Integration of Behavior Models' Accuracy in Design Decisions Using AHP, FMEA and Physical Prototyping

M. El Amine
Qualified Professor
Mechanical and integrated engineering team M2I ENSAM-Meknès
Morocco

K. Hmina
Assistant professor
Mechanical and integrated engineering team M2I ENSAM-Meknès
Morocco

M. Sallaou
Higher Education Professor
Mechanical and integrated engineering team M2I ENSAM-Meknès
Morocco

The embodiment design phase consists of rough selections/arrangements of materials, technologies used, dimensions, and main components. During this phase, many behavior models are used to verify the achievement of design objectives. The lack of confidence in these models due to the assumptions adopted causes designers to realize many prototypes during product development, causing time/cost-consuming loops of the "trial-and-error" procedure. We propose a decision model that integrates the accuracy of behavior models into decision-making. The objective is to limit the use of physical prototypes and improve the quality of decision-making. Each design alternative is evaluated using two indicators. The first is a desirability indicator that measures the level of completion of design objectives. The second indicator assesses the risk associated with the accuracy of behavior models using AHP, FMEA, and experimental tests on a prototype. The proposed approach was applied to the development of a solar collector.

Keywords: *Decision making, Embodiment design, Model accuracy, AHP, FMEA, Prototyping,*

1. INTRODUCTION

Decision-making is an inherent part of product develop–ment and occurs throughout the whole development process, whether it is to define the operating principles of the future product or to choose its geometric characteristics. During the preliminary design phase of product development, these decisions can influence up to 70% of future lifecycle costs [1,2]. The key to pro–duct development success is leading the development to the most appropriate design concepts at the beginning of the development project. Appropriate theories, methods, and tools must then guide the choices made during the preliminary design phase.

As seen in Fig. 1, the preliminary design is com–posed of concept research, concept selection, and em–bodiment design. In the present study, only embodiment design is considered. It consists of a rough selection of materials, technologies, main components (types, posi–tioning), and structure dimensions.

Nowadays, numerical calculation and different be–havior models are central to the embodiment design stage. They allow substituting physical experimentation to observe the product's behavior and verify compliance with the design requirements [3]. However, because of the multitude of assumptions used in these behavior models, the accuracy of the provided results and their ability to realistically represent the behavior of the design solution remains a crucial issue for design engi–neers. In the absence of adequate methods to measure the level of accuracy of the behavior models used, as well as the impact of this level of accuracy on the reliability of decision-making, design choices are often based on professional habits and experience and the "know-how" of designers [4]. As a consequence, design engineers are often obliged to use physical prototyping for each evolution of the product architecture. Physical prototyping is the only way to verify the accuracy of the results obtained by the behavior models. To this day, excessive use of physical prototyping remains a frequent cause of development budget overruns and development deadlines.

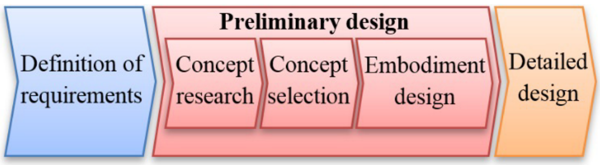

Figure 1. Illustration of the Design Process

The lack of accuracy in behavior models has three main sources: hypotheses/assumptions used during the development of the model, uncertainty in model para–meters, and inaccuracy of digital resolution [5]. The assessment of behavior model accuracy is a difficult task. This is particularly true when it is impossible to observe the real behavior of this object. When significant back-ground data exists, the use of statistical tools such as case-based reasoning or artificial neural networks can be envisaged [6-10]. However, using statistical or artificial intelligence tools requires a huge amount of information, which is rarely available in the company. Because of the difficulties in assessing models' accuracy, there have been few attempts to develop a decision-making method that considers model accuracy.

The Method of Imprecision (MoI) was used in different fields to deal with uncertainty during embo–diment design [11-14]. This method uses fuzzy repre–

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Correspondence to: Dr Khadija Hmina
Assistant Professor, Mechanical and integrated engineering team M2I ENSM-Meknes, Morocco
E-mail: khadija.hmina@gmail.com
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sentation to allow the engineer to formalize uncertainty when evaluating design solutions. It consists first of modeling the inaccuracy in the design parameters by linking the latter's values over the interval between 0 and 1. Fuzzy arithmetic is then used in the last step to propagate this inaccuracy to performance values, such as maximum resistance, deformation, etc. The main shortcoming of MoI in our case is that the fuzzy representation of design parameters includes not only the inaccuracy in behavior models but also other sources of inaccuracy [11].

When a "reference" behavior corresponds to the behavior observed in the real system, it becomes easier to measure model accuracy. The "reference" behavior is usually obtained from experimentation on a physical prototype. In this case, the accuracy is defined as the deviation between the result predicted by the behavior model considered and the "reference" behavior [15]. Based on this definition, the accuracy measures can be decomposed into local or global measures [16]. A local measure can be obtained, as an example, by the minimum or maximum of the absolute deviations between the values predicted by behavior models (denoted pi) and reference values (denoted $\tilde{p}_i$):

$$MAX = \min_{j \in \{1,\dots,n\}} \left| \tilde{p}_i - p_i \right| \quad (1)$$

$$MIN = \min_{j \in \{1,\dots,n\}} \left| \tilde{p}_i - p_i \right| \quad (2)$$

A global measure of model accuracy allows, for example, the general trend of error in the entire design space to be obtained. For example, a global measure can be provided by the sum of the deviations squared (Equation 3) or simply by the sum of absolute deviations (Equation 4):

$$MSE = \frac{1}{n} \sum_{j=1}^{n} \left(\tilde{p}_i - p_i \right)^2 \quad (3)$$

$$MAE = \frac{1}{n} \sum_{j=1}^{n} \left| \tilde{p}_i - p_i \right| \quad (4)$$

Reference [17] evaluates the quality of a behavior model using three criteria which are: parsimony, accuracy, and specialization. In their approach, the accuracy is assessed based on the distance between the result provided by the behavior model and those of a "reference" behavior which corresponds, in most cases, to the behavior observed on the real system.

The accuracy measures based on the deviation between predicted behavior and a "reference" behavior have the advantage of being objective. However, these measures consider a limited number of comparison points. Therefore, it can be difficult to justify their validity for all the design alternatives that one wishes to evaluate. This presents the main obstacle for the designer when he wants to explore a large design space.

Within the present work, we propose a decision-making method that aims to maximize the satisfaction of design objectives while taking into account the risk related to the accuracy of the behavior models used. Such a method aims to reduce development time by reducing the number of "trial-and-error" loops and the number of prototypes manufactured during product development. In the second section, the proposed approach is presented, and the two main indicators used are detailed. In the third section, the proposed decision-making method is applied to a case study, and then the results are presented and discussed.

2. PROPOSED APPROACH

We propose to treat the problem via two models; each one is associated with an output indicator. The first model aims to assess the degree of satisfaction with the design objectives based on the proposed behavior models without considering their level of accuracy. The subjective preferences of the decision-maker are integrated via the interpretation and aggregation models developed.

The second model aims to assess the risk associated with the inaccuracy of the behavior models used. Such a breakdown aims to facilitate decision-making by allowing the decision-maker to express his aversion to risk. The two indicators are determined for each design solution. A design solution in our context is defined by setting design parameters such as product dimensions, materials used, thicknesses, etc. The overall structure of the approach is given in Fig. 2.

Once the two indicators are assessed for each design solution, the final step consists in looking in the design space for the design solution that maximizes the satisfaction of the design objectives (first indicator) and that minimizes the risk related to the lack of accuracy in behavior models.

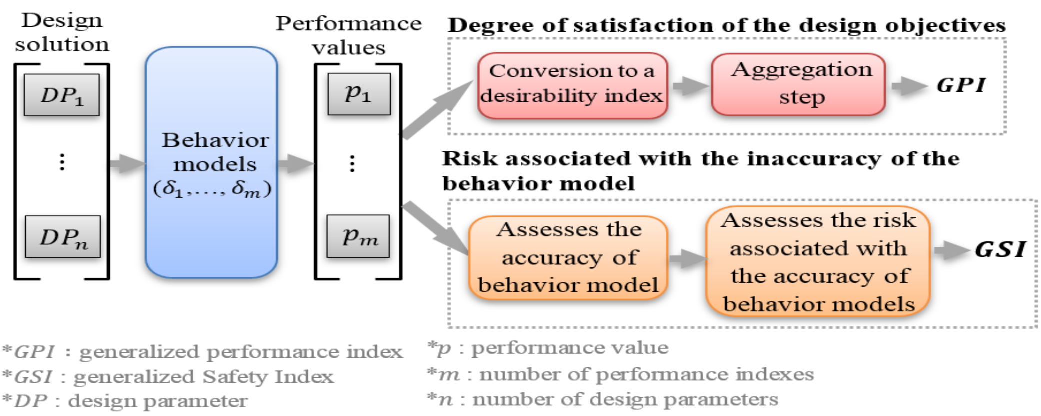

Figure 2. Overall Structure of the Proposed Approach

2.1 Generalized Performance Index (GPI)

The purpose of using the Generalized Desirability Index is to assess the degree of fit between the initially established design goals and the results obtained by behavior models. Starting from a certain design solution (defined by setting design parameters), the behavior models (denoted δi) are first used to determine performance values (denoted pi). Each design criterion is associated with a performance value. For example, the design objective "Resisting external load" is associated with the performance value "maximum load supported", expressed in Newton. Each performance value pi is thus associated with a behavior model δi. It is worth noticing that the models' accuracy is not taken into account at this stage. The approach used to assess the GPI is described in Fig. 4.

Starting from performance values obtained, a prefe–rence value (scale-free) comprised between 0 and 1 is associated with each performance value pi in order to assess the degree of satisfaction for the corresponding design objective. In the present paper, the transforma–tion from performance pi to preference value (denoted pi) is realized by the mean of desirability functions. The desirability functions used must be adjustable according to designers' preferences. These functions allow us to me-asure the degree of satisfaction and thus reflect the sub-jective judgment of the designers. As can be seen in Fig. 3, these functions are composed of three zones. The first zone corresponds to the interval in which the perfor-mance value perfectly meets the designer's objective. The desirability index is equal to 1 in this case. The second zone corresponds to an interval in which this performance value totally unmet the designer's objective. The desira–bility index is equal to 0 in this case. The value of pi from which the desirability becomes null is called the accep–tability threshold (ATi). The third zone is an intermediate zone. The performance value obtained partially meets the designer's expectations. The desirability index, in this case, is comprised between 0 and 1. Design engineers initially establish these functions based on their prefe–rences and the design objectives they want to achieve.

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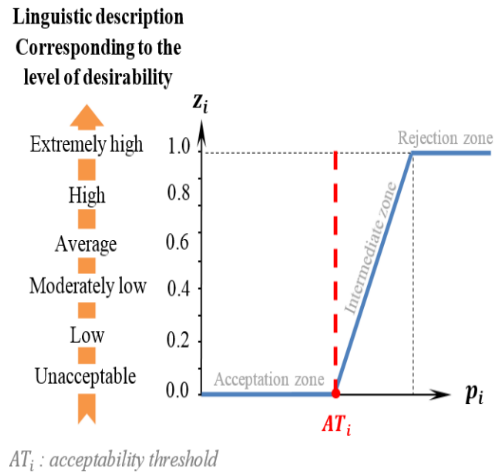

Figure 3. Desirability Functions Used

Once preference values are assessed for a certain design solution, the main challenge is how to combine several preference values to provide a generalized judgment on the design solution. In this way, it becomes possible to compare several design solutions.

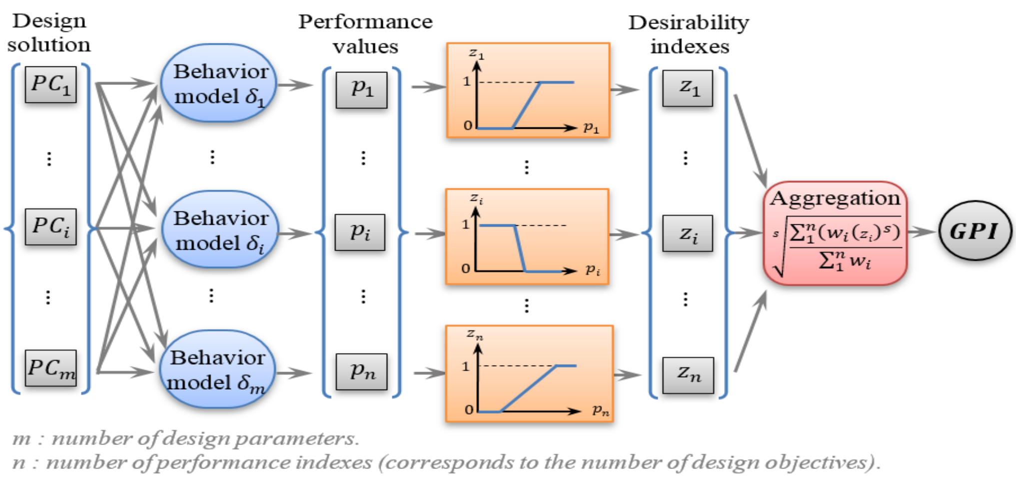

Fig. 4 Model Used to Obtain Generalized Performance Index

2.2 Evaluating the accuracy of behavior models

In the present section, the first evaluation of accuracy is proposed using the reference solution. This reference solution corresponds to a design solution that was prototyped and tested. Therefore, the designers have the real behavior (real performance values) of this reference solution. This first evaluation, as explained in [16], stipulates that the measurement of the accuracy of a model must be done by comparing the result predicted by the behavior model with that obtained by experimentation on a physical prototype. The results to be compared in our case are the performance values pi. Based on this definition, the accuracy of a behavior model δi in our case is obtained from the distance between the performance value (denoted p^*_i) predicted by the behavior model δ_i and the performance value (denoted $\tilde{p}_i^*$) obtained from experimentation on refe–rence solution:

$$GPI = \sqrt[s]{\sum_{i}^{n}\left(w_i\left(z_i\right)^s\right)} \tag{5}$$

In order to determine the parameter s and the weights w_i, we used the method of indifference points [13]. This method is based on the definition of indi–fference design solutions that have the same perfor–mance, to determine simultaneously the value for trade-off parameter s and the weights w_i.

$$E_i = \left|\tilde{p}_i^* - p_i^*\right| \tag{6}$$

Note that the measure of accuracy obtained by (6) is expressed in the same dimension as the performance variable pi. Therefore, we propose to normalize this measurement by transforming it to a dimensionless value between 0 and 1, reflecting the level of satis–faction with the objective of accuracy. Such standar–dization also aims to simplify the integration of accu–racy into decision-making. To normalize the measu–rement given in (5), we first set a threshold deviation value, denoted Ei,s. Compliance with this threshold is a necessary condition for using the behavior model. The choice Ei,s varies from one objective to another and calls on the expertise of the designer: this choice results from knowledge related to the expected values of the performance value pi. The standard measurement of the accuracy of the model δi is obtained by the relative difference between the measured distance Ei, as shown in (7), and the threshold distance Ei,s, such as is expres–sed in the following relation:

$$MOE_i = \begin{cases} \left|\dfrac{E_{i,s} - E_i}{E_{i,s}}\right| & if \quad E_i \leq E_{i,s}. \\ 0 & if \quad E_i > E_{i,s}. \end{cases} \tag{7}$$

This normalization step has the same objective as desirability functions since it also allows the integration of the preferences of the designers vis-à-vis the objective of accuracy. Thus, an accuracy MOEi equal to 1 corresponds to the case where the behavior model δi is completely exact (the most favorable case) because the value of pi that it provides is identical to that obtained by physical experimentation. An accuracy equal to 0 means that the model of behavior δi is unusable (the worst case) because of the non-respect of the threshold value of distance Ei,s.

In the present section, an accuracy measurement was proposed based on the distance between the perfor–mance predicted by the behavior model and that mea–sured on the reference solution. However, the proposed accuracy measurement is relevant only when the design parameters (such as product dimensions, materials used, etc.) of the proposed design solution are identical to those of the reference solution (prototype). The main remaining question is how to generalize the measu–rement of accuracy to the whole design space (Whatever the design parameters are). To overcome this issue, we proposed in the present section to multiply the accuracy measure proposed in Equation 7 by a correction factor. The objective is to adapt this measurement when the design parameters are different from those of the re–ference solution (prototype). This correction factor is explained in the rest of this section.

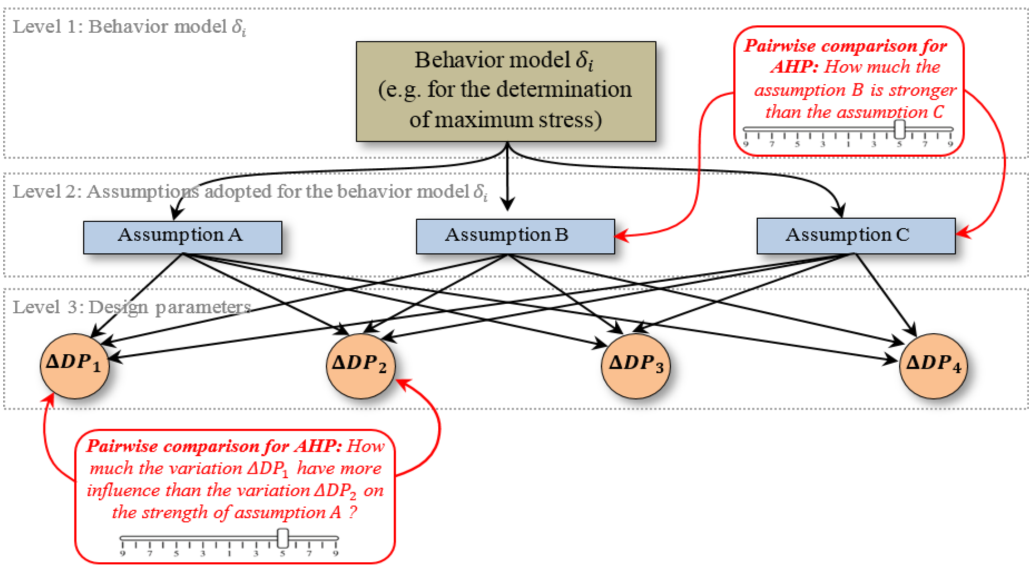

Fig. 5 Use of AHP to Evaluate the Strength of Assumption

The strength of assumptions is also dependent on the variation of design parameters. For example, some assumptions can be neglected (become weak) when one or more design parameters belong in a certain range. On the contrary, other design parameters may have zero impact on the assumption, regardless of the values of these design parameters. Another kind of pairwise com–parison is performed in the second phase of AHP to consider the impact of design parameters on the dif–ferent assumptions. This time, we focus on level 3 of the hierarchy shown in Fig. 5. For each assumption, pair–wise comparisons are performed between design para–meters according to the level of impact on the assump–tion considered.

Using the results of the two stages of pairwise com–parisons (levels 2 and 3), the criteria weights are obta–ined using the matrix normalization method [21]. A we–ight is thus attributed to each design parameter. The obtained weight, comprised between 0 and 1, reflects the influence of the design parameter's variation on the beha–vior model's accuracy. The obtained weights are denoted kij, where i is the index of the behavior model consi–dered, and j is the index of the design parameter. The closer the parameter kij to zero, the higher the im–pact of the design parameter DPj of the behavior model δi.

At this stage, we first measure the accuracy of the behavior model based on the distance from the reference solution, as shown in (7). However, this measure is appropriate only for the prototyped design solution. On the other hand, the factors kij, obtained using AHP, represent the impact of varying design parameters on the accuracy of the behavior model. The final step consists of multiplying the first measure of accuracy MOEi by factors kij in order to obtain a single indicator of accuracy capable of covering the entire design space:

Other assumptions may be very weak and have a neglected impact on the result. The more strong an assumption is, the more impact it has on the accuracy of the behavior model. In order to take into account this as–pect, the next step of the proposed method is to hie–rarchize the different assumptions according to their stre–ngths. In the present work, we used the Analytic hie–rarchy process (AHP) [20]. This method uses pair–wise comparisons between assumptions. In the first phase, the designers performed pairwise comparisons between assu–mptions. The pairwise comparison procedure is illus–trated in Fig. 5. As seen in the figure, a linguistic desc–ription associated with a numerical scale is used to ease pairwise comparisons, and the outcomes of all these comparisons are organized in the judgment matrix.

$$OMA_i = MOA_i \times \prod_{j=1}^{n} k_j^i \tag{8}$$

The general approach to measure the overall measure of the accuracy OMA_i is described in Fig. 6.

2.3 Generalized Safety Index (GSI)

Approach In the previous section, we proposed a measure of behavior model accuracy. In this section, the objective is to integrate this measure of accuracy into decision-making. The approach used is similar to the FMEA (failure modes and effects analysis) process. The failure, in our case, corresponds to the non-respect of the acceptability threshold (ATi).

The intuitive notions of rational human behavior can be formalized into a set of axioms that must be satisfied by an aggregation operator when the latter is used for a product design problem [12]. One of the most important axioms is that of annihilation, which is specific to design problems. Other authors have argued its validity for design problems [22,23]. This axiom states that if the desirability index (denoted zi in our study) for any design objective is zero (unacceptable), then the overall prefe–rence (denoted GPI in our case) of the design alternative is also zero, which means that the design solution is un–acceptable. This is in contrast to a decision-making situ–ation in which all goals can be converted into monetary units, such as decisions in the field of economics. In this case, two goals can always be negotiated.

At the level of performance values *pi*, this is expressed by the need to respect the acceptability threshold ATi (Fig. 3), specific to each performance variable *pi*. In this section, the objective is to assess the risk posed by the inaccuracy of the behavior models on non-meeting these acceptability thresholds. In addition to the level of accuracy of the model, the estimation of this risk depends on two other aspects which are:

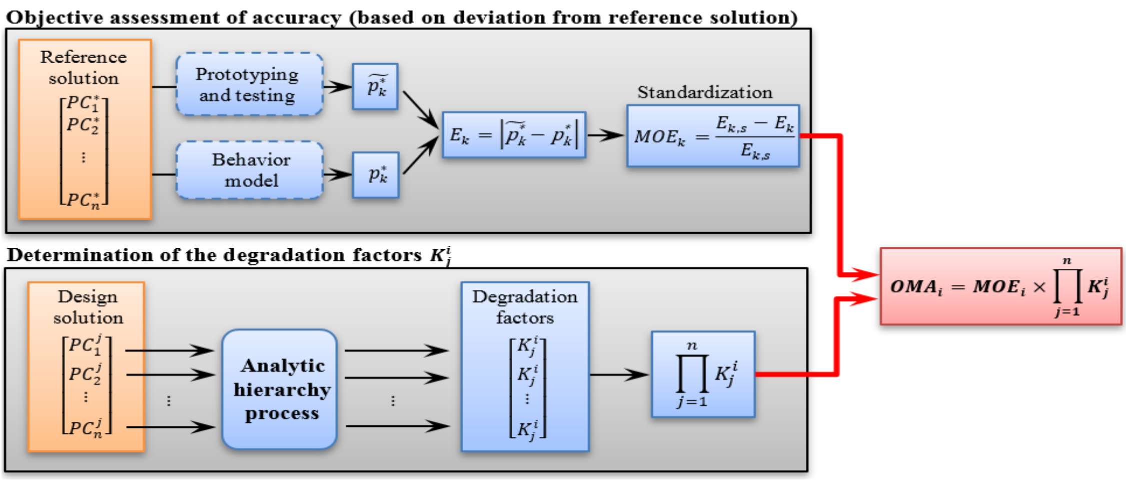

Fig. 6 Approach to Determine the Overall Measure of the Accuracy of a Behavior Model δi

The safety margin in relation to the threshold of acceptability: we consider that the higher the safety margin between the value of *pi* (provided by the mo–del) and the acceptability threshold ATi, the less risk there is of seeing this threshold not respected because of the inaccuracy of the model of behavior used. In the present paper, this safety margin will be called “risk occurrence” and will be noted Oi, where i is the index of the performance value considered. As shown in (9), we define Oi as the relative difference between the value of *pi*, obtained by the behavior model *δi*, and the acceptance threshold ATi.

$$O_i = \begin{cases} \left| \dfrac{p_i - AT_i}{AT_i} \right| & \text{if } p_i \text{ meets } AT_i. \\ 0 & \text{if } p_i \text{ does not meet } AT_i. \end{cases} \tag{9}$$

The severity of the failure to meet the acceptability threshold. Taking into account this aspect makes it possible to give more consideration to the design objectives, for which the non-respect of the threshold ATi is the most critical. This severity factor is denoted by Si, where i represents the index of the performance variable pi considered. Si will be determined using a scale of values (ranging from 0.2 to 1) associated with a semantic scale. A value of Si of 0.2 corresponds to the most critical level. The scale used for our application is given in Table 1.

Table 1 Graph representations

Severity index S_i	Associated linguistic description
0.2	Catastrophic impact: the non-respect of acceptability threshold AT_i has catastrophic consequences for the fate of the product; The product cannot be accepted;
0.4	Critical impact: failure to comply with the threshold AT_i leads to very serious undesirable repercussions on the quality of the product;
0.6	Major impact: non-compliance with the threshold AT_i has very significant repercussions on the quality of the product;
0.8	Significant impact: the non-respect of the threshold ATi entails a rather important repercussion on the quality of the product;
1.0	Minor impact: non-compliance with the threshold AT_i has no significant impact on product quality; It can be validated without problem;

The safety index SI_i for a design solution and for a behavior model δ_i is determined according to the mea–sure of accuracy OMA_i, occurrence O_i, and severity S_i by the following expression:

$$SI_i = OMA_i \times O_i \times S_i \tag{10}$$

Once the index SI_i is calculated for each of the be–havior models δ_i, the generalized safety index for the design solution studied is calculated by taking the minimum of the indices, as expressed by the relation following expression:

$$GSI = \max_{i \in \{1,\dots,n\}} SI_i \tag{11}$$

where i is the index of the behavior model, and *n* is the number of behavior models used (it corresponds to the number of performance values).

We chose to use the minimum because we want to be conservative in the risk assessment: we consider that the riskiest performance value provides information on the overall risk associated with the solution.

3. APPLICATION TO THE INDUSTRIAL CASE

In the present section, the proposed method is applied to a real industrial case. The component studied in our case is a parabolic trough collector (PTC) collector. The main role of a collector in a concentrated solar power (CSP) plant is both to redirect and concentrate sunlight onto an absorber in order to heat the working fluid. The recovered heat is then used to produce high-pressure steam, which drives a turbine to generate electricity. A part of the generated heat can be stored in salt tanks. This allows electricity to be produced independently of the sun's cycle. In addition, the generated heat can be used for other industrial or urban applica–tions such as desalination, cooling, air conditioning, etc.

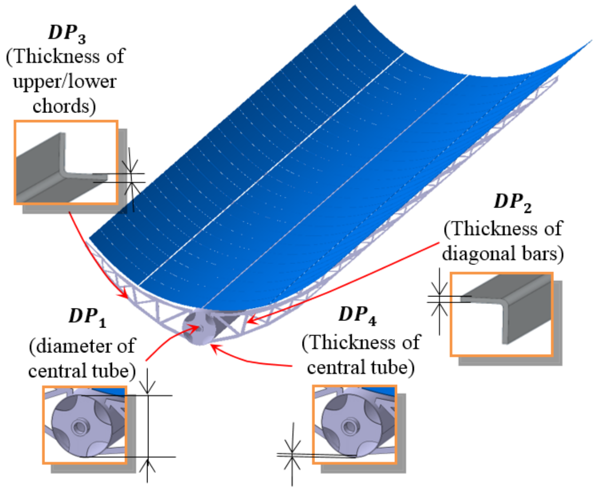

Fig. 7 PTC Solar Collector Structure and Design Parameters

As we can see in Fig. 7, a PTC solar collector is mainly composed of reflective mirrors and a supporting structure whose function is to maintain the shape of the reflective mirrors. A fixing device is made between the reflective mirrors and the supporting structure to ensure the connection between the two. The solar collector is driven by a rotating movement in order to adapt to the position of the sun during the day. In our study, only the supporting structure is studied.

The overall objective is to ensure the optimum concentration of the sun's rays, in a way that is sustainable over time, while being competitive. The overall objective is thus broken down into three main design objectives which are: "have a low manufacturing cost", "have high optical performance" and "withstand the external environment well".

In this case study, the design objective "optical per–formance" refers to the ability of the reflector to conc–entrate and reflect the sun's rays correctly on the absor–ber tubes. The latter directly influences the thermal effi–ciency of the plant. In order to limit the percentage of rays that deviate from their target, it is necessary to limit the deformations of the reflecting mirrors and, therefore, specifically of the reflecting support as much as pos–sible.

The performance value associated with this objec–tive is the fraction of reflected sunbeams that fail to reach receiver tubes (denoted p_1). This fraction must be as low as possible to ensure good thermal efficiency. The behavior model used to determine this fraction is explained in [24]. Regarding the second design objec–tive, the collector must resist the extreme wind in the chosen implementation site. The performance value associated with this objective, denoted p_2, is the fraction between the wind speed supported by the structure and the maximum wind speed in the implementation site. This fraction must be higher than 1. The behavior model used to determine these performance values is also detailed in [24]. This model is based on shell-type finite element analysis with a highly refined meshing in nods connections. The cost of raw materials used for the manufacturing of collectors represents about 50% of the overall investment cost for a PTC plant [25,26]. For this reason, the performance value associated with the ob–jective "manufacturing cost" is the supporting structure mass, denoted p_3.

Different stakeholders in the development project were involved to determine the different parameters ne–eded for the determination of *GPI* (fig. 4). These parameters are the trade-off parameter s and the weights w_i. The weights obtained for the objectives "optical per–formance", "wind resistance" and "manufacturing cost" are respectively $w_1 = 0.21$, $w_2 = 0.24$ and $w_3 = 0.55$. The preference functions for the three design objectives are also established during this phase.

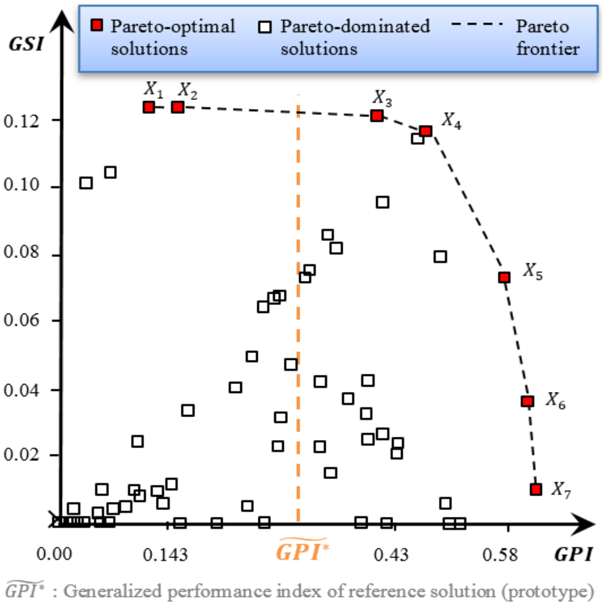

Fig. 8 Results Obtained for the Two Indicators GPI and GSI

The two behavior models associated with the two design objectives, "optical performance" and "wind re-sistance," are both based on shell-type finite element analysis with highly refined meshing. In these two mo-dels, we assume the absence of the buckling pheno-menon. We also assume that the diagonal bars of the truss structure are concurrent with the nodes. These are the two assumptions used in these models. For the third design objective, the behavior model simply determines the structure mass based on the choice of design para-meters. This model is thus considered accurate.

A physical prototype has already been made and then tested by the company. The prototype testing re-sults are used in the present paper to measure the be-havior models' accuracy. A set of 240 design solutions was established to explore the design space. Each of these solutions is a particular combination of design parameters. Each design solution is evaluated in terms of generalized performance index *GPI* and generalized safety index *GSI*. The results are shown in Fig. 8.

Only 50 of the 240 design solutions evaluated meet the minimum validation requirements (compliance with the acceptability thresholds AT_i). In Fig. 8, we can see that among these 50 design solutions, there are only seven Pareto-optimal solutions. The other 43 design solutions are dominated. Therefore, they have no inte–rest in our study.The best-performing design solution (best *GPI*) is solution X^1, followed very closely by solution X^1. However, the disadvantage of these two design solu–tions is their low level of safety, which results in low *GSI*. The candidate solution X^4 is less efficient than the solutions X^1 and X^2 (difference of the order of 16%), but it presents a very large improvement in the indicator GSI (difference of the order of 550%). X^6 and X^7 are the safest design solutions because they have the highest GSI. However, the improvement in the GSI is not very noticeable compared to the design solu–tion X^4. How–ever, the degradation of performance is very significant (low *GPI*). We then consider that the design solutions X^6 and X^7 are of little interest in our case.

The design solution X^4 is one of the most interesting solutions because it presents a good performance/safety compromise. However, the design engineers must pro–pose actions to improve the safety of this solution before validating it definitively. For example, a more developed behavior model can be developed to evaluate the optical performance and wind resistance. The other possible action to make the solution X^4 safer would be to manufacture another physical prototype and perform mechanical tests to ensure compliance with the two ob–jectives of mechanical strength and optical performance. Although it is effective, this action requires more time and resources.

1. CONCLUSION

In the present work, we proposed a decision-making approach to support the designer in making these design choices during the embodiment design phase. This approach aims to facilitate the definition of the product architecture. In order to set the design parameters based on the results of behavior models requires taking into account their level of accuracy. Thus, we first developed an approach to measure the accuracy of the behavior models used. The measure of accuracy obtained is based on AHP and prototype testing. The main originality of the measure obtained is its ability to cover the entire design space. In the last step of the process, this accuracy measure is used to assess the risk of non-compliance with the minimum acceptability thresholds. A generalized performance index is also used for each design solution to assess the overall level of satisfaction with the design objectives. Therefore, the decision-maker has the possibility of exploring the entire design space in search of design solutions that offer the best compromise between performance and risk linked to the inaccuracy of the behavior models. By participating in improving the reliability of the choices made on the basis of model results, the proposed approach reduces the use of physical prototyping, which consumes a lot of time and resources.

In industrial development projects, the ability of designers to predict the inaccuracy of the predictions provided by the behavioral models used contributes to reducing the number of physical prototypes. Indeed, the prototyping activity may be limited to candidate solu–tions with a high level of inaccuracy. However, the pro–cedure for calculating the different indexes used in the proposed approach involves complex mathematical cal–culations that may be beyond the scope of a design engineer's conventional tasks. This difficulty can be partially overcome by developing software tools that can be integrated into product digital mock-up (DMU)

An interesting perspective would be the consi–deration of robustness in the evaluation of design solu–tions. This third evaluation would take into account the impact of variability in the input data (design para–meters and parameters of the surrounding environment) in the fluctuation of the performance of the candidate solution. The management and interpretation of more than two qualification indices currently constitute a real scientific obstacle: what compromise can be achieved? Will the use of a Pareto front be essential to visualize the solutions (although this one seems unusable beyond 3 indices)?

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NOMENCLATURE

AT_i	acceptability threshold
DI	desirability index
DP	local heat transfer coefficient
GPI	generalized performance index of a candidate solution
$\widetilde{GPI}^*$	generalized performance index of reference solution
GSI	generalized safety index
k_i^j	degradation factor
m	number of performance indexes
MAE	the sum of absolute deviations
MSE	the sum of the deviations squared
n	number of design parameters
OMA_i	overall measure of the accuracy
O_i	occurrence
p_i	performance predicted by behavior models
$\tilde{p}_i$	reference performance
S_i	severity
SI_i	severity index
X^i	Candidate solution

Acronyms

AHP	analytic hierarchy process
CSP	concentrated Solar Power
FMEA	failure modes and effects analysis
GOWA	generalized ordered weighted averaging
MoI	method of imprecision
PTC	parabolic trough collector

ИНТЕГРАЦИЈА ТАЧНОСТИ МОДЕЛА ПОНАШАЊА У ОДЛУКЕ О ДИЗАЈНУ КОРИШЋЕЊЕМ АХП, ФМЕА И ФИЗИЧКОГ ПРОТОТИПА

М. Ел Амине, К.Хмина, М. Салаус

Фаза пројектовања остварења састоји се од грубог избора/распореда материјала, коришћених техноло–гија, димензија и главних компоненти. Током ове фазе, многи модели понашања се користе за вери–фикацију постизања циљева дизајна. Недостатак по–верења у ове моделе због усвојених претпоставки доводи до тога да дизајнери реализују многе прото–типове током развоја производа, узрокујући петље које захтевају време/трошкове у пос–тупку „проба-грешка". Предлажемо модел одлучивања који инт–егрише тачност модела понашања у доношење од–лука. Циљ је ограничити употребу физичких прото–типова и побољшати квалитет доно–шења одлука. Свака алтернатива дизајна се оцењује коришћењем два индикатора. Први је индикатор пожељности који мери ниво испуњености циљева дизајна. Други индикатор процењује ризик повезан са тачношћу модела понашања помоћу АХП, ФМЕА и експе–рименталних тестова на прототипу. Предложени приступ је примењен на развој соларног колектора.