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A COUPLED MODEL BASED SYSTEMS ENGINEERING AND MULTI-CRITERIA DECISION MAKING APPROACH TO DEFINE AFFORDABLE REQUIREMENTS

Johanna Ceisel
Patrick Koch
Alex Van Der Velden
Dassault Systemes
Americas, USA

ABSTRACT

Programs have traditionally defined system requirements based on mission requirements and former system characteristics with limited knowledge on how their decisions impact the overall design space. This paper describes a methodology that combines model based systems engineering (MBSE) and multi-criteria decision-making (MCDM) to define affordable requirements prior to the design cycle. Two unmanned aerial vehicle (UAV) concepts were modeled in a multi-disciplinary simulation process environment using SIMULIA's Process Composer application. Then the results were loaded into SIMULIA's Results Analytics application, an advanced analytics and decision support tool, for performance versus affordability requirement trade-off analysis. Results Analytics is able to uncover data patterns, show design space sensitivity to requirements, and explicitly prioritize and quantify requirements employing a design ranking algorithm.

INTRODUCTION

The days of performance at any cost are over for the defense industry due to the economic downturn and public policy. Yet, threats are still eminent. Programs must now do more with less. The affordability challenge is further exasperated by shifting mission requirements and an increasing trend in system complexity, which results into longer lead times and cost overruns. Model Based Systems Engineering (MBSE) is a key enabler to overcome these challenges. However, ultimately requirements will lead the system engineer to a region of a design space, which may or may not be preferred by the program. MBSE and Multi-Criteria Decision Making (MCDM) need to be coupled and incorporated into the requirements definition stage in order to provide a ranking algorithm to represent the voice of the customer, which is based on knowledge of the design space.

METHODOLOGY

The process of ranking alternatives falls under the research field of Multi-Criteria Decision Making since in a majority of cases multiple conflicting objectives are present in a design problem and a compromise between various objectives is required. For example, the speed and maneuverability is normally in direct opposition to the survivability of the system. The difficulty of the problem is always increased by the presence of more than one criterion. “There is no longer a single optimal solution to an MCDM problem that can be obtained without incorporating preference information. The concept of a single optimal solution is replaced by the set of non-dominated solutions where it is not possible to move away from such solution to any other without sacrificing in at least one criterion. Generally, however, the set of non-dominated solutions is too large to be presented to the decision maker for his or her final choice.” [7] A tool is needed to help the decision maker focus on his preferred solutions by applying preferences (priority and weight) and allowing the user to observe how the preferences affect the ranking of the design alternatives in addition to feasibility assessment (e.g. requirement trade-off analysis). [8] Once preferences are determined, a ranking algorithm is created. The design ranking algorithm is just an aggregation function, such as a weighted sum, with the user’s hierarchy, weights/preferences, objectives, and thresholds taken into account. Although simple in concept, this is the critical link between requirement definition and model based systems engineering that was missing in the past. The ranking algorithm represents the customer as system engineering trades are being made. The systems models represent the design space to the decision maker. MBSE coupled with MCDM now gives decision makers the ability to rigorously assess large space of design alternatives. Inspired through work on the DARPA Adaptive Vehicle Make (AVM) Fast Adaptive Next-Generation (FANG) program, the above methodology is achieved through the following four basic steps:

A. Define preliminary requirement hierarchy, priority, objectives, and thresholds
B. In parallel, generate design alternatives based on a model based systems engineering library
C. Load generated alternatives and conduct requirement trade-off analysis
D. Based on the requirement trade-off analysis, finalize and share design ranking algorithm

These steps are illustrated in Figure 1 below.

UNMANNED AERIAL VEHICLE USE CASE

In order to illustrate the methodology, an unmanned aerial vehicle (UAV) use case was selected. Aluminum machined and composite Resin Transfer Molding (RTM) concepts were modeled at the conceptual level. Both concepts have an axisymmetric fuselage with integrally hoop stiffening.

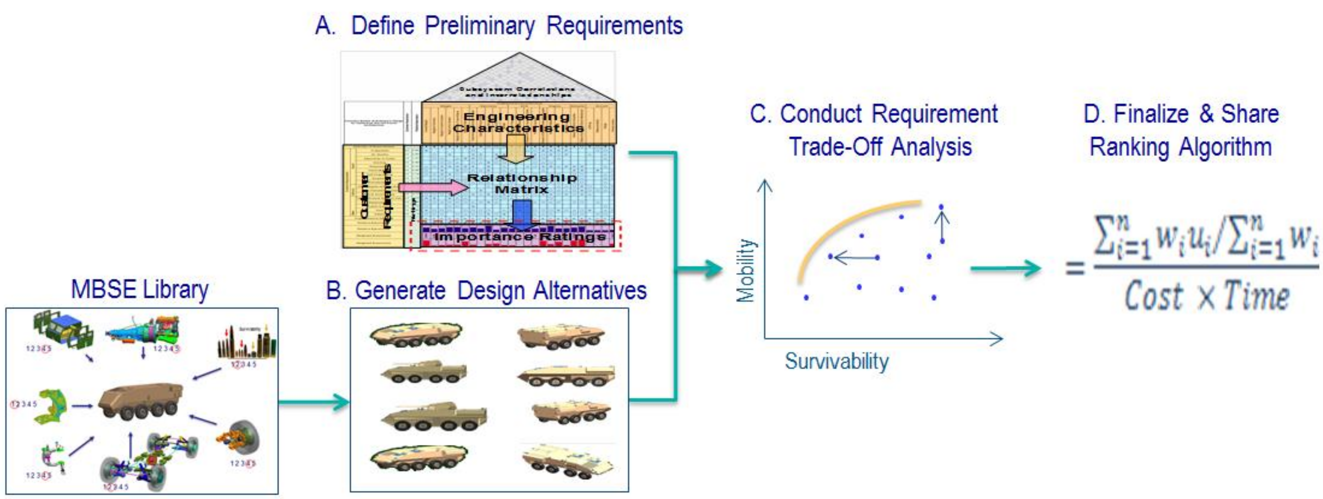

Figure 1: Methodology

Figure 2: UAV Conceptual Design

For the requirement definition and trade-off analysis, SIMULIA's Results Analytics was used. Results Analytics is a web based, trade-off and decision support tool on the 3DExperience platform, which enables users to transform scientific data into decisions. 3DExperience is Dassault Systemes' (DS) common platform, where all DS applications share a common data model, lifecycle policy, security controls, and knowledge management system. Results Analytics enables the above methodology through advanced analytics, interactive visualizations, collaborative decision support, and tight integration with simulation and Requirement Central. Requirement Central is a requirements management application on the 3DExperience platform as well. For instance, a user is able to easily manipulate a requirement hierarchy and priority via a mind map view, which in turn updates the ranking algorithm, re-ranks the design alternatives, and assesses feasibility. Users can quickly see how their objective definition and preferences impact the design space.

For alternative generation, SIMULIA's Process Composer was used, which is a multi-disciplinary simulation process environment. Users are able to graphically integrate via drag and drop any application, using "out of the box" interface library of adapters. Adapters are the building blocks of a simulation process and can be either native (CATIA, Abaqus, etc.) and non-native (Excel, Matlab, etc.). Process Composer also features advanced design exploration adapters, such as Design of Experiments (DOE), Optimization, and Surrogate Modeling execution. For this use case, a DOE was used to generate alternatives for both concepts.

Table 1: Preliminary Requirements

Requirement	Units	Objective	Threshold
Customer			
Range	Miles	Maximize	> 400
Endurance	Hrs	Maximize	>3
Payload Volume	Inches^3	Maximize	>=600
Total Cost Per Unit	$USD	Minimize	
Engineering			
Empty Weight	lb	Minimize	
Manufacturing			
Production Hours per Unit	Hours	Minimize	

Preliminary Requirements Definition

Illustrative preliminary requirements were defined and organized by three stakeholders (customer, engineering, and manufacturing), which is shown in Table 1. The preliminary requirements were then loaded into ENOVIA's Requirements Central and then imported into Results Analytics. Using the Mind Map view, users are able to quickly change the requirement priority and hierarchy via drag and drop, which also transforms the ranking algorithm. Based on this requirement hierarchy, scores and weights are aggregated accordingly, so this is an important first step to generating the ranking algorithm. For this example, the hierarchy is only two levels deep with customer, engineering, and manufacturing representing the first level. Range, Endurance, etc. compose the second level under customer and so on. Figure 3 shows the Mind Map view. In the FANG program, the requirements were much more complex; over 100 requirements and five levels deep with performance, cost, and time

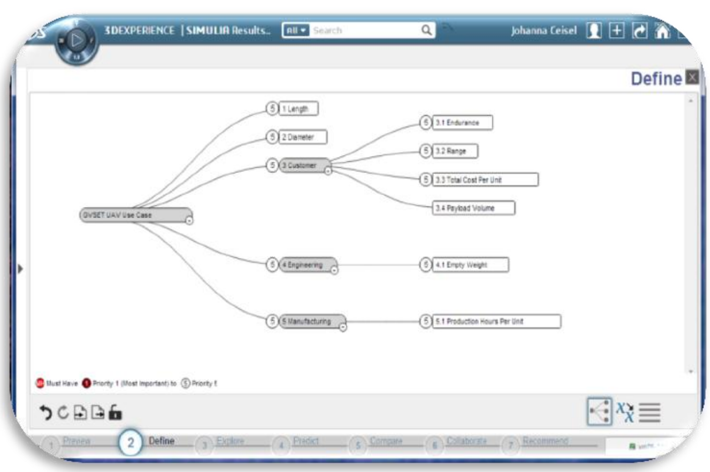

Figure 3: Results Analytics Mind Map View

representing the first layer; speed, survivability, maneuverability, etc. in the second layer under performance and so on. Requirements can quickly become difficult to manage. The Mind Map view aids users to quickly generate the hierarchy and in turn the ranking algorithm. In another view, users are able to enter upper/lower thresholds and objectives. Objectives can be defined as either continuous (maximize, minimize) or targeted (target). The thresholds and objectives were entered as shown in Table 1.

Alternative Generation

In parallel, a simulation process was created in Process Composer, representing three disciplines: Design, Performance, and Manufacturing. The simulation process encompasses three activities with adapters within each activity. The first activity is the parametric, conceptual fuselage created in CATIA, which calculates empty weight and volume. The calculator adapters within this activity are used for unit conversions, while the CATIA adapter accesses the conceptual model within the 3DExperience platform for perturbation. The second activity calculates range and endurance based on Breguet's equations. The third activity calculates production hours and cost using weight based surrogates fitted from data generated from Galorath's SEER-H total lifecycle cost modeling application. The cost and hour estimating relationships are based on weight, manufacturing process, material, and complexity based on aerospace UAV structures. The simulation process is shown below in Figure 4. A Latin Hypercube DOE was run for each concept. Length, Diameter, and Thickness were varied per concept per DOE. For this use case, all three activities were run on the same workstation. However, Process Composer gives the user the ability to assign compute stations or affinity groups for each activity, which then calls SIMULIA's Compute Orchestration Services (COS). COS is an intelligent execution engine that automatically governs the distribution of simulation processes across a network of computers, on-premise or on-cloud.

Requirement Trade-off Analysis

After both DOEs are run, the result files are seamlessly loaded and merged from Process Composer to Results Analytics for trade-off analysis. This step is the heart of the methodology, where decision makers can perform what-if requirement trade-off analysis and understand the impact of their decisions on the design space. Based on the preliminary requirements defined earlier, loaded designs from the result files are automatically scored, ranked, and assessed for feasibility. Feasibility indicates the capability of a design to meet a set of requirements. In Results Analytics, designs are assessed and placed in three categories:

- Infeasible – Does not meet one or more requirement thresholds
- Dominated – Meets thresholds, but better designs exist
- Best Design or Pareto – Meets thresholds and non-dominated design

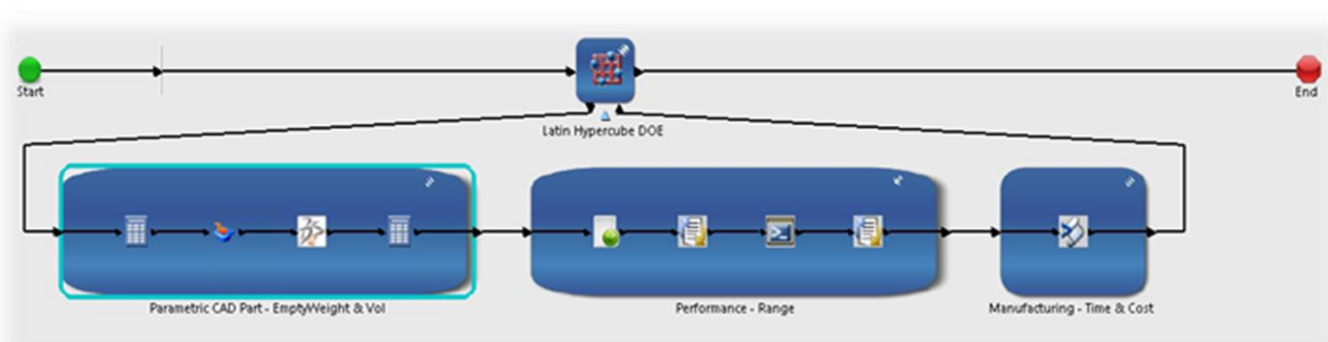

Figure 4: UAV Simulation Process

In the UAV use case, 3101 out of 3900 designs are marked infeasible. Figure 5 shows the Table View with feasibility assessment shown by color in each row (Green–Pareto, White–Dominated, Red-Infeasible). The parameters that are violating a threshold and causing infeasibility are marked in bold font. In this case, range is causing the top ranking designs (see below) to be infeasible. A decision maker can now easily see how their threshold definition affects the design space and assess if it is truly an important constraint. Not all thresholds are important. Sometimes thresholds are based on previous platform capabilities versus the actual need, such as mission or threat. There are other times where the design space, especially at the system level, is over constrained by thresholds (e.g. all design points are marked as infeasible) and decision makers need to reevaluate before a proposal is issued. In this case, range was relaxed to 300 in order to open up the design space.

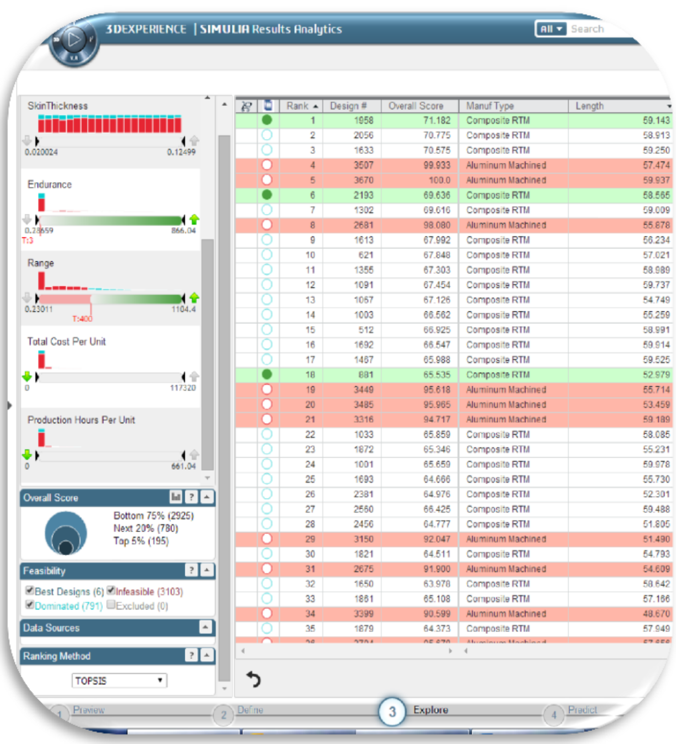

Figure 5: Table View with Feasibility Assessment

In addition to feasibility assessment, the designs are also being scored and ranked based on the weighted sum ranking method. Weighted sum is the simplest and most recognized MCDM ranking method. In Results Analytics, weighted sum method is selected by default. The score value of each design point is simply a sum of all objective values, each multiplied by the final, aggregated weight factor (based on hierarchy). For the weighted sum method to be valid all objectives must be normalized and brought into the same range, which Results Analytics does automatically, otherwise effects of different objective functions will not be equally represented. Users can also choose Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranking method. TOPSIS is a MCDM ranking method that employs the concepts of the positive ideal point (best objective values for all criteria) and the negative ideal point (worst objective values in all criteria) in the objective domain. Design alternatives are ranked based on the shortest geometric distance from the positive ideal point and the longest geometric distance from the negative ideal point in terms of the objective values. [8] In general, TOPSIS will rank a balanced solution higher, even if the design is dominated, while Weighted Sum will rank a cutting edge or non-dominated solution higher. Both ranking methods are provided to accommodate the decision maker's profile. There are many types of MCDM methods, such as additive shortfall and multiplicative. Results Analytics currently only has the top requested, two options. Eventually, users will be able to enter their own MCDM method into the app. In this use case, the ranking method was changed to TOPSIS, since most military programs prefer a more balanced solution to requirements to perform the mission. Concepts that are more balanced now rank higher. The feasibility is reassessed and good as well.

Finally, weight trade-offs can be performed. Since explicitly weighting a requirement is very difficult for a user, priorities are assigned categorically by the user (e.g. MH-Must Have, Priority 1 – Most Important to Priority 5 – Least Important) and automatically translated into weights by Results Analytics in the preliminary requirement definition phase. However, this is intended to only serve as starting point for scoring and ranking. Users at this point can conduct what-if weighting scenarios to capture their true preferences by changing the weights via the slider bars and seeing the effect on the design ranking. Figure 6 shows the Collaborate view, which displays the weight slider bars and rank with score breakdown bar chart. For example in the UAV use case, all the designs meet performance (range and endurance) thresholds, so the weighting on these requirements can be reduced and other criteria, such as affordability (cost) increased. By increasing the weight on cost, more affordable concepts are ranked higher, while meeting performance requirements. In the future, more advanced methods, such as Analytic Hierarchy Process (AHP) coupled with multi-viewing and online voting will be used to elicit preferences from stakeholders as well.

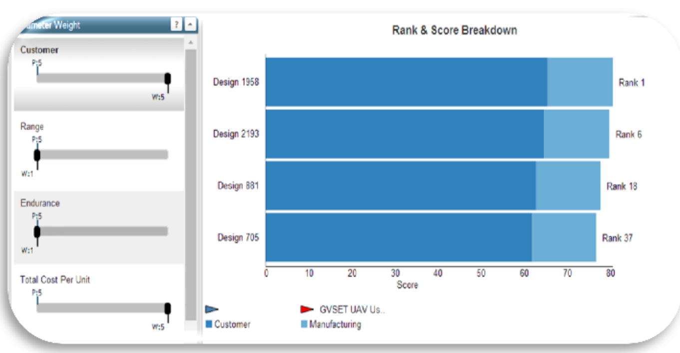

Figure 6: Collaborate View

Users can continue to perform what-if scenarios by iterating upon the hierarchy, thresholds, objectives, ranking method, and weights until the design ranking reflects their true intended desire or outcome for the program. They can also insert benchmarks as points of comparison. Once finalized, all of the ranking components can be captured and shared in the form of a ranking algorithm.

Ranking Algorithm

Sharing a ranking algorithm as part of the request for proposal (RFP) process versus just a set of requirements, allows the program to better represent their preferences versus leaving it open to system integrator's interpretation. It also enables OEMS to focus on more high value, innovative activities, such as finding optimal designs and gaps in technology for investment or partnership. It also gives the program a transparent and defensible tool to justify award decisions. The FANG program was a good use case, where the requirements were heavily weighted towards manufacturability versus performance. The contestants that understood this ended up winning a million dollars. The downside is the ranking algorithm must reflect what the program wants. [10] Otherwise, OEMs could contest award decisions. One way to mitigate this would be to evaluate and monitor designs through-out the design cycle and update the ranking algorithm as necessary to ensure the desired outcome.

CONCLUSION

In conclusion, model based systems engineering needs to be coupled with multi-criteria decision-making in order to create a ranking algorithm to accurately represent the voice of the customer to systems engineers. The benefits of this approach is explicit representation of requirements, rigorous assessment of large design spaces, and improved, rational decisions that are transparent, traceable, and defensible. In turn, these capabilities will accelerate innovative design, while reducing cost. Further areas of research include preference elicitation, risk assessment, and technology portfolio insertion.

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