A Study of Fuel Efficiency and Emission Policy Impact on Optimal Vehicle Design Decisions

Jeremy J. Michalek[1]
e-mail: michalek@umich.edu

Panos Y. Papalambros
Professor

Steven J. Skerlos
Assistant Professor

Department of Mechanical Engineering,
University of Michigan,
Ann Arbor, MI 48109

Recent environmental legislation, such as the European Union Directive on End-of-Life Vehicles and the Japanese Home Electric Appliances Recycling law, has had a major influence on product design from both an engineering and an economic perspective. This article presents a methodology for studying the effects of automobile fuel efficiency and emission policies on the long-term design decisions of profit-seeking automobile producers competing in an oligopoly market. Mathematical models of engineering performance, consumer demand, and manufacturing costs are developed for a specific market segment, and game theory is utilized to simulate competition among firms to predict design choices of producers at market equilibrium. Several policy scenarios are evaluated for the small car market, including corporate average fuel economy (CAFE) standards, carbon dioxide (CO_2) emissions taxes, and diesel technology quotas. The results indicate that leveraging CO_2 taxes on producers for expected life cycle emissions yields diminishing returns on fuel efficiency improvement per regulatory dollar as the taxes increase, while CAFE standards achieve higher average fuel efficiency per regulatory dollar. Results also indicate that increasing penalties for violation of CAFE standards can result in lower cost to producers and consumers because of the effects of competition, and penalties based on fuel economy or emissions alone may not be sufficient incentive for producers to bring more costly alternative fuel vehicles into the market. The ability to compare regulations and achieve realistic trends suggests that including engineering design and performance considerations in policy analysis can yield useful predictive insight into the impact of government regulations on industry, consumers, and the environment.
[DOI: 10.1115/1.1804195]

Keywords: Environmental Policy; Optimal Design; Game Theory; Oligopoly; Emissions; CAFE; Discrete Choice Analysis; Econometrics; Logit; Green Engineering

1 Introduction

Optimal design studies commonly consider tradeoffs among engineering performance metrics. To explore such trade-offs, multiple conflicting objectives can be combined within a Pareto-optimal approach, but the scalarization preferences (e.g., weights) are often difficult to evaluate, and typically the problem must be iteratively reformulated [1,2]. Alternatively, conflicts among technical objectives can be resolved if they are viewed in the context of the producer's overall objective to maximize profit [3]. In automotive manufacturing, profitability depends upon a vehicle's engineering performance and cost, as well as its appeal to consumers and the regulatory restrictions imposed by government. In this investigation, we consider each of these points and evaluate how regulatory fuel-economy and emissions policies can impact the design decisions made by profit-seeking producers.

Automobile producers provide private goods (vehicles) for private profit (investors), but externalities (emissions) are generated with costs that are publicly shared. For example, costs associated with driving high-emission vehicles in the southern coast of California can generate pollution costs estimated at $10,000 or more per year [4]. Despite regulatory enforcement over the past three decades, vehicle emissions still significantly impact U.S. air quality, accounting for up to 95% of city CO emissions, 32% of NO_x emissions, and 25% of volatile organic compound emissions [5]. These emissions create smog, increase atmospheric greenhouse gas concentrations, create human health risks, and damage agricultural, ecological, and urban infrastructure systems. Since the market in which goods are traded does not automatically provide individual incentives to reduce publicly shared environmental damage (the "tragedy of the commons" [6]), government regulatory policies have been imposed on vehicles at both national and state levels to provide emission reduction incentives. Examples include the Clean Air Act [7], which regulates tailpipe emissions, corporate average fuel economy (CAFE) standards [8], which require vehicle fleets to meet target average fuel efficiencies, and quotas for "cleaner" vehicles, such as California's "zero emissions vehicle" (ZEV) regulation. While National Ambient Air Quality Standards established by the Clean Air Act still have not been achieved in many major U.S. cities, recent attempts to regulate further the vehicle design process toward producing "cleaner" vehicles have had only limited success. One example is California's attempt to achieve 10% sales in ZEVs from its top seven automotive manufacturers by 2003 [4]. The ZEV technology quota policy has suffered from the high cost (average purchase cost of $35,000) and poor range (approximately 90 miles) of electric vehicles [9], resulting in limited consumer appeal. The policy is now under review, with low polluting gasoline and highly fuel efficient gasoline-electric hybrids likely to comprise the bulk of the 10% quota [10]. The example demonstrates the importance of simultaneously considering technology capabilities, costs, and consumer preferences when developing environmental policies.

In this article, a quantitative methodology is developed for considering engineering design performance and constraints, producer objectives, consumer choice, and competition among producers in the analysis of environmental policy. This methodology permits specific policies to be analyzed in the context of their

[1]Corresponding author.
Contributed by the Design Theory and Methodology Committee for publication in the JOURNAL OF MECHANICAL DESIGN. Manuscript received May 9, 2003; revised March 19, 2004. Associate Editor: C. Dym.

impacts on consumers, producers, and total air quality, leading to estimates of cost and effectiveness for different environmental policies under consideration.

2 Background

Policy research related to the automotive industry has focused primarily on the effects of changing CAFE standards. One such study by the National Academy of Sciences [11] identified technologies that could be implemented in all vehicles today, including estimated cost and fuel savings associated with each technology. Specifically, the effects of incremental changes in CAFE standards on vehicle price, performance, demand, and product mix were evaluated. While external factors such as gasoline price were also included in the assessment, the report considered only the inclusion of new technologies in existing engines. Longer term options to change new vehicle design decisions were not considered. The same is true for a recent European Union report on the Auto-Oil II Program, which targets reductions in automobile emissions [12]. In the report, future vehicle emissions levels were forecast as functions of fuel quality using atmospheric emissions and impact models. Although alternative emissions policies were evaluated for their economic efficiency in reducing emissions, the option for producers to change design decisions in response to policy was not considered.

A different study by Greene and Hopson [13] examined the impact of various regulatory strategies on average fuel economy using a mathematical programming model. Regulatory options included raising the CAFE standard, making a fuel-economy standard voluntary, and creating a weight-based metric. Although regulatory options were evaluated in the context of their impact on producers and consumers, the market positions of manufacturers were taken as constant, and few longer-term design changes were considered.

While these previous models analyze important aspects of emissions policies, there are opportunities to extend their scope of consideration. Previous investigations assume each manufacturer will maintain its current product mix, making only incremental technology improvements to existing products (e.g., direct injection, variable valve timing, etc.). In contrast, this article provides an economic oligopoly analysis where each firm designs its product mix, changing design variables in response to regulations and competition. Previous studies also rely on assumptions about consumer willingness to pay for increased fuel economy rather than using attribute-based consumer choice models derived from past purchase data. This article uses an optimization framework to integrate quantitative models for each component, including emissions, engineering design, cost, consumer demand, and producer profit. The framework is modular and hence allows for the substitution of alternative models for any of the various models employed in this study. Moreover, the producers in this investigation are abstract; that is, the results obtained do not apply to a specific producer's actions, but rather represent the general market trend created by government incentives. Therefore the model created here is able to evaluate trends of cost and effectiveness created by alternative policies that aim to reduce automobile emissions through improved fuel economy.

The remainder of this article proceeds as follows. Section 3 describes the proposed policy analysis methodology, including the development of individual models for engineering performance, consumer demand, cost, producer profit, and regulation. The models are utilized to establish oligopoly market competition between firms, where policy impacts are analyzed at Nash equilibrium. The results of the investigation are summarized in Sec. 4.

3 Methodology

The general modeling framework used to capture producer and consumer behavior in this study is shown in Fig. 1, where individual analysis models are shown as black boxes. Producers are assumed to make product design and production decisions that maximize profit. Consumers are assumed to choose from the available alternatives those products that have maximum utility based on a model of their preferences. Policy can influence these decisions by imposing penalties and incentives toward the modification of producer and consumer behavior. This investigation considers several policy scenarios that have direct impact on producer behavior such as CAFE standards, carbon dioxide (CO_2) emissions taxes, and diesel technology quotas.

In this framework, each producer k decides on a set of designs to produce J_k including design decisions, prices, and production volumes for each design. Design topology M and design variables $\mathbf{x}$ (such as engine size) determine product characteristics $\mathbf{z}$ (such as fuel economy), calculated using an engineering performance analysis model. Design variables, production volume V, and regulation penalties c^R also determine producer cost c, calculated by the cost analysis model. The set of competitors' designs $\{J-J_k\}$ are viewed by producer k as static parameters, and consumers make purchasing choices among the set of producer and competitor products J based on product characteristics and prices p. Purchasing choices determine demand for each design q calculated by the demand model, and resulting profits Π are calculated in terms of p, q, and c. Resulting profit is used as the objective function for producer k's optimization model, and the dotted line in Fig. 1 represents the feedback loop for iterations of the optimization algorithm. The optimization model represents each producer's attempt to maximize profit by making the best design, pricing, and production decisions. Government regulation can influence this process by imposing penalties on producers, thereby affecting production costs and design decisions. Note that this study is limited to government regulation directly affecting producers without impacting consumer behavior such as driving habits or preference structures.

In the present model, all producers are profit driven, so production volume will equal product demand at an optimum. This assertion is valid for continuous demand functions with negative price elasticities since any producer who wishes to produce a lower volume of a product (for example, because of capacity constraints or marginal cost curves) has no incentive to produce less volume than that for which there is demand. Instead, the producer can simply raise the price until demand is lowered to the desired production volume, so it is assumed that $V_j=q_j$ from this point forward.

The objective of each producer is modeled as profit maximization (Π, revenue minus cost) subject to engineering constraints as follows:

$$\begin{aligned} &\text{maximize} \;\; \Pi_k=\left(\sum_{j\in J_k} q_j p_j\right)-c_k \\ &\text{with respect to } \{M_j,\mathbf{x}_j,p_j\}\forall j\in J_k \qquad (1) \\ &\text{subject to engineering constraints} \end{aligned}$$

Profit for each producer is calculated as a function of the producer decision variables by combining the engineering performance, consumer demand, cost, profit, and regulation models described in Secs. 3.1–3.5. The size n_k of the set J_k is a variable in this formulation. For a fixed n_k and fixed engine types M_j for each vehicle, the model (Eq. (1)) is a smooth, continuous optimization formulation that can be solved with gradient-based methods. To take advantage of this property, separate optimization runs are formulated for each combinatorial set of $n_k\in\{1,2,\ldots,n_{\max}\}$ and $M_j\forall j\in J_k$, and gradient-based methods are used to determine the optimal solution for each value of n_k. The most profitable solution among these cases is then taken as the optimum solution.

While this modeling framework is presented as a single loop of sequential computation solved all-at-once, it is possible to break the problem into smaller pieces using multistage approaches [14,15] or decomposition and coordination optimization methods such as collaborative optimization (CO) [16] and analytical target

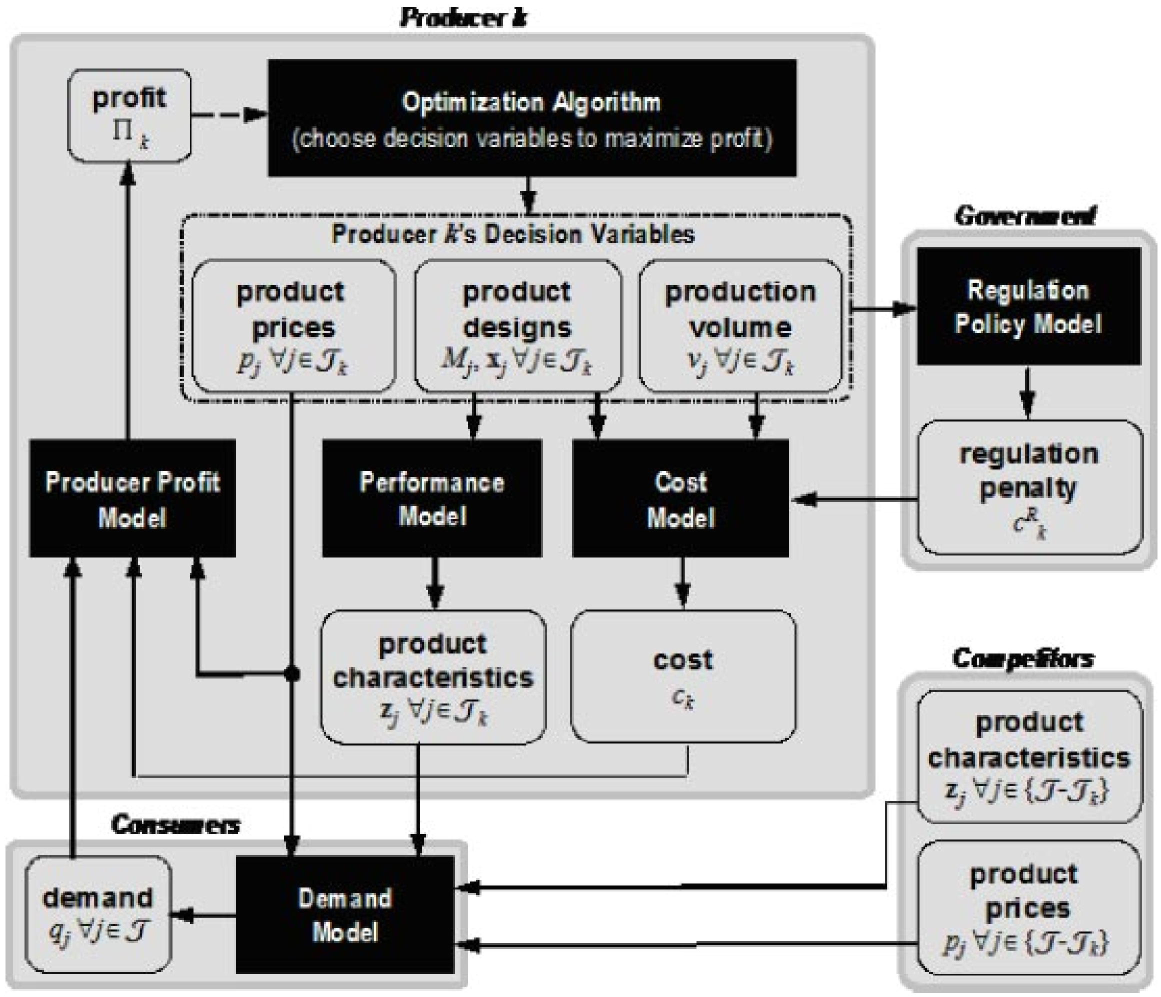

Fig. 1 Overview of the modeling framework

cascading (ATC) [17]. For example, ATC can be used to design complex engineering systems by coordinating hierarchies of design decisions for vehicle systems, subsystems and components [18], or decomposition methods such as CO and ATC could be used to coordinate marketing and business planning models with engineering design models [19–21].

3.1 Engineering Performance Model. The engineering performance model takes design decisions $\mathbf{x}_j$ as input and predicts performance characteristics $\mathbf{z}_j$ that can be calculated for each design j. Several analysis models were explored for vehicle modeling, and ADVISOR [22,23] was chosen because of its availability and appropriate level of detail for this study. ADVISOR contains models for conventional, electric, hybrid electric, compressed natural gas, and fuel cell vehicles. Experimentally-derived engine maps are used to estimate fuel economy and emissions characteristics across engine operating conditions. The vehicle is simulated through a driving cycle, and fuel economy, performance characteristics, and vehicle emissions are calculated for the cycle.

In this study, vehicles are assumed to differ only by engine design, so the default small car vehicle parameters were used in all simulations (based on the 1994 Saturn SL1), and only engine variables were changed. ADVISOR offers a set of nine gasoline and eleven diesel engine types. Each engine type has a base size b_M, corresponding to the power output of a tested engine, which can be scaled to predict performance of larger or smaller engines. (ADVISOR allows scaling parameters between 0.75 and 1.50). The EPA Federal Test Procedure (FTP-75) driving cycle was used for all simulations. Two engine types, $M=\{\text{SI102},\text{CI88}\}$, were utilized in this study with two design variables: the engine scaling parameter x_1 in the range [0.75, 1.50], and the final drive ratio x_2 in the range [0.2, 1.3]. The computed outputs (performance criteria) include the gas mileage (gasoline equivalent) z_1 in miles per gallon (mpg) and the time to accelerate from 0 to 60 mph, z_2, in seconds. The engine type $M=\text{SI102}$ refers to a spark ignition (gasoline) engine with $b_{\text{SI102}}=102$ kW based on the 1991 Dodge Caravan 3.0 L engine, while $M=\text{CI88}$ refers to a compression ignition (diesel) engine with $b_{\text{CI88}}=90.5$ kW based on an Audi 2.5 L engine. Other engine types were explored but turned out to be oversized or undersized for this study. For a particular choice of engine type M, ADVISOR acts as a function f_M mapping $\mathbf{x}$ to $\mathbf{z}$:

$$\mathbf{z}=f_M(\mathbf{x}), \tag{2}$$

where $\mathbf{z}=[z_1,z_2]^T$, and $\mathbf{x}=[x_1,x_2]^T$. ADVISOR simulations were computed for evenly spaced points in a 13 by 19 point grid covering the ranges of x_1 and x_2, respectively, for each engine type, and the responses were used to create a set of surface splines as surrogate models for ease of computation during optimization. Sample contour plots of the simulation results are shown in Fig. 2.

3.2 Consumer Demand Model. The consumer demand model is based on discrete choice analysis (DCA), which presumes users make purchasing decisions based on the *utility* value of each product option. Utility u is measured in terms of an observable deterministic component v, which is taken to be a function of product characteristics, and a stochastic error component ε.

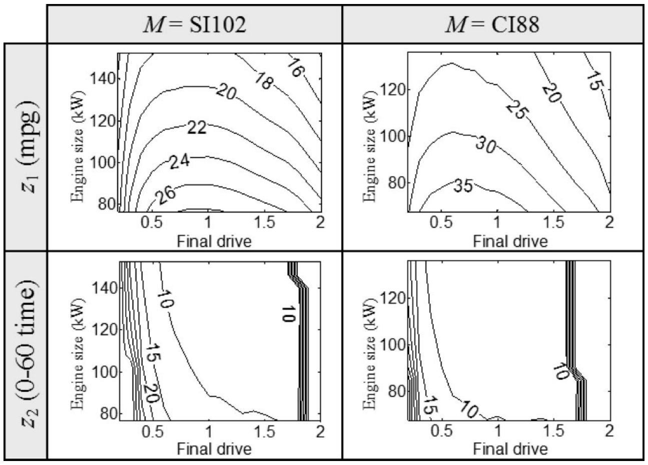

Fig. 2 ADVISOR simulation result contour plots

The probability P_j of choosing a particular product j from the set J is calculated as the probability that product j has a higher utility value than all alternatives.

$$P_j = \Pr(v_j + \varepsilon_j \geqslant v_{j'} + \varepsilon_{j'}; \forall j' \in J) \tag{3}$$

Various probabilistic choice models follow the DCA approach, including the logit model [24] and the probit model [25]. The logit model, developed by McFadden to study transportation choices, has been used extensively in the marketing literature and has recently been applied to engineering design problems [20,21,26]. The model assumes that the unobserved error component of utility ε is independently and identically distributed (iid) for each alternative, and that ε follows the extreme value (double exponential) distribution (i.e., $\Pr[\varepsilon < x] = \exp[-\exp(-x)]$). In practice, it takes a large amount of data to distinguish results predicted by the logit model from those predicted by the probit model, which assumes normal distributions for the error terms. The logit model is used here because of its simplicity, transparency of interpretation, capability to extend predictions to new designs, and the availability of existing models for automotive demand. It yields a simple closed form solution, while the probit model does not. Assuming the double exponential distribution for the ε terms in Eq. (3), the probability P_j of choosing alternative j from set J is computed [27] as

$$P_j = \frac{e^{v_j}}{\sum_{\hat{j} \in J} e^{v_j}}. \tag{4}$$

Each utility function v_j depends on the characteristics $\mathbf{z}_j$ and the price p_j of design j. Given a functional form for $v_j(\mathbf{z}_j)$ based on observed data, regression coefficients are found such that the likelihood of generating the sample data with the model is maximized. For example, Boyd and Mellman [28] fit a simple logit model to automotive sales data based on price, fuel economy, and acceleration (among other vehicle factors). After an analysis of several other vehicle choice models [29–34], the Boyd and Mellman model was chosen for this study for the following reasons:

- The model is based on product characteristics that can be related to engineering design, as opposed to consumer demographics.
- The independent variables include the vehicle's price, fuel economy, and acceleration, which match the characteristics predicted by the engineering performance model under consideration in this study.
- The model was fit to a large volume of annual market data and validated using data from a subsequent year.

The utility equation developed by Boyd and Mellman[1] is

$$v_j = \beta_1 p_j + \beta_2 \left(\frac{100}{z_{1j}}\right) + \beta_3 \left(\frac{60}{z_{2j}}\right) \tag{5}$$

where $\beta_1 = -2.86 \times 10^{-4}$, $\beta_2 = -0.339$, $\beta_3 = 0.375$, p_j is the price of vehicle j, z_{1j} is the gas mileage of vehicle j, and z_{2j} is the 0–60 mph acceleration time of vehicle j. Although several other variables were included (e.g., vehicle style, noise, and reliability), these variables were assumed constant across all vehicles for this study. Since logit choice predictions depend on the differences between utility values, factors that are constant across alternatives do not affect predictions of choice, and they can be ignored. Other factors, such as advertising, promotions, aesthetics, and brand image were also assumed equal across alternatives. While the Boyd and Mellman demand model is adequate for a preliminary analysis, it does introduce several sources of error:

- The model was fit to purchase data from 1977–1978.
- The model utilizes purchase data only; consumers who chose not to purchase vehicles were not studied. Thus, we can predict only *which* vehicles consumers will purchase, not *whether* they will purchase, and the size of the purchasing population is treated as fixed, independent of vehicle prices (i.e., there is no outside good).
- The model is an aggregate model, and therefore it does not account for different segments or consumer groups.
- The use of the logit model carries with it a property called *independence from irrelevant alternatives* (IIA), which implies that as one product's market share increases, the shares of all competitors are reduced in equal proportion [27]. For example, a model with the IIA property might predict that BMW competes as equally with Mercedes as with Chevrolet. In reality, different vehicles attract different kinds of consumers, and competition is not equal. In this investigation, predictive limitations of the IIA property are mitigated since the model is applied only to the small car market (a relatively homogeneous market) rather than to the entire spectrum of vehicles.

The demand model above was developed by Boyd and Mellman to study the effects of fuel economy standards on the market, and it should be sufficient to capture the trends important in a general analysis, even if the numbers vary for today's consumers. For the purposes of this study, the assumption was made that the size of the car-buying population s is 1.57 million people. This figure is based on 11 million people that bought cars in 1977 [35] and an assumption that the size of the small car market was about 1/7 of the total market.[2] The Boyd and Mellman model was then applied to the small car sub-market, with recognition that this could introduce additional error since the model was developed based on the entire car market. Using the logit model with a fixed market size s, the demand q_j for product j is

$$q_j = sP_j = s\frac{e^{v_j}}{\sum_{\hat{j} \in J} e^{v_j}}, \tag{6}$$

where v_j is defined by Eq. (5).

3.3 Cost Model. Production cost is modeled as a function of the vehicle design, and all producers are assumed to have the same manufacturing cost structure. In practice, differences in equipment, assets, suppliers, and expertise exist between manufacturers. However, assuming consistent production cost structures across manufacturers is appropriate for oligopoly analysis,

[1] The coefficients β_1 and β_2 were assumed here to be negative, even though they are listed as positive in the Boyd and Mellman article. In the text the authors describe the variables as having a negative relationship even though all coefficients are listed as positive in the regression summary.

[2] Further research indicated that a better estimate of the size of the small car market may be 2/7 of the total market [36].

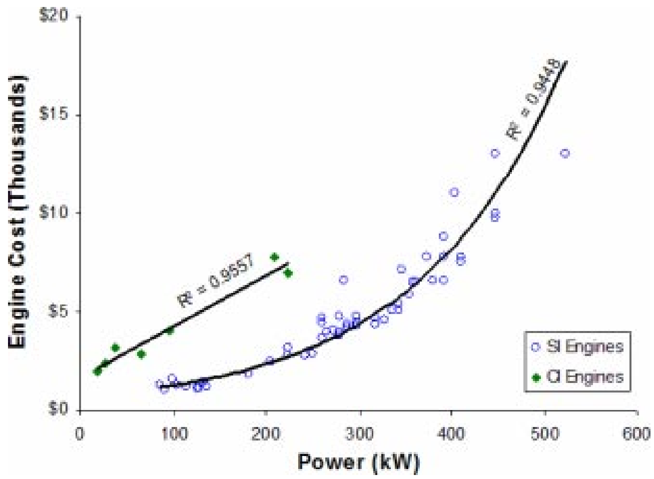

Fig. 3 Manufacturing cost for SI and CI engines

and it is useful to analyze trends even if individual numbers differ between firms. In this analysis, the total cost to manufacture a vehicle c^{P} is decomposed into two components: the investment cost to set up the production line c^{I} and variable cost per vehicle c^{V}. The variable cost is comprised of the cost to manufacture the engine c^{E} and the cost to manufacture the rest of the vehicle c^{B}, so that $c^{\mathrm{V}}=c^{\mathrm{B}}+c^{\mathrm{E}}$. The cost to manufacture q units of a vehicle with topology M and design variables $\mathbf{x}$ is then

$$c^{\mathrm{p}}(M,\mathbf{x})=c^{\mathrm{I}}+qc^{\mathrm{V}}(M,\mathbf{x})=c^{\mathrm{I}}+q(c^{\mathrm{B}}+c^{\mathrm{E}}(M,\mathbf{x})) \tag{7}$$

where it is assumed that $c^{\mathrm{B}}=\$7500$ for all vehicles based on data for the Ford Taurus [37], and $c^{\mathrm{I}}=\$550$ million per vehicle design for all manufacturers based on an average of two figures for new production lines [38]. The cost to manufacture an engine is modeled as a function of engine power, as determined by a regression analysis of data obtained from manufacturing, wholesale, and rebuilt engine costs [39–44]. Wholesale and rebuilt engine prices were assumed to be close to manufacturing prices, and these data fit the curve well. The resulting functions are

$$c^{\mathrm{E}}(M,\mathbf{x})=\begin{cases}\beta_4\exp(\beta_5 b_M x_1) & \text{if } M\in \mathrm{SI}\\ \beta_6(b_M x_1)+\beta_7 & \text{if } M\in CI\end{cases} \tag{8}$$

where $\beta_4=670.51$, $\beta_5=0.0063$, $\beta_6=26.23$ and $\beta_7=1642.8$. These functions are plotted in Fig. 3, and all designs considered in this study fall within the range of the data. As expected, the cost associated with manufacturing diesel engines is higher than for gasoline engines. It is possible that increased diesel production volumes would change this cost structure, but this possibility was not explored in this study. Although both cost regression models rely on maximum engine power as the only dependent variable, Fig. 3 demonstrates that the regressions fit the data well and predict realistic cost trends.

The total cost to producer k is the sum of the production costs for each vehicle in k's product line and the regulation cost c^{R}, as described in Sec. 3.5.

$$c_k=\left(\sum_{j\in J_k} c_j^{\mathrm{P}}\right)+c_k^{\mathrm{R}} \tag{9}$$

3.4 Profit Model. The profit model for each producer k is calculated simply as revenue minus cost:

$$\Pi_k=\left(\sum_{j\in J_k} q_j p_j\right)-c_k=\left(\sum_{j\in J_k} q_j(p_j-c_j^{\mathrm{V}})-c^{\mathrm{I}}\right)-c_k^{\mathrm{R}} \tag{10}$$

where c_k^{R} is the regulation cost for producer k (defined in Sec. 3.5). The model assumes that all transactions happen instantaneously without consideration of the time value of money, opportunity costs, or changes in production loads over time. Demand is predicted over the course of one year, with all costs and revenue occurring during that year. The inclusion of dynamic time considerations brings with it a plethora of uncertainties and issues that are difficult to model, and is therefore left for future consideration. Note that it is assumed that the investment cost c^{I} is completely paid during this year. In practice, the investment cost associated with designing and building production lines and planning supply chains is spread over several years with only minor changes to the vehicles during those few years, implying that this model will tend to over-predict investment cost.

3.5 Regulation Policy. Four producer penalty policies were used to define c^{R}: the no-regulation base case ($c^{\mathrm{R}}=0$), CAFE standards, CO_2 emission taxes, and diesel vehicle sales quotas. Each of these policies applies a penalty cost to the producer as a function of the fuel economy, emission properties, or fuel type of the producer's vehicles. The specific applications of the penalty policies are described below.

3.5.1 Corporate Average Fuel Economy (CAFE). CAFE regulations establish minimum average fuel economy standards that each producer's vehicle fleet must meet to avoid penalties. To define a CAFE policy, both the fuel economy standard and the penalty must be specified. In this study, only a single market segment is utilized, although CAFE regulations in the United States apply to all passenger vehicle markets in which the producer operates. (Multiple market segments are left for future consideration.) The current CAFE fuel economy standard for cars, $z_{\mathrm{CAFE}}=27.5$ mpg, was used here, and two different penalty charges were explored: the current standard, $\rho=\$55$ per vehicle per mpg under the limit, and a hypothetical double-penalty scenario. Additional future credit for vehicle fleets with average fuel economies greater than the standard was not modeled. The total cost incurred by design j is therefore $\rho q_j(z_{\mathrm{CAFE}}-z_{1j})$, where ρ is the penalty, q_j is the number of vehicles of type j that are sold, z_{CAFE} is the CAFE limit, and z_{1j} is the fuel economy of vehicle j. The total regulation cost to producer k is then

$$c_k^{\mathrm{R}}=\max\left(0,\sum_{j\in J_k}\rho q_j(z_{\mathrm{CAFE}}-z_{1j})\right) \tag{11}$$

3.5.2 CO_2 Emission Tax. A vehicle emission valuation study [45] was used to estimate the economic cost to society associated with environmental damage due to the release of each ton of CO_2. Using this valuation, a tax can be imposed on the manufacturer based on the estimated lifetime CO_2 emissions of each vehicle sold due to the burning of hydrocarbon fuel. Tax per vehicle sold can be calculated as $\nu d\alpha_M/z_1$, where ν is the dollar valuation of a ton of CO_2, d is the number of miles traveled in the vehicle's lifetime, α_M is the number of tons of CO_2 produced by combusting a gallon of fuel for engine type M, and z_1 is the fuel economy of the vehicle. The total regulation cost to the producer in this study is

$$c_k^{\mathrm{R}}=\sum_{j\in J_k} q_j\frac{\nu d\alpha_M}{z_{1j}} \tag{12}$$

where $d=150{,}000$ miles, α_M is 9.94×10^{-3} tons CO_2 per gallon for gasoline or 9.21×10^{-3} tons CO_2 per gallon for diesel fuel [46], and the value of ν was varied from \$2/ton to \$23/ton with a median estimation of \$14/ton.

3.5.3 Diesel Fuel Vehicle Sales Quotas. As a regulation method, quotas can be used to force more costly alternative fuel vehicles into the market [10]. In this case, a hypothetical policy is considered that introduces a large penalty cost for violation of a quota on percent diesel sales as a way to enforce adoption of a higher fuel efficiency vehicle alternative. Diesels were selected due to data availability, their competitive fuel efficiency and acceleration characteristics, and their similarity to gasoline engines in unobserved characteristics such as range and existence of supporting infrastructure, which allows application of the demand model without introducing large errors. It is left for future work to consider regulation of emissions such as NO_x and particulate matter, which tend to be larger in diesel engines and which play a significant role in determining environmental tradeoffs between diesel and gasoline engines in practice. The regulation cost is modeled as

$$c_k^{\mathrm{R}} = \max(0, \rho(q_k^{\mathrm{SI}} - (1-\phi)(q_k^{\mathrm{SI}} + q_k^{\mathrm{CI}}))) \tag{13}$$

where ρ is the penalty per gasoline vehicle over quota (\$1000), ϕ is the minimum diesel percentage required by the quota (40%), q_k^{SI} is the total number of spark ignition (gasoline) engines sold by producer k, and q_k^{CI} is the total number of compression ignition (diesel) engines sold by producer k.

3.6 Nash Equilibrium Solution Strategy. In a free market, manufacturers have economic incentives to produce and sell products only if there is an opportunity to make profit within the competitive market. To account for competition in the design of vehicles subject to government regulations, game theory was used to find the market (Nash) equilibrium among competing producers. In game theory, a set of actions is in Nash equilibrium if for each producer $k = 1,2,\ldots,K$, given the actions of its rivals, the producer cannot increase its own profit by choosing any action other than its equilibrium action [47]. In the absence of a cartel agreement or strategic dynamic actions, game theory predicts that the market will stay stable at this point. It is assumed that this market equilibrium point can provide a reasonable prediction of which designs manufacturers are driven to produce under various regulation scenarios. It should be noted however that the Nash equilibrium does not model preemptive competitive strategies by producers. Instead, it assumes that each producer will move to increase its profit while treating competitor decisions as constant.

In order to search for the equilibrium point, an algorithm was employed in which each producer separately optimizes its own profit while holding all competitor producer decisions constant. Each producer's optimization model is solved sequentially, and the process is iterated across producers, in turn optimizing and updating each producer's decisions until all producers converge. Then, a parametric study on K is used to determine the largest value of K that produces a Nash equilibrium with positive producer profits, and this point is taken to be the market equilibrium.

Using the models developed in Secs. 3.1–3.5, each producer k will individually attempt to maximize profit by solving the following optimization problem,

$$\text{maximize}\left(\sum_{j\in J_k} q_j(p_j - c_j^{\mathrm{V}}) - c^{\mathrm{I}}\right) - c_k^{\mathrm{R}}$$

$$\text{with respect to} \{M_j, x_{1j}, x_{2j}, p_j\} \forall j \in J_k$$

$$\text{subject to } 0.75 \leqslant x_{1j} \leqslant 1.50$$

$$0.2 \leqslant x_{2j} \leqslant 1.3$$

$$q_j = s\frac{e^{v_j}}{\sum_{j\in J} e^{\mathrm{V}_j}}$$

$$v_j = \beta_1 p_j + \beta_2\left(\frac{100}{z_{1j}}\right) + \beta_3\left(\frac{60}{z_{2j}}\right)$$

$$\mathbf{z}_j = f_M(\mathbf{x}_j)$$

$$c_j^{\mathrm{V}} = c^{\mathrm{B}} + \begin{cases} \beta_4 \exp(\beta_5 b_{\mathrm{SI102}} x_{1j}) & \text{if } M_j = \mathrm{SI102} \\ \beta_6(b_{\mathrm{CI88}} x_{1j}) + \beta_7 & \text{if } M_j = \mathrm{CI88} \end{cases} \tag{14}$$

where $s = (11/7)\times 10^6$, $\beta_1 = -2.86\times 10^{-4}$, $\beta_2 = -0.339$, $\beta_3 = 0.375$, $\beta_4 = 670.51$, $\beta_5 = 0.0063$, $\beta_6 = 26.23$, $\beta_7 = 1642.8$, $b_{\mathrm{SI102}} = 102$ kW, $b_{\mathrm{CI88}} = 90.5$ kW, $c^{\mathrm{B}} = \$7500$, $c^{\mathrm{I}} = \$550\times 10^6$, and c_k^{R} is defined by Eq. (11), Eq. (12), Eq. (13) or zero, depending on which regulation scenario is used. For each producer, competitor products are represented by the set $\{J - J_k\}$, and are considered fixed parameters that affect demand [Eq. (6)]. The first two constraints represent limits on the ability to model variables outside these ranges rather than physical feasibility limits. If these constraints were active, it would represent an inability to model the optimum solution [48]. However these constraints were not active in any of the results, indicating that the optima discussed here are all interior optima and the solutions are valid.

Despite the computational savings gained by creating surrogate models of the engineering performance simulations (splines), the computational burden is still significant. For each producer, separate optimization runs must be computed to determine which combination of vehicles is best for the product line. This combinatorial set of optimization problems is computed for each producer, and each producer model is then iterated several times in the Nash equilibrium solution strategy. In order to reduce the computational burden, the number of designs per producer was limited to a maximum of two ($n_{\max} = 2$). It was shown that this assumption was reasonable because results of all runs indicate that each producer manufactures only one design, implying that there is a lack of incentive to produce multiple designs (except for the quota regulation case where each producer manufactures both an SI and a CI engine).

4 Results and Discussion

The results of the investigation are summarized in Table 1, with a graphical summary of the resulting fuel economy and regulation cost per vehicle provided in Fig. 4. For each regulation scenario, the table shows the maximum number of producers K that yields a positive-profit Nash equilibrium and the market share per producer design. The use of the aggregate demand model results in each producer making the same decisions at market equilibrium, so Table 1 summarizes the decision variables, product characteristics, costs, and profits for a typical producer in each scenario. The fact that all producers are driven to produce the same vehicle design facilitates comparison of the trends that result from each regulation scenario. Additionally, at equilibrium each producer manufactures only a single design rather than a product line (except in the quota case). This result could be changed by modeling cost savings due to economies of scope [49], possible commonality among designs [50], and the use of a heterogeneous model for demand. From Table 1, it is also evident that the model predicts equal profits for all regulation scenarios (except the quota case), and all incurred costs are passed to the consumer at equilibrium. This is because the demand model assumes a fixed car-buying population (there is no option not to buy) and does not consider the utility of outside goods.

It is important to take care when interpreting results of an optimization study that is based on a demand regression model. Even if the demand model succeeds in capturing important trends in consumer purchasing preferences according to measurable characteristics, the metrics do not capture purchasing criteria entirely, as the model ignores unmeasured and unobservable characteristics. For example, the model used in this study predicts a preference for vehicles with faster acceleration; therefore, a vehicle that dramatically sacrifices unmeasured characteristics such as maximum speed for a slight improvement of acceleration time will be preferred according to the model. However, in practice a consumer would observe the unmeasured limitations during a road test, especially if the limitations are extreme. To check for this issue, each optimum vehicle design was tested post hoc to ensure the vehicle's ability to follow the standard FTP driving cycle and achieve a speed of at least 110 mph on a flat road. All vehicle designs in the study passed this test.

Table 1 Nash equilibrium results for each regulation scenario

		Regulation Type							
		No Reg.	Low CO_2	Med. CO_2	High CO_2	CAFE	2·CAFE	Quota	
# Producers	K	10	10	10	10	10	10	5	
Market share	q/s	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	11.9%	8.1%
Engine type	M	SI	SI	SI	SI	SI	SI	SI	CI
Engine size	$b_M x_1$	127.9	127.7	114.3	110.3	113.3	88.4	127.9	98.0
FD ratio	x_2	1.28	1.28	1.28	1.27	1.28	1.29	1.28	0.88
Price	p	$12,886	$13,031	$13,719	$14,259	$13,058	$12,772	$13,372	$16,083
Gas mileage	z_1	20.2	20.3	21.8	22.4	22.0	25.5	20.2	29.8
Accel. time	z_2	7.46	7.46	7.93	8.10	7.97	9.29	7.46	7.84
Investment cost	c_I	$550 mil	$550 mil	$550 mil	$550 mil	$550 mil	$550 mil	$550 mil	$550 mil
Var. cost/vehicle	c_V	$9,001	$8,999	$8,878	$8,844	$8,869	$8,670	$9,001	$11,713
Reg. cost/vehicle	c_R/q	$0	$147	$956	$1,530	$304	$217	$0	$0
Profit	Π	$60.5 mil	$60.5 mil	$60.5 mil	$60.5 mil	$60.5 mil	$60.5 mil	$276 mil	$6.5 mil

4.1 Base Case. As a comparative baseline, the no-regulation case ($c^R=0$) was analyzed first. Without regulation, the model predicts ten producers in the small car market. Each producer manufactures a single vehicle with design variables, product characteristics, and costs shown in Table 1.

4.2 Corporate Average Fuel Economy (CAFE). Table 1 shows that the CAFE regulation results in increased fuel efficiency at a lower manufacturing cost relative to the base case; however, performance is sacrificed, and regulatory costs are incurred (see Fig. 4). The "2•CAFE" case represents a hypothetical doubling of the penalty for CAFE violation, resulting in improved fuel economy, *reduced* regulation costs, and reduced vehicle prices relative to CAFE. In both cases, it is predicted that it is profitable for manufacturers to violate CAFE standards and take the penalty in order to increase market share. The model indicates that full compliance with CAFE is dangerous for producers because competitors can produce larger engines, which are in high demand, and capture market share. However, when CAFE penalties are increased, there is less danger of losing market share to a competitor who sells more powerful engines because all producers are subject to a more stringent penalty. Therefore all producers design smaller, cheaper engines with less risk.

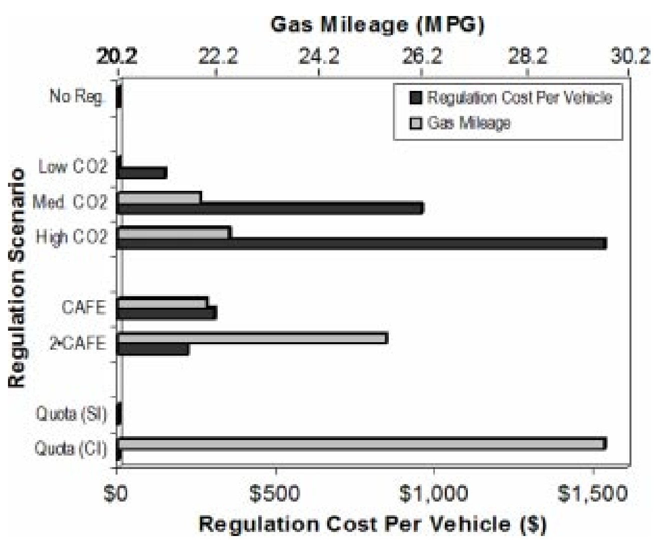

Fig. 4 Resulting vehicle gas mileage and regulation cost per vehicle under each policy

In practice, many producers do not currently accrue CAFE penalties and instead treat the CAFE standard as a constraint [51]. One reason for this is the non-modeled extra costs to the producer caused by violation, such as damage to the producer's reputation (which could affect demand), public and government relations, as well as making future compliance more difficult. The results of this study suggest that these non-modeled aspects may provide significant incentives worthy of further consideration.

4.3 CO_2 Emissions Tax. Comparing the CO_2 emissions tax to the base case, several trends can be observed. As the tax increases, producers tend to design smaller, more fuel-efficient engines while transferring the added regulation cost to the consumer through an increased vehicle price (Fig. 4). A low valuation penalty ($2/ton) has little effect on fuel efficiency with the only significant effect being added regulation costs that are in turn passed on to consumers. The median valuation ($14/ton) has a larger impact, increasing fuel-efficiency by 1.6 mpg, while the high valuation ($22/ton) adds only slight improvement in fuel economy at a substantial regulation cost increase over the median case. These trends predict reasonable real-world scenarios, since regulation provides an incentive to produce smaller, more fuel-efficient engines. However, in practice such increases in vehicle costs could lower the demand and sales of vehicles relative to other modes of transportation or other market segments.

4.4 Diesel Fuel Sales Quota. In the quota policy, producers were forced to offer diesel engines as a minimum percentage of their vehicle fleet ($\phi=40\%$). The results indicate that producers follow this regulation strictly to avoid expensive penalties, producing exactly the minimum required percentage of diesels in their product mix. Since each producer manufactures two vehicle designs, fewer producers result at the market equilibrium.

5 Conclusions

This article presented a methodology for analyzing the impact of fuel economy regulations on the design decisions made by automobile manufacturers. The approach integrates models for engineering design, production cost, consumer demand, producer profit, and producer competition toward predicting the impacts associated with different policies that aim to improve fuel economy. Several trends were observed in the policy scenarios examined in this study. One notable observation is that increased regulation penalties can result in cost savings for all parties (e.g., in CAFE scenarios): Without a regulatory standard, producers cannot afford to make smaller, cheaper engines due to competition; however, when all producers are subject to the same regulation costs, then all producers are driven to produce smaller engines with less risk. On the other hand, increased regulation penalties can also lead to diminishing returns in fuel economy improvement with increased regulation penalties (e.g., CO_2 taxation). The observed trends indicate that the cost-benefit characteristics of a given policy can be modeled in a realistic way, and that a holistic integration of costs, performance, consumer preference, and competition may be helpful for evaluating and selecting environmental policies, as well as for choosing regulatory parameter values.

The study also shows that regulation is necessary to provide incentives for producers to design alternative fuel vehicles (e.g., diesels) that cost more to produce. While diesel engines have better fuel efficiency per unit power, gasoline engines are cheaper to manufacture and are therefore preferred by the market. Future investigations that combine engineering, marketing, and policy models with models of changing consumer preferences and driving habits could be used to predict trends for the diffusion of alternative fuel vehicles, possibly avoiding costly investment in products that are unlikely to achieve wide acceptance and help to focus resources and incentives toward solutions that are likely to make the most impact in reducing environmental damage.

The demand model used in this study indicated that individual consumers prefer vehicle acceleration over fuel economy performance. However, as a society, the same individuals may place value on environmental protection, human health, and sustainability that is not captured in the market of individual decisions. For example, while increased CAFE penalties resulted in decreased costs to producers and consumers relative to other fuel economy policies, they also result in smaller, lower-performance vehicles, which are less preferred by individual consumers. Naturally, it will be necessary to balance social versus individual preferences. To quote from the National Academy of Sciences report [11]: "Selection of fuel economy targets will require uncertain and difficult trade-offs among environmental benefits, vehicle safety, cost, oil import dependence, and consumer preferences. The committee believes that these trade-offs rightfully reside with elected officials."

This research has taken a step toward developing modeling tools to inform such policy tradeoff decisions. Overall the models presented here were successful in predicting realistic long-term trends resulting from several regulation scenarios. Therefore, the abstract oligopoly analysis was able to provide a useful analytical perspective on market incentives resulting from regulation, demonstrating that policy models that include engineering design decisions can be used to improve our general understanding of the interactions between government policy, industry, consumers, and the environment.

Acknowledgments

We gratefully acknowledge Sarah Bahrman and Carl Lenker for their contributions to research on the cost and demand models used in this study and on automotive emissions, economics, and policy. We also thank Professor Fred Feinberg for his helpful input. This work was partially funded by the interdisciplinary Antilium Project of the Rackham Graduate School, the Automotive Research Center, and the National Science Foundation Engineering Research Center for Reconfigurable Manufacturing Systems at the University of Michigan. The generous support of these organizations is appreciated. The opinions expressed are those of the authors and not necessarily those of the sponsors.

Nomenclature

c_k = Total cost for producer k
c^{B} = Base manufacturing cost per vehicle (without engine)
c_j^{E} = Engine manufacturing cost for design j
c^{I} = Investment cost
c_j^{P} = Total production cost for design j
c_k^{R} = Total regulation cost for producer k
c_j^{V} = Variable manufacturing cost per vehicle for design j
d = Lifetime vehicle miles traveled
f_M = ADVISOR simulation for engine type M
j = Vehicle design index
J = Set of all vehicle designs produced
J_k = Set of all vehicle designs produced by producer k
k = Producer index
K = Total number of producers in the market
M_j = Index of vehicle engine type for design j
n_k = Number of designs produced by producer k
p_j = Selling price of design j
q_j = Demand for design j
u_j = Utility of design j
S = Size of the car buying market
v_j = Observable component of utility for production
$\mathbf{x}$ = Design variable vector $(x_1, x_2)^T$
x_{1j} = Engine scaling parameter for design j
x_{2j} = Final drive ratio for design j
$\mathbf{z}$ = Product characteristics vector $(z_1, z_2)^T$
z_{1j} = Fuel economy of design j
z_{2j} = Acceleration time (0–60 mph) of design j
z_{CAFE} = CAFE fuel economy limit
α_M = Tons CO_2 produced per gallon of fuel for engine type M
β = Demand model coefficient parameter
Π_k = Total profit for producer k
ρ = Penalty parameter for regulation violation
ϕ = Minimum diesel sales percentage required by quota
ν = Societal cost valuation per ton of CO_2 in U.S. dollars

References

[1] Diaz, A., 1987, "Interactive Solution to Multiobjective Optimization Problems," Int. J. Numer. Methods Eng., **24**, pp. 1865–1877.
[2] Tappeta, R., and Renaud, J., 2001, "Interactive Multiobjective Optimization Design Strategy for Decision Based Design," ASME J. Mech. Des., **123**, pp. 205–215.
[3] Hazelrigg, G., 1998, "A Framework for Decision-based Engineering Design," ASME J. Mech. Des., **120**, pp. 653–658.
[4] Dixon, L., Garber, S., and Vaina, M., 1996, "California's Ozone-reduction Strategy for Light-duty Vehicles: An Economic Assessment," Rand Publications, 17 February 2004 ⟨http://www.rand.org/publications/MR/MR695.1/⟩
[5] U.S. EPA, *National Emission Inventory, 2000 Air Quality Trends Report*, September 2001, Environmental Protection Agency, Washington, DC.
[6] Hardin, G., 1968, "The Tragedy of the Commons," Science, **162**, pp. 1243–1248.
[7] U.S. EPA, Clean Air Act, Environmental Protection Agency, Washington, DC, 15 November 2002 ⟨http://www.epa.gov/oar/oaq_caa.html⟩
[8] U.S. Congress, Energy Policy and Conservation Act of 1975 (P.L. 94–163).
[9] Gardner, G., 1996, "GM Flips EV1 'On' Switch," *Ward's AutoWorld* March 1996 ⟨http://waw.wardsauto.com/ar/auto_gm_flips_ev/⟩
[10] Associated Press, 2003, "GM Pulling Plug on Electric Cars," *Cable News Network*, 9 April 2003 ⟨http://www.cnn.com/2003/TECH/biztech/04/09/electric.cars.ap/⟩
[11] National Academy of Sciences Committee, Committee on the Effectiveness and Impact of Corporate Average Fuel Economy Standards, Board on Energy and Environmental Systems, Transportation Research Board, National Research Council, 2002, *Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards*, National Academies Press.
[12] Commission of the European Communities, 2000, "A Review of the Auto-Oil II Program," *Communication from the Commission* Brussels, 05.10.2000 Com 626.
[13] Green, D. and Hopson, J., *An Analysis of Alternative Forms of Automotive Fuel Economy Standards for the United States*, Center for Transportation Analysis Publications.
[14] Li, H., and Azarm, S., 2000, "Product Design Selection Under Uncertainty and with Competitive Advantage," ASME J. Mech. Des., **122**, pp. 411–418.
[15] Li, H., and Azarm, S., 2002, "An Approach for Product Line Design Selection Under Uncertainty and Competition," ASME J. Mech. Des., **124**, pp. 385–392.
[16] Balling, R. J. and Sobieszczanski-Sobieski, J., 1994, "Optimization of Coupled Systems: A Critical Overview of Approaches," *AIAA-94-4330-CP, Proceedings of the Fifth AIAA/NASA/USAF/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, Panama City, FL.
[17] Kim, H. M., 2003, "Target Cascading in Optimal System Design," ASME J. Mech. Des., **125**, pp. 474–480.
[18] Kim, H. M., Rideout, D. G., Papalambros, P. Y., and Stein, J. L., 2003, "Ana-

lytical Target Cascading in Automotive Vehicle Design,'' ASME J. Mech. Des., **125**, pp. 481–489.
[19] Gu, X., Renaud, J., Ashe, L., Batill, S., Budhiraja, A., and Krajewski, L., 2002, ''Decision-based Collaborative Optimization,'' ASME J. Mech. Des., **124**, pp. 1–13.
[20] Michalek, J. J., Feinberg, F. M., and Papalambros, P. Y., 2004, ''An Optimal Marketing and Engineering Design Model for Product Development Using Analytical Target Cascading,'' *Proceedings of the Tools and Methods of Competitive Engineering Conference*, Lausanne, Switzerland, April 12–16, 2004.
[21] Michalek, J. J., Feinberg, F. M., and Papalambros, P. Y., 2004, ''Linking Marketing and Engineering Product Design Decisions via Analytical Target Cascading,'' to appear in the *J. Product Innovation Management*.
[22] Markel, T., Brooker, A., Hendricks, T., Johnson, V., Kelly, K., Kramer, B., O'Keefe, M., Sprik, S., and Wipke, K., 2002, ''ADVISOR: A Systems Analysis Tool for Advanced Vehicle Modeling,'' J. Power Sources, **110**, pp. 255–266.
[23] Whitehead, J. W., 2001, *Design and Performance of Derivative-Free Optimization Algorithms Used with Hybrid Electric Vehicle Simulations*, M.S. thesis, University of Michigan Department of Mechanical Engineering.
[24] McFadden, D., 1976, ''Quantal Choice Analysis: A Survey,'' Annals of Economic Social Measurement, **5**, pp. 363–390.
[25] Currim, I., 1982, ''Predictive Testing of Consumer Choice Models that are Not Subject to Independence of Irrelevant Alternatives,'' J. Marketing Res., **19**, 208–222.
[26] Wassenaar, H., and Chen W., 2003, ''An Approach to Decision-based Design with Discrete Choice Analysis for Demand Modeling,'' ASME J. Mech. Des., **125**, pp. 490–497.
[27] Train, K., 2003, *Discrete Choice Methods With Simulation*, Cambridge University Press, New York.
[28] Boyd, J. H., and Mellman, R. E., 1980, ''The Effect of Fuel Economy Standards on the U.S. Automotive Market: An Hedonic Demand Analysis,'' Transp. Res., Part A, **14**, pp. 367–368.
[29] Berkovec, J., 1985, ''Forecasting Automobile Demand Using Disaggregate Choice Models,'' Transp. Res., Part B: Methodol., **19B**, pp. 315–329.
[30] Brownstone, D., Bunch, D., and Train, K., 2000, ''Joint Mixed Logit Models of Stated and Revealed Preferences for Alternative-fuel Vehicles,'' Transp. Res., Part B: Methodol., **34**, pp. 315–338.
[31] Goldberg, P., 1996, ''The Effects of the Corporate Average Fuel Efficiency Standards,'' *National Bureau of Economic Research* Working Paper 5673, Yale University, New Haven, CT.
[32] Manrai, A., 1995, ''Mathematical Models of Brand Choice Behavior,'' Eur. J. Oper. Res., **82**, pp. 1–17.
[33] Wojcik, C., 2000, ''Alternative Models of Demand for Automobiles,'' Econ. Lett., **68**, pp. 113–118.
[34] Yee, J., 1991, ''Effect of Consumption Standards on U.S. Gasoline Consumption,'' Journal of Policy Modeling, **13**, pp. 205–227.
[35] U.S. Department of Transportation, Federal Highway Administration, Office of Highway Policy Information. Source: *Ward's 2001 Automotive Yearbook* and the annual *Ward's Motor Vehicle Facts and Figures Publication*, 23 Jan. 2003 ⟨http://www.fhwa.dot.gov///////ohim/onh00/line4.htm⟩.
[36] U.S. Department of Energy, Office of Transportation Technologies, 2001, *Energy Efficiency and Renewable Energy Network*. Source: Oak Ridge National Laboratory. ⟨http://www.ott.doe.gov/facts/archives/fotw108supp.shtml⟩.
[37] Delucchi, M., and Lipman, T., 2001, ''An Analysis of the Retail and Lifecycle Cost of Battery-Powered Electric Vehicles,'' Transp. Res. Part D: Transport and Environment, **6**, pp. 371–404.
[38] Whitney, D. 2001, ''Cost Performance of Automobile Engine Plants,'' *International Motor Vehicle Program*, Working Papers, Massachusetts Institute of Technology. ⟨http://web.mit.edu/ctpid/www/Whitney/morepapers/Engine.pdf⟩.
[39] *American Speed Enterprises Ent. Racing Engines Homepage*. 23 January 2003 ⟨http://www.amerspeed.com⟩.
[40] *E Diesels Ltd. Homepage*—Diesel Engine Trader. 23 January 2003 ⟨http://www.dieselenginetrader.com⟩ Glasgow, Scotland.
[41] *Ford Motors N'Engine Replacement Co. Homepage*. 23 January 2003 ⟨http://www.ford-motors-engines.com/⟩.
[42] *Hardy Diesels & Equipment Homepage*. 23 January 2003 ⟨http://www.hardydiesel.com/⟩ Jamul, CA.
[43] *National Engine Homepage*. 23 January 2003 ⟨http://www.nationalengine.com⟩.
[44] *Rebuilt Auto Car Engines Co. Homepage*. 23 January 2003 ⟨http://www.rebuilt-auto-engines.com/⟩ Spokane, WA.
[45] Matthews, S., and Lave, L., 2000, ''Applications of Environmental Valuation for Determining Externality Costs,'' Environ. Sci. Technol., **34**, pp. 1390–1395.
[46] Bohac, S., and Jacobs, T., Unpublished Research, Office Communication (15 Nov. 2002) University of Michigan, 1105 WE Lay Auto Lab, 1231 Beal Ave. Ann Arbor, MI 48109-2121.
[47] Tirole, J., 1988, *The Theory of Industrial Organization*, MIT, Cambridge, MA.
[48] Papalambros, P., and Wilde, D., 2000, *Principles of Optimal Design: Modeling and Computation*, Second ed., Cambridge University Press, Cambridge, UK.
[49] Panzar, J., and Willig, R., 1981, ''Economies of Scope,'' Am. Econ. Rev., **71**, pp. 268–272.
[50] Fellini, R., 2003, *A Model-Based Methodology for Product Family Design*, Ph.D. thesis, Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI.
[51] Georgiopoulos, P., Fellini, R., Sasena, M., and Papalambros, P., 2002, ''Optimal Design Decisions in Product Portfolio Valuation,'' *Proceedings of the 2002 ASME Design Automation Conference*, DAC-34097, Montreal, Quebec, Canada, September 29–October 2, 2002.