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Designing Embodiment Design Processes for Blast Resistant Panels

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Designers are continuously challenged to manage complexity in embodiment design-processes, in the context of integrated product and materials design. In order to manage complexity in design processes, a systematic strategy to embodiment design-process generation and selection is presented in this paper. The strategy is based on a value-of-information-based *Process Performance Indicator*. The approach is particularly well-suited for integrated product and materials design, and all other scenarios where knowledge of a truthful design-process and bounds of error are not available in the entire design space. The proposed strategy is applied to designing embodiment design-processes for multifunctional blast resistant panels. It is shown that the proposed strategy based on the Process Performance Indicator is useful in assessing the performance of embodiment design-processes particularly when knowledge of prediction accuracy or its error bounds is not known throughout the whole design space.

Nomenclature

B	in-plane spacing of webs of square honeycomb core
BRP	blast resistant panel
d_i^+, d_i^-	deviation variables for goals in cDSP
cDSP	compromise decision support problem
h_c, h_f, h_b	thickness of core webs and face sheets, respectively
δ, $\Delta\delta$	deflection of back face, variance in deflection of back face
$\bar{\varepsilon}_c$	average crushing strain of core
Γ_{SH}	front face shear constraint 1 value
$H, \bar{H}$	thickness of undeformed and deformed core, respectively
KE_I, KE_{II}	kinetic energy per unit area in panel after stages 1 and 2, respectively
L	half-width of plate
λ_c, λ_s	factors governing strength of core in crush and stretch
M, ΔM	total mass/area of plate, variance in total mass/area
p_0	peak pressure of free-field pulse
ρ_f, ρ_b, ρ_c	density of front face sheet material, back face sheet material, and core base material
R_c	relative density of core
$\sigma_{Y,f}, \sigma_{Y,b}, \sigma_{Y,c}$	yield strength of front face sheet material, back face sheet material, and core base material
t_o	characteristic time of incident pressure pulse
W_{III}^P	plastic work per unit area dissipated in stage three

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I. Frame of Reference

The integrated design of materials and products [31, 32, 43], leveraging phenomena and associated solution principles occurring at multiple levels and scales, is advantageous in the sense that a designer may:

- achieve enhanced design flexibility and increased overall system performance, and
- readily leverage performance predictions from experimentation in many scenarios,
  but, challenging in the sense that a designer has to face:
- strong couplings and interactions between decisions and fundamentally different (multiscale and multiphysics) types of more or less developed analysis models (possibly describing the same physical phenomena) on and within various scales that may fundamentally change upon refinement, and
- significantly greater complexity of design-processes than in conventional systems.

These characteristics in the integrated design of products (mostly complex engineered systems) and (often advanced multifunctional) materials require a designer to manage complexity in embodiment design-processes by designing the network of decisions and models on multiple levels and scales constituting design-processes [42]. The focus in this work is on leveraging performance predictions at certain points in the design space from experimentation or computationally expensive analysis models to evaluate the performance of embodiment design-processes, particularly generated through model replacement. The research question investigated is:

How to design embodiment design-processes when knowledge of prediction accuracy or its error bounds is not known throughout the whole design space?

In response, a generally applicable strategy for designing design-processes, as addressed in Section B, based on a value-of-information-based metric, the Process Performance Indicator addressed in Section A, is proposed.

A. Value-of-Information-Based Metric

Value-of-information-based metrics have been utilized in the design literature to make design process decisions such as how to simplify interactions between design decisions, how much to refine a simulation model, etc. [4, 41, 43]. However, existing metrics for value-of-information do not account for all the aspects or decisions made in designing design-processes. Most of the existing metrics are only based on the additional information that changes knowledge about the probability of occurrence of random events. Existing metrics are based on the knowledge of either a truthful design-process or its error bounds (either deterministic or probabilistic) throughout the whole design space, where only an instance of the final product may be considered an equivalent of truth [46]. Also, these metrics deal with design-process simplification and refinement either *a)* through simplifying and refining interactions or *b)* through simplifying and refining analysis models in a complex network of decisions and analysis models [4, 28, 30, 43, 46].

Therefore, a new metric, the Process Performance Indicator, is presented to address both, simplifying and refining interactions as well as analysis models in design-processes while not being dependent on the knowledge of a truthful design-process or its error bounds (either deterministic or probabilistic) globally, i.e., throughout the whole design space. Especially in the integrated design of products and materials, experimental measurements are frequently available or relatively easy to generate for designers. Accepting model validity, this experimental data can hence be leveraged to assess the value of a specific design-process to the decision maker by evaluating the Process Performance Indicator only with respect to local information at specific points in the design space. Besides experimental testing, those points can also be readily obtained through evaluating computationally expensive analysis models at specific points in the design space.

B. Strategy for Designing Design Processes

In this context there is a need for a systematic strategy to generate and select design-processes. Such a strategy should support a designer in answering questions such as *a)* how appropriate is a design-process, and *b)* what is the potential for refining a design-process. Since engineering analysis is expensive and time consuming, designers should select an appropriate design-process, i.e., a valid, least complex design-process that provides sufficient accuracy and resolution from a decision-centric perspective. From a decision-centric perspective, the design-process is used to support better decision-making to solve a given problem.

Therefore, we propose a systematic strategy to design-process generation and selection from a decision-centric perspective with a value-of-information-based design-process performance indicator at its core. This Process Performance Indicator, defined in Section III. The Process Performance Indicator and systematic strategy to design-process generation and selection are particularly well suited to account for opportunities and challenges of integrated product and materials design, but, are also generally applicable.

C. Example: Blast Resistant Panel Design Problem

As an example, consider the design of panels that resist blasts by absorbing large amounts of energy per unit mass compared to solid plates. In one application, panels designed accordingly can be attached on the outside of military vehicles to protect them from explosions. In the Blast Resistant Panel (BRP) design problem investigated in this paper, BRPs are to be designed in order to ensure satisfactory performance, i.e., protection against blasts, while minimizing overall system weight. Examples of BRPs are illustrated in Figure 1.

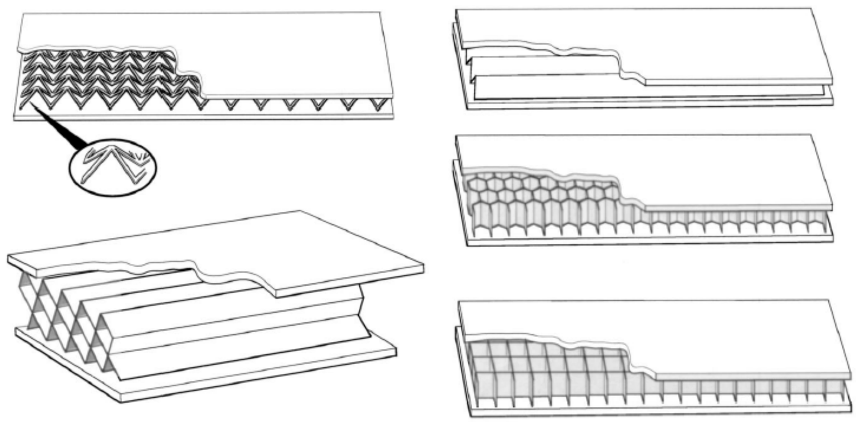


Figure 1. Sample blast resistant panels [20]

The design of such multifunctional BRPs involves decisions on both the system and material level. On the system level for example, a decision has to be made on configuring a multilayer BRP – potentially featuring various panel concepts, ranging from monolithic to composite panels, or unreinforced to stiffened to multilayer sandwich panels. Also, a designer is confronted with material level decisions to better achieve performance requirements. For example, by selecting a sandwich structures to configure the overall containment system, various microscale cellular material or truss structure core configurations can be designed that feature increased energy dissipation per unit mass and are robust to changes in blast loads.

Having selected a BRP concept, more or less complex design-process alternatives can be selected for concept exploration, such as analytical models, static or dynamic Finite Element Analysis models, detailed multiscale analysis models potentially accounting for fluid-structure interactions, or even prototypes. In this context, the goal is to show how to support a designer in managing complexity by using the value-of-information-based metric and design-process generation and selection strategy presented in Section III. First, existing approaches to managing complexity are reviewed in Section II.

II. Literature Review

We present an overview of the existing approaches used for managing complexity. Having discussed the approaches to managing complexity, value-of-information-based approaches to embodiment design-process design are distinguished from model validation in Section 2.2 and current research efforts are reviewed and critically evaluated in Section 2.3.

A. Managing Complexity

An increase in accuracy in the design process is generally accompanied by increased complexity. But, increased complexity is neither a necessary nor sufficient condition for accuracy. In this work we refer to accuracy as an exact or careful conformity to truth [60]. Therefore, a basic assumption of this work is that increased complexity leads to increased accuracy. This increase in complexity and associated accuracy however comes at the cost of additional modeling efforts and decreased computationally efficiency, which in this work refers to the speed with which information for decision making is generated and provided to decision makers. For example, while complex design-processes lead to better designs, less complex design-processes are faster and more resource efficient.

The primary concern treated in this vein is thus that of making a cost-benefit trade-off associated with obtaining additional information. Costs are incurred through the expenditure of resources (e.g., via modeling, experimentation, etc.). Value is determined with respect to effectiveness in reducing uncertainty. However, models inevitably incorporate assumptions and approximations that impact the precision and accuracy of predictions. "Tightening" assumptions and approximations may or may not increase the value of information on the system level. Therefore, it is proposed to analyze design-process performance before additional modeling resources are allocated in order to instantiate a satisficing design-process. A satisficing design-process is a design-process that is "good enough" [52], acknowledging the fact that an "optimal" design-process does not exist in real-world scenarios.

In this context, ways for identifying a satisficing design-process alternative that is as complex as necessary and as computationally efficient as possible are to refine or simplify

- interactions (couplings) between coupled decisions and analysis models, or
- complexity of individual analysis models.

However, "simple" design-processes may result in the achievement of inferior overall system performance. Hence, in order to help a designer to achieve satisficing solutions, a set of interaction patterns to model design-processes in integrated product and materials design has been developed [18, 32, 40, 43]. Based on the work of Panchal [40], one such set consists of nine patterns based on the type of information flow between different entities. The patterns are organized in a matrix, whose rows are *a)* information flow between simulation models, *b)* information flow between decisions, and *c)* multifunctional decisions. The columns of the matrix are *a)* independent interaction, *b)* dependent interaction, and *c)* coupled interaction.

The work presented in this paper is based on the interaction patterns proposed by Panchal [40]. However, the focus in this work is not only on quantifying the impact of simplifying interactions but also model replacement within networks of decisions and models resulting in more or less complex design-process alternatives. However, a fundamental assumption in this work is that design-processes are used to make satisficing decisions. From this decision-centric view of design, selection of design-process alternatives is driven by the need to improve a designer's decision making capability to solve the given problem, not the necessary but more scientific need of validating analysis models constituting design-processes, as discussed in the following section.

B. Model Validation Versus Design-Process Design

In principle, the complete space of models [22] from random guess to the actual product or "build-it-to-model-it" model is possible. The premise that a more truthful model can always be constructed must be considered [9, 11]. In this work, only an instance of the final product may be considered an equivalent of truth [46]. Hence, the focus in this work is on evaluating simulation-based design-process alternatives, where the decisions and models can be formulated mathematically and solved computationally, to design-process alternatives comprised of the most truthful analysis models available.

In the past few decades, significant efforts have focused on *i)* developing accurate analysis models for various aspects of a complex system, and *ii)* high performance computing tools to support these complex models. In spite of the significant progress in both these areas, modeling all aspects of a complex system in a simulation model is not possible using available computational resources. Thus, the goal in this work is to manage complexity by identifying satisficing design-process alternatives from a decision-centric perspective. The goal is not to increase scientific knowledge or validate analysis models constituting design-processes as reviewed in the literature [49, 50].

A fundamental assumption in this work is that the analysis models constituting design-processes have been validated. Hence, the focus in this work is not on validation, but evaluating the value of design-process alternatives to a designer in a given problem context from a decision-centric design perspective. Seldom it is desirable for engineers to use the most precise model available, as reducing systematic or random model errors (random model errors are often due to variability in the model parameters and initial and boundary conditions) typically costs more in terms of development and computational expense. A designer however almost always seeks to use the least expensive design-process alternative that is adequate for decision making to solve the given problem.

The threshold defining adequacy is subject to one's value judgment. The choice of an appropriate model may depend on specific characteristics of the decision at hand, including the preference of a designer, the uncertainty in other problem parameters, and the importance of the decision. Since a decision maker is often conservative, a design-process alternative is acquired and used that is more complex than is really required, unnecessarily spending additional resources. Hence, information economics tradeoffs as explored in the following section have been investigated in the context of designing design-processes.

C. Managing Complexity by Designing Design-Processes Using Value-of-Information-Based Metrics

In general, design-processes can be designed using various metrics. Direct metrics for example relate directly to a designer's preferences, such as cost, execution time, accuracy, design freedom [53], etc. On the other hand, indirect metrics, related to direct metrics, include concurrency [27], complexity, uncertainty, stability, convergence, robustness, modularity, and reconfigurability. However, often direct or indirect metrics cannot be readily or rigorously evaluated. Hence, various approaches to quantify the strength of couplings in different ways [12, 26, 44] or the sensitivity of system level outputs to system level inputs [7, 8, 16, 17, 21, 24, 48, 54] for identifying and removing weak couplings have been developed. The effectiveness of these scale-, matrix- or sensitivity-based approaches however reduces drastically in *i)* complex design processes, *ii)* highly non-linear or discontinuous objective functions, and *iii)* large changes in design variables.

In order to address the shortcomings of the approaches reviewed above, a class of metrics referred to as value-of-information derived from the field of information economics has been developed. Information Economics [4, 5, 40] is defined as "…the study of choice in information collection and management when resources to expend on information collection are scarce" [4]. It was first introduced by Howard [23]. Many of the information economics principles have been developed and employed previously in economics, as reviewed by Lawrence [28]. However, the key difference between engineering design applications and economics applications is the availability of perfectly known probability distributions that engineers often lack in practice [6]. Lawrence [28] and Panchal [40] provide a comprehensive overview of the value-of-information-based concept.

However, various metrics derived from the value-of-information-based concept have been developed in engineering design. For example, Agogino and coauthors [10, 61] present a metric called the Expected Value of Information (EVI) and use it for a catalog selection problem [10] in the conceptual design phase [39]. Poh and Horvitz [45] use a value-of-information metric for refining decisions in the following three dimensions – quantitative, conceptual, and structural. However, in previous research efforts by Howard [23], Agogino & coauthors [10], and Lawrence [28] the value of information is calculated by considering only the stochastic variability, where the decision can be made by maximizing the expected value of the objective function.

In order to model uncertainty for evaluating value-of-information, it has generally been assumed that the precisely characterized joint and conditional probability distributions are available. If these probability distributions are not available, approaches have been proposed to generate those through an educated guess that is based on the designers' prior knowledge. Also, in order to address the problem of lack of knowledge about the probability distributions, Aughenbaugh and co-authors [4] present an approach of measuring the value of information based on probability bounds on the value of information that are calculated by a designer during the information collection process using imprecise probabilities in a p-box approach.

The aforementioned efforts do not address the case of decision making under uncertainty that cannot be represented using probability functions. However, Ling and Paredis [30] present a value-of-information-based approach for model selection for the particular scenario in which the systematic error in the models can be bounded by an interval. However, the underlying assumption is that an interval-based characterization of the error in model output is truthful and available throughout the entire design space.

Furthermore, error bounds do not necessarily indicate anything about a model's usefulness. Also, Doraiswamy and Krishnamurty [15], Radhakrishnan and McAdams [46] or Cherkassky [14] consider cost-benefits trade-offs in selecting models of various levels of abstraction in engineering design. They present a utility-based framework in which a designer can reason about model uncertainty assuming a perfect model is available. This perfect model is then used as a benchmark for rating other possible model alternatives.

Also, Panchal and coauthors [43] present a value-of-information based metric called Improvement Potential to account for the non-probabilistic uncertainty resulting from simplification of interactions between models and decisions. The improvement potential is quantified as $P_i = max(U_{max}) - (U_{min})^*$, where $max(U_{max})$ is the maximum expected payoff that can be achieved by any point in the design space and $(U_{min})^*$ is the lowest expected payoff value achieved by the selected point in the design space (after making the decision without added information). Similarly to the approaches reviewed above, the Improvement Potential metric is based on the assumption that information about bounds on utility (i.e., the lower and upper bounds on the overall system outcome) is available globally, i.e., throughout the whole design space. The reliance on lower and upper bounds for the use of this metric currently restricts its use for the specific cases where information about these bounds is unavailable. Hence, scenarios where this information is unavailable are not handled using the metric.

Research Gap: Existing research efforts and their limitations are summarized in Table 1. In various circumstances, especially in the context of integrated product and materials design on multiple levels and scales, a designer has access to different kinds of analysis models constituting design-process alternatives that embody different assumptions, but, the error bounds on those models are unavailable throughout the whole design-space. However, in the context of integrated product and materials design, it is not practically feasible to either know a model's error or associated probability bounds throughout the whole design space or generate those through an "educated guess" in terms of p-boxes. Also, it is not feasible to know the behavior of a most truthful model throughout the whole design space. Hence, current value-of-information-based metrics need to be extended particularly for the integrated design of product and materials and other engineering scenarios, where system behavior is readily predicted through experimentation, prototype or specimen testing, or evaluation of computationally expensive design-processes.

Further, the assumption of aforementioned approaches is that designers have the knowledge of a complete network of decisions and analysis models, which is first simplified and then sequentially refined again. Based on this knowledge, the least complex network configuration is executed. Then, the network configuration is sequentially refined and evaluated until a satisficing design-process alternative is achieved. However, this is a significant limitation in the integrated design of product and materials on multiple levels and scales, because the number of interactions is significantly higher than in conventional product design, and the number of network configurations prohibits the sequential exploration of design-process alternatives. Hence, due to the number of interactions and design-process alternatives, knowledge of the complete network of decisions and analysis models upfront as well as sequential exploration of design-process alternatives is unavailable. Therefore, it is proposed to develop and evaluate less complex design-processes based on "simple" analysis models first before investing in additional modeling.

Table 1. Limitations of existing design-process design efforts addressed in this paper

Research Effort		Limitations
1 (SIC)	*Scale-based* or *Incidence-matrix-based evaluation of Coupling strength*	Quantification of coupling strength in a more or less mathematically rigorous manner only.
2 (SC)	*Sensitivity-based evaluation of Coupling strength*	Evaluation of coupling strength mostly in multilevel design-processes based on analyzing sensitivity at specific points in the design space.
3 (VE)	*Value-of-information-based decision Evaluation*	Value-of-information-based evaluation for decision problems based on the assumptions that uncertainty can be described using exact probability distributions.
4 (VP)	*Value-of-information-based P-box approach*	Value-of-information-based evaluation of decision models based on the assumptions that uncertainty can be described using imprecise (intervals of) probabilities throughout the whole design space.
5 (VIP)	*Value-of-information-based Improvement Potential metric*	Value-of-information-based evaluation of coupling strength in multiscale design-processes based on the assumptions that uncertainty can be described using intervals throughout the design space.
6 (US)	*Utility-based model Selection*	Model selection using utility theory based on the assumption that utilities for cost and model accuracy of models are available.
7 (VS)	*Value-of-information-based model Selection*	Model selection using utility theory and value of information based on the assumptions that an interval-based error characterization is available throughout the whole design space.

In order to address the aforementioned limitations and challenges, summarized in Table 1, a strategy to systematic design-process generation and selection from a systems perspective including a value-of-information-based Process Performance Indicator are presented in the following sections. Both are then applied to the design of multifunctional BRPs.

III. Systematic Strategy for Design-Process Generation and Selection

Before addressing the value-of-information-based strategy to design-process generation and selection in Section B, the value-of-information-based Process Performance Indicator is presented in Section A.

A. Metric for Value of Information for Decision Making

The proposed value-of-information-based Process Performance Indicator presented in this section is used within the design-process generation and selection strategy to evaluate (in other words quantify the performance of) design-process alternatives. Since assuming availability of error or associated probability bounds of a most truthful design-process alternative throughout the whole design space is not feasible in many engineering scenarios, design-processes are evaluated locally in this work, i.e., at specific points in the design space.

System behavior predictions through experimentation, prototype or specimen testing, or evaluation of extremely computationally expensive design-process alternatives are considered to represent the *most truthful design-process alternative*. However, the outcome of a design-process is evaluated using a *payoff function,* particularly, the decision maker maps model outputs into expected utility. This approach is based on the premise that the appropriateness of a design-process depends on the impact on a designer's decisions in terms of expected utility. When more complex analysis models comprising a more refined design-process alternative are instantiated, it is equivalent to addition of information for decision making. Value is measured in the context of system performance rather than in absolute accuracy. Hence, design-process alternatives are selected on the basis of the model's overall benefit, payoff or utility to a designer [40]. If evaluation of the Process Performance Indicator shows that a designer's objectives are met and the potential benefits by adding more information to the system is not likely to improve the design decision, the evaluated design-process alternative is appropriate for designing.

1. Definition Process Performance Indicator

The Process Performance Indicator is evaluated by quantifying the difference between the overall system performances at specific points, i.e., locally, in the design space, as described below. In order to illustrate this value-of-information-based metric, consider a scenario as shown in Figure 2, where the horizontal axis is the value of a design variable and the vertical axis is the corresponding expected overall payoff that is achieved by selecting the design variable. The design variable can be some physical dimension or material property that the designer has control over, whereas the expected overall payoff represents profit depending on system performance. In this example, a designer's objective is to maximize expected payoff by appropriate selection of the design variable value.

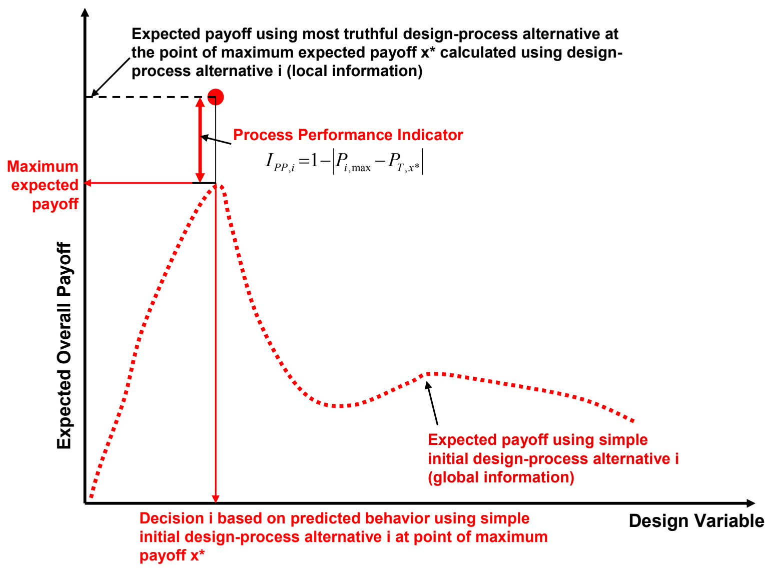


Figure 2. Process Performance Indicator single design-process alternative [33]

The dotted line in Figure 2 represents the expected payoff predicted by using an initial design-process alternative 1, representing global information. The corresponding dot (local information) represents the expected payoff using the most truthful design-process alternative at the design variable value where the less complex initial design process alternative 1 predicts maximum expected payoff. Since global evaluation of a most truthful design-process alternative is usually not feasible, design-processes are evaluated locally, i.e., at a specific point in the design space. Thus, the value-of-information-based Process Performance Indicator refers to the difference in payoff between the outcomes of decisions made using the most truthful design-process alternative and the outcome achieved using less complex (accurate) design-process alternatives.

Definition: In mathematical terms for a given design-process alternative i compared to the most accurate design-process alternative available at the point of maximum expected payoff in the design space calculated using design-process alternative i, x^*, the ***Process Performance Indicator*** $I_{pp,i}$ becomes:

$$I_{PP,i} = 1 - \left| P_i - P_{T,x^*} \right| \qquad \text{Equation 1}$$

where P_i is the expected payoff in the design space calculated using design-process alternative i and P_{T,x^*} is the expected payoff of the most truthful design-process alternative at the point of expected payoff x^* calculated using design-process alternative i. Hence, if the Process Performance Indicator value is 1, the benefit from using a more accurate design-process alternative is very likely to be negligible. This would imply that the design-process alternative evaluated is appropriate for decision making. On the contrary, if its value is low, one should definitely consider developing a more refined design-process alternative.

2. Definition Process Performance Indicator for Multiple Design-Process Alternatives

The same concept extends to higher dimensional problems where there are many design variables and the payoff is determined by multiple conflicting criteria. In the case of multiple design variables, the curve corresponds to a multidimensional surface. In the case of multiple design criteria that affect the expected payoff, the criteria are combined together into an overall expected payoff function based on designer's preferences. Furthermore, most likely more than one design-process alternative is to be evaluated as illustrated in Figure 3. Calculation of the Process Performance Indicator however proceeds accordingly as described above.

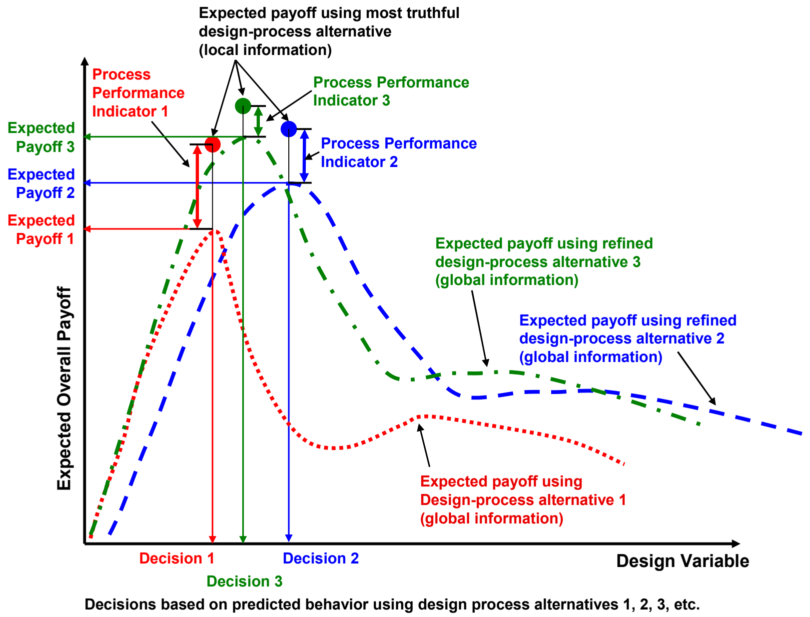


Figure 3. Process Performance Indicator multiple design-process alternatives [33]

However, evaluating of the Process Performance Indicator does not necessarily need to be conducted at the global maximum of the expected payoff function as proposed above. Depending on the decision criterion used, the Process Performance Indicator could also be evaluated at flat regions in the design space when a designer has more preference on finding robust solutions [13, 55]. Also, multiple points in the design space can and should be used to refine the Process Performance Indicator evaluation. The designer has the freedom to choose the number and locations at which the Process Performance Indicator is evaluated. When using multiple points in the design space for evaluation, different strategies, so far commonly used in response surface generation for metamodeling may be leveraged. Representative guidelines to sample the design space, i.e., evaluate the Process Performance Indicator at multiple points in the design space, are presented in Table A1. Those guidelines may be as simple as for example a uniform distribution or as elaborate as for example a sequential metamodeling techniques based on maximizing entropy [29]. It is recommended to choose a specific guidelines based on the problem and design space at hand.

When determining the Process Performance Indicator at multiple points in the design space, it may be evaluated based on the maximum absolute difference or average of the difference in expected payoff achieved comparing the most accurate design-process alternative available with a less complex design-process alternative, depending on the given scenario and the designer's mindset. If a designer's mindset is extremely conservative or the design-problem at hand is characterized by extreme uncertainty, scenario 1 – a worst-case scenario – is recommended. In scenario 2, a designer may choose to use the mean of all Process Performance Indicators obtained. Besides the arithmetic mean, other mean calculation may be considered, such as the geometric mean, harmonic mean, etc. In scenario 3, a designer may weigh certain points at which the Process Performance Indicator is evaluated differently.

Scenario 1 (maximum):

$$I_{PP,i} = 1 - \left| P_{i,\max} - P_{T,x^*} \right| \qquad \text{Equation 2}$$

Scenario 2 (arithmetic mean):

$$I_{PP,i} = 1 - \frac{1}{n} \sum_{i=1}^{n} \left| P_{i,\max} - P_{T,x^*} \right| \qquad \text{Equation 3}$$

Scenario 3 (weighted mean):

$$I_{PP,i} = 1 - \frac{\sum_{i=1}^{n} w_i \cdot \left| P_{i,\max} - P_{T,x^*} \right|}{\sum_{i=1}^{n} w_i} \qquad \text{Equation 4}$$

Note that the absolute value of the difference in expected payoff is chosen to represent the Process Performance Indicator, less complex design-process alternatives may "over-" or "under-"predict system behavior, even though only "underprediction" is illustrated in Figure 3. In this work, multi-attribute utility functions based on a designer's preferences are leveraged as expected payoff functions. Hence, responses for a specific design variable combination (potentially evaluated under statistical variability and imprecision) translates into payoff represented as a multi-attribute utility function based on a designer's preferences.

B. Design-Process Generation and Selection Strategy

In this section, the focus is on systematic generation and selection of design-process alternatives from a decision-centric perspective based on the Process Performance Indicator. In order to evaluate the appropriateness of different design-process alternatives, it must be recognized that different design-process alternatives result in different design outcomes. The selection of an appropriate design-process alternative thus depends on the impact on designers' decisions quantified through the Process Performance Indicator.

However, the strategy is to evaluate and select design-process alternatives starting from the least complex, but still valid configuration. Based on this initial least complex, but valid configuration, design-process alternatives are generated by either *a)* instantiating or simplifying interactions between coupled decision and analysis models in a network, or *b)* increase or decrease complexity of individual analysis models of an existing complex design-process alternative.

An overview and specific steps of the proposed strategy for design-process design is presented in Figure 4. Step A relates to formulating the design decision using compromise DSPs as discussed in Section 1. In Step B, a least complex initial design-process alternative is selected and evaluated as described in Section 2. In Step C, the decision point is determined by solving for maximum payoff, as outlined in Section 3. In Step D, the most truthful design-process alternative is evaluated, as discussed in Section 4. In Step E, the resulting Process Performance Indicator is evaluated, and a decision has to be made to whether select this design-process alternative (Step G), or refine the given design-process alternative (Step F), as outlined in the Sections 5, 6, and 7.

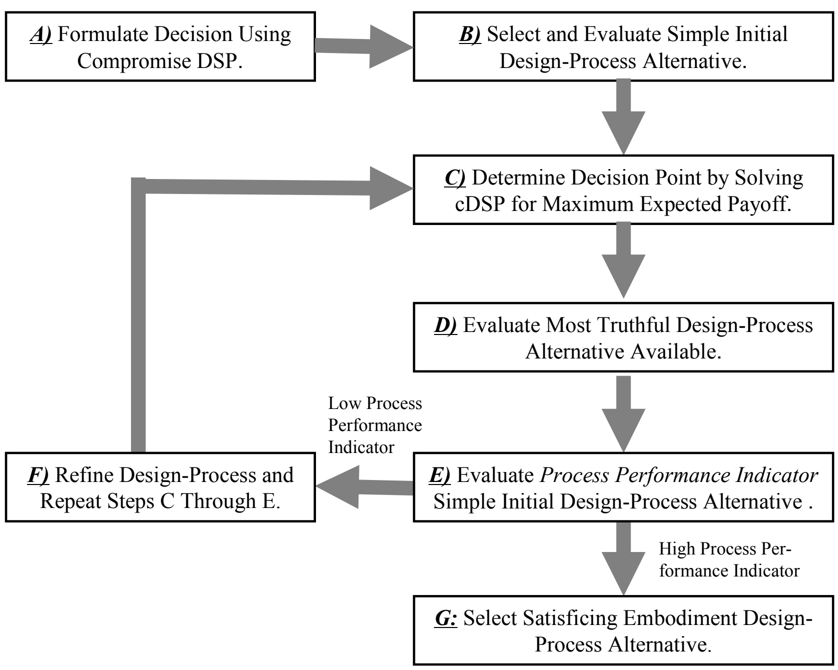


Figure 4. Overview design-process design strategy [33]

1. Step A: Formulate Decisions Using Compromise DSPs

The first step in the method is to formulate the design decisions. The decision-centric templates used in this work are rooted in the Decision Support Problem (DSP) Technique [34], specifically the compromise Decision Support Problem (cDSP) [35]. The cDSP is one implementation of decision-based design approaches [38], for solving multi-objective, non-linear, optimization problems. Mathematically the cDSP is a multi-objective decision model which is a hybrid formulation based on mathematical programming [2] and goal programming [1].

Particularly, the decision formulation used is the utility-based cDSP formulation [51], consisting of information about design variables, responses, analysis models used for evaluating responses from design variables, a designer's preferences, constraints, and goals. In an environment such as ModelCenter®, the instantiated computational objects that can be manipulated are the constraints, variables, parameters, goals, response and analysis computational templates. Preferences for achievement of goals are modeled as utility functions. Utility theory is used for mathematical modeling a decision maker's preferences in the context of risk or uncertainty. It provides a consistent means of numerically expressing the decision maker's preference when there is trade-off between multiple goals under uncertainty [59].

2. Step B: Select Least Complex Design-Process Alternative

In the second step, a least complex but valid initial design-process alternative is selected. In this step, ensuring model validity, i.e., predicting trends correctly is crucial. Based on the results of the following steps, a designer decides whether to use the information produced by the least complex (but valid) initial design-process alternative or perhaps refine the design-process. Evaluating the value-of-information-based Process Performance Indicator for a particular network of decisions and analysis models comprising a design-process alternative determines whether there is a need to develop a more refined design-process alternative. If for a given design-process alternative the evaluation of the value-of-information-based Process Performance Indicator reveals that a designer's objectives are met and the potential benefits of additional modeling by adding more details to the system are not likely to improve the design decision, the current design-process alternative is selected.

3. Step C: Determine Decision Point

In Step C, the selected least complex initial design-process alternative is evaluated based on the weighted objective function given in the utility based cDSP formulation. The point in the design space that minimizes the objective function, called the decision point (dp), is determined. With respect to evaluating the performance of the least complex initial design-process alternative, sensitivity in the main effect should be analyzed. However, acquiring more information to analyze sensitivity is beneficial, but, depends on the computational efficiency of the most truthful design-process alternative. The information obtained is used to evaluate the most truthful design-process alternative in the following section.

4. Step D: Select and Evaluate Most Truthful Design-Process Alternative

In Step D, the most truthful design-process alternative is selected and evaluated. It serves as a baseline for determining the Process Performance Indicator locally at the specific decision points where expected maximum payoff occurs as identified in Step C. Again, ensuring model validity is crucial.

5. Step E: Evaluate Process Performance Indicator Least Complex Initial Design-Process Alternative

Having evaluated both the least complex initial and most truthful design-process alternative at the identified decision points, the Process Performance Indicator is evaluated. If the Process Performance Indicator is evaluated at multiple points, a sampling guideline and an evaluation scenario must be selected. In most cases, a conservative evaluation scenario of using the minimum of the values determined at different decision points is recommended. This however, depends on the decision maker's mindset and given design problem context. However, having determined an overall Process Performance Indicator, its value is to be evaluated to decide whether or not the decision maker considers the current design-process alternative satisficing or prefers to refine the design-process alternative by refining the design-process. If the decision maker decides to refine the design-process alternative, Step F follows; otherwise Step G.

6. Step F: Refine Design-Process and Repeat Steps C Through E

If the decision maker decides to refine the design-process alternative based on the Process Performance Indicator value, Steps C through E are to be repeated. Step F may be repeated until a satsificing design-process alternative, most likely with a Process Performance Indicator of close to the maximum possible value of 1, is obtained. However, it is emphasized that evaluation of the Process Performance Indicator is based on the assumptions that analysis models are valid, i.e., predict trends correctly. If that assumption is violated Process Performance Indicator values are certainly not in line with system behavior.

7. Step G: Select Satisficing Embodiment Design-Process Alternatives

Results of the design-process alternatives generated and evaluated in terms of their Process Performance Indicator are used to select a satisficing embodiment design-process alternative. Selection thus involves making the trade-off between gathering more information to refine performance predictions, in other words develop more refined design-process alternatives, or using the design-process alternative developed for decision making. If from a decision-centric perspective there is a very low chance additional information gathering (i.e., further refining the design-process, at increased computational and modeling expense) will have a great impact on the design decision at the Process Performance Indicator value obtained. The specific design-process alternative is selected.

To demonstrate the use of the systematic strategy to design-process generation and selection as well as the Process Performance Indicator, the design of multifunctional BRPs is addressed in Section IV.

IV. Designing Multifunctional Blast Resistant Panels (BRPs)

By applying the systematic design-process generation and selection strategy, the goal is to find a satisficing design-process alternative in the context of designing multifunctional BRPs. Design-process alternatives and the additional modeling potential are evaluated through the value-of-information-based Process Performance Indicator from a decision-centric view of design, as described in Section B. However, designing multifunctional BRPs is challenging and has been focused on many previous research efforts, as reviewed in Section A.

A. Blast Resistant Panels

Various BRP concepts have been explored, ranging from simple compression, tension, bending, torsion, splitting, flattening, crushing or inversion of structures to more complex foam, honeycomb, weave, micromechanism or microtruss structures. A detailed review of existing BRP concepts is given in the literature [33]. However, a key characteristic of BRP concepts should be a long, flat plateau of the stress-strain curve at near-constant load to maximize energy dissipation truncated by a regime of densification in which the stress rises steeply. Hence, materials constituting BRPs should have two dominant properties: the energy dissipated per unit mass, and the stress at which this energy is dissipated [19]. The latter should be predictable and uniform to ensure that the force transmitted remains below a critical level that upon impact/blast might otherwise cause structural damage. The former governs the thickness of the energy dissipating material needed to absorb the required amount of energy. In cases when energy dissipation is to be maximized, a combination of high plateau stress and strain is required. Usually, an initial buckling response is less important, from an energy point of view, than a subsequent post-buckling (yielding) behavior, which is associated with large strains and deflections.

Based on these requirements, out-of-plane honeycomb core sandwich structures have been selected as the most promising BRP concepts [33]. The benefits of sandwich construction hence mainly depend on the core topology. Core designs that afford simultaneous crushing and stretching resistance, such as out-of-plane honeycomb cores, are preferred to those that are bending dominated, such as foam cores. Additional benefits of sandwich construction derive from fluid/structure interaction effects [20, 62]. Details on the systematic selection of out-of-plane honeycomb core sandwich structures and a detailed concept exploration of various BRP concepts can be found in the literature [33].

The square honeycomb core sandwich panel BRP concept selected consists of a front face sheet, cellular core with an out-of-plane honeycomb, and back face sheet as shown in Figure 5. The front face sheet receives the initial pressure loading from the blast. The topology of the core is designed to dissipate a majority of the impulse energy in crushing. The back face sheet provides additional protection from the blast as well as a means to confine the core collapse and store strain energy in bending and stretching. The responses of interest are the maximum deflection of the back face sheet and the overall panel weight. Both must not exceed a maximum deflection and a maximum mass per unit area.

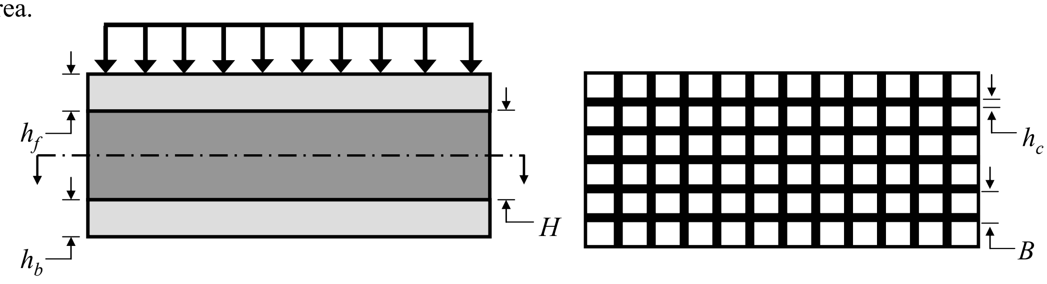


Figure 5. Out-of-plane honeycomb core sandwich panel BRP concept

Results presented in this paper are for the dynamic response to impulsive blast-type loads. In all cases, a uniformly distributed impulse per unit area, I, is applied to the plate at time t = 0. For the sandwich panel investigated in this paper, the impulse is applied only to the front face sheet towards the blast, again as a uniform initial velocity, $v = I/\rho h_f$, where h_f is the front face sheet thickness. The rational for replacing the pressure pulse acting on the panel by an initial impulse rests on the fact that the period of the blast pulse is short compared to the response time of the panel – the period, t_0, characterizing the leading portion of a blast pulse is typically on the order of a tenth of a millisecond [63].

Following early work by Taylor [56], the time variation of the free-field pressure at any point in the fluid engulfed by the pulse starting at t_0 is characterized as follows [63]:

$$p = p_0 e^{-t/t_0} \qquad \text{Equation 5}$$

where p is the pulse pressure, p_0 is the peak pressure of free-field pulse, and t_0 is the characteristic time of the incident pressure pulse. Therefore, the momentum per area of the free filed pulse becomes [63]:

$$I_0 = \int p dt = p_0 t_0 \qquad \text{Equation 6}$$

When the pressure pulse impinges on the panel it sets the plate in motion and is partly reflected. The time at which the panel achieves its maximum velocity coincides with the onset of tensile stress (negative pressure) at the interface between the fluid and the panel, leading to cavitation in the fluid shortly thereafter. According to Xue and Hutchinson [62], the maximum possible moment, i.e., twice the free-field moment impulse per area, $2I_0$, is transferred to the panel in air for a blast of short duration, unless the panel is exceptionally thin. Hence, in case of sandwich panels for independent face sheet thicknesses and material properties, the kinetic energy transferred from blast is [63]:

$$E_{kin,sand} = 2\frac{I_0^2}{m} \qquad \text{Equation 7}$$

where m for sandwich structures equals the mass of the front face sheet, m_f. From this equation, it becomes obvious that there is a penalty associated with employing sandwich construction versus solid panel construction. The initial kinetic energy must be dissipated by the structure. Subject to the same initial momentum impulse, the ratio of initial kinetic energy per unit area imparted to the sandwich front face sheet compared to that imparted to the solid plate is h/h_f. Thus, if the goal for the sandwich panel is to sustain smaller deflections than the solid plate of equal mass when subject to the same initial impulse, then the sandwich panel must absorb more than twice the energy as its solid counterpart, as expressed in Equation 3. For the interested reader, Muchnik [36] investigated and compared uniform and spherical pressure waves in the context of blast resistant panels. The difference however has appeared to be negligible in the early stages of design. Hence, in this paper, blast pressure waves with different pressure over time distributions – assumed to be only uniformly distributed over a panel – are investigated.

B. Systematically Generating and Selecting Design-Processes for Blast Resistant Panels

Having selected an out-of-plane honeycomb core sandwich panel BRP concept, more or less complex design-process alternatives can be selected for concept exploration, such as analytical models, static or dynamic Finite Element Analysis models, detailed multiscale analysis models potentially accounting for fluid-structure interactions, or even prototypes. In this context, the goal is to show how to support a designer in managing complexity by using the value-of-information-based metric and design-process generation and selection strategy as follows.

1. Step A: Formulate Decisions Using Compromise DSPs

The first step is to formulate the design decision. The decision formulation used is the utility-based cDSP formulation given in Table 2, consisting of information about design variables, responses, simulation models used for evaluating responses from design variables, a designer's preferences, constraints, and goals. Here, focus is on safety, i.e., minimum deflection first, and minimum weight second. Goals are weighted accordingly. However, the utility-based cDSP template formulation is instantiated in the computational environment of ModelCenter® (from Phoenix Integration). In an environment such as ModelCenter®, decision templates are computational objects that can manipulated, as illustrated in Figure 6.

During concept exploration using partially instantianted cDSP formulations, response surfaces throughout the feasible design space are explored and extreme values are identified first. Concept exploration using partially instantiated compromise DSP formulations is a necessary activity to fully instantiated compromise DSP formulations. In particular, main effects are identified to simplify the decision formulation by turning variables with minor effect on performance prediction into constants. As a result of various concept explorations using partially instantiated cDSPs, top panel height, bottom panel height, core wall thickness, core height have been identified as main effects. Therefore, the focus in the following is on exploring design variables down to mesoscales, i.e., top-, core-, and bottom-panel height as well as core wall thickness for the out-of-plane honeycomb sandwich panel BRP concept. Material variables associated with smaller scale effects, in other words the elements constituting parts of the containments system, are fixed as constants. Based on systematic selection procedure [33] as well as commonly known material properties (as for example summarized by Ashby [3]), a square honeycomb core sandwich panel concept with aluminum front-face sheet, titanium core and (quasi-isotropic) polymer carbon fiber composite back-face sheet is selected as the most promising BRP concept for maximum energy dissipation and explored in the following.

In order to fully instantiate a utility-based cDSP template, conditional utilities for individual attributes must be elicited. Also, subjective probability functions for uncertain events must be elicited. Concept exploration using partially instantiated cDSP templates has shown that results are by far more sensitive to uncertainty in blast loading than material property uncertainties. Therefore, a subjective probability function with respect to the most uncertain event – blast loading – is determined. Other uncertainties, such as material property uncertainties, are neglected. However, in the context of designing BRPs, preferences are elicited for mean and variance of deflection as well as mean and variance of total mass to find robust solutions [13, 55, 57], based on uncertainty in blast loading.

Blast peak pressure are specified to vary be between 190 and 280 MPa. Hence, beliefs regarding the blast peak pressure are elicited through a series of elicitation questions. Answers to these questions then are points on a cumulative distribution function of a designer's subjective probability with respect to the blast peak pressure. A maximum likelihood estimation is conducted to estimate the subjective probability distributions elicited. The software tool Arena-Input-Analyzer is used to perform these maximum likelihood estimations. The triangular distribution (2.6e+008, 2.7e+008, 2.8e+008) provides the smallest estimated squared error of 0.0399. This triangular distribution is very conservative, tending towards the "worst case" blast peak pressure – a result of the conservative mindset when eliciting beliefs. With that, the utility-based cDSP template formulationcan be fully instantiated as computational objects in ModelCenter, as specified in Table 2.

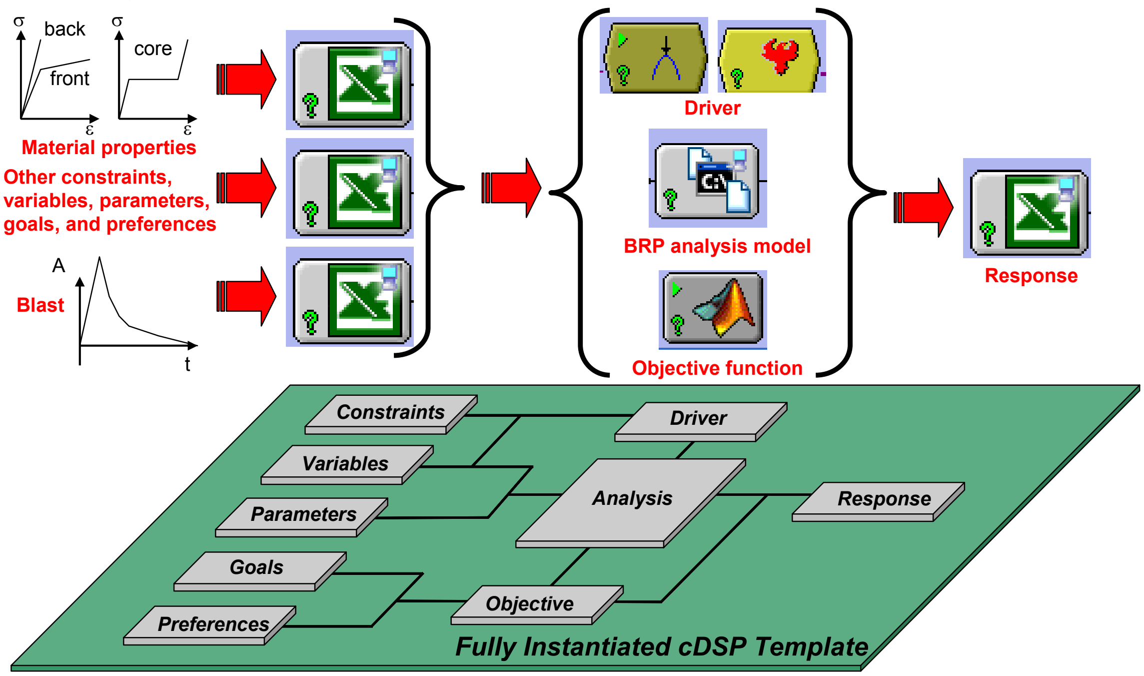


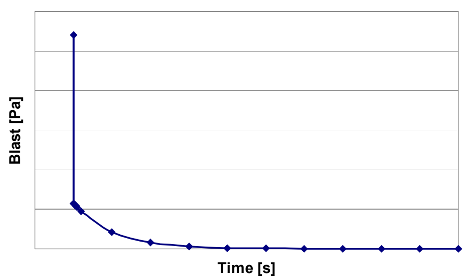
Figure 6. Utility-based cDSP template instantiated in ModelCenter

2. Step B: Select Least Complex Design-Process Alternative

A design-process based on a well-established analytical analysis model is used as the least complex initial design-process alternative to predict performance, i.e., deflection and mass per area, of square honeycomb core sandwich structures. The analysis model used is based on the work of Fleck and Deshpande [20], Hutchinson and Xue [25], as well as Muchnik and coauthors [37]. The work of Hutchinson and Xue is based on a proper treatment of underlying physical mechanisms. Also, it matches very well with experiments and extensive finite element validations [25]. At the same time, it is easy to implement and computationally efficiently (simulation times in the order of seconds). Therefore, it is accepted as a valid and feasible analysis model, and used to instantiate as the initial design-process within the design-space bounds defined in the cDSP formulation.

Following the three phase deformation theory, the impulse of the blast is received by the front face sheet and momentum is transferred in Phase 1. In Phase 2, some of the kinetic energy is dissipated through crushing of the core layer. The crushing strain is used to determine the crushed height of the core layer and is derived by equating the plastic dissipation per unit area in the core to the loss of kinetic energy per unit area in Phase 2. In Phase 3, the remaining kinetic energy must be dissipated through bending and stretching of the back face sheet. The equation for deflection is derived by equating the remaining kinetic energy per unit area to the plastic work per unit area dissipated through bending and stretching. The average plastic work per unit area dissipated in Phase 3 is estimated by summing the dissipation from bending and stretching. Blast pressure loading is modeled through an impulse load as specified in Table 2. The equation for deflection δ is determined by equating the average plastic work per unit area dissipated in Phase 3 to the kinetic energy at the end of Phase 2 and is shown in Equation 8. The mass/area M is given in Equation 9. For details in deriving these equations, the interested reader is referred to the literature [37].

Table 2. Utility-based cDSP template formulation

Given:	
Impulse load defined by uniformly distributed pressure, p [Pa], over time, t [s] 	$[(t, p)] =$ $[(0, 5.7628\text{x}10^{7});(1\text{x}10^{-8}, 2.8\text{x}10^{8});$ $(1\text{x}10^{-7}, 5.7570\text{x}10^{7});(1\text{x}10^{-6}, 5.7055\text{x}10^{7});$ $(2\text{x}10^{-6}, 5.6487\text{x}10^{7});(5\text{x}10^{-6}, 5.4817\text{x}10^{7});$ $(6\text{x}10^{-6}, 5.4272\text{x}10^{7});(1\text{x}10^{-5}, 5.2144\text{x}10^{7});$ $(2\text{x}10^{-5}, 4.7182\text{x}10^{7});(1\text{x}10^{-4}, 2.1200\text{x}10^{7});$ $(2\text{x}10^{-4}, 7.7991\text{x}10^{6});(3\text{x}10^{-4}, 2.8691\text{x}10^{6});$ $(4\text{x}10^{-4}, 1.0555\text{x}10^{6});(5\text{x}10^{-4}, 3.8829\text{x}10^{5});$ $(6\text{x}10^{-4}, 1.4285\text{x}10^{5});(7\text{x}10^{-4}, 5.2550\text{x}10^{4});$ $(8\text{x}10^{-4}, 1.9332\text{x}10^{4});(9\text{x}10^{-4}, 7.1119\text{x}10^{3});$ $(1\text{x}10^{-3}, 2.6163\text{x}10^{3})]$
Uncertainty in peak blast, p_0 [Pa]	triangular distribution ($2.6\text{x}10^{8}$, $2.7\text{x}10^{8}$, $2.8\text{x}10^{8}$)
Vertical length full,-size panel L_V [m]	$L_V = 1$
Horizontal length full-size panel, L_H [m]	$L_H = 1$
Area, A [m^2]	$A = 1$
Core cell spacing, B [m]	$B = 0.1$
Sandwich core cell shape	square
Shear-off resistance Γ_{SH}	$\Gamma_{SH} = 0.6$
Core crushing and stretching factors for a square honeycomb	$\lambda_c = 1$, $\lambda_s = 0.5$,
Boundary conditions	clamped on all edges
Mesh size front face sheet, core, and back face sheet	0.02
Poisson's ratio	0.3
Young's modulus front face sheet, E_f [Pa]	$88.5\text{x}10^{9}$
Yield strength front face sheet, $\sigma_{Y,f}$ [Pa]	$510\text{x}10^{6}$
Density front face sheet, ρ_f [kg/m^3]	2500
Young's modulus back face sheet, E_b [Pa]	$450\text{x}10^{9}$
Yield strength back face sheet, $\sigma_{Y,b}$ [Pa]	$4.\text{x}10^{9}$
Density back face sheet, ρ_b [kg/m^3]	1550
Young's modulus core, E_c [Pa]	$140\text{x}10^{9}$
Yield strength core, $\sigma_{Y,c}$ [Pa]	$1250\text{x}10^{6}$
Density core, ρ_c [kg/m^3]	4360
Utility function (preferences) for mean of deflection	$U_{\delta} = \dfrac{-6.68\cdot10^{-7}}{1-e^{5.55\cdot10^{-5}\delta}} + 6.07\cdot10^{-3}$
Utility function (preferences) for variance of deflection	$U_{\Delta\delta} = -1.83 + 2.83\cdot e^{-0.78\Delta\delta^{0.25}}$
Utility function (preferences) for mean of total mass	$U_W = 1.5\cdot e^{-e^{-0.79+1.33\cdot10^{-2}W}}$
Utility function (preferences) for variance of total mass	$U_{\Delta W} = -1210 + 1210\cdot e^{-1.49\cdot10^{-4}\Delta W^{0.73}}$
Deviation variables:	$d_{\delta}^{-} = d_W^{-} = d_{\Delta\delta}^{-} = d_{\Delta W}^{-} = 0$

Find:	
Geometry:	
- front face sheet thickness	h_f
- back face sheet thickness	h_b
- core thickness	H
- core wall thickness	h_c
Value of deviation variables:	d_{δ}^{+}, $d_{\Delta\delta}^{+}$, d_{W}^{+}, *and* $d_{\Delta W}^{+}$
Satisfy:	
Constraints:	
Mass per area w must not exceed 150 kg/m^2	$w < 150$
Deflection must not exceed 10% of span, i.e., 0.1 m, for specified boundary conditions	$\delta < 0.1$
Relative Density R must be greater than 0.07 to avoid buckling	$R = \frac{2Bh_c - h_c^{\ 2}}{B^2} \geq 0.07$
Front face shear-off constraints	$\frac{2p_0 t_0}{h_f\sqrt{\rho_f \sigma_{y,f}}} \leq \Gamma_{SH}$
	$\frac{\rho_c HR}{\rho_f h_f} \leq \frac{4}{\sqrt{3}}$
Deviation variables must be greater than or equal to zero and multiply to zero	$d_i^{\ +} \cdot d_i^{\ -} = 0 \ \wedge \ d_i^{\ +}, d_i^{\ -} \geq 0$
	for $i = \delta, \Delta\delta, W, \Delta W$
Goals:	
Minimize deflection, δ	$d_{\delta}^{\ +} = 1 - U_{\delta}$
Minimize variance of deflection, $\Delta\delta$	$d_{\Delta\delta}^{\ +} = 1 - U_{\Delta\delta}$
Minimize weight, W	$d_{W}^{\ +} = 1 - U_{W}$
Minimize variance of weight, ΔW	$d_{\Delta W}^{\ +} = 1 - U_{\Delta W}$
Bounds:	
Front face sheet thickness h_f [m]	$0.001 \leq h_f \leq 0.05$
Back face sheet thickness h_b [m]	$0.001 \leq h_b \leq 0.05$
Core thickness H [m]	$0.01 \leq H \leq 0.1$
Core wall thickness h_c [m]	$0.0001 \leq h_c \leq 0.04$
Minimize:	
Deviation Function	$Z = k_{\delta}d_{\delta}^{+} + k_{\Delta\delta}d_{\Delta\delta}^{+} + k_W d_W^{+} + k_{\Delta W}d_{\Delta W}^{+}$ with $k_{\delta} + k_{\Delta\delta} + k_W + k_{\Delta W} = 1$

$$\delta = \frac{-3\left(\sigma_{Y,b} h_b \bar{H}\right) \pm \sqrt{9\sigma_{Y,b}^2 h_b^2 \bar{H}^2 \left(\frac{1}{L^2}\right) + \left(\frac{3I_0^2\left[\sigma_{Y,f} h_f + \sigma_{Y,c} R_c H \lambda_S + \sigma_{Y,b} h_b\right]}{\left(\rho_f h_f + \rho_c R_c H + \rho_b h_b\right)}\right)}}{\left(\left[\sigma_{Y,f} h_f + \sigma_{Y,c} R_c H \lambda_S + \sigma_{Y,b} h_b\right]\right)} \qquad \text{Equation 8}$$

$$\text{where } \bar{H} = H\left(1 - \bar{\varepsilon}_c\right) = \left(H - \frac{2I_0^2\left(\rho_b h_b + \rho_c R_c H\right)}{\lambda_c R_c \sigma_{Y,c} \rho_f h_f \left(\rho_f h_f + \rho_b h_b + \rho_c R_c H\right)}\right)$$

$$M = \rho_b h_b + R_c \rho_c H + \rho_f h_f \qquad \text{Equation 9}$$

3. Step C: Determine Decision Point

The selected least complex initial design-process alternative is evaluated based on the weighted objective function given in the utility based cDSP template formulation in specified in Table 2. The point in the design space that minimized the objective function is called the decision point (dp), specifically decision point 1 in Table 3.

With respect to evaluating the performance of this design-process alternative in the following, a +/- 5 % sensitivity in the main effect, i.e., front-face sheet height as determined earlier, is analyzed – referring to decision point number 2 and 3 in Table 3. This information is then used to evaluate the most truthful design-process alternative in the following section.

Table 3. Decision point determination initial design-process alternative.

DP #	Design Variables				Responses				Z_1 [-]
	h_f [m]	h_b [m]	H [m]	h_c [m]	δ [m]	$\Delta\delta$ [m]	W [kg]	ΔW [kg]	
1	0.015	0.03	0.052	0.038	0.097	0.004	225.47	10^{-21}	0.467
2	0.01575	0.03	0.052	0.038	0.0997	0.004	226.32	10^{-13}	0.466
3	0.01425	0.03	0.052	0.038	0.106	0.005	222.57	10^{-13}	0.466

4. *Step D: Select and Evaluate Most Truthful Design-Process Alternative*

Focusing on simulation-based design, an ABAQUS explicit FEM model, as illustrated in Figure 8, is considered as the most truthful design-process alternative for functionally integrated modeling and concept exploration. The commercial software package ABAQUS 6.6 CAE in its explicit version has been used to conduct simulations. ABAQUS explicit is a well established tool in the materials domain to predict accurately the plastic deformation. ABAQUS models have been transformed into scripts that can be read and executed by the interpreter built into ABAQUS. The script mode allows to selectively iterate specific sections of the underlying ABAQUS code if desired and automate repetitive tasks.

The full-size blast resistant panel is assumed to be clamped on all edges and hence symmetrical in x and y direction. Therefore, in order to reduce the simulation time, the full-size panel is divided into quarter panels of which only one is simulated. As shown in Figure 7, quarter panel 1 and 2 are symmetric with respect to the y axis. Hence, they are free to move and deform in the y direction but constrained in x direction along the y axis. Also, they are free to rotate in x direction while rotationally constrained in y direction. The same condition is applied on the bottom edge of panel 1 by only switching y and x directions.

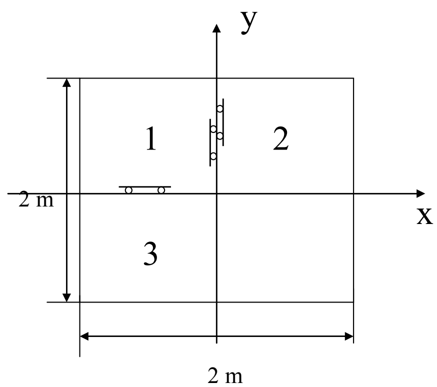


Figure 7. Full-size panel divided quarter panels

For conceptual design space exploration, a standard (uniform) mesh is used. If the mesh size is decreased, and thereby the number of elements and nodes is increased, the accuracy of the FEA method can be increased. To achieve the best tradeoff between accuracy and simulation time, finer mesh should be assigned to some parts and coarser to others in future research. For rapid concept exploration in this paper however, the standard (uniform) mesh size can only be changed for major sections, such as front face sheet, core, or fill materials, as a whole.

Of course, the use physical models, prototypes or experiments as the most truthful design-process alternative would result in a more enhanced design-process performance evaluation. However, with respect to the focus on the early embodiment and conceptual design phases and widespread use of FEM models to validate analysis models in the domain of materials design, the scope of this work is limited to simulation-based design. Hence, the ABAQUS FEM model validated in the work of Muchnik [36] is used as the most truthful design-process alternative.

The ABAQUS FEM model is a computationally expensive model. Complexity increases with the increase in mesh density. However, the key to selecting and evaluating a FEM analysis model as the most truthful design-process alternative is to determine the mesh size at which discretization errors converge to zero. In this work, Richardson extrapolation [47] is used as the strategy to evaluate discretization errors, i.e., errors that consist of the difference between the exact solution of the governing equations and the corresponding solution of the algebraic system. Discretization errors are primarily associated with both the mesh (structured, unstructured, uniform, etc.) and the discretization method (Finite Elements, Finite Volumes, Boundary Elements, Spectral methods, etc.) [58]. Assuming that the exact solution is smooth enough that the Taylor series expansion for the error is justified, the formal convergence (error) is of second order, and the mesh spacing is sufficiently small such that the leading-order error term dominates the total discretization error (i.e., the convergence is monotonic in the asymptotic range), the discretization error, ε_h, is estimated using two different nested meshes, h_i and h_j (assuming that the refinement ration $r = h_i/h_j > 1$), as

$$\varepsilon = \phi_{exact} - \phi_{h_i} \cong \frac{\phi_{hj} - \phi_{h_i}}{r^2 - 1} \qquad \text{Equation 10}$$

where ϕ_{exact} is the "exact" solution of the governing equations at a given point x, ϕ_h is the discrete solution. Using the Richardson extrapolation error estimation in the context of the ABAQUS FEM analysis model, a mesh size of 0.005 is determined as the mesh size at which discretization errors converge to zero.

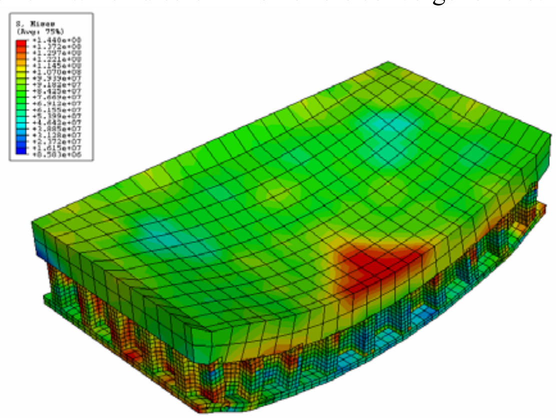


Figure 8. Most truthful design-process alternative

5. *Step E: Evaluate Process Performance Indicator Least Complex Initial Design-Process Alternative*

Evaluating both the least complex initial and most truthful design-process alternative at the identified decision points, the Process Performance Indicator is determined. Results with respect to the least complex initial design process alternative are shown in Table 4.

The overall Process Performance Indicator for the least complex initial design-process alternative becomes 0.588. This is based on the conservative estimate of using the minimum value of the values determined at different decision points, i.e., based on Scenario 1.

Table 4. Process Performance Indicator initial design-process alternative 1

DP #	Design Variables				Z_1 [-]	Z_T [-]	PPI_1 [-]
	h_f [m]	h_b [m]	H [m]	h_c [m]			
1	0.015	0.03	0.052	0.038	0.467	0.0553	0.588
2	0.01575	0.03	0.052	0.038	0.466	0.0553	0.589
3	0.01425	0.03	0.052	0.038	0.466	0.0553	0.589
						Overall PPI_1:	**0.59**

6. *Step F: Refine Design-Process and Repeat Steps C Through E*

The Process Performance Indicator of about 0.59 of the least complex initial design-process alternative is not high compared to the maximum possible value of 1. Also, relatively simple analysis models can be derived from the most truthful design-process alternative with relative ease. Hence, a more refined design-process alternative based on the ABAQUS FEM model is developed. Since the ABAQUS FEM model is a computationally expensive model, performing design space exploration using this analysis model directly is difficult. Hence, instead of this analysis model, less computationally expensive response surfaces are used. Using a central composite sampling method and full quadratic model fitting to the observed data, Steps C through E are repeated. Results are shown in Table 5. The Process Performance Indicator of this refined design-process alternative 2 is 0.63 based on Scenario 1.

Table 5. Process Performance Indicator refined design-process alternative 2

#	Design Variables				Responses				Z_2 [-]	Z_T [-]	PPI_2 [-]
	h_f [m]	h_b [m]	H [m]	h_c [m]	δ [m]	$\Delta\delta$ [m]	W [kg]	ΔW [kg]			
1	0.0057	0.028	0.0356	0.034	$4\ 10^{-5}$	0.003	145.3	0.025	0.0796	0.448	0.63
2	0.00599	0.028	0.0356	0.034	$4\ 10^{-5}$	0.003	145.8	0.025	0.0797	0.446	0.63
3	0.0054	0.028	0.0356	0.034	0.001	0.003	144.31	0.025	0.1432	0.450	0.69
										Overall PPI_2:	**0.63**

Since the process performance indicator of about 0.63 of this refined design-process alternative is still not high compared to the maximum possible value of 1, a central composite sampling method and quadratic stepwise regression model fitting to the data obtained from the ABAQUS FEM model is developed. Repeating Steps C through E with this design-process alternative 3, a Process Performance Indicator of 0.9 is calculated based on Scenario 1. Results are shown in Table 6.

Table 6. Process Performance Indicator refined design-process alternative 3

#	Design Variables				Responses				Z_3 [-]	Z_T [-]	PPI_3 [-]
	h_f [m]	h_b [m]	H [m]	h_c [m]	δ [m]	$\Delta\delta$ [m]	W [kg]	ΔW [kg]			
1	0.0054	0.031	0.0345	0.034	$3\ 10^{-8}$	$6\ 10^{-24}$	145.08	$2\ 10^{-14}$	0.151	0.052	0.898
2	0.0057	0.031	0.0345	0.034	0.0016	$2\ 10^{-19}$	146.909	$2\ 10^{-14}$	0.154	0.052	0.898
3	0.0051	0.031	0.0345	0.034	0.0014	$2\ 10^{-19}$	143.591	$4\ 10^{-14}$	0.152	0.052	0.9
										Overall PPI_3:	**0.9**

A Process Performance Indicator of about 0.9 achieved with design-process alternative 3 could still not be high enough to a designer with a conservative mindset. Hence, design-process alternative 3 is refined based on a more exhaustive sampling method. Using a full factorial level 3 sampling method and quadratic stepwise regression model fitting to the data obtained from the ABAQUS FEM model, design-process alternative 4 is developed. Repeating Steps C through E with this design-process alternative, a Process Performance Indicator of 0.98 is calculated based on Scenario 1. Results are shown in Table 7.

Table 7. Process Performance Indicator refined design-process alternative 4

#	Design Variables				Responses				Z_4 [-]	Z_T [-]	PPI_4 [-]
	h_f [m]	h_b [m]	H [m]	h_c [m]	δ [m]	$\Delta\delta$ [m]	W [kg]	ΔW [kg]			
1	0.0077	0.0067	0.01	0.015	0.097	$1\ 10^{-24}$	80.82	$7\ 10^{-15}$	0.009	0.029	0.98
2	0.0081	0.0067	0.01	0.015	0.097	$1\ 10^{-24}$	82.12	$4\ 10^{-15}$	0.011	0.029	0.982
3	0.0073	0.0067	0.01	0.015	0.101	$5\ 10^{-17}$	79.16	$9\ 10^{-15}$	0.016	0.028	0.988
										Overall PPI_4:	**0.98**

7. *Step G: Select Satisficing Embodiment Design-Process Alternatives*

Results of the various design-process alternatives generated and evaluated in terms of their Process Performance Indicator are summarized in Table 8 and illustrated in Figure 9. Making the trade-off between gathering more information to refine performance predictions, in other words develop more refined design-process alternatives, or using the design-process alternative developed so far for decision making, the central composite sampling method and quadratic stepwise regression model fitting to the data obtained from the ABAQUS FEM model yields a performance indicator of at least 0.98 based on Scenario 1. Details of the analysis models used are summarized in Table 9.

Table 8. Summary of results design-process generation and selection

Design-Process Alternative	Design Variables				Responses				PPI_i [-]
	h_f [m]	h_b [m]	H [m]	h_c [m]	δ [m]	$\Delta\delta$ [m]	W [kg]	ΔW [kg]	
1 (initial)	0.015	0.03	0.052	0.038	0.097	0.004	225.47	10^{-21}	**0.59**
2	0.006	0.028	0.036	0.034	$4\ 10^{-5}$	0.003	145.3	0.025	**0.63**
3	0.0054	0.031	0.0345	0.034	$3\ 10^{-8}$	$6\ 10^{-24}$	145.08	$2\ 10^{-14}$	**0.9**
4	0.0077	0.0067	0.01	0.015	0.097	$1\ 10^{-24}$	80.82	$7\ 10^{-15}$	**0.98**

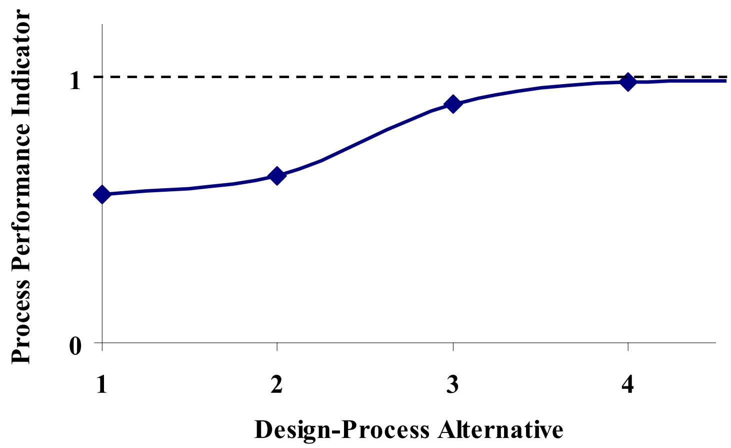


Figure 9. Comparison of results achieved

Even though a Process Performance Indicator of 0.98 is achieved, analysis models could still be refined by for example increasing the number of elements in the FEM model, using a more exhaustive sampling method, or leveraging more enhanced model fitting. As the analysis model is refined, the value of the Process Performance Indicator is likely to increase. But, from a decision-centric perspective there is a very low chance that this additional information gathering, in other words further refining the design-process, at increased computational expense will have a great impact on the design decision at the Process Performance Indicator value obtained. Hence, design-process alternative 4 is chosen for decision making.

Table 9. Summary of analysis models used

Design-Process Alternative	Description (simulation times with respect to a Dell Dimension XPS_GEN_5 Intel® Pentium® CPU 3.60GHz 2.00 GB of RAM)
1 (initial)	Analytical analysis model (simulation time ~ seconds)
2	Response surface analysis model of a ABAQUS explicit FEM model with a mesh size of 0.02 using a central composite sampling method and full quadratic model fitting to the observed data (simulation time ~ seconds)
3	Response surface analysis model of a ABAQUS explicit FEM model with a mesh size of 0.02 using a central composite sampling method and quadratic stepwise regression model fitting to the observed data (simulation time ~ seconds)
4	Response surface analysis model of a ABAQUS explicit FEM model with a mesh size of 0.02 using a full factorial level 3 sampling method and quadratic stepwise regression model fitting to the observed data (simulation time ~ seconds)
Most truthful	ABAQUS explicit FEM model with a mesh size of 0.005 (simulation time ~ 20 minutes)

The blast resistant panel with a 7.7 mm thick aluminum front face sheet, a 6.7 mm thick polymer carbon fiber composite back face sheet thickness of, a 1 cm thick titanium square honeycomb core with a core cell spacing of 1 dm and a core wall thickness of 1.5 cm is accepted as a preliminary layout. This preliminary layout now is to be further explored and detailed during the embodiment and detail design phases through for example experimental testing and rapid prototyping as well as planning of realization and value-chain processes depending on the preferred design-processes followed.

V. Closure

In response to the question of how to design embodiment design-processes when knowledge of prediction accuracy or its error bounds is not known throughout the whole design space, a generally applicable strategy for designing design-processes based on a value-of-information-based Process Performance Indicator has been presented. Key to this approach is on leveraging performance predictions at certain points in the design space obtained from experimentation or computationally expensive analysis models to evaluate the performance of embodiment design-processes. Focusing on generating embodiment design-processes through model replacement, the proposed strategy and Process Performance Indicator have been validated based on designing multifunctional BRPs.

The advantage of the systematic strategy to design-process generation and selection is that designers do not need to use the most complex design-process for decision making. However, more than one refinement step may be required for determining the right level of design-process refinement. In the worst case, multiple executions of design processes at increasing levels of refinement may result in computational expenses that exceed the total cost of evaluating the most truthful design-process alternative. Hence, there is a tradeoff that calls forth a designer's judgment based on the expected benefits from stepwise refinement through local evaluation.

As a practical contribution the Process Performance Indicator provides the designer with important feedback on the confidence or certainty in having selected an appropriate design-process alternative. The main advantage of the metric is that it is least complex to evaluate and quantifies the impact of design process decisions. Evaluating results obtained in the context of designing multifunctional BPRs, it has been shown to be advantageous to use the generally applicable strategy based on the Process Performance Indicator presented in this paper.

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Appendix

Table A10. Representative guidelines to evaluate the Process Performance Indicator at multiple points in the design space

Sampling Guidelines	Description
Random distribution	In random sampling new sample points are generated without taking into account the previously generated sample points.
Uniform distribution	A uniform distribution of sampling points throughout multiple dimensions of the design space can be used as a sampling method.
Simple grid distributions	Simple grids can be used to define sampling points through for example tessellation by congruent rectangles.
Fractional factorial [73]	Fractional designs are expressed using the notation l^{k-p}, where *l* is the number of levels of each factor investigated, *k* is the number of factors investigated, and *p* describes the size of the fraction of the full factorial used such that $1/(l^p)$ is a fraction of the full factorial design.
Central composite [74]	For an input of k factors in coded form denoted as $\mathbf{x} = (x_1, \ldots, x_k)$, sample points are determined as: - n_f cube points with $x_i = -1, 1$ for $i = 1, \ldots, k$ - n_c center points with $x_i = 0$ for $I = i, \ldots, k$ - 2k star points (or axial points) of the form $(0, \ldots, x_i, \ldots, 0)$ with $x_i = a, -a$ for $i = 1, \ldots, k$
Box-Behnken [75]	Each factor is placed at one of three equally spaced values, which should be sufficient to fit a quadratic model containing squared terms and products of two factors.
Orthogonal array [76]	The orthogonal method is defined by the fact that all pairs of its factors are orthogonal, i.e., statistically independent from each other.
Latin hypercube [77]	In Latin-hypercube sampling, a square grid containing sample positions is a Latin square if (and only if) there is only one sample in each row and each column. A Latin hypercube is the generalization of this concept to an arbitrary number of dimensions, whereby each sample is the only one in each axis-aligned hyperplane containing it.
Importance Sampling [78]	Importance sampling is a variance reduction method in that certain variables of the random input have more impact on the parameter(s) being estimated than others.
Minimax [79]	The minimax method provides a ranking of k values in order of increasing information content. The least informative k values in the upper half of k-space, together with their counterparts in the lower half, are omitted. This procedure contains both maximization (of a posterior distribution) and minimization (of the error).