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AN INDUSTRIAL TRIAL OF A SET-BASED APPROACH TO COLLABORATIVE DESIGN

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ABSTRACT

A set-based multiscale and multidisciplinary design method has been proposed in which distributed designers manage interdependencies by exchanging targets and Pareto sets of solutions. Prior research has shown that the set-based method (SBM) has the potential to reduce the number of costly iterations between design teams, relative to centralized optimization approaches, while expanding the variety of high-quality, system-wide solutions. These results have been obtained with representative examples in a laboratory setting.

The goal of this research is to investigate whether similar results are obtained from an industrial trial, implemented in an industry design environment. The SBM is applied to the design of a downhole module for our industrial partners at Schlumberger, a developer of oilfield tools and services. The design was conducted on location at Schlumberger by an intern who converted the existing Schlumberger design process into a set-based design process. Results indicate that the SBM delivers the benefits predicted in the laboratory, along with a host of advantageous side effects, such as a library of back-up design options for future design projects.

1. INTRODUCTION

Complex design problems are typically explored by decomposing them into sets of coupled, distributed sub-problems. Decomposition usually occurs according to scales, disciplines, and/or components. Products that are decomposed by scales or components might be split into modules, assemblies, components, and even parts. For other applications, divisions according to discipline may be more natural. For example, an airplane design might be divided into aerodynamics, structural analysis, control systems, and other subproblems. Matrix organizations may have divisions according to both scale and discipline. Each of these subproblems is typically solved by a designer or design team with specialized knowledge and tools. In this paper, the design groups responsible for the constituent subproblems are called subsystem design teams.

After a system-level design problem is decomposed, the activities of the subsystem design teams need to be coordinated by identifying coupled design parameters that link their subproblems and by specifying a protocol for exploring each subproblem that identifies appropriate values for coupled parameters. Two broad categories of protocols have been proposed in the literature: point-based design optimization methods and set-based design exploration methods.

General set-based philosophies have been advocated in the automotive industry [1,2]; in that setting, the exchange of rich sets of solutions (relative to single point solutions) has been shown to increase the diversity of options available for achieving consensus with collaborators and thereby reducing costly iterations. Set-based approaches differ from optimization-based approaches in which point solutions are exchanged in an iterative, automated fashion, under the guidance of one or more optimization algorithms. The difficulty with point-based optimization techniques—such as analytical target cascading [3], simultaneous analysis and design [4], concurrent sub-space optimization [5,6], collaborative optimization [7], and BLISS [8]—is that they require extensive iteration between design teams. In contrast, set-based approaches are intended to reduce iteration between distributed designers by exchanging richer collections of information. In exchange, the solutions tend to be *satisficing* [9] or approximate solutions that are 'good enough' but not necessarily optimal. Set-based coordination strategies have taken several forms, including: robust design techniques for generating ranged sets or intervals of design specifications that can be shared with collaborating designers [10-15]; fuzzy set theory [16,17] for modeling uncertain or imprecise parameters (such as preferences for performance variables) during negotiation; metamodeling approaches for zooming into regions of interest [18]; and game theoretic approaches for coordinating the competitive reactions of designers to one another's decisions [19-28]. Other methods such as multiobjective genetic algorithms provide a set of distinct possibilities as opposed to a range [29-33], but they are resource intensive.

In the set-based method (SBM) used in this paper, designers collaborate by exchanging targets for shared parameters, followed by Pareto sets of solutions that represent achievable tradeoffs between coupled parameters [34-36]. The sets of solutions provide a diversity of options for achieving system-level performance goals and system-wide feasibility with minimal iteration. The SBM is described in detail in Section 2, but Figure 1 illustrates the essence of the approach. The design activity begins at the system level through the generation of targets. If the target values are not attainable (as is often the case), the subsystem teams search for a set of solutions that are as close to the target as possible—the Pareto frontier. Following the subsystem design activities, the final design is chosen from the set of resulting solutions. By proposing more than one target for each parameter and then creating more than one solution, more of the design space is explored. This leads to two benefits. First, a greater variety of solutions is created which improves the chances of finding a good solution quickly. Second, there is a smaller chance of not finding any feasible solutions—an outcome that would lead to expensive iterations.

In previous work, we have outlined the SBM and applied it to representative examples in a laboratory setting [34-36]. This prior research has shown that the SBM has the potential to reduce the number of costly iterations between design teams, relative to centralized optimization approaches, while expanding the variety of high-quality, system-wide solutions. The goal of this research is to investigate whether similar results are obtained from an industrial trial, implemented in an industry design environment. The SBM is applied to the design of a downhole module for our industrial partners at Schlumberger, a developer of oilfield tools and services. The design was conducted on location at Schlumberger by an intern who converted the existing Schlumberger design process into a set-based design process. The results are compared with

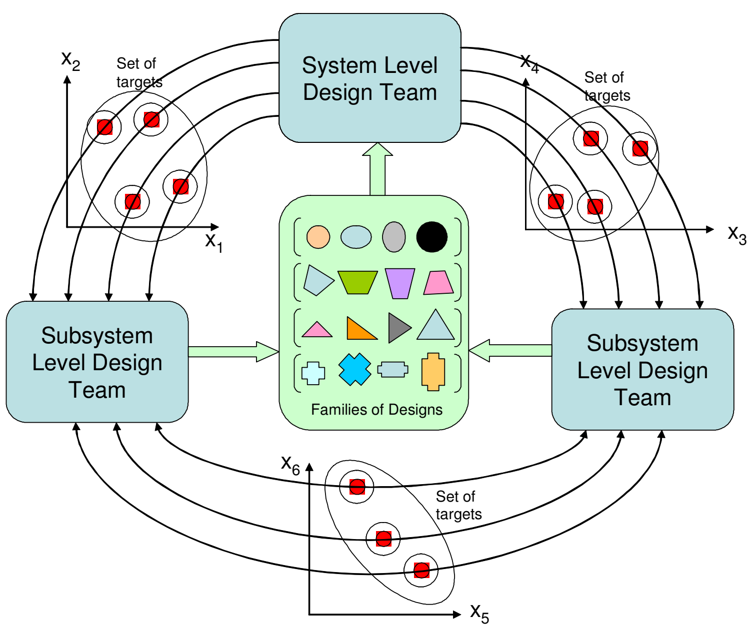

Figure 1. The Set Based Design Methodology

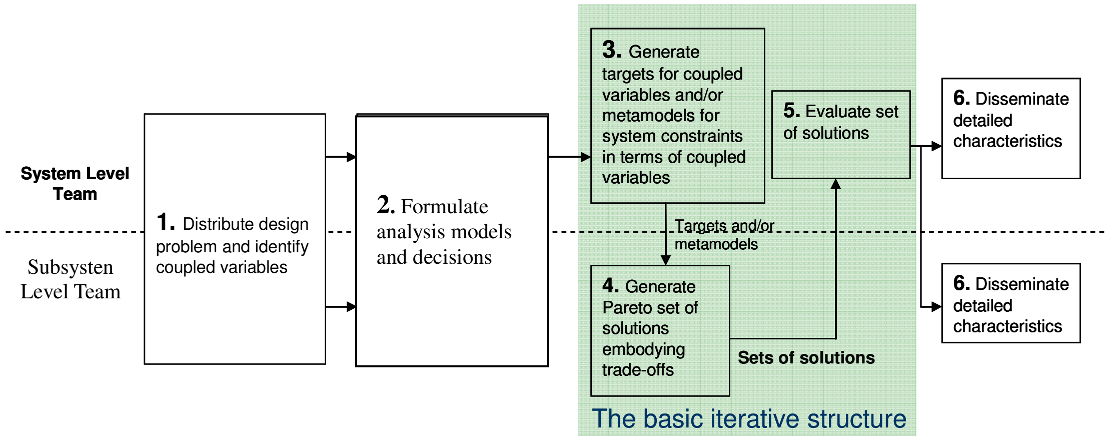

Figure 2. Schematic Representation of a Set Based Approach to Multiscale Design [10]

prior results obtained for the same design problem, without the benefit of the SBM.

The research approach is detailed in Section 3, following a description of the SBM in Section 2. Results are presented in Section 4 and discussed in Section 5.

2. OVERVIEW OF THE SET BASED DESIGN METHOD

The six general steps of the SBM are illustrated in Figure 2. The first step is to distribute the design problem between design teams and to define the significant coupled parameters that link the distributed design problems. The problem is distributed based on scales, disciplines, components, or other boundaries typical to the company environment. In Step 2, each design team formulates its design problem as a compromise Decision Support Problem [37] and constructs supporting analysis models. As illustrated in Figure 4, the compromise DSP is a mathematical model of the multiobjective decision to be solved. Details are available in [37]. Step 3 includes a strategy for generating a set of targets for the coupled parameter values that produce satisfactory system level results. A simple two level Latin hypercube sampling technique [38] has proven to be an effective strategy for generating the targets from the system level model for the subsystem level teams with a low computational cost. At the first level of Latin hypercube sampling, the desired ranges of the system level inputs are divided into intervals from which design instances are sampled randomly, with one design point sampled from each interval as illustrated in Figure 3. These designs are evaluated, and if desired, a second level of Latin hypercube sampling is used to generate additional design points in the neighborhood of each feasible design uncovered by the first level of sampling. From these samplings, a set of targets is chosen to pass to the subsystem level design teams. In Step 4, the subsystem design teams insert the targets into their compromise DSP's and solve them to identify Pareto sets of solutions that match the targets as closely as possible. The results are communicated to the system level team, which evaluates the options and selects the final design in Step 5. In Step 6, the final design choice is carried forward to the detailed design phase.

As it is currently formulated, the SBM assumes continuous coupled parameters, but discrete and discontinuous

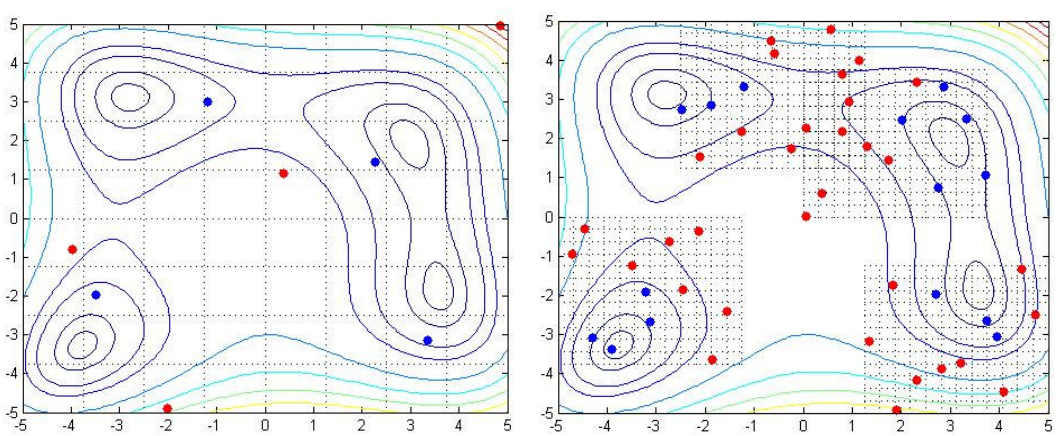

Figure 3. An Example of a Two-Level Latin Hypercube Sampling Strategy

Given:

The model and its parameters

n number of system parameters

$p+q$ number of system constraints

p number of equality constraints

q number of inequality constraints

m number of system goals

$g_i(\mathbf{x})$ constraint functions

$f_k(d_i)$ objective function to be minimized at priority level k for the Archimedean case

W_i weight for the Archimedean case

Find:

x_j $j = 1 \ldots n$ system parameters

d_i^-, d_i^+ $i = 1 \ldots m$ deviation parameters

Satisfy:

$g_i(\mathbf{x}) = 0$ $i = 1 \ldots p$ equality constraints

$g_i(\mathbf{x}) \leq 0$ $i = p+1 \ldots p+q$ inequality constraints

$A_i(\mathbf{x}) + d_i^- - d_i^+ = G_i$ $i = 1 \ldots m$ system goals, $A_i(\mathbf{x})$, to achieve targets G_i

$x_{j\,min} \leq x_j \leq x_{j\,max}$ system parameter bounds

$d_i^-, d_i^+ \leq 0, d_i^- \cdot d_i^+ = 0$

Minimize:

$Z = \Sigma_{i=1 \ldots m} W_i(d_i^- + d_i^+)$ objective function for the Archimedean case

Figure 4. The compromise Decision Support Problem Formulation [37]

design spaces, including configurational design parameters, can be considered within the subsystems. The importance of being able to consider different configurations is exemplified in the design of a downhole module in Section 4. Also, by minimizing iterative exchanges, the SBM supports active involvement of expert designers in the design process. Designers themselves solve the compromise DSP's, formulate and validate analysis models, interpret solutions, and carry out other tasks that are difficult to automate. Fully automated search and modeling is not required.

3. RESEARCH APPROACH

The SBM is being developed as part of a collaborative partnership between academic and industrial researchers at UT Austin and Schlumberger, respectively. A focus of this effort is continuous validation and refinement of the SBM via application to design problems in the laboratory and in the industrial environment. Laboratory trials with representative example problems have shown that the SBM yields satisfactory system–wide solutions with much less computational expense and significantly fewer system-wide iterations than centralized, point-based optimization approaches [34-36]. In fact, for multidisciplinary and multiscale problems investigated to date, the SBM yields solutions within 10% of the optimum with 90% less computational expense and only 1 global iteration [34-36]. Also, discrete event simulations have been developed to simulate the collaborative design process. Results indicate that cycle times are likely to be significantly lower and less variable for the SBM, relative to highly iterative design processes [39]. All of these results are from campus-based investigations, whereas an industry-based trial is needed to fully investigate the effectiveness of a set-based approach in an industrial product development process.

In this paper, the SBM is used to solve an industry design problem in the industrial setting at Schlumberger. The goal is to compare the solution quality and overall process efficiency of the SBM, relative to Schlumberger's current design process, and to identify any qualitative advantages or barriers to applying the SBM in an industrial setting.

Towards this goal, a design problem was selected by our industry partner as an example of a collaborative design problem at Schlumberger. The problem entailed the design of a downhole module for oil and gas drilling applications. The module consisted of several components (housing, chassis, bumpers) and required design engineers from several disciplines. The design problem had already been solved by Schlumberger engineers. The existing solution provided a reference point for *a posteriori* comparison with the SBM solutions, but it was carefully concealed from the UT Austin authors who re-solved the design problem.

The SBM trial took place on site at Schlumberger over a period of approximately two and a half months. The trial was led by the first author who collaborated with a team of approximately six Schlumberger experts (technicians, design engineers, and project managers) with experience in the original design of the module. The size of the team and the allocation of design responsibility within the team were consistent with past designs. During the SBM trial, the first author obtained experimental data from the previous design process, upon request, but Schlumberger experts did not discuss their previous embodiment with him.

Application of the SBM to the Schlumberger design problem is described in the next section.

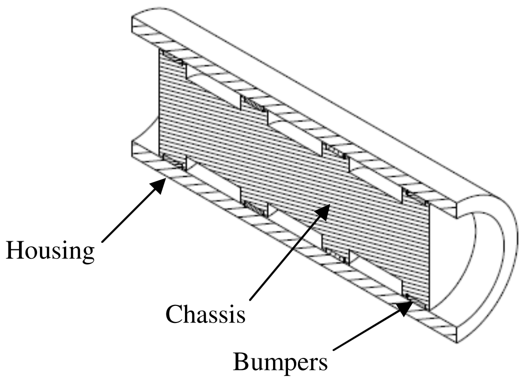

Figure 5. CAD Model of a Downhole Assembly Cross-Section

4. INDUSTRIAL TRIAL OF THE SBM

The focus of the industrial trial was to evaluate the effectiveness of the SBM for solving a collaborative design problem at Schlumberger; specifically, the design of a downhole module for surviving transverse shock loads. As illustrated in Figure 5, there are three primary mechanical components of the module that contribute to its response to shock loads: the housing, the bumpers, and the chassis. The housing encases the chassis and the functional components mounted on the chassis while the bumpers isolate the chassis from the housing. The design of these three parts together determines the module's survivability to a transverse shock.

The design process is organized according to the six steps of the SBM, as follows:

Step 1: The first step of the SBM is to decompose the problem into subproblems. In this case, the company's typical decomposition is along part boundaries. The system level design team creates the assembly housing and evaluates the shock resistance of the assembly. The subsystem level chassis design team creates the frame to which the functional components are mounted. The subsystem level bumper team designs the dampening interface between the housing and the chassis. Decomposing the problem along these boundaries creates interfaces between each design team that involve geometry definition and other subsystem properties that feed into a system level model for evaluating transmissibility. The transmissibility is assumed to depend on the mass and stiffness of the housing, chassis, and bumper, as well as the damping coefficients of the bumper according to the P-diagram in Figure 6. This system-level problem can be decomposed into a hierarchical problem with coupled parameters indicated in Figure 7. The system level downhole assembly team minimizes the transmissibility of the system. The chassis design team is responsible for determining the chassis stiffness and weight, while the bumper design team is responsible for determining the bumper stiffness, weight, and damping coefficient. The coupled parameters represent the shock transmission characteristics of their respective components, and they depend on each component's geometry and materials, which are adjusted during the design process.

Step 2: In Step 2, each design team creates analysis models for their respective components. At the system level, the transmissibility ratio is defined as the ratio of the maximum acceleration of a component on the chassis to the amplitude of the acceleration applied to the system. For example, if a 250g

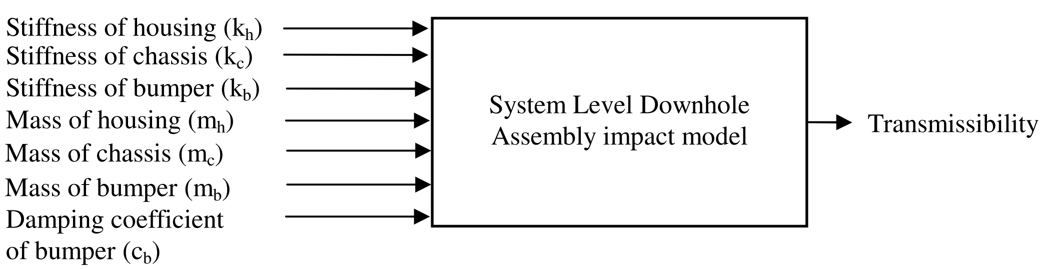

Figure 6. P Diagram for the System Level

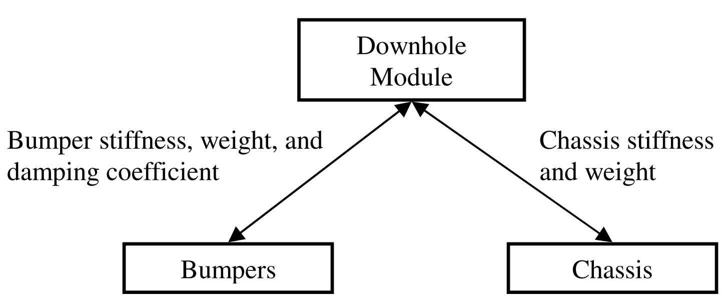

Figure 7. The Downhole Design Hierarchy

$$\text{Transmissibility} = 8.73 - (0.263)m_h - (0.0097)m_c + (1.5E\text{-}12)k_h + (1.75E\text{-}10)k_c - (76.3)m_b + (5.07E\text{-}09)k_b + (0.063)c_b - (0.001)c_b^2 + (4.08E\text{-}06)c_b^3 - (6.1E\text{-}09)c_b^4 + (3.22E\text{-}12)c_b^5$$

Figure 8. System Level Transmissibility Model

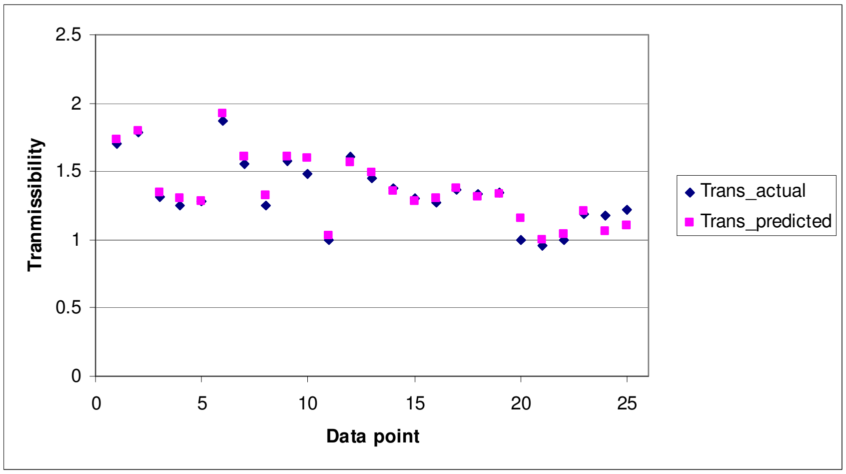

Figure 9. System Level Transmissibility Model with the Experimental Data

acceleration is applied to the system, and a maximum acceleration of 500g is recorded on a part on the chassis, then the transmissibility is 2.0. For systems with rigid support and continuous distribution of mass, the transmissibility is approximately 1.0. For systems with considerable damping, the transmissibility is less than 1.0. Most assemblies are neither rigid nor sufficiently damped, and transmissibility ranges from 1.0 to 10.0 and beyond. A satisfactory limit for this transmissibility is a ratio of 2.0, which is qualified through a drop test conducted with a prototype. In this case, no drop test simulation methodology exists, but experimental data is available from previous tests. Using this data, the transmissibility is modeled with a polynomial regression, as shown in Figure 8, as a function of the independent variables identified in Figure 6. This model has an R- Squared value of 0.952, an R-Squared adjusted value of 0.91, a maximum and minimum error of 0.148 and 3.76E-3, respectively, relative to the experimental data, and an average percent error of +/- 3.67%. Figure 9 overlays the model with the experimental data. It should be noted that the regression model is only as accurate as the historical data used to fit it, and it can only be used reliably over the range for which historical data is available. A preferable approach is to use the historical data to calibrate an analytical model that extrapolates more broadly to new design configurations, but an analytical model proved very difficult to develop for this application.

As shown in Figure 7, the subsystem teams (bumper and chassis) are required to analyze the stiffness, mass, and damping coefficients of their respective components. The mass is determined directly from CAD models and the stiffness from finite element modeling. The damping is calculated from damping ratios for constituent materials that are corrected for geometry and loading magnitude based on the results of experimental tests.

Step 3: In step three of the SBM, the system-level design team generates targets for the coupled parameters. The targets provide insight into values that the system-level team is seeking from the subsystem teams. When specifying targets, the aim of the system-level design team is to identify several satisfactory regions of the system-level design space. Satisfactory regions of the design space are defined in terms of values of the coupled parameters that lead to satisfactory system-level performance. For the system level transmissibility model, a satisfactory design has a

Table 1. Ranges for Input Variables in Latin Hypercube Sampling

Variable	Lower limit	Upper limit
m_h	30 kg	80 kg
m_c	5 kg	30 kg
m_b	0.005 kg	0.1 kg
k_h	1.00E+12 N/m	1.50E+13 N/m
k_c	1.00E+07 N/m	1.00E+10 N/m
k_b	1.00E+04 N/m	5.00E+08 N/m
c_b	1 N/(m/sec)	1000 N/(m/sec)

Table 2. Satisfactory Points from the Level 1 Sampling

S.No	m_c (kg)	c_b (N/m/sec)	k_b (N/m)	m_h (kg)	k_c (N/m)	m_b (kg)	k_h (N/m)	Transmissibility
1	5.26	76.96	3.50E+08	49.29	8.08E+09	0.09	6.22E+12	1.59
2	10.50	463.77	9.86E+08	76.10	6.65E+08	0.08	1.13E+13	1.63

Table 3. Satisfactory Points from the Level 2 Sampling

S.No	m_c (kg)	c_b (N/m/sec)	k_b (N/m)	m_h (kg)	k_c (N/m)	m_b (kg)	k_h (N/m)	Transmissibility
1	5.26	76.96	3.50E+08	49.29	8.08E+09	0.09	6.22E+12	1.59
1-1	5.00	80.81	3.38E+08	46.82	7.91E+09	0.09	6.18E+12	1.98
1-2	5.08	77.51	3.53E+08	51.04	7.68E+09	0.09	6.09E+12	0.99
2	10.50	463.77	9.86E+08	76.10	6.65E+08	0.08	1.13E+13	1.63
2-1	10.13	467.08	9.93E+08	78.82	6.32E+08	0.07	1.11E+13	0.80

transmissibility value less than 2.0.

To identify targets, two levels of Latin sampling are performed using iSIGHT, a design exploration and automation software tool [40]. The first level Latin sampling is a comprehensive design space exploration, while the second level Latin sampling is a local design space exploration around satisfactory points from the first level. Using the satisfactory limit of 2.0 for transmissibility as a filter, only the solutions less than that value are considered as potential targets. The ranges for the input values are shown in Table 1. Table 2 shows the satisfactory points culled from the 151 points generated by the first level of sampling. The results from the second level of sampling are recorded in Table 3. In the table, 1-1 and 1-2 refer to the satisfactory secondary sample points in the neighborhood of the first satisfactory point. To conclude step 3 of the SBM, the five target designs from Table 3 are passed to the subsystem teams as targets.

Step 4: At this point in the SBM, the subsystem design teams strive to achieve their targets as closely as possible. For the sake of clarity and brevity, this discussion focuses on the

Table 4. Chassis Designs

Chassis type	m_c target (kg)	k_c target (N/m)	m_c achieved (kg)	k_c achieved (kg)
Type 1	5.263	8.08E+09	6.861	3.07E+07
Type 2	5.263	8.08E+09	8.521	9.08E+08
Type 3	5.263	8.08E+09	7.7819	1.34E+06
Type 4	5.263	8.08E+09	12.889	5.69E+09
Type 5	5.263	8.08E+09	9.095	6.20E+08
Type 6	5.263	8.08E+09	9.055	6.69E+08
Type 7	5.263	8.08E+09	10.02	1.45E+10
Type 8	5.263	8.08E+09	10.58536	3.42E+09
Type 9	5.263	8.08E+09	8.602	1.94E+09

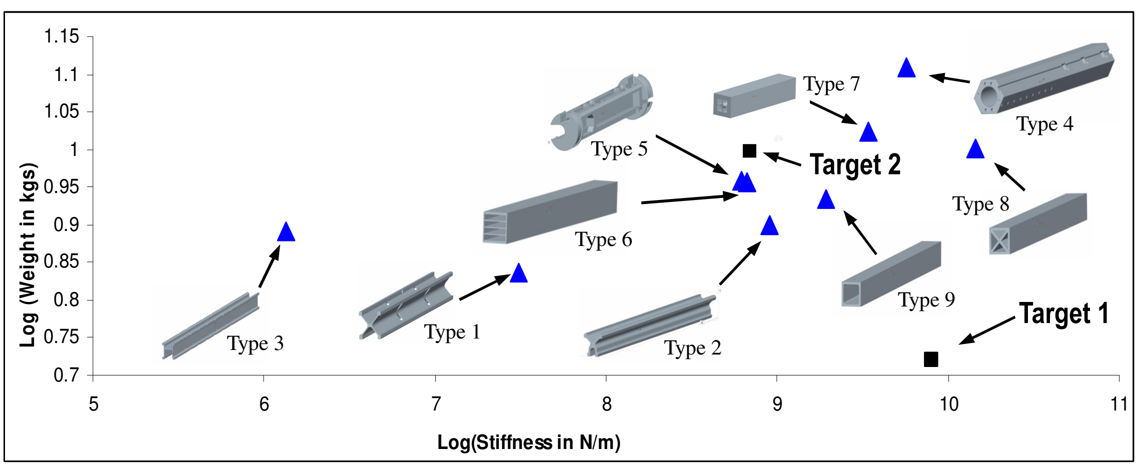

Figure 10. Chassis Designs and Chassis Design Team Targets

Table 5. System Level Results After Subsystems Pass Back Design Sets

S.No	Transmissibility	Chassis type	Bumper type
1	1.10	Type 4	Type 1
2	1.52	Type 4	Type 1
3	1.14	Type 8	Type 1
4	0.90	Type 9	Type 1
5	1.55	Type 1	Type 2
6	1.69	Type 2	Type 2
7	1.54	Type 3	Type 2
8	1.63	Type 5	Type 2
9	1.64	Type 6	Type 2
10	1.87	Type 9	Type 2
11	0.86	Type 2	Type 2
12	1.66	Type 4	Type 2
13	0.81	Type 5	Type 2
14	0.82	Type 6	Type 2
15	1.28	Type 8	Type 2
16	1.04	Type 9	Type 2

design task of the chassis design team and assumes that the housing and bumper design teams match their design targets. In this test case, nine separate chassis topologies are designed and evaluated for their mass and stiffness as documented in Table 4. These designs are compared with their targets in Figure 10. None of the nine chassis designs meet a target exactly, but they do represent different tradeoffs between achieving targets for mass and stiffness.

As illustrated in Figure 10, the SBM facilitates design and evaluation of different configurations at the subsystem levels. Each of the illustrated configurations could be further refined parametrically, but the configuration changes provide the most significant mass-stiffness tradeoffs. Exploring these tradeoffs is the goal of the subsystem level design teams in Step 4. Furthermore, the SBM allows each team to adjust configurations (in addition to continuous parameters) as they search for designs that meet the targets as closely as possible. The nine chassis design points are combined with five bumper designs from the bumper subsystem group (to match each of the five target parameter values in Table 3), resulting in a total of forty-five solutions to be returned to the system level for step 5 of the SBM.

Step 5: The system level design team is free to choose any of the options returned to them from the subsystem design teams. Of the forty-five potential solutions, sixteen have acceptable transmissibility, and they have been listed in Table 5. When choosing among the options, the system level team may apply other qualitative criteria, such as ease of assembly and the extent of available space for inserting other components, as needed. This freedom is significant because the system level team has a wide variety of options and hence the accompanying flexibility to select a design that meets their criteria, some of which may not have been captured in the original response model for transmissibility.

Step 6: The final step of the SBM is to disseminate the choice for the most preferred design.

In the next section, the results of this application of the SBM are compared to the company's current design process.

5. DISCUSSION

Prior to implementation of the SBM, Schlumberger's design process favored physical prototyping over simulation. Also, it did not follow a formal process for decomposing a design problem into sub-problems and focusing on coupled parameters that link the sub-problems. The first contribution of the SBM was to provide Schlumberger with a formal means for mapping the impact of subsystem-level design decisions on system level performance by: (1) decomposing design problems, (2) defining coupled variables, and (3) creating suitable simulation models according to Steps 1 and 2 of the SBM. This shift potentially transitions the company towards a design by simulation philosophy with the ultimate goal of replacing prototyping with validated simulation models.

The second contribution of the SBM was to provide Schlumberger with a framework for exploring interdependencies between system level and subsystem level activities. According to Steps 3-5 of the SBM, each local team simultaneously considers sets of options in terms of targets and Pareto sets of solutions that are communicated between collaborators. For prior Schlumberger design projects in which coupled parameters were identified, the interface was typically fixed early in the design process and often by engineering managers. In contrast, the SBM specifically encouraged exploration of the design space across the interfaces and postponement of coupled parameter freezing until later in the design process.

The third contribution of the SBM was to offer a means for potentially improving design outcomes while reducing cycle time. The result of Schlumberger's prior design process was the Type 1 chassis. The Type 1 chassis is indeed part of the set of final designs generated by the SBM. (Recall that the SBM was applied by the first author without knowledge of the prior solution.) This outcome demonstrates that the SBM generates at least equivalent design quality as the collaborating company's existing design method. It is interesting to note that the Type 1 chassis was not the closest design to the targets in Figure 10. This outcome reinforces the need to keep multiple Pareto solutions alive in the subsystem design processes because system-level designers must reconcile the designs of multiple subsystems by weighting some criteria heavier than others (e.g., low mass versus high stiffness) and possibly considering additional criteria (e.g., manufacturability and assembly) when selecting among the available options.

Comparing design process execution times was very difficult in this case. The SBM application was conducted over a period of two and a half months at Schlumberger. Since the SBM process followed the original Schlumberger design process in time, the SBM process benefited from the results of prior prototype testing (for example, for building the transmissibility model in Figure 8). Accordingly, we cannot claim conclusively that the implementation of the SBM was shorter than the company's typical design process. However, the amount of time allotted to the design of the downhole module using the SBM was certainly no greater than the amount of design time typically allowed.

Generally, we observed several qualitative advantages of the SBM, relative to the company's current design strategy. These advantages position the company for potentially significant increases in efficiency and quality. Examples include:

1. A more thorough and systematic exploration of the design space;
2. Exploration of tradeoffs that are inherent to each design;
3. Identification of several satisfactory solutions, providing more freedom of choice for designers and reducing iteration;
4. A library of backup design options for meeting changing requirements without additional design activity; and
5. Increased concurrency of design activities.

The first and second points were demonstrated when the system level metamodel captured the outcomes of past experimentation and provided potential directions for future low transmissibility design targets. Also, since the chassis design team evaluated a Pareto set of configurations, rather than a single target-matching design, more was learned about the potential impact of the design choices on the module transmissibility. Tradeoffs inherent to the design problem were uncovered and explored, such as the tradeoff between mass and stiffness found in the chassis design. The third point was demonstrated when the final design choice for chassis Type 1 was provided to the system level design team as an option, even though it was not the closest solution to the system-level target. It turned out to be superior to the other options for reasons not considered in the generation of the targets. If only the chassis closest to the targets were returned to the system level, a further iteration might have been necessary as more design requirements were considered. Point four speaks to the potential benefit of the SBM in terms of building and archiving design knowledge in the form of sets of tradeoff solutions that can be used in future design activities. Examples could include scaling or making small changes in functional requirements. Finally, point five highlights the parallel nature of the set based method such that several configurations can be simultaneously evaluated analytically or experimentally. From this discussion, one can see that the SBM provides the steps toward realizing significant future time savings during the product development process.

The framework for the SBM covered in this paper is a work in progress. Current and future work on the SBM includes improving the set-based strategies of collaborative design coordination through studies of processes with more scales and interactions. Other sampling strategies are being explored to determine the most efficient and effective method for identifying targets. Interactive studies of collaborative design processes are also being used to improve and validate the process. Finally, the implications of the SBM for process management are being investigated with discrete event simulations of set-based design processes.

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