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A PARETO APPROACH TO ALIGNING PUBLIC AND PRIVATE OBJECTIVES IN VEHICLE DESIGN

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ABSTRACT

The quest for producing vehicles friendlier to the environment is often impeded by the fact that a producer private good objective, such as maximum profit, competes with the public good objective of minimizing impact on the environment. Contrary to commercial claims, there may be no defined decision maker in the vehicle production and consumption process who takes ownership of the public good objective, except perhaps the government. One way eco-friendly products could become more successful in the marketplace is if public and private good objectives become more aligned to each other. This paper introduces three metrics for comparing Pareto curves in bi-objective problems in terms of relative level of objective competition. The paper also presents a quantitative way of studying an individual firm's trade-off between profit and fuel consumption for automotive products, currently undergoing an historic evolution in their design. We show how changes in technology, preferences, competition, and regulatory scenarios lead to Pareto frontier changes, possibly eliminating it altogether.

1 INTRODUCTION

Quantitative studies of trade-offs between competing objectives are ubiquitous. They typically focus on finding Pareto points [1] and the preference structure for selecting one point among many —or vise versa. Preferences or constraints that lead to the trade-off relationship are assumed fixed.

However, changes to the mathematical structure and input parameter values of the optimization model can lead to changes in the shape of the attainable set and its Pareto boundary. These changes can be captured by the objective function gradients and constraint activity shifts. Furthermore, psychologists have shown and recent work in the design community has begun to explore that decision maker preferences do not necessarily exist a priori. This finding implies decision maker preferences may be influenced by evolving tradeoffs—hence the value of studying them systematically [2-5].

Economic externalities affect decision-making. An externality exists when consumers and producers do not explicitly consider all costs and benefits associated with their choices, as observed by society. A negative externality occurs when a decision maker does not bear the full cost of a decision and over-produces or over-consumes. Figure 1 shows the market equilibrium point compared with the societal ideal with respect to supply and demand, and price.

Negative externalities related to automobiles include traffic congestion, harmful pollutant emissions, road degradation, accidents, and greenhouse gas (GHG) emissions. Mechanisms such as fuel taxes, emissions standards, and fuel economy standards reduce some of these externalities. However, one may argue that they do not internalize the total cost to society, and that an externality still exists, particularly with respect to GHG emissions. This paper will not discuss public valuation [6] or finding the "right" price for GHG emissions. Instead, the paper presents analysis of the trade-off between profit and fuel consumption to support the private decision of a producer to act in its best interest.

This paper continues work studying public and private interest in vehicle design [7, 8] and formalizes metrics for comparing trade-off scenarios. We adopt an enterprise-wide trade-off model [7, 9, 10] with two objectives: a private one (a firm's stated business objective to maximize profit) and a public one (a firm's stated social objective to minimize environmental impact). The enterprise balances these competing objectives with price and product design as decision variables.

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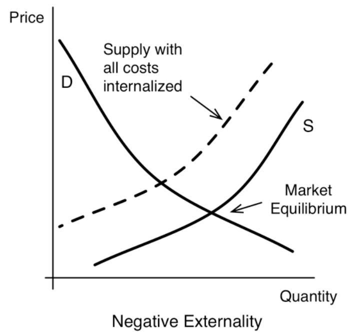


Figure 1: Negative externalities result in market equilibrium away from societal ideal equilibrium

The environmental impact metric used in this paper is fuel consumption per distance traveled, as vehicle use constitutes as much as 85% of GHG and other emissions [11, 12]. For a fixed number of vehicle miles traveled, emissions decrease as vehicle fuel economy increases.

We hypothesize that we can measure how much two objectives compete in a Pareto problem. The less they compete the more aligned they are. A multicriterion or Pareto optimization problem is stated as:

$$\begin{aligned} &\min \;\; \mathbf{f}(\mathbf{x}) \\ &\text{Subject to: } \mathbf{h}(\mathbf{x}) = 0;\; \mathbf{g}(\mathbf{x}) \le 0;\; \mathbf{x} \in \mathcal{X} \end{aligned} \tag{1}$$

Here $\mathbf{f}(\mathbf{x})$ is a vector of criteria of interest $f_i,\, i = 1,\, \ldots,\, n$. The set of variable values $\mathbf{x}$ that satisfy all constraints is the feasible (design) domain, $\mathcal{S}$. The range set of all vectors $\mathbf{f}$ mapped from the feasible domain is the attainable set $\Xi = \{\mathbf{f}(\mathbf{x}) \mid \mathbf{x} \in \mathcal{S}\}$. A point in Ξ, $\mathbf{f}^*(\mathbf{x})$ is said to be non-dominated, or Pareto optimal, if there exist no $\mathbf{f}(\mathbf{x})$ such that $\mathbf{f}(\mathbf{x}) \le \mathbf{f}(\mathbf{x}^*)$, $f_i(\mathbf{x}) < f_i(\mathbf{x}^*)$ for at least one i.

Ideal values are the optimal values obtained using one criterion at a time,

$$f_i^\circ = \min\left\{ f_i(\mathbf{x}) \mid \mathbf{h}(\mathbf{x}) = 0, \mathbf{g}(\mathbf{x}) \le 0, \mathbf{x} \in \mathcal{X} \right\}, i = 1, \ldots, n .$$

Nadir values are the worst values for each criterion found in the set of Pareto optimal points. For a bi-criterion problem the nadir value for one criterion can be found when the other criterion reaches its ideal value: $f_i^N = \{ f_i(\mathbf{x}) \mid f_j(\mathbf{x}) = f_j^\circ \}$ [13]. The ideal or utopia point is the vector of ideal values for all criteria, $\mathbf{f}^\circ = \left[f_1^\circ \;\; f_2^\circ \right]'$.

The remainder of the paper is organized as follows. Section 2 introduces metrics for how much two objectives compete. Section 3 describes the bi-objective vehicle design optimization problem used in the demonstration study. It is stated at the enterprise level and includes engineering, market demand, cost, and price equilibrium models. Sections 4 and 5 introduce and examine design scenarios where the public and private good objectives exhibit varying levels of competition. Section 6 offers a summary and conclusions.

2 MULTICRITERION TRADE-OFF METRICS

We consider now how we can compare different Pareto sets. A design scenario is defined here as the Pareto set generated by a given problem statement and its associated parameter values. A design scenario can be classified as superior to another using the concept of a meta-Pareto set, which includes all non-dominated criteria vectors selected from the union of all the individual Pareto sets under consideration [14, 15].

The concept of criterion alignment is introduced to compare Pareto sets in terms of how much their objectives compete with each other. Two objectives are said to be aligned when both attain their ideal values simultaneously. A Pareto curve is more aligned than another when (i) the effective curvature of the normalized Pareto curve is greater; (ii) it spans a smaller area in the criterion space; (iii) it is less sensitive or "flat". Three metrics, each emphasizing a different aspect of criteria alignment, are proposed in order to facilitate comparisons between design sets: Effective curvature, area, and sensitivity. With the exception of curvature, the metrics are relative and can be used to compare trade-offs only for problems with identical criteria.

2.1 Effective Curvature:

The effective curvature κ indicates the relative convexity or concavity of a particular trade-off. To calculate κ we normalize the Pareto set between 0 and 1 for each criterion: $f_i'(\mathbf{x}) = f_i(\mathbf{x}) - f_i^\circ / f_i^N - f_i^\circ$, and define the minmax solution $L_\infty^A = \min L_\infty = \min \|\mathbf{f}'\|_\infty$, $\|\mathbf{f}'\|_\infty = \max\left\{ \left|f_1'\right|, \left|f_2'\right| \right\}$, that minimizes the maximum deviation from either ideal value, $0 < L_\infty^A < 1$. This solution is at the intersection of the curve $f_2' = f_1'$ and the Pareto set, and is used to calculate κ by finding the curvature of the hyperbola $y = 1/(Ax + B) - C$, intersecting the coordinate axes at 1. Then

$$\begin{aligned} &\kappa = 3\sqrt{2}(2L_\infty^A - 1)^2 / \left(2L_\infty^{A\,2}(L_\infty^A - 1)^2\right),\;\; 0 < L_\infty^A \le 1/2, \text{ convex} \\ &\kappa = -3\sqrt{2}(2L_\infty^A - 1)^2 / \left(2L_\infty^{A\,2}(L_\infty^A - 1)^2\right),\; 1/2 < L_\infty^A < 1, \text{ concave} \end{aligned} \tag{2}$$

Thus κ is a monotonically decreasing, smooth, piecewise function with respect to L_∞^A, with vertical asymptotes at 0 and 1 and an inflection point at 0.5. Criteria compete less as κ increases, indicating increasing convexity and L_∞^A closer to 0. Figure 2 shows differences in curvature for a normalized Pareto set. In general,

$$-\infty < \kappa < \infty \begin{cases} \lim_{x\to 1} \kappa \to \infty, & \text{perfectly competing} \\ 0 < \kappa < \infty, & \text{severely competing} \\ -\infty < \kappa < 0, & \text{marginally competing} \\ \lim_{x\to 0} \kappa \to -\infty, & \text{perfectly aligned} \\ \kappa = 0, & \text{balanced trade-off} \end{cases} \tag{3}$$

2.2 Area:

The area metric is the area of the rectangle that inscribes the Pareto set, defined as $\Phi = |X_s Y_s|$ where $X_s = \left(f_1^N - f_1^\circ\right)/\lambda_1$, $Y_s = \left(f_2^N - f_2^\circ\right)/\lambda_2$ for the bi-objective problem, with λ_i, $i = 1$, 2, chosen by the designer, to compute a scaled range for

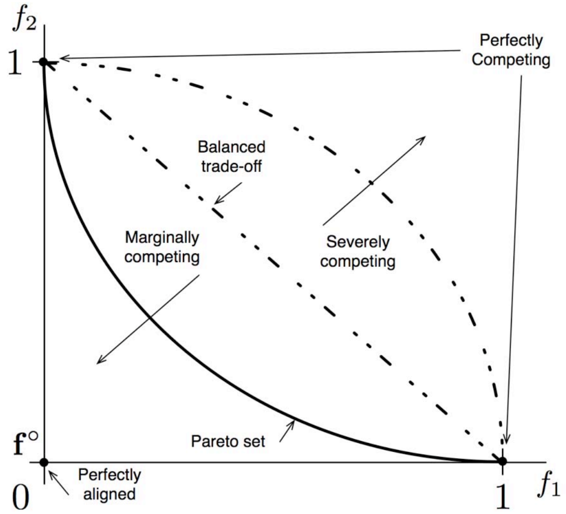


Figure 2: Normalized criterion space showing competition severity as a function of Pareto set curvature

criterion i. Criteria compete less or are more aligned, as the area is reduced.

A useful heuristic for selecting λ_i is to consider the smallest change in f_i that would be meaningful, i.e., one that gives a unique solution in a practical application. For example, for a miles/gallon criterion, a difference of 0.1 mpg may be the smallest significant unit. The scaled values of f_i would then be multiples of the significant unit. Setting $\lambda = 1$ maintains the original scale. Scaling based on a significant unit is useful for comparing Pareto sets because the scale of the relative changes in each criterion is preserved. This would not be the case if the Pareto set was normalized or if a value unique to each design scenario was used, such as f_i°. Selecting scaling factors implies some judgment on the relative value of each criterion, just as normalizing or leaving criteria unscaled implies a relative weighting.

2.3 Sensitivity:

The sensitivity metric is defined relative to each criterion $\Delta_{X_s} = \frac{Y_s}{X_s}$, $\Delta_{Y_s} = \frac{X_s}{Y_s}$. A lower value of Δ_{X_s} means, criterion Y is less sensitive to changes in criterion X. The sensitivity metric reflects the change in one criterion given a change in the other criterion over the entire Pareto set; it indicates the shape of the rectangle that inscribes the Pareto set. A criterion is more or less sensitive as the rectangle becomes more eccentric. Balanced sensitivity occurs when $Y_s / X_s = 1$.

3 ENTERPRISE VEHICLE DESIGN MODEL

The decision maker is assumed to be a single automobile manufacturer, Firm X, offering a single vehicle in a narrow class, namely, five-passenger, midsize, crossover vehicles. Vehicle design and pricing results are generated based on a hypothetical marketplace consisting of nine vehicles based roughly on 2007 models. Vehicle attributes not included in the demand and cost models were similar, including standard seating, towing capacity, and approximate cargo volume. The Firm X vehicle is assumed to have a towing capacity of 3500 lbs. as enforced by the towing constraint.

The profit objective π is represented by simple near-term profit for a one-year period: $\pi = revenue - cost$. Vehicle demand is a function of the vehicle attributes and prices of all vehicles; attributes are functions of seven design variables; cost is a function of design variables and sales volume. Models used to estimate attributes, cost, and demand are based on the literature and some new developments described below. We assume that all firms produce the number of vehicles equal to the expected demand for their product.

The social or public good objective is to minimize fuel consumption/distance traveled. Rate of fuel consumption is only an approximation for minimizing environmental impact, but a factor most likely to be under manufacturers' control. Since a surrogate (rate of fuel consumption) is used rather than the externalities themselves (e.g., GHG emissions, criteria air pollutants, and nonrenewable resource use), some relevant factors are neglected, for example, the rebound effect of increased vehicle miles traveled when the cost of driving is reduced by improvements in fuel economy.

The flow of information between profit, demand, attributes, and cost follows the development of Michalek et al. [7]. However, we assume that Firm X has control over vehicle design and price while the other firms control only price.

3.1 Vehicle Engineering Model:

An engineering model was developed using the AVL Cruise software package [16]; it calculates the following attributes using powertrain simulations, curve-fits from empirical data, or analytical expressions: fuel economy, *MPG*; 0-60 mph time, *Acc060*; styling, as used in the demand model (length + width)/height, *Styl1*; 30-50 mph acceleration time while towing, *Acc3050*; maximum grade at 65 mph while towing, *Grad65Tow*; vehicle top speed, *MaxSpeed*; static rollover score based on static stability factor [17], *Rollover*; estimated engine length, *EngLength*; cargo volume index behind 2nd row, *CVI*; ramp breakover angle, *A147*; angle of departure, *A107* [18]; vehicle center of gravity position in longitudinal and vertical direction, *CG_long*, *CG_vert*; vehicle curbweight and gross vehicle weight rating, *VehMass*, *GVWR*; bumper to driver heel crush space, *CrushSpace*; and, estimated peak deceleration in front crash test, *MaxDecel*. The variables are: engine bore, *EngBore*; engine bore to stroke ratio, *EngBoretoStroke*; final drive ratio, *FinalDrive*; vehicle length, width, and height, *L103*, *W105*, *H101*; and vehicle wheelbase, *L101*.

The $\varepsilon -$constraint method [19] was used to find Pareto points of the problem: $\min \mathbf{f} \mid \mathbf{f} = \left[-Profit,\ \ fuelconsump\right]$ by varying the constraint parameter *MinMPG* between f_{MPG}^{N} and f_{MPG}°.

The constraint set is as follows:

$$
\begin{aligned}
&g_1 = MinTowGrad - Grad65Tow \le 0\\
&g_2 = 13^\circ - A107 \le 0\\
&g_3 = 12^\circ - A147 \le 0\\
&g_4 = 29\ \text{ft}^3 - CVI \le 0\\
&g_5 = CVI - 60\ \text{ft}^3 \le 0\\
&g_6 = Rollover - .21 \le 0\\
&g_7 = 50\% - 100\left(1 - CG_{long} - L104 / L101\right) \le 0\\
&g_8 = 5\% - Grad65Tow \le 0\\
&g_9 = Payload + VehMas - GVWR \le 0\\
&g_{10} = MinCrushSpace - CrushSpace \le 0\\
&g_{11} = MaxDecel - 20(9.81\ \text{m/s}^2) \le 0\\
&g_{12} = \begin{array}{l} 2TireFlop + 2MidRailWidth + \\ EngLength + 50.8) - (W105 - 254) \le 0 \end{array}\\
&g_{13} = L101 + L104 - L103 \le 0\\
&g_{14} = 120\ \text{mph} - MaxSpeed \le 0\\
&g_{15} = MinSitheight - H101 \le 0\\
&g_{16} = MinMPG - MPG \le 0
\end{aligned}
\tag{4}
$$

Vehicle simulations were configured to represent a standard automatic transmission front wheel drive vehicle with a gasoline engine. In addition to powertrain specifications (i.e., gear ratios, gear shifting schedule, engine number of cylinders, vee or inline configuration, bore, and stroke, valvetrain configuration, and final drive ratio.) *Cruise* also receives other vehicle parameters as inputs, including curb weight, frontal area, drag coefficient, tire radius, and center of gravity location under various loads. Over 30 parameters were tuned for midsize crossover vehicles based on data from one 2007 model. All other parameters were left at the default passenger vehicle levels.

Cruise characterizes engine performance by reference to engine maps derived from experimental results of a baseline engine. The fuel consumption map is taken from a 2.5 l, V-6 engine with $BMEP_{Ppeak}$=1068 kPa. The full load characteristic is scaled from the Duratec35 engine ($BMEP_{Ppeak}$=1085 kPa) used in the Ford Edge. Engine maps were scaled for each design iteration as functions of *EngBore* and *EngBoretoStroke* following established scaling relationships [20, 21]. We assume the peak power brake mean effective pressure of the Firm X vehicle engine (1085 kPa) and mean piston speed at peak power out (18.1 m/s) are constant for all designs. The advanced friction module found in *Cruise*, which incorporates engine and valvetrain architecture, based on [22] was used to integrate frictional engine losses into the simulations.

Five vehicle simulations were executed using *Cruise*: FTP (US urban cycle) and HFET (US highway driving cycle) estimate combined fuel economy rating according to 2008 EPA MPG-based guidelines [23]. Shifting gears from standstill was used to predict 0-60 acceleration and vehicle top speed; shifting gears from 30-50 mph was used to estimate 30-50 mph time with towing simulated by adding the max trailer weight to the mass of the vehicle; max gradeability estimates the percent grade achievable at 65 mph with towing simulated using the virtual trailer option that allows specification of trailer mass and an estimate of losses.

Surrogate models were obtained from *Cruise* simulations to reduce computational expense, using Latin hypercube experimental designs. Satisfactory polynomials were found for both driving cycles and the gradeability simulation (R^2: 0.998 City, 0.994 Hwy, 0.997 Grade). Two neural nets were generated in Matlab, one for *Acc060* and one for *MaxSpeed*, both of which had R^2 values for the training points and the test points above 0.99.

A regression was fit (R^2:0.92) to estimate curb weight:

$$
\begin{aligned}
VehMass = {} & c_1(L103 \times W105)^2 + c_2(L01 \times W105) + c_3 EngDisp\\
& + c_4 FWD + c_5 AWD + c_6 4WD + c_7 RWD + c_8
\end{aligned}
\tag{5}
$$

using data for 2005 light-duty trucks from Ward's automotive yearbook [24]. Here *EngDisp* is the engine displacement volume, and *FWD*, *AWD*, *4WD*, *RWD* are dummy variables {0,1} for driveline configuration.

Cargo volume and rollover constraints [17] were relaxed (g_4(min CVI) from 32 ft^3 to 29 ft^3, g_6(max rollover score) from 0.1999—a 4-star rating—to 0.21) to account for differences between the model and real world data.

Attributes for competing vehicles were gathered from the Internet including values for all design variables, transmission ratios, and other model parameters [25-27]. Single *Cruise* simulation runs were performed for each vehicle and the values of the attributes were recorded. In most cases the computed values of *MPG* and *Acc060* for each vehicle were used in the market equilibrium model rather than the reported values to avoid bias given discrepancies between simulated and real-world performance. The vehicle simulation was rerun using the reported curb weight for *VehMass* in cases where the vehicle curb weight prediction deviated by more than 50 kg from the reported curb weight.

3.2 Vehicle Demand Model:

A logit model was chosen for representing demand, due to its ease of interpretation congruent with random utility theory [28], and widespread use. We considered only vehicles from a very narrow class and thus reduced the risk of violating the independence of irrelevant alternatives assumption with the introduction or exclusion of a particular vehicle. All other purchase possibilities are represented in the utility of the outside good v_{og}.

The choice share of a given product is defined for the logit model as the probability of choosing product i given products 1, …, n as follows,

$$
\Pr(i) = e^{v_i} \Big/ \left(e^{v_{og}} + \sum_j e^{v_j}\right),\ v_i = \sum_k \beta_k \varphi(z_k)\ \text{for } k \text{ attributes.} \tag{6}
$$

From the literature of demand models for the auto industry [29-31] we adopted a model similar to Boyd & Mellman [32]. It assumes aggregate (homogeneous) preferences, a logit form of the choice model, and a utility model that is linear in the coefficients with vehicle attributes: *price*, fuel consumption, the inverse of 0-60 acceleration time, a styling factor *Styl1* based on external vehicle dimensions.

The Boyd & Mellman model was estimated using model year 1977 vehicle data, and as such, caution should be taken when interpreting results. Vehicle price was converted to

1977 dollars using the consumer price index; 0-60 times improved dramatically from 13.8s in 1977 to 9.6s in 2007 [33]. A 1s shift (rather than the full 4.2s) to acceleration times generated vehicle designs similar to the existing market for the baseline scenario implying that preference for acceleration increased.

Conveniently, the assumed price of gas in 1977 dollars was $0.70 (roughly $2.40 in 2007 dollars—at the low end of the observed range of gas price in 2007). The average decrease in fuel consumption (≈30%), as tested by the EPA, is accounted for by using the updated adjusted values [23] for fuel economy, rather than the EPA test values, and then shifting the mpg value by the 0.7mpg remaining difference, implying people value improvements in fuel economy at roughly the same level but expect higher average fuel economies.

The model was further calibrated by setting market size to the total vehicles sold in the US in 2007 (14.87 M), and v_{og} was set to produce a total demand for the 9 hypothetical vehicles roughly equivalent to the 2007 sales of the real vehicles (≈600,000). Adjusting market size and v_{og} in this way rather than using the segment market size and a modest v_{og} did not shift the design decisions of Firm X, but did provide downward pressure on prices to bring them inline with observed values.

Market demand for each vehicle is estimated to be the product of the market size cap and the choice share. Other choice model formulations such as the mixed logit [28] allow for preference heterogeneity. Studying the impact of choice model selection on the Pareto set outcomes could be the subject of future work.

One difficulty in calibrating models between years is that not only have the purchase power of the dollar decreased and the average vehicle attributes changed, but the average price of vehicles in real dollars has increased [29].

Attributes of the competing vehicles are listed in Table 1. Time is given in seconds, fuel economy in miles/gallon, and length in inches. The *Styl1* attribute and utility are dimensionless. We assume all vehicles use regular gasoline.

3.3 Vehicle Cost Model:

The cost model, modified from De Weck [34] and Cook [35], is based on assigning a cost to a hypothetical average vehicle and then computing the cost for a specific vehicle based on deviations from the average. Approaching cost modeling in this way enables design-specific cost differences to be considered without requiring a complete bottom up cost structure. The initial cost value is generated from assumptions about average profit margin α =20% (OEM + dealer), as well as the average operating leverage ϕ=0.35 (relative distribution of fixed vs. variable costs). No learning curve effect was assumed.

Table 1: Hypothetical midsize crossover vehicle market excluding Firm X vehicle

Make	Acc060	MPG	L103	W105	H101	Styl1	B&M Util.[1]
xEdge	7.7	19	185.7	75.8	67.0	3.9	5.75
xEndeavor	8.4	19	190.8	73.6	69.6	3.80	5.42
xHighlander	7.9	19	184.6	71.9	67.9	3.78	5.52
xMurano	8.0	20	187.6	74.0	66.5	3.93	5.82
xSanta Fe	8.2	19	184.1	74.4	67.9	3.81	5.48
xXL7	7.9	18	190.8	73.6	69.6	3.80	5.43
xTribeca	8.3	19	189.8	73.9	66.4	3.97	5.68
xVue	8.4	21	181.3	71.5	66.5	3.8	5.64

[1] Vehicle utility based on adjusted B&M model excluding price

Variable vehicle cost is broken down into four subsystems, where the relative cost of each subsystem is a function of design variables and parameters. Powertrain (30%) (*EngBore*, *EngBoretoStroke*), Chassis (35%) (*W105*, *L101*), Body (30%) (*L103*, *H101*, *W105*), Wheels (5%) (*Wheel diameter*, a fixed parameter in this study). Total cost is calculated according to the following.

$$\begin{aligned} C_{tot} &= C_{var} + C_{fix} \\ C_{fix} &= \phi \times AvgUnitC_{var} \times AvgSales / (1-\phi) \\ C_{var} &= SalesVol \times UnitC_{var} \end{aligned} \tag{7}$$

3.4 Price Equilibrium Solution Strategy:

Each competitor optimizes profit with respect to vehicle price given the product designs and prices of all competitors. Firm X then optimizes product design and price variables, concluding one iteration. Iterations continue until price changes fall below a threshold constraint (≈ $80). The vehicle prices (and Firm X design variables) are now set such that no firm can make a different decision that would improve its own profits while the choices of the other firms remain fixed—approximating a Nash equilibrium [36].

A complete product equilibrium process would allow each competitor to optimize designs as well as prices with respect to all others' designs and prices. However, given the use of a homogenous multinomial logit model and identical underlying engineering and cost models, each firm would choose identical designs and prices, as seen in [7]. Instead, assuming fixed competitor designs coincides with vehicle planning where a firm makes some educated assumptions about the products competitors will produce. During product launch and subsequent sales, all competitors are at liberty to adjust prices freely while the designs remain fixed. Competitive behavior [37] among auto manufacturers considering the full market has been modeled, for example [38, 39]. The simplified approach shown here includes competitive effects sufficient to illustrate trends without greatly increasing the computational complexity of the model.

4 DESIGN SCENARIOS

We examine design scenarios that translate into model changes and new Pareto sets. The criterion alignment metrics and the overall value of each scenario are compared. A Pareto set that dominates another Pareto set has greater value. We divide design scenarios into four 'mechanisms': technology, preference, competition, and regulation. Table 2 gives the initial parameter values for the baseline case. Table 3 lists each design scenario and the corresponding model changes. Each model change is implemented individually, and all other parameter values are kept at the baseline levels. The unscaled results are shown in Figure 3 and discussed in Section 5. All design scenarios consider 9 producers including Firm X.

4.1 Baseline Case:

The vehicle price (*MSRP*), market share (within segment), and expected profit for each firm are listed in Table 4 for the $f^{\circ}_{-profit}$ solution. Table 5 shows the attribute values for f°_{profit} and $f^{\circ}_{fuelconsump}$ for the baseline case.

4.2 Technology:

Two technology scenarios are considered. The drag coefficient is changed to 0.4 and 0.34 from 0.37, and the powertrain cost parameter is changed from 30% to 20% and 40%. The difference in cost is absorbed evenly by the chassis and body subsystems.

4.3 Preference:

Individual preferences for products change over time based on externalities (e.g., rising fuel prices or increased public concern for global warming) and based on changes to the performance levels and salience of the observable characteristics of a product. Advances in technology and government regulation are two influences that may change the observable product characteristics of a product such as the automobile. For example, increased consumer interest may be placed on fuel economy and derivative characteristics of advanced powertrains (e.g., range, access to refueling). Of course, advertising is another mechanism that influences preferences.

The importance of acceleration in the baseline case is contrasted to the case where consumers are completely indifferent to 0-60 acceleration given that the vehicle meets towing, top speed, and 30-50 mph acceleration requirements.

We postulate new fuel consumption coefficients in the demand model assuming preference is proportional to cost of transportation in real dollars. This analysis assumes that preference for the other attributes with respect to price remain unchanged, which has the unavoidable side effect of changing the elasticities between fuel consumption and the other attributes. The β_{MPG} coefficients are listed with the corresponding fuel price in 2007 dollars: $\beta_{MPG} = \{-.239, \$1.69;\ -.339, \$2.40;\ -.439, \$3.10;\ -.639, \$4.51\}$

Several alternative styling forms were considered. Three forms are reported, i) A longer, lower, wider form, where increases in width are more important than increases in length; ii) minimalist styling that emphasizes reduction in all three exterior dimensions; iii) an "inverted" form that is taller, shorter, and thinner.

Changing parameter values or functional form of product attributes in the utility model changes the computed values of utility. The utility of the outside good was updated to preserve the relative difference between the average utility value of the 8 original vehicles and the utility of the outside good for all preference and regulatory scenarios. Finally, all firms will react to changes in consumer preference. However, only Firm X changes vehicle design in this example. The resulting profits should be considered inflated relative to market expectations, but the trend in vehicle design (i.e., the relative change of fuel economy) should be preserved.

Table 2: Design scenario parameters for baseline

Market assumptions	**Market Size**	**Utility of outside good**	**Dealer markup**	**Number of Firms**
	14,870,000	9.1	8%	9
Relative cost breakdown	**Powertrain**	**Chassis**	**Body**	**Wheels**
	0.3	0.35	0.3	0.05
Choice model coefficients	**MPG**	**ACC**	**Styl1**	**Price**
	-0.339	0.375	1.37	-0.000286

Table 3: Design scenarios listed by mechanism and model parameter level

Mechanism	Levels 1	2	3
Technology			
C_D	0.34	0.40	
Powertrain cost	20%	40%	
Preference			
Accel. Indifference	$\beta_{ACC} = 0$		
Fuel economy	-0.239	-.439	-.639
Styling preference	$\frac{W105 \times 2 + L103/2}{H101}$	$\frac{-(W105 + L103 + H101)}{2000}$	$\frac{10 \times H101}{W105 + L103}$
Competition			
Price-cutting	21,000 (xVue)	23,000 (xVue)	
Market size volatility	12,870,000	16,870,000	
Regulation			
Price-ceiling	\$20,000	\$22,000	\$24,000

Table 4: Prices, market shares, and expected profits for all firms for the baseline case

	xEdge	xMurano	xHighlander	xSanta Fe	xTribeca
MSRP	\$26,900	\$26,700	\$26,000	\$26,300	\$25,900
Market Share	12%	13%	10%	9%	12%
Profit	\$314mil.	\$373mil.	\$197mil.	\$151mil.	\$319mil.

	xVue	xXL7	xEndeavor	Firm X
MSRP	\$25,900	\$26,900	\$27,100	\$27,400
Market Share	11%	10%	8%	15%
Profit	\$257mil.	\$193mil.	\$68mil.	\$543mil.

4.4 Competition:

Two scenarios are considered that deal with the competitive landscape facing Firm X. First, the effect of a price-cutting strategy by another firm is examined at approximately \$3,000 and \$5,000 below the baseline equilibrium price. Second, market volatility is considered by varying annual US vehicle market size ± 2 million vehicles.

4.5 Regulation:

Numerous regulatory scenarios can be explored using the proposed framework. Only one policy, a mandatory price ceiling at \$24,000, \$22,000, and \$20,000, is reported here. A natural consequence of a price ceiling policy is that demand exceeds supply. Losses by many firms in these scenarios indicate that the worst performing firms would exit the market and fewer vehicles would be produced overall.

5 DISCUSSION

The results of each design scenario, including the baseline case, are shown in Figure 3 grouped by mechanism. The criterion alignment metrics are listed in Table 6. Section

5.1 compares the value or magnitude of the scenarios, and Section 5.2 discusses the criterion alignment metrics.

L103 is large at $f^{\circ}_{-profit}$ and shrinks along the Pareto frontier. Vehicle cost, *MPG*, and *ACC060* are all negatively correlated with vehicle size. *H101* is constrained by the minimum sitting height constraint. *W105* is constrained by the rollover constraint and *L103* and *L101* are constrained by the minimum angle of departure and cargo volume constraints. In the absence of preference valuation for cargo volume, legroom, or other spatial features of the vehicle, Firm X will seek to build the smallest vehicle possible. The *Styl1* attribute, which rewards increases in length and width, moves the design away from the constraint boundaries at the most profitable solutions. *L103*, *L101*, and *W105* are above average for the hypothetical marketplace and *H101* is slightly below average. The minimum towing grade constraint becomes active at $f^{\circ}_{fuelconsump}$.

Most of the Pareto sets follow a similar form given that the constraint activity remained the same across most scenarios—a gradual decrease in profits for about 1/2 the fuel consumption change followed by a steeper region of profit loss for the remaining fuel consumption change. The top speed constraint is active up to the elbow in the direction of decreasing fuel consumption and is no longer active beyond that point. Also near the elbow, *EngBore* meets the lower bound imposed by the model. However, *EngBoretoStroke* does not reach its lower bound so the engine displacement continues to decrease modestly as fuel consumption decreases.

The attainable set for all scenarios is limited by the same set of constraints on vehicle characteristics. The scenarios have the effect of shifting output levels of the objective functions (e.g., the technology scenarios) and shifting the boundary of the attainable set that is Pareto optimal (e.g., the preference scenarios). New scenarios that modified, introduced, or excluded constraints could change the boundary of the attainable set. On the other hand, the Pareto frontier in an unconstrained problem would depend only on the gradients of the objective functions.

5.1 Scenario Dominance:

The globally dominant meta-Pareto set tracks along the market size of 16.87 million, then follows the indifference to acceleration, and then the C_D=0.34 scenario.

In the low fuel consumption region, expensive powertrains produce results in the market similar to higher preference for fuel economy. When powertrains are expensive (40% vs. 30%) fuel economy improves for the max profit solution; however, it is still more profitable to balance acceleration and fuel economy rather than reduce engine size and cost, and focus on fuel economy. Such a result may explain one reason many hybrids have been tuned towards performance and not solely to maximize fuel economy.

Table 5: Firm X vehicle attributes for ideal -profit and fuel consumption values for the baseline case

Make	Acc060	MPG	L103	W105	H101	Styl1	Util.[2]
Firm X $f^{\circ}_{-profit}$	7.2	18.4	196.6	74.4	67.0	4.05	6.03
Firm X $f^{\circ}_{fuelconsump}$	9.8	21.1	187.3	74.2	67.0	3.90	5.48

[2] Vehicle utility based on adjusted B&M model excluding price

Intuitively, increased market size increases profits. Non-intuitively, artificially lowering the price of a single vehicle had a negligible effect on Firm X decisions. This result demonstrates one of the weaknesses of the simple logit model: there is no way to account for the substitution patterns we would expect, i.e., more sales for the reduced price model coming from shifting demand within the segment rather than the entire vehicle fleet (the outside good). Preliminary studies using the segment size as the market size and a modest value of outside good utility showed results for a price cut by one firm very similar to a price ceiling on the entire segment.

5.2 Trade-off Metric Comparison:

Values for the three metrics are listed in Table 6. Each metric shows a range of values across the analyzed scenarios. Area and sensitivity were computed using scale factors of $\lambda_{-profit} = \$100,000$ and $\lambda_{fuelconsump} = 0.02$ gal/100 mi .

The acceleration indifferent scenario comes closest to showing how the bi-objective problem can collapse to a single solution when the gradients of the two objectives are very similar. The importance of the *Styl1* attribute preserves a trade-off. Another type of collapse could occur when one objective becomes completely indifferent to the other objective. This can occur when the gradients of each objective are uncoupled or only weakly coupled. In other words, the objectives depend on few if any of the same design variables..

Comparing the metric values and Figure 3 shows that localized effects of the Pareto curves are not accounted for by the metrics. The trade-off region of interest to a vehicle producer is the region immediately around the max profit point. For most scenarios, the trade-off in this region is much more shallow than the overall trade-off as indicated by the sensitivity metric, and the curvature is much closer to 0 than indicated by the curvature metric. The metrics could be reapplied to a designated region of the Pareto curve to define metrics for local curvature, area, and sensitivity.

There are clear changes to the nature of the trade-off as the *MPG* attribute increases in importance. The area decreases as $f^{N}_{fuelconsump}$ decreases. The curvature decreases dramatically between the baseline and the $\beta_{MPG} = -0.639$ case because the shallow trade-off region is no longer Pareto-optimal, and the sensitivity increases because the range of fuel consumption decreases dramatically while the range of profit changes less. The styling importance impact on profit and fuel consumption is mixed. Particularly interesting is the Styl1(1) scenario where width is valued more than length. Increased profits can be achieved and a firm is severely penalized for decreasing fuel consumption.

Reduced drag coefficient leads to increase in the area metric as the Pareto set improves in value, which is inconsistent with the trend in the preference scenarios. One interpretation of these results is that improvements in vehicle design (e.g., improved drag characteristics) have great potential for decreasing environmental impact, but these changes alone will lead only to marginal changes at $f^{\circ}_{-profit}$ when they occur in isolation of other model changes.

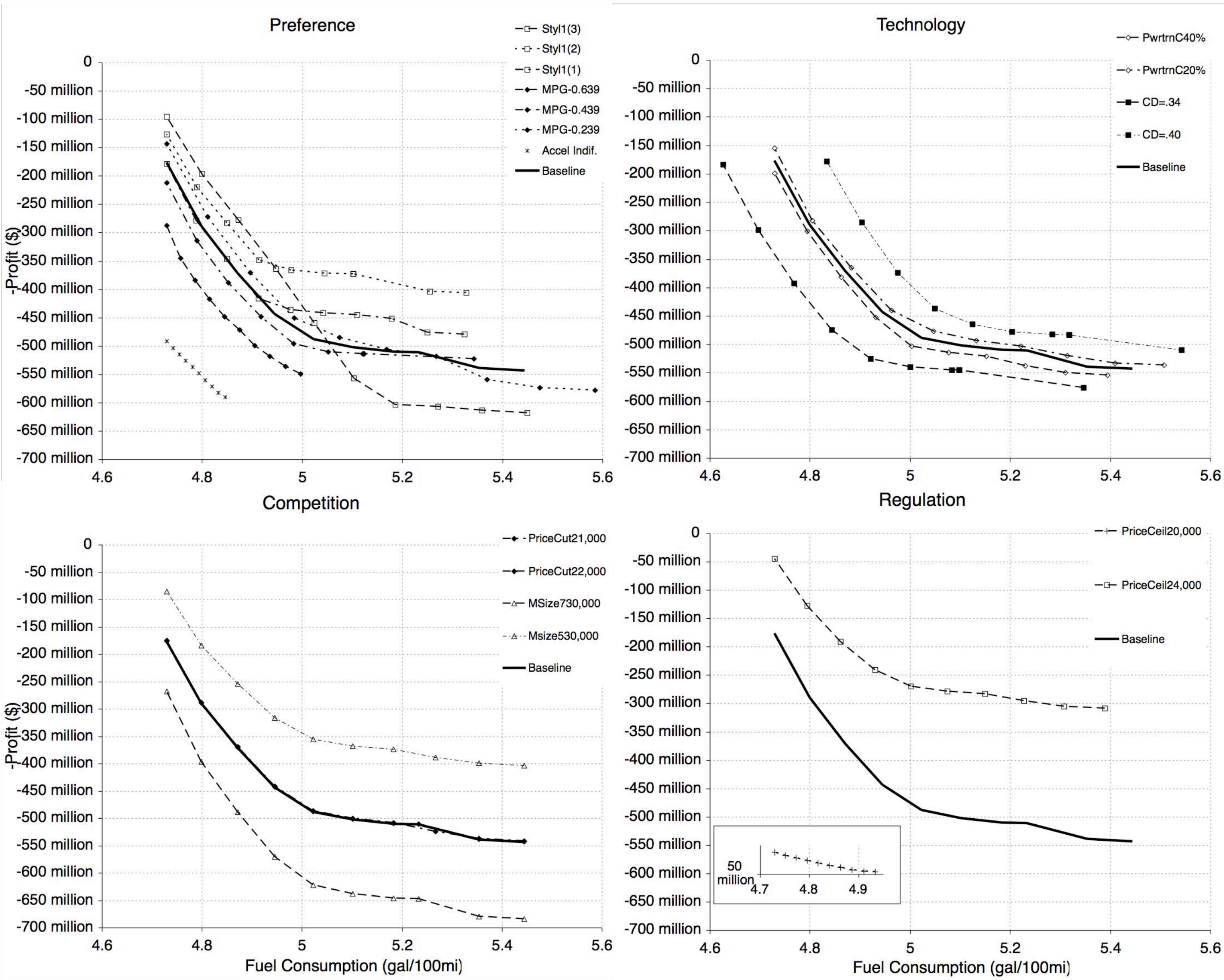


Figure 3: Results for all design scenarios showing -Profit vs. Fuel Consumption

Price ceiling scenarios decreased fuel consumption at the cost of reduced profit levels. Trends for the metrics are summarized in Table 7. For example, the first line of the table should be read, "As preferences change such that the value of the Pareto set improves, curvature and area decrease while sensitivity increases." Some trends are not monotonic. Results for effective curvature were mixed over all the scenarios. As a whole, the trade-off metrics show increasing alignment for improved Pareto set values when changes are made with respect to technology or preference, and they show increasing alignment for inferior Pareto set values when changes are made with respect to competition or regulation.

6 CONCLUSIONS

This paper presents three metrics for measuring bi-objective trade-offs and illustrates their application in a vehicle design problem. The area metric is of practical significance to decision makers in that larger trade-off area means more to gain (lose) in the trade-off decision. The area metric also appears to give the best overall assessment of criterion competition considering the working definition of criteria alignment, i.e., both objectives achieve single objective optimality simultaneously. The other two metrics actually show increased competition for most cases when the area metric decreases. In fact the smallest area values coincide with the smallest curvature values, likely indicating that as ideal values move closer together for a given problem formulation, smaller regions of the attainable set boundary are Pareto optimal and are thus more and more closely approximated by a straight line. This effect should be explored in other multi-objective problems with different Pareto frontier shapes (e.g., a concave frontier), and future work should investigate directly how the problem structure (i.e., objective gradients and constraint activity) ties to the metrics. The curvature metric, which can be compared across problems, may serve to classify multiobjective problems according to typical Pareto frontier shapes.

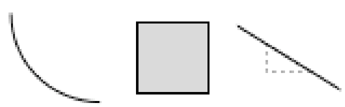
The enterprise vehicle design problem is an example of a class of problems where decision maker preferences are heavily weighted to one objective (e.g., profit). The sensitivity metric can be useful in such problems, especially if it is applied locally around the $f^{\circ}_{-profit}$ solution. A firm considering producing a vehicle away from $f^{\circ}_{-profit}$ for strategic reasons could then formulate a risk assessment for each scenario given the sensitivity of profit with respect to their choice. Scenarios with lower Δ_{X_s} values will be less sensitive to design choices away from $f^{\circ}_{-profit}$.

Another insight drawn from the metrics is that decreased objective competition does not predicate superior solutions compared to a more competing scenario. For example, one intuitive yet important trend in the results is that when the area metric decreases due to changes in the objective gradients (e.g., consumer indifference to acceleration) the design scenario has potential to improve value for both stakeholders. However, when area decreases are due to changes in constraints (e.g., a price ceiling), the overall value of the scenario decreases for at least one stakeholder.

Caution should be taken in interpreting the results of this study. The intent is not to represent a true market equilibrium, but to represent a design scenario as it may appear to a vehicle manufacturer making assumptions about the vehicle designs of competitors. Significant obstacles remain in studying max profit formulations in vehicle design including questions about underlying demand model validity, econometric interpretations of changes to the demand model parameters, and realistic cost models, among others. Furthermore, other regulatory scenarios can be considered, such as a CAFE standard, fuel tax, or CO_2 tax. Therefore, the numerical results presented here are useful in illustrating the proposed concept of public-private alignment rather than suggesting specific decisions.

Table 6: Criteria alignment metrics for each design scenario

Design Scenario



	Curvature	Area	Sensitivity Δ_{X_s}
Baseline	5.7	131,000	103
Technology			
C_D 0.34	6.1	142,000	109
C_D 0.40	7.4	117,000	93
Powertrain cost 20%	6.3	149,000	98
Powertrain cost 40%	5.3	118,000	107
Preference			
Accel. Indifference	0.02	5,750	168
Fuel economy -0.239	5.3	186,000	102
Fuel economy -0.439	6.4	95,000	101
Fuel economy -0.639	0.8	35,000	195
Styl1(1): $\frac{W105 \times 2 + L103/2}{H101}$	7.0	89,000	101
Styl1(2): $\frac{-(W105 + L103 + H101)}{2000}$	7.1	84,000	94
Styl1(3): $\frac{10 \times H101}{W105 + L103}$	1.8	188,000	145
Competitive			
Price-cutting $21,000	5.7	131,000	102
Price-cutting $23,000	5.7	131,000	102
M. size vol.(12,870,000)	5.7	114,000	89
M. size vol.(16,870,000)	5.7	149,000	116
Regulatory			
Price-ceiling $24,000	6.1	87,000	80
Price-ceiling $22,000	7.2	57,000	60
Price-ceiling $20,000	0.3	10,000	98

Table 7: Trends in trade-off metric values with respect to changes in Pareto set value

	Value	Curvature	Area	Sensitivity
Preference	↑	↓	↓	↑
Technology	↑	mixed	mixed	↑
Competition	↓	none	↓	↓
Regulation	↓	mixed	↓	mixed

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