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A TOOL FOR DESIGN EXPLORATION AND OPTIMIZATION WITH DYNAMIC POWERTRAIN SIMULATION MODELS

Stephen Cooper, PhD
Systems Analysis
General Dynamics Land Systems
Sterling Heights, MI

Frank Patterson, PhD
ELSYS, SERD
Georgia Tech Research Institute
Atlanta, GA

Ramprasad Krishnamachari, PhD
John Srodawa
David Nickel
General Dynamics Land Systems
Sterling Heights, MI

Santiago Balestrini- Robinson, PhD
Tommer Ender, PhD
Jack Zentner, PhD
Georgia Tech Research Institute
Atlanta, GA

Michael Claus
TARDEC
Warren, MI

ABSTRACT

Powertrain system design and integration for ground vehicles is often accomplished using a dynamic simulation to evaluate vehicle performance. This paper applies modern multi-disciplinary design, analysis, and optimization methods to facilitate powertrain system design through dynamic simulation analysis. A collection of surrogate modeling-based MDAO tools are applied to a representative powertrain example to explore the available design space, analyze the feasibility of system performance goals, and make decisions about systems design. Surrogate modeling is shown to facilitate visualization, information synthesis, and decision making in a highly dimensional design problem. Surrogate-based optimization is also demonstrated on the example powertrain design problem to uncover a Pareto frontier of design options for further analysis.

INTRODUCTION

In the design of a powertrain system for a ground vehicle, it is common to use a dynamic simulation model to assess the powertrain-based vehicle performance. It is necessary to perform several iterations with different combinations of design and control variables in order seek an optimal design of such a system. This becomes all the more difficult when the detailed simulation models are composed of different component models, e.g., engine, transmission, cooling, and take considerable time to run through each iteration. System designers would benefit greatly if a design exploration and optimization approach was available that could seamlessly assimilate the powertrain simulation model, run iterations in an automated way, and provide results for evaluation. This paper presents an approach developed under contract with the US Army Tank Automotive Research, Development and Engineering Center (TARDEC) for the Advanced Powertrain Demonstrator Program. The main focus of this paper is to demonstrate the capability available from an approach that can help a powertrain system designer identify better and balanced designs while reducing design process time and resources. This paper uses a simplified powertrain integration design problem to illustrate the application of a suite of modern multi-disciplinary design, analysis, and optimization (MDAO) methods. While not an in-depth analysis of any one method, the approach gives a general review of how MDAO might be applied in the context of the given problem. The background of and reasons behind each

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method used are discussed, as well as some potential expansions that might be needed for increased complexity. The methods themselves provide a starting point for understanding the application of MDAO to complex problems, and can be tuned to a given problem as necessary. This is accomplished in a two-part approach for utilizing MDAO on the powertrain integration that will allow for an interactive design space exploration as well as optimization of the powertrain model.

POWERTRAIN SYSTEM DESIGN

The powertrain system design problem under consideration involves exploring the design space to identify a powertrain solution that best meets vehicle performance and other design criteria. This involves studying how component performance characteristics such as power densities (e.g., for the engine) affect the powertrain size and weight which then influence similar vehicle parameters that affect the vehicle powertrain-based mobility performance. The design exploration capability allows one to explore upfront and understand, for example, the net effect of improvement in an individual component performance versus their overall system integration burden.

MULTI-DISCIPLINARY DESIGN ANALYSIS AND OPTIMIZATION

Multi-disciplinary design, analysis, and optimization (MDAO) is a growing field revolving around the design and optimization of complex systems, in which the strong interaction of multiple disciplines and subsystems necessitates the collaborative manipulation of design parameters throughout the system [1]. Interdisciplinary couplings and often a diversity of conflicting constraints and objectives can create a high dimensional problem that is difficult to navigate manually or with traditional techniques. The practice of MDAO involves the integration of analysis, optimization and decision making techniques to solve complex engineering problems spanning multiple disciplines and subsystems. The process can bridge traditional engineering disciplines (e.g., structures, thermal, control) as well as other lifecycle and economic system properties (e.g., cost, reliability). Utilizing advance modeling and simulation (M&S), MDAO has become an essential part of the design and analysis of complex systems, allowing decentralized teams to collaborate on approaches satisfying multiple, often conflicting, design objectives. General Dynamics, Land Systems (GDLS) has developed a representative dynamic ground vehicle powertrain representative modeling and simulation architecture in MathWorks® Simulink® which serves as the foundation for illustrating this proposed effort.

The need for engineers to analyze and predict complex systems and technologies has led to the development of increasingly complex and accurate modeling and simulation tools. Surrogate models, or metamodels, are mathematical approximations of more computationally expensive analysis or experiments, build from a small, targeted number of evaluations over the design space. While they provide many benefits, surrogates are primarily designed to help relieve the intensive computational cost or run time of high fidelity analysis [2]. Design-of-Experiment (DOE) methods are commonly used to generate the smallest necessary sample of observations that can be used to build a surrogate. Once data is available, surrogates can be built using a multitude of techniques spanning various fidelities. Polynomial response surfaces are often the most common surrogating techniques, and can also be used to screen inputs for more efficient modeling. Other common surrogate techniques involve artificial neural networks, support vector machines, Gaussian process prediction (Kriging), and radial based functions. More advanced approaches may include multifidelity methods combining surrogates of different fidelities to model complex design spaces [3].

Surrogate models have been used for a variety of analyses and in an assortment of industries, including the automotive industry [4-6]. Surrogate models can be used as an enabler to help designers and decision-makers explore and understand the design space. Because prediction runs of the surrogate models are so computationally inexpensive (particularly when compared to the time consuming modeling and simulation environment they represent), they can be used to facilitate interactive design space visualization to help designers identify relationships and areas of interest [6, 7]. In essence, they can be used as a real-time means to answer questions about the design space.

Surrogates also can be used to characterize and explore design spaces probabilistically, using approaches like Monte Carlo Simulation (MCS) or Bayesian methods [4]. These methods can allow for design under uncertainty, accounting for noise variables (e.g., requirements, environment) that are beyond the designer’s control, as well as to illustrate the difficulties of achieving design goals in terms of their probability [5]. Design trade-offs can be conducted manually, by manipulating the surrogates directly to achieve the desired design effect, or automatically, by using them in concert with some optimization or other computational logic.

The application of MDAO also encompasses optimization, and often multi-objective optimization. Designers should seek to thoroughly understand the nature of a design space and the tradeoffs that lie therein, but optimization provides mathematical and/or logical means to help identify promising solutions in complex and multi-dimensional problems. Multi-objective optimization is one of the central pillars of MDAO, and encompasses mathematical optimization problems that involve satisfying more than one objective function simultaneously (and potentially multiple

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constraints). In most non-trivial design problems, a set of Pareto-optimal solutions exist, each of which represents a feasible option where improvement in any one objective will result in degradation of another. A simple example is a decision maker's desire to maximize a vehicle's payload, survivability, and range. However, the more payload and/or survivability (e.g., armor), the lower the maximum range will be, assuming all other variables remain constant. The set of all these potential solutions is referred to as the Pareto Frontier and is one of the simplest means to represent the tradeoffs a decision maker has to make. Various multi-objective optimization methods and approaches are often concerned with thorough and efficient means to identify Pareto optimal solutions based on the decision makers' preferences between objectives.

By utilizing multi-objective optimization methods like the NSGA-II [8] used in the example here, a subset of Pareto optimal solutions can be found for the designer to explore and select from. Moreover, by integrating a surrogate based optimization approach, considerable time can be saved in the optimization process.

APPLICATION OF MDAO TO A POWERTRAIN INTEGRATION PROBLEM

The application of MDAO methods to powertrain system integration for a ground vehicle is demonstrated here through an example design problem formulated to fit the time constraints of the research effort. A dynamic vehicle simulation including drivetrain and powertrain systems was developed in Simulink® and wrapped using a MATLAB® script to perform automated runs.

The Simulink® model uses a scalable map based engine model derived from a prototype engine [9] for max engine powers of 750 to 1500 hp. The model accounts for vehicle mass, rotating mass, cooling loads, parasitic loads, driveline losses and road loads. The cooling load is based on reasonable industry values [10] and is varied with temperature and power according to standard fan laws. Road loads consist of grade, rolling resistance and drag. A scalable transmission model is employed for 4 to 32 gears with a torque converter that is locked for all but gear 1. An adaptive shift strategy is employed that enables optimum gear shifting for performance during acceleration and for optimum fuel efficiency at constant speed. The engine volume scales with power and power density. The transmission volume scales with max engine power, number of gear sets and a technology adjustment. The vehicle weight is then adjusted assuming a fixed payload volume and armor size. The model also imposes a cooling penalty for increased engine power density. All scaling factors and volumes are representative approximations based on the performance of ground vehicles in the weight range addressed in this analysis [10].

The design parameters used for the example problem are outlined in Table 1. For the generation of surrogate models and analysis of the design space, a dummy variable, Gear Ratio Range (0.0, 1.0], was created to replace Maximum Total Gear Ratio. It represents the remaining range between minimum gear ratio and maximum gear ratio and is used to set maximum gear ratio. In addition to the design parameters, several other parameters were also modeled, as discussed later. Note, the other parameters are represented as normalized values. These parameters represent potentially uncertain requirements (payload volume), and vehicle design parameters that may be fall out from other design activities (i.e., vehicle rough density, vehicle drag coefficient). Some, namely the two tech factors, are representative of potential improvements in technology, modeling the effect that advancements in technology may have on transmission weight and volume. While these parameters may not be under the designers direct and free control, they can prove critical in helping decision makers make informed choices.

The design of the vehicle was based on its performance with respect to the objectives listed in Table 2. Each objective has been normalized linearly against a threshold goal corresponding to an objective value of 1.0. The feasibility of the powertrain integration design was considered with respect to the given goals for each objective.

Primary Design Parameters	**Lower Bound**	**Upper Bound**	**Baseline**
Maximum Engine Power (hp)	750	1500	-
Minimum Total Gear Ratio	0.20	4.0	-
Maximum Total Gear Ratio	0.20	22.5	-
Number of Gears	4	32	-
Engine Power Density (normalized)	0.38	1.0	-
Other Parameters	**Lower Bound**	**Upper Bound**	**Baseline**
Payload Volume (normalized)	0.8	1.2	1.0
Vehicle Rough Density (normalized)	0.8	1.2	1.0
Vehicle Drag Coefficient (normalized)	0.8	1.2	1.0
Transmission Weight Tech Factor	0.75	1.0	1.0
Transmission Volume Tech Factor	0.75	1.0	1.0

Table 1: Vehicle Design Parameters and Ranges

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The vehicle simulation was automated using a MATLAB script for expedited data collection. A simple Latin Hypercube Design of Experiments (DOE) was used to exercise the model, collecting data to train surrogate models. In addition to each objective, additional data was collected to characterize the simulation run, including final engine RPM, power, transmission gear, and simulation time. This helped to filter out simulations that did not converge, and further understand potential designs. The first DOE was performed with only the primary design parameters varied, and the other parameters held constant.

The resulting data from the simulation runs turned out to exhibit several complex multi-modal behavior with respect to the modeled objectives. Traditional response surface models did not provide the desired model fidelity for the given data, and thus Kriging models with a Gaussian correlation function were optimized for increased model accuracy throughout the design range [11]. By modeling carefully individually modeling each objective, sufficient models were generated.

Objective	**Goal**
Fuel Economy (30 mph, hot day, Primary-Road) (FuelEconomy_30)	≥ 1.0
Fuel Economy (50 mph, hot day, Primary -Road) (FuelEconomy_50)	≥ 1.0
Fuel Economy (tactical idle, hot day) (FuelEconomy_idle)	≤ 1.0
Top Speed (standard day, Primary-Road) (MaxSpeed_0)	≥ 1.0
60% Grade Speed (standard day, Primary-Road) (MaxSpeed_60)	≥ 1.0
Vehicle Weight (Mbtons)	≤ 1.0
Accel. Time (to 30 mph, standard day) (AccelTime_30)	≤ 1.0
Sprocket Power Density at Top Speed (SpktPowDens)	≥ 1.0

Table 2: Design Objectives

Design space exploration

Surrogate modeling immediately enables the application of a host of design space exploration methods and techniques by facilitating the quick generation of larger and specifically targeted data sets. The dimensionality and sheer size of this data can be quickly overwhelming. However, it is a problem which can be addressed through carefully developed design space visualization tools and techniques. The development of visualization-enabled design space exploration and the visualization of multidimensional problems with multiple objectives has become increasingly important in the design of complex systems [12]. The need for the visualization and

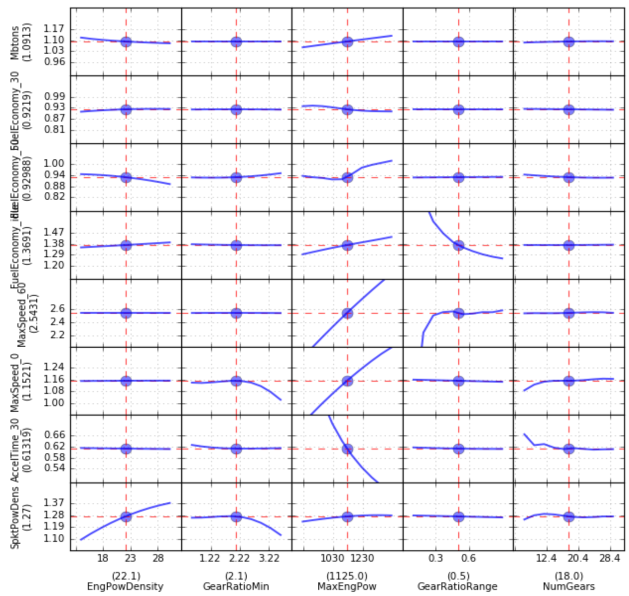

Figure 1: Dynamic Sensitivities Tool

understanding of complex multidimensional datasets is a growing field of interest, particularly with the emergent prevalence of machine learning. This has led to the development of a number of modern toolsets for just this need.

The Python programming language has a growing list of open source libraries providing free access and collaborative development of many of the tools used here for both regression in surrogate modeling [13] and data analysis and visualization [14, 15]. The authors often rely heavily on the use of these libraries to collaboratively create custom design tools to solve complex problems.

One such tool that can be used to explore the available design space is a dynamic sensitivities plot (also called a prediction profiler) [7]. Utilizing the surrogate models, the design space can be quickly queried to determine the individual effect of every design parameter on the constraints and objectives. The dynamic sensitivities chart, shown in Figure 1, illustrates the local sensitivity of each response (objective) with respect to just the design parameter for that column at the design point indicated. This essentially shows each of the partial derivatives at a given design point. The designer can then interactively drag the vertical red lines to change design parameters and explore the design space using this tool.

In Figure 1 the designer can see a number of relationships. For example, sprocket power density is shown at the given design point to be most sensitive to engine power density, and while much increase in minimum gear ratio could be detrimental to sprocket power density, any further reduction wouldn't provide much gain. This is likely due to the effect of gear limiting on top speed.

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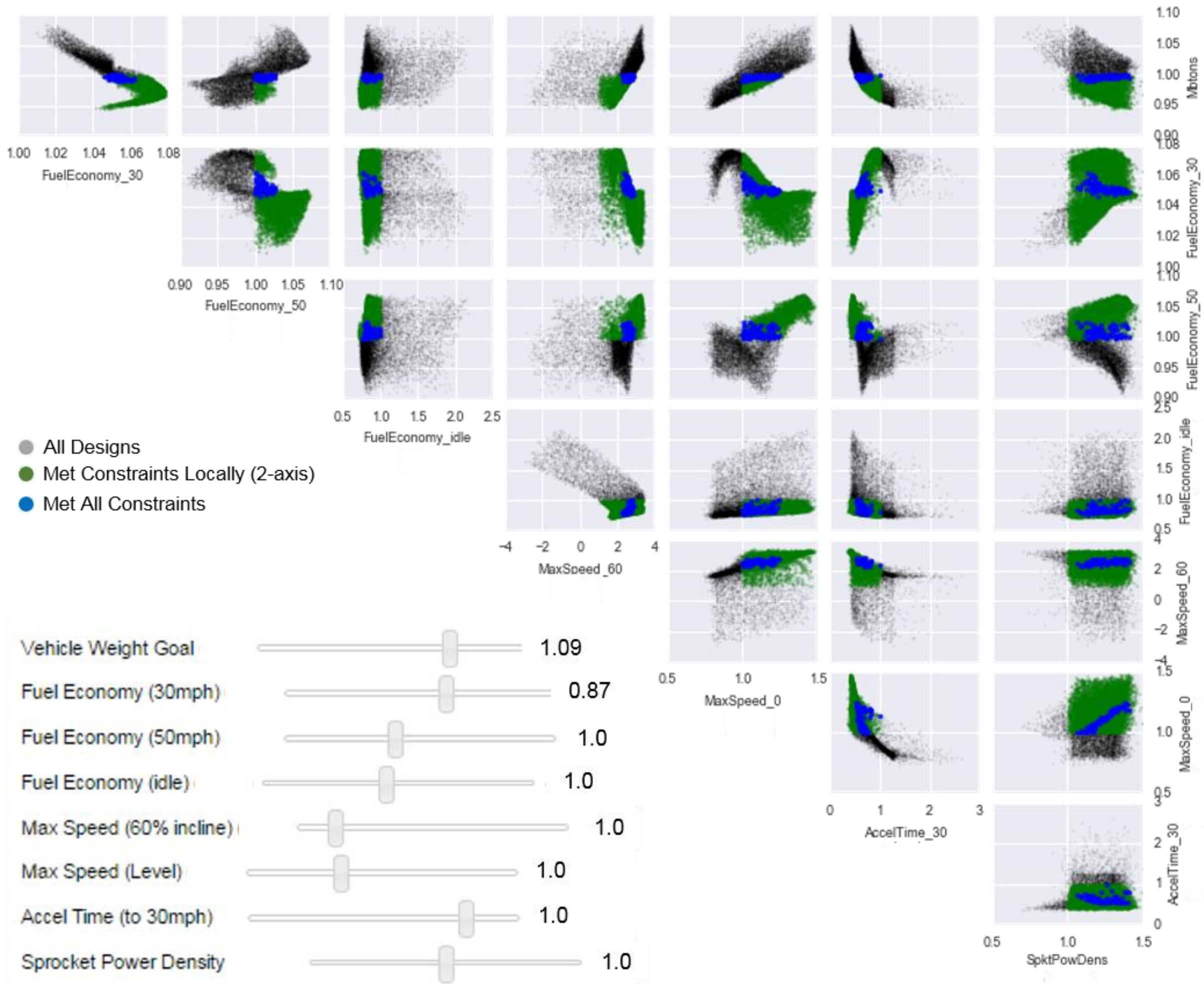

Figure 3: Example Filtered Scatterplot Matrix

Another common visualization method is the parametric, interactive contour profiler (not shown) [7]. This visualization shows the design space in two dimensions as defined by any two input parameters, with the other parameters fixed. Shaded contours are then drawn in the design space indicating regions of the design space that are not feasible with respect to a given constraint of objective. This allows designers to understand the interactions of various constraints and where feasible design space lies with respect to design parameters.

These approaches can be combined with traditional visualizations that might only be able to provide limited information in a multi-dimensional problem before they become too hard to quickly interpret. Figure 2 shows the relationships of several key objectives as engine power density is varied. Multiple lines are shown that represent high and low maximum engine power. The improvement of

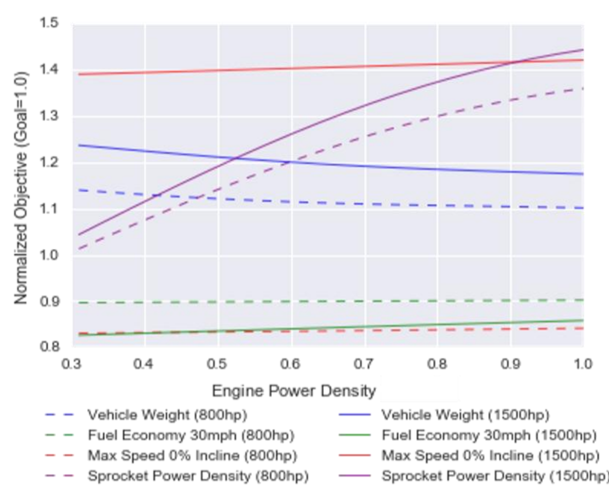

Figure 2: Key Objective Trends vs. Engine Power Density and Max Engine Power

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the illustrated objectives can be seen with increased power density, but the rate of improvement is also seen to decrease.

The core design space was also characterized using simple probabilistic design methods in order to try and better understand how the design goals relate to the available design space. A number of techniques are available to facilitate this approach, including fast probability integration [16] and Bayesian approaches [17], but given the scale of the problem and the development of surrogates, a simple Monte Carlo Simulation was sufficient. The surrogate models were used to generate 10,000 pseudo-random cases using uniform distributions for each of the design parameters.

One potential method of visualizing the design space across objective and constraint dimensions enabled by Monte Carlo Simulation is the scatterplot matrix. With filtering, this analysis can be used with a so-called “inverse design” technique to slowly draw back constraint values and goals to identify a limited number of feasible options that the decision makers can more easily understand.

An example of this technique is illustrated in Figure 3, where each objective goal was interactively varied to show regions of the design space that met all goals simultaneously. The scatterplot matrix shows solutions (in green) that meet just the two goals corresponding to each individual subplot, as well as those (in blue) that meet all eight goals. This clearly illustrates the inherent difficulty of understanding the design space in higher dimensions that cannot be conventionally visualized. In order to find solutions that were feasible across all objectives in Figure 3, some of the goals from Table 2 had to be significantly relaxed. This is an early indication that the desired designs may not be feasible given the limitations of the design parameters in the problem.

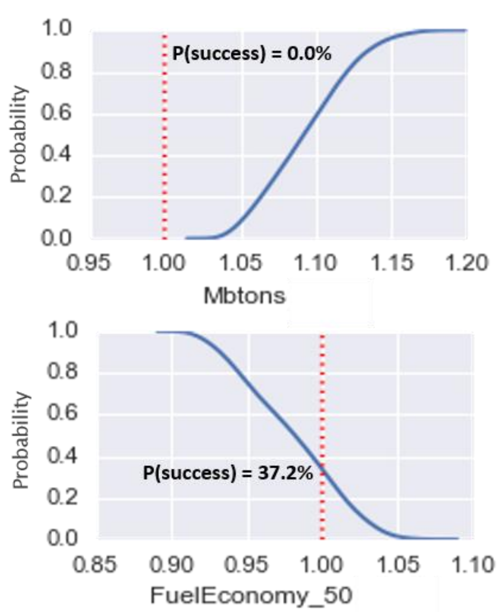

Figure 4: CDFs for Weight and Fuel Economy at 50mph

Each constraint and objective can also be assessed with respect to its likelihood of meeting a given value. In probabilistic design this is accomplished through the generation of either a cumulative distribution function (CDF) or a probability density function (PDF) for each design objective or constraint. These distributions represent the feasible design space by illustrating the possible outcomes of every potential combination of design variables [16]. These results can immediately identify areas of concern, showing goals and constraints with little to no likelihood of being met, and driving high level decisions (e.g. relaxation of requirements, concept re-design, or pursuit of advanced technology).

The CDFs generated for the advanced powertrain demonstration integration in this exercise immediately show several potential impediments in the system design. Figure 4 shows example CDFs for vehicle weight and fuel economy

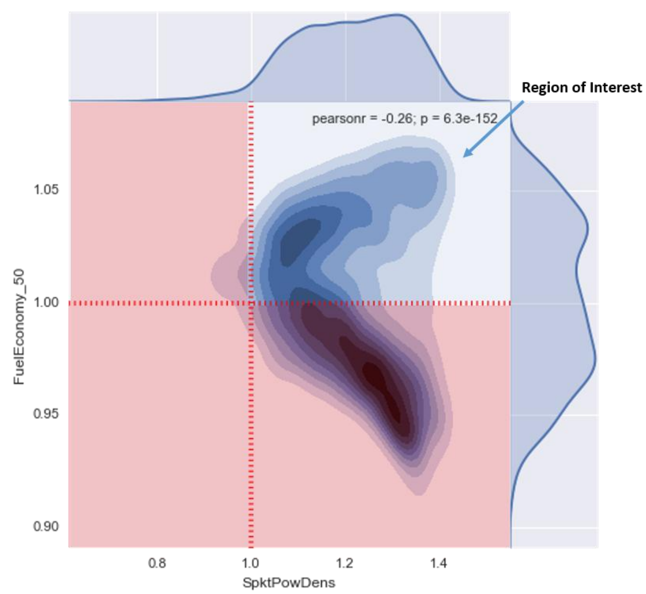

Figure 5: Joint Probability Distribution for Sprocket Power Density and Fuel Economy at 50 mph

at 50mph. No feasible designs were found with weights below the desired threshold goal, illustrated by the corresponding 0% chance of success indicated by the CDF. This primarily is due to the minimum limits imposed on the non-powertrain volume. This indicates that even at their most favorable extremes with respect to only vehicle weight, the available design parameters did not have large enough ranges to produce a design with a low enough weight. On the fuel economy at 50 mph CDF, the goal has roughly a 0.37 chance of success as only 37% of the designs identified meet this individual goal.

These methods only indicate the performance of a single objective, however and a design is only considered feasible if it performs adequately with respect to all constraints and objectives. The 37% of the design space that meet the shown fuel economy goal may not be the same designs that meet or exceed other objectives. Joint distributions, such as the one shown in Figure 5 can quickly be generated with the Monte Carlo data to illustrate feasible designs in multiple dimensions. With filtering, the designs in areas of interest can then be more closely investigated.

It was clear that the primary design parameters did not provide a feasible design space capable of meeting the threshold goals, and decisions had to be made as to how to proceed with the design. A second DOE was run, but this time the other parameters in Table 2 were also varied. A more complicated design problem with numerous technology factors or requirements might require more complicated approaches [18], such as fixing the design parameters to run a separate DOE, but the limited number of total parameters allowed for modeling through an inclusive experiment. New kriging surrogate models were then developed using the second DOE to model the objectives based on all ten of the listed parameters.

With only two technology factors available in the design problem, analysis of technologies was a simple process. More complicated design problems may include discrete technology options with fixed projected improvements (or detriments) to given system attributes. These often require more complex analysis and selection methods [19]. Here, both technology factors could simply be varied to understand their effect on the design. Figure 7 shows the effect of varying the technology factor to represent both a weight and volume reduction in the transmission (factors were varied simultaneously for maximum effect). As shown, while the probability of lower weight vehicles is shifted slightly, it still does not meet the desired goal.

With the limited technology factors and their small effect on the objectives that did not reach goals, the last step was to

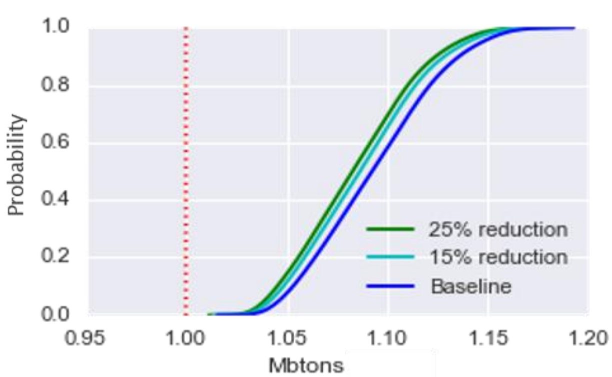

Figure 7: Effect of Transmission Technology Gains on Vehicle Weight

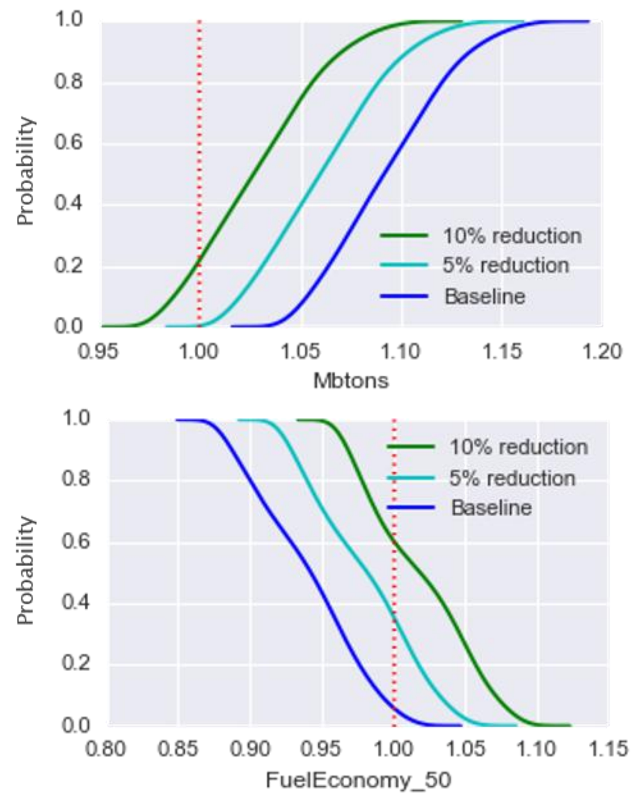

Figure 6: Effect of Payload Volume on Vehicle Weight and Fuel Economy

look at potential reductions to requirements. Payload Volume has a direct effect on vehicle weight, shifting the potential design space in favor of lower weights by reducing the volume as shown in Figure 6, as well as desired effects on other performance parameters. However it should be noted that none of the technology factors or requirements had any substantial effect on tactical idle fuel efficiency, due largely to the fixed load and rpm. For the final optimization the vehicle payload volume was reduced by 10%, and both transmission technology factors were set to 0.9. This ensured that each objective could be met individually, but that finding design candidates to meet all objectives simultaneously would be difficult.

Optimization

Optimization is another core element of MDAO and can also be used as part of a design space exploration. Though less common than their single-objective counterparts, a number of multi-objective optimization methods exist. Appropriate methods are generally selected based on the nature of the problem, the type of design parameters, and how the designers rank or weight the objectives. While mathematically characterizing the surrogate models is

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possible for the Kriging models used, it was desired to check and potentially improve the fits of the models as our optimization progressed to ensure an accurate process. The problem was also expected to expand to include some discrete parameters in future work, likely focused on selecting shift strategy and determining module cooling architectures. For these reasons a genetic algorithm method was utilized here.

The Nondominated Sorting Genetic Algorithm II (NSGA-II), first developed by Deb [8], is a popular means of addressing problems with multiple objectives and constraints to develop a large set of Pareto-optimal solutions. The NSGA-II maintains independence between objectives rather than combine them into a single fitness function. All potential candidates are sorted into a hierarchy of fronts based on Pareto dominance (rank), as well as assessed for their relative distance in the objective space to other candidates along each frontier (crowding distance). Candidate solutions are then sorted and selected based on having the best Pareto rank and being in the least crowded regions. This promotes the survival of a diverse set of Pareto optimal solutions.

The specific goals or preferences between objectives are not numerically considered during this particular multi-objective optimization process. By trying to find a Pareto set of alternatives, the designer can view a subset of design alternatives that would have the best chance of meeting all the goals simultaneously. If a perfect solution doesn't exist on the Pareto frontier, it would not exist in a dominated design region.

A number of approaches have been proposed for integrating surrogate models into the optimization process to relieve the computational expense of costly modeling and simulation [20-22]. A simplistic semi-adaptive approach was used in this case, utilizing the Kriging surrogates to reduce the time of calculating each population's fitness values, with the full optimization procedure in Figure 8. After each generation, a sample of points along the best identified frontier was selected for validation against the original Simulink® simulation. If any of these points had an

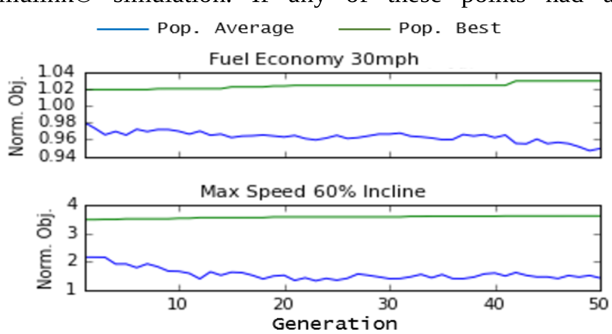

Figure 9: Example Objective Progress for Optimization

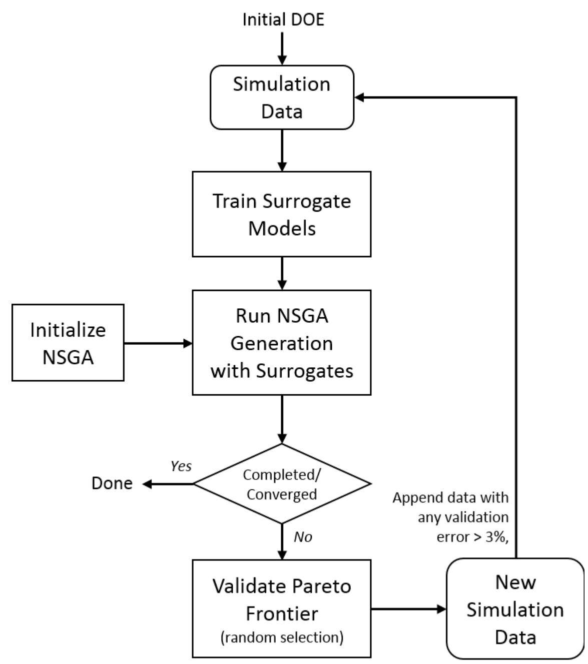

Figure 8: Surrogate Enabled Optimization

objective with validation error greater than a given threshold, that point was then screened for validity and added to the fitting data. Surrogates were then refit to the new data after each generation and validated against a sample of the combined data. If the fit for a given objective was improved, the Surrogate models were then updated to the new models to be used in future generations of the NSGA.

The approach is a relatively simple, but effective one. More complicated methods to take advantage of surrogate modeling with various optimization techniques are becoming more common in MDAO [23]. Some more advanced methods that might be advantageous in very non-linear design take advantage of iterative localized surrogate modeling or combine heuristics like genetic algorithms with local gradient-based techniques [24].

The optimization was run for a fixed 50 generations, with a population of 70 and mutation and crossover rates at 0.025 and 0.65 respectively. After each generation 5 identified Pareto points were randomly selected for the validation step. A fixed validation portion of 20% was utilized with all the available data and several fitting and validation metrics were tracked for each surrogate. The decision was made to update the surrogate models only if the normalized root mean squared error (RMSE) improved after fitting following each generation. These decisions were made specifically to try and improve performance of the surrogates and NSGA for this application, while other problems might require other customized tuning or other adjustments.

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Figure 10 shows the progress of the NSGA by plotting each member of the Pareto frontier for each generation. Progress is often difficult to visualize in higher dimensions this way, but shifts towards better solution can clearly be seen for some objectives, as well as the distribution against each goal value (drawn in red). The algorithm also was forced to compromise several objectives to achieve non-dominated results with respect to other objectives. Some examples of this are also shown in Figure 9, where population averages steadily decrease for fuel economy and max incline speed as their best solutions in those dimensions are dominated in other dimensions by new candidates.

This effect could potentially be eliminated in future implementations of the optimization by creating a fitness function that emphasizes satisficing threshold goals for multiple constraints of objectives without rewarding candidates for over-achieving in a single dimension.

The final population of the NSGA was sorted to check for design candidates that met all of the objectives. Seven specific design candidates that met all the other objective goals simultaneously were found, and these candidates are indicated in Figure 10. It appears from the progress of the optimization that more candidates may have been found had the optimization been run for a longer time. These candidates were also validated using the original simulation, with all surrogated objectives showing errors below 5%, except maximum 60% incline speed, where predictions of low speeds resulted in small absolute errors that were larger in relative terms.

Conclusions

Using a representative dynamic simulation model of a powertrain system for a ground vehicle, this paper has explored a selection of MDAO tools and methods for design exploration and optimization. In order to achieve the accuracy of powertrain system analysis desired, a significantly complex and computationally expensive simulation model is required. Leveraging surrogate modeling allows for quick visualization and interactive exploration of the design space. This provides an efficient means to explore and understand a complicated multi-dimensional design space, limiting time consuming simulation runs. Probabilistic tools were also included to provide a simple example of characterizing the feasibility of the problem. This approach also demonstrates how design feasibility and system effectiveness information can inform early system decisions with respect to requirements, concepts, and technology.

The surrogate models were also utilized to perform a multi-objective optimization. This demonstrates a resource

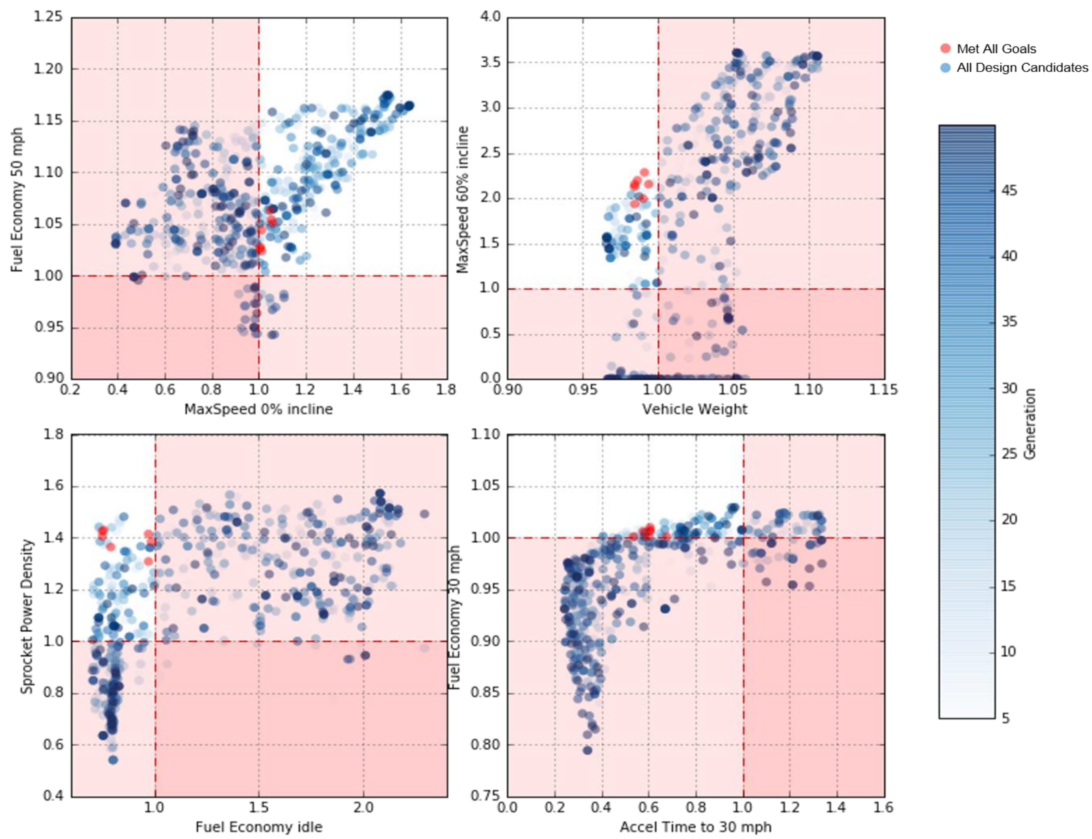

Figure 10: Optimization Progress Scatter Plot

efficient approach to finding a Pareto frontier of validated potential design candidates.

This paper demonstrates a relatively simplistic example and application of a suite of helpful MDAO methods. Presenting how these tools might benefit such a simple problem, the path is paved for including MDAO earlier in the design process when more design and integration decisions are available. By integrating more subsystems and disciplines, and potentially including economic and mission effectiveness models early in conceptual design, MDAO approaches can provide increased benefits for overall system value. Additionally, inclusion of more system-wide technology factors and potentially a suite of specific technologies, return on investment for specific technologies can be forecasted. This process can be, and has been, used to drive decisions about technology investment and the feasibility of future system requirements.

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