Vehicle Family Optimization using Integrated Engineering and Marketing Tools

Scott Ferguson1 and Kemper Lewis2
University at Buffalo – State University of New York, Buffalo, New York 14260

Joseph Donndelinger3
Vehicle Development Research Laboratory, General Motors Research and Development Center, Warren, Michigan 48090

Traditionally, preliminary vehicle design has been a highly iterative process, largely because it is difficult to develop designs that are both highly desirable and technically feasible. The levels of iteration and difficulty increase substantially when multiple vehicles sharing common design elements are designed simultaneously. In this paper, we present a framework for rapidly generating highly desirable and technically feasible preliminary designs for both individual products and product families. Feasibility is assessed using a Technical Feasibility Model (TFM) and desirability is estimated using a market model based on the S-Model. The market model spans multiple market segments with segment-specific customer preferences and is parameterized using sales volume and performance data from existing vehicles.

Optimal vehicle designs are generated within each individual market segment by simultaneously exercising the marketing model and the TFM. The results of these optimizations reveal opportunities for potentially improving the customer-perceived value of the vehicles currently offered for sale in each market segment. The design variables for the individually optimized designs are then investigated for commonality using the performance-to-design space mapping capabilities in the TFM. This analysis shows that in design space, some variables are already shared between the individually optimized vehicles; additional candidates for communization are also identified. A product platform optimization problem is then formulated to investigate tradeoffs between the customer-perceived value of the designs and communality between the designs. The results of this optimization suggest opportunities for increasing communality between designs with minimal decreases in customer-perceived value.

Nomenclature

\[ a_i = \text{meta-model surface coefficient} \]
\[ b_i = \text{meta-model surface coefficient} \]
\[ E_i = \text{price elasticity for an individual competitor within a market segment} \]
\[ F_i = \text{objective functions} \]
\[ f^* = \text{value of vehicle design} \]
\[ f^{\text{P}^*} = \text{individually optimized value of vehicle design} \]
\[ g = \text{performance measure for preliminary vehicle design} \]

1 Graduate Research Assistant, Department of Mechanical and Aerospace Engineering; smf7@eng.buffalo.edu. Student Member AIAA
2 Associate Professor, Department of Mechanical and Aerospace Engineering; kelewis@eng.buffalo.edu. Associate Fellow AIAA.
3 Staff Research Engineer, General Motors Research and Development Center; joe.donndelinger@gm.com. Member AIAA

American Institute of Aeronautics and Astronautics
One of the fundamental goals in preliminary vehicle design is to develop a design that is both highly desirable and technically feasible. Desirability is measured from the customer perspective; performance specifications drive the customer-perceived value of the vehicle which, along with price, drives the vehicle’s market share. Feasibility is measured from the engineering perspective; proposed designs are evaluated to build confidence that they can be realized and manufactured. Traditionally, analyses of desirability and feasibility have been conducted within the marketing and engineering domains (respectively) in a separate and iterative fashion. The goal of this research is to develop a framework for integrating analyses in the marketing and engineering domains during the preliminary stages of the product development process. Additionally, this framework is to be applicable for balancing desirability and feasibility not only for single vehicles, but for entire vehicle families whose entries span multiple market segments with unique customer preferences.

This paper will explore the optimization of a preliminary vehicle design through application of a Technical Feasibility Model and a market simulator. The optimized preliminary designs will be compared to the original baseline vehicle in each market segment. Additionally, by mapping the performance characteristics of the proposed vehicles back into design space, opportunities for commonizing design variables between vehicles may be identified, potentially leading to reductions in manufacturing and design costs. Taken to its fullest extent, examination of opportunities for commonality will also identify opportunities for eliminating variants from the product family. The technical background leveraged throughout this paper is presented in the next section.

II. Background

This research occurs at the intersection of several technology areas: application of a technical feasibility model, market simulation using aggregate yet non-uniform customer preferences, and product family design. This section contains an overview of the relevant material from each of these areas.

A. Technical Feasibility Model

The integration of analytical tools from various disciplines within a common framework to enable multidisciplinary design analysis and optimization has become a well-established practice in vehicle development\textsuperscript{1-2}. The popularity of these frameworks has given rise to a number of research programs within the engineering design community. The Center for Research in Computation and its Applications (CERCA) has developed the Virtual Airplane Design and Optimization framework (VADOR)\textsuperscript{3}, Sandia National Labs have developed the Design and
Analysis Kit for Optimization (DAKOTA)\(^4\) and researchers at NASA Langley have developed the Framework for Inter-Disciplinary Optimization (FIDO)\(^5\).

A Technical Feasibility Model (TFM)\(^6\) may be developed by sampling a multidisciplinary design framework such as those discussed above to collect a set of Pareto-optimal solutions\(^7\), then representing the Pareto set with an approximation model, and finally implementing an algorithm for evaluating the feasibility of test points based on their position relative to the approximation of the Pareto set. If the TFM is parameterized such that all performance objectives are to be minimized, then by definition a test point is feasible if it lies above this Pareto frontier, it is feasible and Pareto optimal if it lies on the Pareto frontier, and it is infeasible if it lies below the Pareto frontier.

This assessment of technical feasibility addresses the question of whether or not the desired levels of performance can be attained. It does not, however, address the question of how they may be attained. A means of mapping relationships between performance space and design space is required to address the additional question of how to realize a desired combination of performance measures in a vehicle design. This capability has been incorporated into the TFM used in this work\(^6,8\) allowing commonality in design space to be considered along with customer-perceived value in the vehicle family design problem.

In this framework, a preliminary vehicle design is considered optimal if it is both Pareto-optimal in the engineering domain and its customer-perceived value has been maximized in the marketing domain. This consumer value is defined relative to a baseline vehicle in each market segment, as established by an S-Model based market model. The theory describing this marketing model is described in the next section.

B. S-Model Market Simulation

The S-Model\(^9\) has been developed for evaluating product design alternatives based on market performance. Application of the S-Model has been demonstrated for a variety of complex products, most notably passenger vehicles\(^10\). In this paper, a vehicle’s customer-perceived value as determined in the S-Model is used as a surrogate for the vehicle’s overall marketplace competitiveness. It can be shown that changes in customer-perceived value translate directly to changes in sales volume and market share if competitors do not change their product offerings and if the price of each product in the market is unchanged, neither of which are unreasonable assumptions.

The market model used in this work has been developed in two phases. In the first phase, a Demand-Price analysis was conducted to determine the customer-perceived values of the vehicles being offered for sale. In the second phase, segment-specific weighting factors for product attributes were determined by regressing value curve parameters on customer-perceived vehicle values in each market segment being investigated.

DEMAND-PRICE ANALYSIS

Demand-Price Analyses are performed to infer the customer-perceived values of competing products based on their transaction prices and market shares. A product’s value may be estimated using the equation:

\[
V_i = P_i + (m_i + 1) \left[ \frac{N^2 \bar{P}}{(N+1)E_i} \right]
\]

where \(V_i\) is the product’s value, \(m_i\) is the product’s market share, \(P_i\) is the product’s price, \(N\) is the number of products in the market segment, \(\bar{P}\) is the market segment average price, and \(E_i\) is the price elasticity for an individual competitor within the market segment\(^9\).

As shown in Fig. 1, in the S-Model customer-perceived value is defined to be the intercept of a product’s linearized demand curve with the price axis. Thus, a product’s customer-perceived value determines the position of its linearized demand curve. As a product’s functional performance improves relative to an established baseline, its demand curve shifts outward. This creates a competitive advantage - meaning, for example, that more products could be sold at a given price or that the products would command a higher price at constant sales volume. Note that if price remains constant, changes in market share are directly proportional to changes in customer-perceived value, as discussed above.
While the Demand-Price analysis addresses the question of what the perceived values are for each product in a market segment, it does not address the question of why. To address this question, as well as to estimate the customer-perceived value for products that do not yet exist, transfer functions are required for relating changes in product performance to changes in customer-perceived value. In the S-Model these transfer functions are known as value curves. The procedures for developing and applying value curves are discussed below.

DEVELOPING AND APPLYING VALUE CURVES

S-Model value curves are used to translate changes in vehicle functional performance into vehicle value for each attribute of a preliminary design. These changes in vehicle value, \( v(g) \), are attributable to changes in product performance measures and are expressed as ratios relative to the value of a baseline vehicle using the equation:

\[
v(g) = \frac{V(g)}{V_0} = \left[ \frac{(g_c - g_I)^2 - (g - g_I)^2}{(g_c - g_I)^2 - (g_0 - g_I)^2} \right] ^ \gamma
\]

in which \( V(g) \) is the customer-perceived value of a vehicle with performance \( g \), \( V_0 \) is the customer-perceived value of the baseline vehicle, \( g_I \) and \( g_C \) are the ideal and critical values of the S-model curve for a performance measure, \( g_0 \) is the performance of the baseline vehicle, and \( \gamma \) is a weighting factor representing the importance of the product attribute. The ideal point of the value curve is defined as the performance level at which the derivative of the value curve reaches zero, meaning that any further improvement in this performance measure does not improve the customer-perceived value of the vehicle. The critical point is defined as the performance level at which the value curve crosses the performance axis, meaning that at this point or beyond the performance of the product is so poor that the customer perceives the vehicle to have absolutely no value. The ideal \((g_I)\) and critical \((g_C)\) points are established globally for each performance measure. The weighting factor, however, may vary between market segments to account for differences in customer preferences. The effect of the weighting factor on the value curve is shown in Figure 2. At its maximum value of 1, the value curve has a parabolic form. As the weighting factor approaches zero, the value curve begins to resemble a heaviside function. Value curve parameters are typically determined through market research\(^1,12\); however, in this work they have been determined via regression.
Using performance data and customer-perceived values for existing vehicles, weighting factors for each performance measure in each segment may be found through regression. Eq. 3 may then be used to estimate the changes in customer-perceived value driven by changes in each measure of product performance. These changes in customer-perceived value are then aggregated to determine the net change in the customer-perceived value of the vehicle using Eq. 4:

\[
V(\mathbf{g}) = V_o \prod_{i=1}^{n} \psi(g_i)
\]  

in which \(V\) is the net value of the vehicle, \(V_o\) is the value of the baseline vehicle, \(\mathbf{g}\) is a vector of \(n\) product performance measures, and \(\psi(g_i)\) is the individual value ratio from Eq. 3.

The TFM may be used in conjunction with a market simulator such as the S-Model to rapidly develop a feasible, efficient, and highly desirable design. However, this approach contains no provisions for identifying and capitalizing upon potential engineering or manufacturing synergies between products. Product family design methods may be applied to this end. In this context, product family design methods are applied to identify opportunities for commonizing design parameters across vehicles to benefit from synergies in engineering or manufacturing.

C. Product Platform Design

Creating a family of products has become a major focus of many manufacturing companies as it reduces cost while allowing for product variety. However, this increase in commonality inhibits the ability to create designs that are fully optimized for performance within their individual market segments. Therefore, the challenge presented lies in determining which components to share when designing the product family while minimizing any resulting decreases in performance. There have been many instances of leveraging product platforms in the design community. Simpson et al. proposed a method based upon a market segmentation grid using compromise decision support and goal programming\(^\text{13}\). Another approach used cost gain models while satisfying performance and budget constraints\(^\text{14}\). Siddique et al. investigated how product variety concepts could be applied to the underbody of an automotive design\(^\text{15}\). In this work, they concluded that these concepts could be applied due to the integral nature of the automotive architecture. Other work has examined how modules influence the development of product platforms, using a fixed modular architecture\(^\text{16,17}\). Papalambros et al study product platforming when considering “mild variants” such that they could be guided by sensitivity information when optimizing their commonality decisions\(^\text{18}\).

This paper will examine opportunities for commonizing design parameters between vehicles based on optimization results from the TFM and market simulation framework. Mapping the results of the performance characteristics of the proposed vehicle in each market segment to the design space, commonalities in vehicle design parameters will be identified. This study will be completed by formulating the product platform optimization problem as presented by Fellini et al.\(^\text{19}\). In this work, Fellini has developed an optimization problem to maximize commonality subject to performance loss constraints resulting in the single objective optimization problem of Eq. 5.
\[
\max \sum_{i,j \in P} \omega_{ij} D_a (x_i^p - x_j^q) \quad \forall p, q \in P, \ p < q
\]

subject to:
\[
\begin{align*}
g^p (x^p) &\leq 0 \\
h^p (x^p) &= 0 \\
f^p (x^p) &\geq (1 - L^p) f^p^*
\end{align*}
\]  

In this notation, products \( p \) and \( q \) are members of the set \( P \), which denotes the totality of products being designed. The performance constraint bounds \( f^p \) are based upon performance loss factors \( L^p \) and the individual product optimas \( f^p^* \). The performance loss factors are defined by the designer and are considered input parameters in this formulation. The incorporation of the term \( \omega_{ij} \) accounts for designer preferences for sharing the design variables \( x_i^p \) and \( x_j^q \).

The main term of the objective function, \( D_a \), is an approximation of a heaviside function whose value is unity when \( x_i^p = x_j^q \) and zero otherwise. This approximated function ranges between zero and one, and is continuously differentiable. Defined in Eq. 6, this term approaches the behavior of a heaviside function as \( \alpha \) approaches zero.

\[
D_a (x_i^p - x_j^q) = 1 - \frac{1}{\left( \frac{x_i^p - x_j^q}{\alpha} \right)^2 + 1}
\]  

Therefore, the methodology is executed as follows:

1. Determine the optimal configuration for the individual products
2. Identify the design variables that can be shared between products and assign associated weighting factors \( \omega_{ij} \)
3. Determine the acceptable performance loss factors \( L^p \)
4. Solve the commonality optimization problem

Completion of these steps will reveal platforming opportunities and present associated performance losses in generating the product family. The designer is then tasked with assessing whether the platforming solutions are preferable to the individually optimized vehicles. For cases in which the commonality between two designs is very strong, it may also be prudent to eliminate a variant from the product family. Such a decision could be made, for example, if a single new product offers increased customer value in more than one market segment. This would provide for substantial reductions in manufacturing complexity and cost with only a minimal tradeoff in customer value.

Now that the theoretical foundation for this paper has been presented, these concepts will be applied to a simple case study problem. This case study problem will first discuss the identification of the market segments used and the creation of the market model. Applying the market model to create preliminary vehicle design concepts, a proposed vehicle will be created for each segment that possesses an optimal perceived value. Finally, these vehicles will be analyzed for potential product platform opportunities, and the tradeoffs between sharing components and architectures versus the loss in perceived value will be examined.

III. Case Study: Passenger Sedan Design

This case study involves the design of a hypothetical family of three passenger sedans, each residing in a different market segment. The framework used in this case study is shown in Figure 3. A TFM covering the performance measures shown in Table 1 and the design variables shown in Table 2 has been used in this framework along with a market model that covers, except for \( F_5 \), all of the performance measures shown in Table 120. The inputs to the framework are initial values for the performance measures of each vehicle. These performance measures are then optimized for each vehicle individually using the TFM in conjunction with the market model such that the customer-perceived value of each vehicle is maximized subject only to the constraint that its combination of performance measures is assessed as either feasible or feasible and Pareto optimal by the
The design variables corresponding to each vehicle’s optimum performance are then queried and overlaid to identify opportunities for commonizing design variables.

Table 1. Description of performance metrics measured

<table>
<thead>
<tr>
<th>Objective</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_1$</td>
<td>Vehicle acceleration measurement</td>
</tr>
<tr>
<td>$F_2$</td>
<td>Height packaging measurement</td>
</tr>
<tr>
<td>$F_3$</td>
<td>Fuel consumption metric</td>
</tr>
<tr>
<td>$F_4$</td>
<td>Interior width measurement</td>
</tr>
<tr>
<td>$F_5$</td>
<td>Cargo volume measurement</td>
</tr>
</tbody>
</table>

Table 2. Design Variables used in creation of the TFM

<table>
<thead>
<tr>
<th>Design Variable</th>
<th>Description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>Vehicle length measurement</td>
<td>Continuous</td>
</tr>
<tr>
<td>$x_2$</td>
<td>Partial vehicle length measure</td>
<td></td>
</tr>
<tr>
<td>$x_3$</td>
<td>Partial vehicle length measure</td>
<td></td>
</tr>
<tr>
<td>$x_4$</td>
<td>Passenger position measurement</td>
<td>Continuous</td>
</tr>
<tr>
<td>$x_5$</td>
<td>Vehicle height measurement</td>
<td>Continuous</td>
</tr>
<tr>
<td>$x_6$</td>
<td>Vehicle width measurement</td>
<td>Continuous</td>
</tr>
<tr>
<td>$x_7$</td>
<td>Powertrain selection</td>
<td>Discrete</td>
</tr>
</tbody>
</table>

A. Market Model Development

A “good, better, best” marketing strategy is being implemented for the vehicle family in this case study. The manufacturer’s current product entry is defined as the baseline vehicle in each market segment. This information is summarized in Table 3.

Table 3. Market model and baseline vehicle description

<table>
<thead>
<tr>
<th>Market Segment</th>
<th>Ranking</th>
<th>Baseline Vehicle Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Segment 1</td>
<td>“Good”</td>
<td>Brand A</td>
</tr>
<tr>
<td>Market Segment 2</td>
<td>“Better”</td>
<td>Brand A</td>
</tr>
<tr>
<td>Market Segment 3</td>
<td>“Best”</td>
<td>Brand A</td>
</tr>
</tbody>
</table>

To conduct the Demand-Price Analyses, sales volume and transaction price data were compiled for vehicles offered for sale in each market segment during the 2000-2004 model years. Vehicles that were redesigned during that timeframe were considered to be separate market entries for statistical purposes. Demand-Price analyses were then conducted for each model year within every segment to produce annual estimates of customer-perceived value for each vehicle in every segment. These estimates were then normalized relative to the customer-perceived value of the baseline vehicle. An example of the Demand-Price analysis results is shown in Table 4.
Table 4. Market segment 2 value analysis

<table>
<thead>
<tr>
<th>Vehicle Year</th>
<th>Vehicle</th>
<th>Normalized Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>Brand B</td>
<td>0.975</td>
</tr>
<tr>
<td>2001</td>
<td>Baseline vehicle</td>
<td>1.0</td>
</tr>
<tr>
<td>2003</td>
<td>Brand C</td>
<td>0.939</td>
</tr>
</tbody>
</table>

Given overall customer-perceived values of existing vehicles along with their performance specifications, value curve parameters may be found by regression using Eq. 3 and Eq. 4 as structural equations. The number of objectives for which value curve parameters could be found was limited by the number of degrees of freedom available in the market data; hence value curves were developed only for performance objectives $F_1$ through $F_4$ in Table 1. The weighting factors for these performance measures within each market segment are shown in Table 5.

Table 5. Segment-Specific Weighting Factors for Value Curves

<table>
<thead>
<tr>
<th>Market Segment</th>
<th>$\gamma(F_1)$</th>
<th>$\gamma(F_2)$</th>
<th>$\gamma(F_3)$</th>
<th>$\gamma(F_4)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Segment 1</td>
<td>0.233</td>
<td>0.835</td>
<td>0.60</td>
<td>0.538</td>
</tr>
<tr>
<td>Market Segment 2</td>
<td>0.887</td>
<td>0.737</td>
<td>0.90</td>
<td>0.742</td>
</tr>
<tr>
<td>Market Segment 3</td>
<td>0.857</td>
<td>0.345</td>
<td>0.387</td>
<td>0.448</td>
</tr>
</tbody>
</table>

Some interesting trends may be observed in the weighting factors. The weighting factor for Objective $F_1$ (acceleration) is relatively low in Market Segment 1 while the weighting factors for the remaining objectives are relatively high, suggesting that acceleration is neither a product differentiator nor a customer exciter in this segment and that purchase decisions in this segment are more heavily influenced by differences in fuel economy and interior accommodation than by differences in acceleration. An opposite trend is observed in Market Segment 3; the relatively high weighting factor for Objective $F_1$ and the relatively low weighting factors for the other objectives suggest that purchase decisions in this segment are heavily influenced by differences in acceleration while differences in other performance measures have relatively little bearing on purchase decisions. The weighting factors are rather high for all objectives in Market Segment 2; perhaps this is a niche segment in which customers are generally willing to pay premium prices for premium products.

The regression solution of the weighting factors provides the necessary information to complete the market model. Now, given the performances of a preliminary design, it is possible to predict the overall value of the design with respect to the baseline vehicle of its segment. Combining the abilities of the market model with the TFM will allow this value to be determined while ensuring feasibility of the proposed design. This process is discussed in the next section.

B. Individual Vehicle Optimization

The goal of this exercise is to identify the feasible and Pareto-optimal performance point with maximum customer-perceived value for each market segment. These solutions are found by applying the optimization problem formulation presented in Eq. 7:

$$\text{Maximize: } F_{\text{NormScore}}$$

Subject to: $g_i(F_j) : F_j - (a_0 + \sum_{k=1}^{4} (a_k F_k + b_k F_k^2)) \leq 0$

$$g_2(F_j) : LB(F_j)^{\text{MS}} \leq F_j \leq UB(F_j)^{\text{MS}}$$

$$g_3(F_j) : LB(F_j)^{\text{TFM}} \leq F_j \geq UB(F_j)^{\text{TFM}}$$

for $i = 1...5$

for $j = 1...5$

(7)

Where $F_{\text{NormScore}}$ is the customer-perceived value of the vehicle normalized relative to the customer-perceived value of the market segment baseline vehicle. There are three constraints imposed in this optimization problem. The first is an inequality constraint that forces the final solution to lie either on or within the feasible region of the Pareto frontier of the TFM. The second order equation in this constraint represents a metamodel of the Pareto frontier where each $F$ refers to one of the performance objectives. The second inequality constraint places bounds on the allowable design variables, in this case the values of the performances, defined by the ranges of performances.

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among existing vehicles in each market segment. The final inequality constraint ensures that performance specifications for every vehicle remain stay within the domain of the TFM.

To ensure that the solution to the optimization problem was realistic for each market segment, it was necessary to introduce the second inequality constraint. Solutions without this constraint were examined to possess behaviors that maximized certain performance measures due to the behavior of the market model. This was mainly due to the lack of a monetary cost function that would penalize the increase of certain measurements. The inequality constraints were established based upon the upper and lower bounds seen by actual vehicles that were produced and fit in a given market segment. Implementation of these constraints helped provide a more realistic solution to what would be expected in a real-world production scenario. Enacting these constraints also provided increased realism in the product platform optimization, and will be discussed further in the next sections.

The solutions of the individually optimized vehicles all possessed greater perceived value than their baseline counterparts. Comparing each of the three proposed sedans to their baseline counterparts, the tradeoffs in performance become apparent. Table 6 shows the value of $F_{\text{NormScore}}$ for each of the proposed vehicle designs, as well as the performance differences when compared to the baseline vehicles.

<table>
<thead>
<tr>
<th>Performance Objective</th>
<th>Market Segment 1</th>
<th>Market Segment 2</th>
<th>Market Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_1$ (-11.6%)</td>
<td>0.2%</td>
<td>16.98%</td>
<td></td>
</tr>
<tr>
<td>$F_2$ 2.63%</td>
<td>0.5%</td>
<td>1.0%</td>
<td></td>
</tr>
<tr>
<td>$F_3$ 8.3%</td>
<td>17.16%</td>
<td>3.54%</td>
<td></td>
</tr>
<tr>
<td>$F_4$ (-2.86%)</td>
<td>(-4.19%)</td>
<td>(-5.54%)</td>
<td></td>
</tr>
<tr>
<td>$F_5$ 10.3%</td>
<td>3.75%</td>
<td>5.42%</td>
<td></td>
</tr>
<tr>
<td>Normalized Value</td>
<td>1.075</td>
<td>1.162</td>
<td>1.031</td>
</tr>
</tbody>
</table>

These results indicate that based on the marketing model, the greatest value increases were gained by changing objectives $F_1$ and $F_3$. As there were not enough degrees of freedom to include a performance value for the cargo volume metric, changes in this measure occur solely for the purpose of ensuring design feasibility. As a result of the optimization, all the proposed preliminary designs lie on the Pareto frontier of the TFM. In all market segments, the major tradeoff leading to an overall value increase is a decrease in $F_4$ with offsetting increases in other objectives. Recalling the discussion in the previous section, there is also a noticeable reduction in $F_1$ for the product in the first market segment. This result is expected due to the relatively low weighting factor for this objective in this market segment, as changes in this measure have only small impacts on overall vehicle value.

One of the most powerful capabilities of the TFM used in this work is its ability to map performance to their corresponding design variables. For each non-dominated point in performance space, the corresponding region in design space is tabulated and represented by mean value and a design tolerance. Therefore, the centroid of this region in design space represents the nominal values of design variables required to obtain the desired performance measures, with tolerances determined by the bounds of the mapped region. Mapping the performances of the individually optimized vehicles in each market segment to the corresponding values in design space allows for the identification of shared design variables. The mapping of seven geometric design variables is shown in Fig.4.

Figure 4. Design Space Mapping for Preliminary Vehicle Designs
In this figure, the centroids of design space regions for market segments 1, 2, and 3 are represented by a circle, an $x$, and a diamond, respectively. The bars extending outward from the centroids represent the tolerances on each of the design variables. These results show that there are some design variables – such as $x_3$, $x_4$, and $x_5$ – that could be shared by all three vehicle designs. Design variables $x_3$ and $x_5$ share a common centroid for all three vehicles. On the other hand, some design variables do not overlap at all, identifying unique characteristics of each vehicle. The results suggest that the vehicles in market segments 2 and 3 are more likely to share design variable values than vehicles 1 and 2 or vehicles 1 and 3.

C. Vehicle Family Optimization

The individual optimization of the three vehicles in this section demonstrates the benefit of combining a Technical Feasibility Model with a market model. Feasible designs with high customer-perceived value were identified in every segment. In addition, by exercising the performance to design space mapping capability of the TFM, some opportunities for communization of design variables have already been identified. The performance-to-design mapping also suggests that additional opportunities for communization of design variables remain, presumably with some tradeoff in the optimality of the individual vehicles. These tradeoffs are formulated and discussed in the next section.

DETERMINING FAMILY SHARING WEIGHTS

For the vehicle model used in this case study, all of the variables in the design space are eligible to be shared between the different vehicle designs. However, the likelihood of the three vehicles sharing all design variables and maintaining an acceptable customer value is low. As demonstrated in the previous section, the vehicles in Market Segments 2 and 3 had similar configurations and had more potential sharing opportunities. Furthermore, the vehicle in Market Segment 2 is more likely to share a design variable with vehicles in Market Segments 1 and 3, than the vehicle in Market Segment 1 sharing with Market Segment 3. These trends are consistent with the “good, better, best” marketing strategy outlined earlier. Such trends can be programmed into the vehicle family optimization by setting appropriate values for the family sharing weights $\omega_{ij}^{pq}$ in Eq. 5.

In a uniformly weighted product family optimization, the likelihood of design variables being shared between any two products is the same. However, the “good, better, best” strategy suggests that likelihood of sharing should be higher between Market Segments 1 and 2 and Market Segment 2 and 3 and lower between Market Segments 1 and 3. A set of family sharing weights developed to encourage these trends in design variable sharing and used in this optimization are shown in Table 7. The weights in Table 7 were selected to equally promote sharing between Segments 1 and 2 and Segments 2 and 3 while discouraging sharing between Segments 1 and 3. As the weights must necessarily sum to one, the weight for Segments 1 and 3 was reduced. These weights are unique for each problem and may be changed as needed to produce the desired results.

<table>
<thead>
<tr>
<th>Market Segment 1</th>
<th>Market Segment 2</th>
<th>Weighting Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segment 1</td>
<td>Segment 2</td>
<td>0.4167</td>
</tr>
<tr>
<td>Segment 1</td>
<td>Segment 3</td>
<td>0.1666</td>
</tr>
<tr>
<td>Segment 2</td>
<td>Segment 3</td>
<td>0.4167</td>
</tr>
</tbody>
</table>

DETERMINING ACCEPTABLE PERFORMANCE LOSS FACTORS

As defined in Eq. 5, the performance loss factor $L^p$ establishes a lower bound for the acceptable loss of $f_v$ in this case vehicle value, when trading performance for increased product platforming. This value is left entirely at the discretion of the designer. For this problem, two different loss factors were investigated, $L^p = 0.1$ and $L^p = 0.05$. The 10% performance loss case was established as an absolute lower bound as two vehicle allowable values were below 1.0, as seen in Table 8.
As the goal of this optimization is to promote sharing of design parameters within the vehicle family development while still realizing gains in customer-perceived value relative to the current market offerings, this was considered to be an acceptable maximum lower bound constraint.

During the first attempts at solving the product family optimization problem, the lowest allowable value deviation was constrained to be 1. This constraint was relaxed in subsequent attempts, resulting in increased design variable sharing and overall improvements in solution quality. With the selection of the family sharing weights and performance loss factors, the necessary elements in Eq. 5 have been defined, and the product family optimization can proceed.

**SOLVING THE COMMONALITY OPTIMIZATION PROBLEM**

The optimization problem defined in Eq. 5 was solved using a simulated annealing algorithm. The performance measures of the three individual vehicles were defined to be the design variables in the optimization. Given a set of performance measures, the TFM mapped the appropriate centroid and tolerance in the design space. However, the nature of the design variable mapping posed a unique challenge in formulation of the optimization problem. It stands to reason that design variables may be considered shared between two vehicles if their hyperboxes in design space overlap completely. It is less clear, however, how sharing should be reckoned when hyperboxes overlap partially.

This issue was overcome by considering only the smaller of two design tolerances when evaluating design variable sharing. If the smaller design tolerance overlapped the centroid of the larger design hyperbox, the two designs were considered to share the same value for the design variable. Figure 5 shows the percentage of design variables shared among the three vehicles. While design variables $x_3$ through $x_5$ are shared 100% by the designs, a majority of the remaining variables are not shared at all.

![Figure 5. Design Variable Sharing Among the Three Vehicles](image)

The 10% performance loss factor had the lowest objective function value of the three cases at a value of 3.874. The values of the minimized objective functions and the customer-perceived values of the three market segment vehicles are shown in Table 9. These results show that there is a direct correlation between the increase in loss factor and an increase in the amount of design variable sharing between the vehicles. In both cases with a non-zero loss factor, it was necessary to reduce one of the vehicle values below the segment baseline value to increase design variable sharing. The vehicle with value lower than baseline, is not consistent across solutions, however; it switches from the third market segment to the vehicle in the first market segment. The percentage of design variable sharing for the 10% loss factor solution is compared to that of the individually optimized vehicles in Figure 6; the centroids and tolerances of design variables for the vehicle family optimization are also presented in Figure 6.
Table 9. Product family optimization results comparison

<table>
<thead>
<tr>
<th>Loss Factor</th>
<th>Minimized Objective Function Value</th>
<th>Value of Market Segment 1 Vehicle</th>
<th>Value of Market Segment 2 Vehicle</th>
<th>Value of Market Segment 3 Vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>( L_p = 0.0 )</td>
<td>10.278</td>
<td>1.07</td>
<td>1.16</td>
<td>1.03</td>
</tr>
<tr>
<td>( L_p = 0.05 )</td>
<td>4.088</td>
<td>1.02</td>
<td>1.11</td>
<td>0.98</td>
</tr>
<tr>
<td>( L_p = 0.1 )</td>
<td>3.874</td>
<td>0.99</td>
<td>1.08</td>
<td>1.00</td>
</tr>
</tbody>
</table>

![Figure 6. Design Variable Sharing Results for \( L_p \approx 0.1 \)](image)

In the 10% loss factor solution, all of the design variable values are shared completely except for \( x_1 \) and \( x_7 \). However, sharing exists for those variables because vehicles 2 and 3 share all design variables. These results suggest that it could be beneficial to offer only two vehicles in this product family. By doing so, the costs of designing and manufacturing a third vehicle design are avoided with minimal impact on the competitive position of the product family, effectively realizing all of the benefits of commonality optimization. It should be noted that this type of solution with a reduced number of variants in the product family is not guaranteed for all commonality optimization problems. As might be expected from inspection of the weighting factors on the value curves, the vehicle in the first market segment has unique values for a vehicle length measurement (smaller) and a unique powertrain (less powerful and more efficient).

The results in this section illustrate the tradeoff between individual product performance and design variable sharing within a product family. The individually optimized designs have maximum customer-perceived value, yet offer only limited opportunities for design variable sharing. At some point, design variable sharing comes at the expense of product desirability, but this can be controlled through careful tuning of performance loss factors. Ultimately the definition of an appropriate tradeoff between commonality and product desirability is left to the decision-maker.

IV. Conclusion

This paper presents a methodology for preliminary vehicle design and optimization using an engineering-based Technical Feasibility Model and a market simulation model along with product family design optimization to promote commonality between vehicle designs. A TFM provides a means of assessing the feasibility of a combination of performance measures of a preliminary design as well as performance-to-design space mapping capability. Application of the TFM along with a market model provides a means of identifying preliminary designs that are both technically feasible and highly desirable. The use of weighting factors in the S-Model to represent non-uniform customer preferences has been illustrated and it has been shown that these weighting factors may be found through regression using market and performance data for existing vehicles.

Mapping individually optimized vehicles from performance space to design space revealed a substantial level of natural design variable commonality. Three of the seven design variables were common among all three vehicles, while a fourth was common among two of the vehicles. Further investigation showed that the second and third market segments denoted as “better” and “best”, were inclined to have similar design variable values. Such a result aided in setting the weights for the commonality optimization, as it was seen that the segments furthest from each other were not naturally inclined to share design variable values.
The product family optimization focused on promoting commonality within the three vehicles while maintaining specified minimum levels of performance. A performance loss factor of 0.10 was found to possess the best tradeoff between commonality and value degradation. Loss factors greater than 0.10 allowed unacceptable losses in customer-perceived value. Mapping from the performance space to the design space also proved to be more complicated for the commonality optimization. Using the tolerances of both designs allowed for too much design space overlap. In an extreme case, this technique returned common designs whose centroids were 16% of the design space apart. For the purpose of the commonality optimization, only the smallest of the two design tolerances was used. This allowed for correct application of the design tolerance mapping approach, identifying commonalities only where they truly existed. The commonality optimization resulted in the vehicles in the second and third market segments to have a completely common design.

References


