0.6
PC_4	920			PC^*_4	930				

The design parameters of solution A and the refe–rence solution belong to the interval of (PC_i) which de–fines the level of hypothesis (L_1) and which corres–ponds to a score (sh_i) equal to 1. The weights (w_{ij}) of the performance parameters obtained according to the stu–died hypotheses were also estimated using the AHP method Table 4.

Table 4. Levels of hypotheses considered and (w_{1j}) of the performance (P_1) parameters

H_i	sh_i	w_1	w_2	w_3
H_1	1	0,71	0,16	0,13
H_2	1	0,12	0,36	0,51
H_3	1	0,10	0,24	0,64

Refer to (2) and (3) the confidence indicators of the reference solution and solution A and the subjective accuracy were calculated respectively Table 5.

Table 5.The confidence indicators (IC_1,IC^*_1) and the sub–jective indicators (SAI_1) of solution A

Confidence indicator of reference solution			Subjective accuracy		
IC^*_1	IC^*_2	IC^*_3			
0.99	0.99	0.98	SAI_1	SAI_2	SAI_3
Confidence indicator of solution A			0.21	0.24	0.61
IC_1	IC_2	IC_3			
0.99	0.75	1			

The evaluation of solution A was carried out using the overall accuracy indicator (OAI) and the envi–ronmental impact indicator (E_i). The results obtained for this solution are presented in Table 6.

Table 6. Indicators (OAI) and (E_i) of solution A

Solution A	E_i (%)	OAI (%)
	67.6	37.5

5. RESULTS AND DISCUSSION

The use of the method of design experiment allowed to generate of 10000 solutions, resulting from all possible combinations between the different values of design parameters. The main objective of this step is to have the best combination that leads to the most optimized mass. This will also permit us to deduce the effects of each subjective accuracy indicator on the mass and, consequently, on the environmental indicator; these effects were represented in the form of coefficients, each of which signifies: (i)A_1: the impact of P_1 on the mass, (ii)A_2: the impact of P_2 n the mass, (iii) A_3: the impact of P_3 on the mass.

Since the number of solutions obtained is very high, a "Pareto front" analysis was performed to limit the number of solutions evaluated to facilitate the choice of the optimal solution, a "Pareto front" analysis was performed. The design parameters that were evaluated correspond to small variations of the initial parameters of solution A. Actually, we took an interval of 10 values for each design parameter with a step of 0.1.

The analysis was conducted based on two indicators: the global exactitude indicator and the environmental indicator. Indeed, the Pareto front permits to the designer to have a certain readability of the dominant and dominated solutions and to choose according to the objectives of the company, which has the best compromise between these two indicators. This, of course, in the case where the two indicators converge towards different objectives (e.g., high accuracy and high environmental impact indicator).Otherwise, the choice of the solution is easier to make by the decision maker.

Figure 5 represents the 10000 solutions evaluated using the behavior model, including the optimal solution.

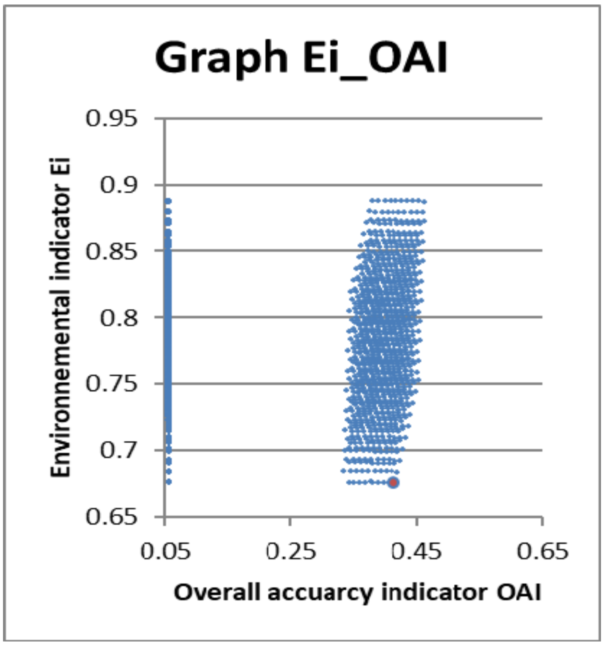

Figure 5. (OAI) and (E_i) for each candidate solution for the solution A

According to the analysis performed on the Pareto front graph, the optimal solution was the one that corresponds to a high accuracy indicator (*OAI*) and, at the same time, a minimal environmental indicator (E_i) (Table 7).

The results obtained show that the optimal solution corresponds to the solution that has the optimal design parameters that allowed to have the most optimized mass as well as the most performing parameters.

Tableau 7. The accuracy and environmental impact indicators of the optimal solution

Optimal solution			
Design parameters		OAI	E_i
PC_1	2.5 mm	41.4%	67.5%
PC_2	3.5mm		
PC_3	4.4 mm		
PC_4	920 mm		

6. CONCLUSION

In this work, a method for evaluating the accuracy of behavior models during the embodiment phase has been proposed and tested on a collector for a solar thermal power plant with Fresnel mirrors « truss structure ». This method proposes two types of indicators; the first one corresponds to a numerical indicator of objective type relatively linked to a reference solution. A subjective indicator that represents the designer's opinion and experience, and that allows the objective measure obtained to be generalized to the entire design space. The evaluation of these two indicators then will allow the designer to have a general vision on the environmental performance of the product through the estimation of the effect of the accuracy of these models on the product environmental impact.

Indeed, one of the main objectives of this work was to show the importance of taking into account the environmental constraint from the beginning of the design process, and to urge companies to follow an eco-design approach to achieve their design objectives. Although our approach facilitates this integration, other considerations must be integrated into our decision-support approach. To this end, we propose a very interesting perspective to accomplish this work: the consideration of robustness in the environmental assessment of design solutions.

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РАНА ЕКОЛОШКА ПРОЦЕНА ПРОИЗВОДА КОРИШЋЕЊЕМ МОДЕЛА ПОНАШАЊА И УТИЦАЈ ЊИХОВЕ НЕТАЧНОСТИ НА ПЕРФОРМАНСЕ ПРОИЗВОДА ПО ЖИВОТНУ СРЕДИНУ

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Одлуке донете током фаза идејног пројектовања значајно утичу на развој животног циклуса производа, утичући на његов еколошки учинак, цену и трајање његове реализације. Међутим, недостатак релевантних информација током ових фаза не омогућава тачну процену пројектних решења. Поред тога, генерише кашњења у распореду и прекорачења буџета додељеног за развој датог решења. У овој перспективи, овај рад има за циљ да процени тачност модела понашања који се користе за истраживање решења током фазе реализације. Ово се заснивало на две мере различите природе, односно објективној тачности, која се оцењује позивањем на реалну израду прототипа датог решења, и субјективној мери тачности која омогућава да се изрази деградација прве мере у односу на референтну. тачка. Ова комбинација ће довести до мере која се може генерализовати на цео простор дизајна. У другом кораку, садашњи рад предлаже процену утицаја тачности ових модела на утицај предложених решења на животну средину. У том циљу је спроведена студија осетљивости на улазним подацима модела (дизајнерски параметри) како би се закључио ефекат добијених резултата (параметри перформанси) на масу и, последично, утицај решења на животну средину. Да би се истакао приступ усвојен у овој студији, примењен је на прави индустријски случај, што је на крају довело до најоптимизованијег решења у смислу тачности и утицаја на животну средину.