Robustness and Real Options for Vehicle Design and Investment Decisions under Gas Price and Regulatory Uncertainties

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Abstract
Manufacturers must decide when to invest and launch a new vehicle segment or how to redesign vehicles existing segment, both under market uncertainties. We present an optimization framework for redesigning or investing in future vehicles using real options to address uncertainty in gas price and regulatory standards like the US Corporate Average Fuel Economy (CAFE) standard. In a specific study involving a product of gasoline, hybrid electric, and electric vehicles, we examine the relationship between gas price and CAFE uncertainties to support decisions by manufacturers on product mix and by policy makers on proposing standards. A real options model is used for the time delay on investment, redesign, and pricing, integrated with a robust design formulation to optimize expected net present value (ENPV) and net present value (NPV) robustness. Results for nine different scenarios suggest that policy makers should consider gas price when setting CAFE standards; and manufacturers should consider the trade-off between ENPV and robust NPVs. Results also suggest that change of product mix rather than vehicle redesign better addresses CAFE standards inflation.

1 Introduction

Successful products designed for the current market may not succeed in the future because of market changes. Future market environments are characterized by various types of uncertainties. For example, uncertain external factors in the automotive market include gas prices, government subsidies, taxes, regulations, and available infrastructures such as fuel and charging stations. Some of these factors impact manufacturers' profit by affecting customer preferences or production cost. These factors change over time, and so manufacturers must decide how and when to redesign existing products in order to adapt to these changes or when to invest in new product segments.

This study presents a product design and investment model based on real options and robust design optimization that can help automotive vehicle manufacturers to make decisions on product mix and policy makers to propose fuel economy standards. We examine specifically the impact of gas price and CAFE standard uncertainties for a product mix of gasoline vehicles, hybrid electric vehicles (HEVs), and electric vehicles (EVs). We focus on powertrain alternatives because they have the largest impact on fuel economy and vehicle performance.

Regarding customer preferences, market data show a strong positive correlation between gas prices and fuel efficiency [1,2], meaning that customers favor fuel-efficient vehicles when gas prices are high. This observation motivates the present study to focus on the impact of uncertainty on gas prices during product planning. The consumer surveys reported in Section 3.3 support this argument. Manufacturers must launch additional fuel-efficient vehicles when gas prices increase to ensure that their products can meet changing market preferences.

Regulations affect vehicle design and cost. The US Corporate Average Fuel Economy (CAFE) regulation is a fleet-level fuel economy standard introduced in 1978 that requires automakers to meet fuel economy targets or pay penalties [3]. CAFE regulation has been reformed over time to set different targets based on vehicle "footprint" defined as the

*Address all correspondence to this author. A previous version of this manuscript was presented at the ASME 2016 International Design & Engineering Technical Conferences (Charlotte, Aug 21-Aug 24) product of track width and wheel base [4]. Manufacturers pay a penalty for miles per gallon (MPG) that fall short of the standard for each vehicle in their fleet. Current CAFE standards are set until 2021 and proposed rules for 2022-2025 will be determined after a mid-term review in 2018 [5]. Political uncertainty on future CAFE standards along with gas price market uncertainty [6] significantly affect automaker decisions to develop electric vehicles. For example, when CAFE standards and gas price are low, automakers might prefer not to invest in electrified vehicles. This study examines how electric vehicle (EV) investment and design can be profitable in the US under US CAFE regulations.

Manufacturers must decide whether to change the current product mix and invest in new product development based on market conditions. In a real options investment strategy, decision makers do not commit to decisions in advance and wait until uncertainty (risk) is reduced (hedged). They commit to a decision at subsequent periods using the latest market information. In this study we assume that Research and Development (R&D) investment provides the manufacturer with the ability to change the product mix after product development is completed. An "option" differs from a "choice." Option implies that an action has been taken to enable the option holder to make choices easily. There is cost associated with creating the option. For example, a manufacturer has the option to expand product mix and redesign for a new segment over time because manufacturers have invested in new powertrain technology and prepared a suitable assembly line to accommodate the new product mix. Manufacturers could choose to develop many vehicles at once but this would be hardly exercising an option. Real options ideas have been previously applied to engineering design [7–15] and these studies are reviewed in Section 2.

We consider as key decisions for the manufacturers the R&D investment on alternative powertrains, redesign decisions (new model year), and prices. R&D investment in a new vehicle entry means investing in HEV or EV, if not currently available. R&D investment is an option that allows the manufacturer to launch a new powertrain as a choice in the future that changes the product mix. We assume that R&D investment includes development cost, as well as plant cost for fabrication, assembly equipment and tooling [16]. We consider variable costs for materials excluding redesign costs of the same powertrain segment (i.e., switching related investment [16]). Manufacturers can produce the redesigned product and decide on its price annually.

R&D investment and redesign decisions differ from financial decisions, such as setting a price, because they cannot be implemented immediately. Cardin et al. [13] accounted a time lag between the decision to enable a flexibility and the decision to make this flexibility operational (time to build). In the automotive industry, the time gap between initial planning and production is at least two years [17]. Thus, decisions pertaining to vehicle model must be made at least two years before the expected sale time.

Traditional real options approaches maximize the Expected Net Present Value (ENPV) by examining possible scenarios [15]. Robust design approaches focus on minimizing the variation in performance. In our study, we integrate real options and Robust Design Pptimization (RDO) to ensure that we maximize ENPV and minimize variance of net present values (NPV) under uncertainty. RDO in engineering typically aims for robust quality under uncertainty even if it sacrifices the expected quality. Uncertainties (noise factors) in RDO can be generated using Monte Carlo (MC) simulations. The mean and variance of quality are then calculated based on these uncertainties. This approach is similar to the real options approach that uses MC simulation. The key difference is that in real options the "option" can affect decisions at a future time, whereas RDO focuses on decisions at the current time.

The study falls under Design for Market Systems (DMS) research [18–24]. DMS utilizes a decision-making framework that maximizes profit by linking demand models (generally discrete choice models) and engineering models. Unlike previous DMS research on this topic, the present study applies time delay on R&D investment, redesign, and pricing using real options and integrating RDO, thus enabling the product planner to consider both expected value and robustness.

The remainder of the article is organized as follows. Section 2 reviews relevant literature. Section 3 introduces the proposed optimization framework and the vehicle market and engineering models. Sections 4 and 5 present and discuss results for the particular study. Section 6 concludes with a summary and limitations of the proposed approach.

2 Related Work: Real Options in Design

This section presents a brief discussion of previous work in real options for design. In investment decisions, Discounted Cash Flow (DCF) is used to evaluate potential investments based on the NPV of projects. Traditional DCF underestimates the value of flexibility of decisions (option values). The real options approach was originally introduced to address this limitation [25, 26]. An option is a right (but not an obligation) to take action depending on the realization of future market environments. Options comprise five types, namely, deferment, abandonment, expansion, contraction, and switching options [26]. In real options, ENPV is introduced by adding Real Option Values (ROV) to NPV: ENPV = NPV + ROV. The investor chooses to invest if ENPV is positive. Hence, even if the NPV is negative, high ROV can result in investment. ROV is obtained from the value of flexibility of decisions in each time stage of analysis.

Three methods are used to compute ROV: Black-Scholes model [27], binomial lattice model [28], and MC simulations [29]. The Black-Scholes model is representative of continuous time models, whereas the binomial lattice model is representative of discrete time models. The Black-Scholes model that was introduced for financial options can yield a closed-form solution. The binomial lattice model provides an intuitive interpretation of results and is applicable to various options. This model assumes that the value of an asset can change in one of only two directions over time, i.e., increase or decrease, to ensure that probability follows a binomial distribution. All possible market scenarios and associated probabilities are represented by a tree structure. Option values in the tree structure are calculated from the end nodes to the starting node in reverse through a backward induction process. When a reasonably large number of time periods is used for the binomial lattice model, the result converges to that of the Black-Scholes model [30]. However, this model is sensitive to parameter inputs. MC simulations randomly generate different scenarios to compute profit distribution and calculate option values from the initial time in chronological order, in contrast to the binomial lattice model. This approach is useful when defining parameters for Black-Scholes models but is difficult to use in binomial lattice models.

Real options have been used in design contexts to facilitate flexibility [31], and as a tool that can be used not "on" but "in" design projects [9]. Zhao and Tseng showed that flexibility is important for infrastructure design, such as parking garages [7]. Kalligeros and de Weck evaluated the value of flexibility in modularized office building design by considering the contraction option of an office complex [8]. Silver and de Weck introduced "time-expanded decision networks" to analyze the effect of lock-in and flexibility in space launch system design and to account for switching cost when choosing launch vehicle configurations [10]. Dong et al. simulated a real options approach using merge, substitute, and reject options for modules in modular product design, and randomly generated data sets rather than actual data [11]. Cardin and Hu designed a waste-to-energy system using MC simulations [15]. They formulated and compared three methods, namely, inflexible decision making in deterministic market conditions, inflexible decision making in uncertain market conditions, and flexible decision making under uncertain market conditions. Suh et al. proposed a design process for flexible product platforms that enables the production of vehicles of different length [16]. MC simulation was used to maximize ENPV under 12 uncertain future scenarios.

Existing studies on real options on vehicle design do not consider gas price and CAFE regulations and generally treat price under uncertainty without addressing the time lag between investment options, design decisions, and price decisions. Most applications use MC simulation as the solution strategy by evaluating several random scenarios. The present study also adopts MC simulation and includes robustness of NPVs in addition to ENPV.

3 Problem Formulation

The proposed problem formulation contains three available decisions, namely, investment on new segment development, existing segment redesign, and price.

(a) Investment: This decision should be made at time $t-\beta$ to launch new product segmentation at time t. Investment timing is a decision variable for real options. We assume β is three years as the time needed to develop a new powertrain. Once investment is made, the new vehicle (with the new powertrain) can be launched after three years and can be redesigned annually. In the design optimization model in Section 3.1 the redesign variables for a new vehicle are added after the investment.

(b) Product redesign: This decision should be made at time $t-\alpha$ to launch a redesigned product at time t because redesigning an existing product takes time $t-\alpha$ to complete. We assumes α is two years.

(c) Price: This decision can be made at time t of product launch.

We considered two market uncertainties, namely, gas prices and CAFE standards. Section 3.2 discusses the details of generating these uncertainties:

(a) Gas price: This uncertainty affects the customers' choice of vehicles. Future gas price scenarios are generated based on historical data and a stochastic model. The generated gas price is used as input in the market demand function.

(b) CAFE standards: This uncertainty may result in annual penalty cost to manufacturers. CAFE standard scenarios for 2022-2025 are generated considering the most optimistic and pessimistic scenarios to manufacturers.

We formulate a multi-objective problem. The first objective is to maximize the ENPV of profit over a given design period with respect to vehicle redesign, prices, and investments for each time using real options. The second objective is to minimize variance of output profits using RDO. This formulation allows us to examine the robustness of solutions obtained from real options.

3.1 Optimization Model Formulation

The overall optimization problem is formulated as follows:

$$
\begin{aligned}
&\max_{I^{(t)},\mathbf{x}^{(t)},\mathbf{p}^{(t)}} \quad w_1 ENPV - w_2\sigma^2_{NPV}\\
&\text{subject to } \mathbf{x}^{(t)}_{lb} \le \mathbf{x}^{(t)} \le \mathbf{x}^{(t)}_{ub}\ \forall t\\
&\qquad\qquad\ \mathbf{p}^{(t)}_{lb} \le \mathbf{p}^{(t)} \le \mathbf{p}^{(t)}_{ub}\ \forall t
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
\text{where } ENPV &= \sum_{s=1}^{S}\Phi_s NPV_s\\
NPV_s &= \{\sum_{t=1}^{T}(\tfrac{1}{1+i})^t[\mathbf{p}^{(t)}\cdot\mathbf{Q}(\mathbf{p}^{(t)},\mathbf{a}^{(t-\alpha)},g_s^{(t)})\\
&\quad -C(\mathbf{x}^{(t-\alpha)}) - I^{(t)}\\
&\quad -CF_s(\mathbf{x}^{(t-\alpha)},\mathbf{Q}(\mathbf{p}^{(t)},\mathbf{a}^{(t-\alpha)},g_s^{(t)}))]\}\\
\sigma^2_{NPV} &= \sum_{s=1}^{S}\Phi_s(NPV_s-\mu_{NPV})^2\\
\mathbf{a}^{(t)} &= A(\mathbf{x}^{(t)})\\
I^{(t)} &\in [0, I_{gas}, I_{HEV}, I_{EV}, I_{gas}+I_{HEV}, I_{HEV}+I_{EV}]
\end{aligned}
$$

Here μ and σ are mean and standard deviation of profits, i is the discount rate, $\mathbf{Q}$ is the demand function, $g_s^{(t)}$ is the gas price of scenario s at time t, C is the vehicle cost function, CF_s is the CAFE penalty cost function of scenario s, and α is the time required for redesign. The coefficients w_1 and

w_2 are weights for the two objectives where $w_1+w_2=1$; when w_2 is 0, the problem maximizes ENPV similar to a conventional real options approach; when w_2 increases, the problem starts to trade-off between ENPV and robustness (variance) of profit outputs. Further, Φ_s is the probability of scenario s; when we assume the same probability for all scenarios, ENPV becomes the average profit of all scenarios. The symbol $(\cdot)$ denotes the dot product of two vectors; $\mathbf{a}^{(t)}$ is the vector of vehicle performance, and A is the performance function representing the simulation model; $I^{(t)}$ is the investment at time t whose value is chosen among $[0, I_{gas}, I_{HEV}, I_{EV}, I_{gas}+I_{HEV}, I_{HEV}+I_{EV}]$; for example, when an investment on HEV and EV is made, $I^{(t)}=I_{HEV}+I_{EV}$. Note that this formulation does not include economies of scale that remains to be addressed in a future study.

The vector of redesign variables at time t representing the powertrain component sizes denoted by $\mathbf{x}^{(t)}$ and the vector of prices at time t denoted by $\mathbf{p}^{(t)}$ are defined based on this investment decision. Both $\mathbf{x}^{(t)}$ and $\mathbf{p}^{(t)}$ are continuous decision variables allowed to vary between lower and upper bounds $[\mathbf{x}_{lb}^{(t)}, \mathbf{x}_{ub}^{(t)}]$, $[\mathbf{p}_{lb}^{(t)}, \mathbf{p}_{ub}^{(t)}]$, respectively. Redesign choice for an existing vehicle, i.e., launching a model year at time t, must be made at $t-\alpha$ while redesign choice of a new vehicle after $t-\alpha$ is available only if the investment of that powertrain is made at $t-\beta$. In the model, decision variables corresponding to the new vehicle type are inserted into the vectors $\mathbf{x}^{(t)}$ and $\mathbf{p}^{(t)}$. The relationship between investments and other decision variables are listed below for five possible cases defined based roughly on the prevailing status of the US vehicle market.

Case 1: A manufacturer who has only gasoline vehicle models can exercise four options.

(i) No investment: $I^{(t-\beta)}=0$, $\mathbf{x}^{(t)}=\mathbf{x}_{gas}^{(t)}$, $p^{(t)}=p_{gas}^{(t)}$
(ii) Investment on HEV: $I^{(t-\beta)}=I_{HEV}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{HEV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{HEV}^{(t)}]$
(iii) Investment on EV: $I^{(t-\beta)}=I_{EV}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{EV}^{(t)}]$
(iv) Investment on HEV and EV: $I^{(t-\beta)}=I_{HEV}+I_{EV}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{HEV}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{HEV}^{(t)}, p_{EV}^{(t)}]$

Case 2: A manufacturer who has only EV models can exercise four options.

(i) No investment: $I^{(t-\beta)}=0$, $\mathbf{x}^{(t)}=\mathbf{x}_{EV}^{(t)}$, $p^{(t)}=p_{EV}^{(t)}$
(ii) Investment on gasoline: $I^{(t-\beta)}=I_{gas}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{EV}^{(t)}]$
(iii) Investment on HEV: $I^{(t-\beta)}=I_{HEV}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{HEV}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{HEV}^{(t)}, p_{EV}^{(t)}]$
(iv) Investment on gasoline and HEV: $I^{(t-\beta)}=I_{gas}+I_{HEV}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{HEV}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{HEV}^{(t)}, p_{EV}^{(t)}]$

Case 3: A manufacturer who has gasoline and HEV models can exercise two options.

(i) No investment: $I^{(t-\beta)}=0$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{HEV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{HEV}^{(t)}]$
(ii) Investment on EV: $I^{(t-\beta)}=I_{EV}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{HEV}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{HEV}^{(t)}, p_{EV}^{(t)}]$

Case 4: A manufacturer who has gasoline and EV models can exercise two options.

(i) No investment: $I^{(t-\beta)}=0$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{EV}^{(t)}]$
(ii) Investment on HEV: $I^{(t-\beta)}=I_{HEV}$, $\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{HEV}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{HEV}^{(t)}, p_{EV}^{(t)}]$

Case 5: A manufacturer who has all gasoline, HEV, and EV models does not have any options.

$\mathbf{x}^{(t)}=[\mathbf{x}_{gas}^{(t)}, \mathbf{x}_{HEV}^{(t)}, \mathbf{x}_{EV}^{(t)}]$, $\mathbf{p}^{(t)}=[p_{gas}^{(t)}, p_{HEV}^{(t)}, p_{EV}^{(t)}]$

3.2 Uncertainty Quantification

The sources of uncertainty considered are price and regulations.

3.2.1 Gas Price Uncertainty

No perfect gas price prediction methods exist but several have been proposed [32, 33]. The Geometric Brownian Motion (GBM) is useful in stochastic oil price modeling [34], and also in real options [14, 15]. Here we benchmark the latest work from the National Bureau of Economic Research [35] that predicts gas price using GBM.

To generate gas price g, GBM is formulated as,

$$g^{(t+1)}=\mu g^{(t)}\delta t+\sigma g^{(t)}W^{(t)}\sqrt{\delta t}+g^{(t)}, \tag{2}$$

where μ is the drift rate, δt is the time difference, σ is the volatility rate, and W is the Wiener process drawing a random value from $N(0,1)$. We use monthly US gas price data from January 2000 to December 2016 to calculate μ and σ, which are the average and standard deviations of $(\ln(g^{(t+1)})-\ln(g^{(t)}))$, respectively. We then generate gas prices from January 2017 to December 2025 using Eq. (2).

We create 3,000 gas price scenarios using Eq. (2) and we classify them based on the 2017-2025 gas price mean values into three Scenario Groups (SGs), namely, low gas price, moderate gas price, and high gas price, as shown in Fig. 1(a). Each group includes 1,000 scenarios used to compare the decisions of manufacturers and policy makers under gas price uncertainty.

3.2.2 CAFE Standard Uncertainty

CAFE standards defined until 2025 are based on vehicle footprints [4,5]. The fuel economy target decreases with the vehicle size and a fleet-level target is calculated using production volume of vehicles of different sizes. Passenger cars and light trucks have corresponding CAFE standards. Here we consider only passenger cars and we assume three product segments: gasoline, HEV, and EV. The standards until 2021 are final while the standards for 2022-2025 have some uncertainty since they can be updated after the mid-term review in 2018 [5,6].

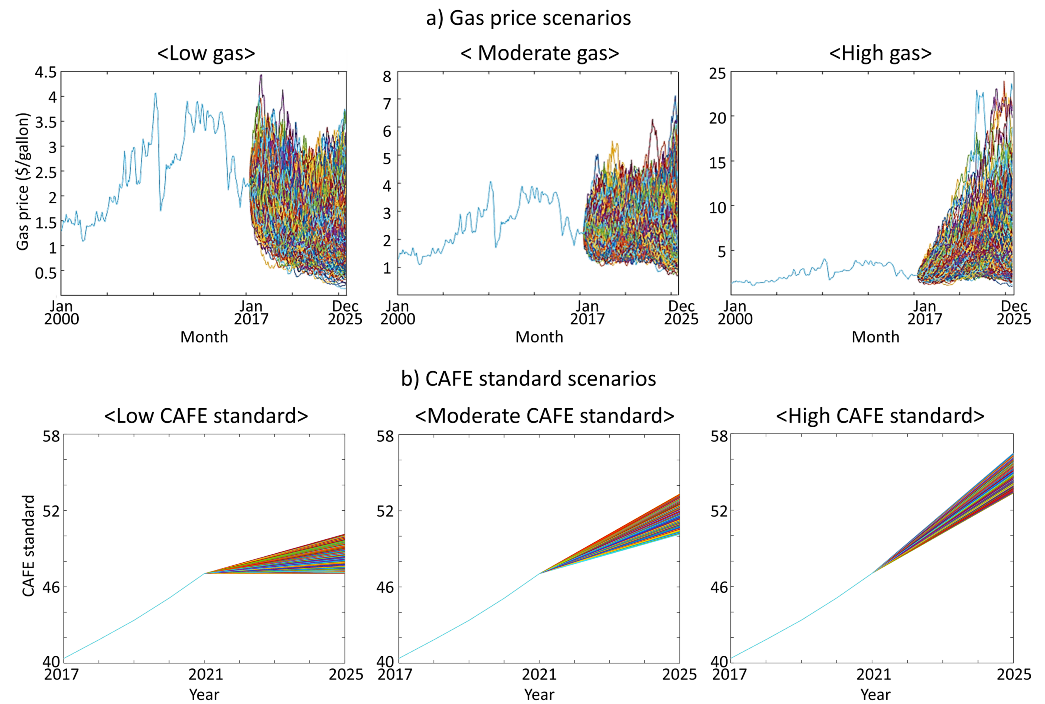

Fig. 1. Generated SGs for gas price and CAFE standard for a vehicle with footprint 45 sq-ft

We model CAFE uncertainty by defining two extreme cases to generate the CAFE standard scenarios for 2021-2025. The worst case for manufacturers is to keep the current standards for 2025 without change. The best case for manufacturers is to use the same standard with 2021 until 2025 without any increase. We draw random values for 2025 between the worst and the best case using a uniform distribution, and use a linear interpolation to calculate CAFE standards between 2021 and 2025. We generate 3,000 scenarios and classify them into three groups based on the value of the CAFE standard in 2025. This process is similar to the one we used for gas prices. Fig. 1(b) shows the three groups of CAFE standards for a vehicle with footprint around 45 sq-ft. We generate the CAFE standard scenarios for each vehicle type, and we assume the EV has footprint size similar to a Nissan Leaf, the HEV similar to a Toyota Prius, and the gasoline vehicle similar to a Toyota Corolla.

Manufacturers pay a penalty for violating the CAFE standard. The current penalty is $55 per MPG for each vehicle below the CAFE standard [5]. This penalty was scheduled to increase to $140 but the application of the rule has been delayed until 2019 [36]. A manufacturer's CAFE is calculated based on the fleet-based harmonic mean:

$$\frac{Q_{gas}+Q_{HEV}+Q_{EV}}{\frac{Q_{gas}}{f_{gas}}+\frac{Q_{HEV}}{f_{HEV}}+\frac{Q_{EV}}{f_{EV}}} \tag{3}$$

where Q is the production volume and f is the fuel efficiency (MPG). The CAFE standard for that manufacturer is calculated using the same formula where f is replaced with the CAFE targets for each vehicle segment.

Plug-in EVs obtain incentive when calculating fuel efficiency in CAFE. The US Department of Energy developed the petroleum equivalency factor (PEF), which is equivalent to 82,049 Wh/gal. This value is generated by dividing gasoline-equivalent energy content of electricity by the fuel content factor of 0.15. For example, the CAFE for EV = PEF (in Wh/gallon)/rated energy efficiency (in Wh/mi) of the EV.

In addition, manufacturers can obtain credit from surplus CAFE targets and use this credit in other years when they cannot meet CAFE targets. The credits can be used -3 years to $+5$ years from the year in which they were acquired [4]. In this study, we assume that manufacturers use all available credits in 2025 and pay off penalties. We model the CAFE penalty function CF using the information above.

3.3 Demand Model

For the consumer demand model Q in Eq. (1) needed to compute profit, we define five vehicle attributes and four levels for each attribute, as shown in Table 1. Vehicle price is a decision variable in the demand model. Vehicle range, MPG, acceleration, and top speed are product attributes determined by the vehicle powertrain design as described in Section 3.4. Part-worth for attribute levels are estimated through hierarchical Bayesian choice-based conjoint analysis [37].

We conducted three conjoint surveys with three different gas price scenarios of $1/gallon, $3/gallon, and $5/gallon to incorporate gas price into the consumer demand model. For example, one of the questions in the survey was "Which of the following vehicles would you be most likely to buy if the current gas price is $3/gallon?" Each subject answered seven questions for each gas price scenario. We assigned the order

Table 1. Vehicle attributes and levels for the demand model

Attributes	Level 1	Level 2	Level 3	Level 4
Vehicle price	\$15K	\$25K	\$35K	\$45K
Range	100 mi	200 mi	350 mi	500 mi
MPG	30	70	110	150
Acceleration (0 to 60)	6 sec	9 sec	12 sec	15 sec
Top speed	80 mph	100 mph	120 mph	140 mph

of three gas price scenarios randomly. A total of 226 subjects with a driver's license residing in the US took this survey on MTurk [38] in 2016.

Using the survey results, we build the individual-level utility model [39],

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} z_{jkl}, \tag{4}$$

where v_{ij} is utility, β_{ikl} are part-worths, z_{jkl} are binary dummy variables and j, k, l, and i represent product alternative, attribute, attribute level, and individual, respectively.

We build three utility models for three gas price scenarios. The relative importance of the attributes is calculated using part-worths to compare these three models as shown in Fig. 2. This result shows that people consider MPG more than other attributes when the gas price increases. We use cubic splines to calculate the interpolated values between discrete part-worths for each gas price in order to build continuous part-worth functions. We build five surface functions (for five attributes) with three axes of gas price.

Given part-worth values, we can calculate vehicle utilities and using them in the multinomial logit model, we estimate the vehicle demand,

$$q_j = s \frac{e^{v_j}}{\sum\limits_{j' \in J} e^{v_{j'}}}, \tag{5}$$

where q_j indicates the demand for vehicle j among a set of competitors J, v_j is the utility of vehicle j, and s indicates the market size.

To calibrate the model, we add the part-worths of three vehicle types (gasoline, HEV, and EV) based on the survey data of previous studies [22] and test the market share (MS) in the actual US market in 2016. In the optimization model we assume that the manufacturer has a gasoline car (similar to Toyota Corolla) and an HEV (similar to Toyota Prius) in the initial market. In addition, the three competitors are one gasoline (similar to Honda Civic), one HEV (similar to Chevrolet Volt), and one EV (similar to Nissan Leaf). In 2016, the market share of those cars was 91% (gasoline), 6% (HEV), and 3% (EV) in the US [40–42]. The model estimates the market share at 89% (gasoline), 9% (HEV), and 2% (EV). This result shows that the model estimates market share sufficiently close. A difference always exists because the actual market considers other attributes, such as brand, which the present model omits.

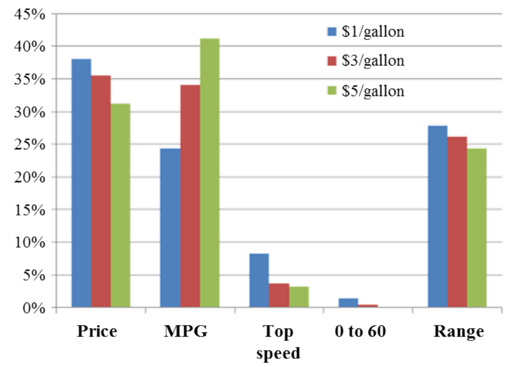

Fig. 2. Attributes importance according to gas price

3.4 Engineering Model

The engineering model, denoted as $A(\mathbf{x}^{(t)})$ in Eq. (1), maps the powertrain design variables $\mathbf{x}^{(t)}$ to the functional vehicle attributes $\mathbf{a}^{(t)}$ used to build the demand model, i.e., MPG, top speed, 0-to-60 mph acceleration time, and range. We assume that powertrain architecture, engine, and electric motor sizes are fixed and only transmission gear ratios and battery sizes are included as powertain design variables. The engineering model estimates vehicle attributes using a physics-based simulation [43]. In this simulation we assume again vehicle specifications similar to Toyota Corolla for the gasoline vehicle, similar to Toyota Prius for the HEV, and similar to Nissan Leaf for the EV. We obtain MPG and range using the average energy consumption for the standard drive cycles, the US Urban Dynamometer Driving Schedule (UDDS) and the US Highway Fuel Economy Driving Schedule (HWFET) [44].

Estimation of energy consumption in a drive cycle requires a supervisory powertrain control strategy for the transmission gear shifts in gasoline vehicles and for the power management between engine and motors in the hybrid/electric vehicles. Several powertrain control strategies have been used in the literature [45, 46]. We omit the details of powertrain control for brevity. Solving the powertrain control problem for every design candidate in the optimization problem is a computationally expensive process especially with an MC simulation approach. To evaluate energy consumption quickly when solving the optimization problem in Eq. (1), we sample the powertrain design space defined by $[\mathbf{x}_{lb}^{(t)}, \mathbf{x}_{ub}^{(t)}]$ using Latin Hypercube Sampling (LHS) and build a metamodel as a function of $\mathbf{x}^{(t)}$ using neural networks. We discuss the parameters used for this metamodel and the results obtained in Section 4.

4 Optimization Results

This section presents results for a manufacturer that has a gasoline vehicle and a HEV, but not an EV, to illustrate the proposed approach. We assume the nine-year time period is 2017-2025; a new model is launched annually and its design decision must be made two years before; to launch an EV, the investment must be made 3 years earlier; after launch, the

EV can be redesigned as a new model annually. We assume the investment on the EV is \$100M based on the reported contract between Toyota and Tesla for developing the RAV4 EV [47].

We assume three competitors for each vehicle type, similar to Honda Civic (gasoline), Chevrolet Volt (HEV), and Nissan Leaf (EV). Based on the total annual sales reported in 2016 for the three competitors, market size is assumed as 405,672 [40–42]. We optimize HEV and EV and use a fixed gasoline vehicle design by benchmarking the Toyota Corolla. Table 2 shows the vehicle attributes for the three competitors and the gasoline vehicle used in the study. We use a 10% risk-free interest rate to calculate the profit.

The four types of decision variables we use for each year during the nine-year period and their bounds are: (1) EV investment option within [0, \$100M]; (2) prices for gasoline vehicle, HEV, and EV, within [\$15K, \$45K], (3) final drive ratio (FR) and planetary gear (PG) ratio for HEV, within [2, 4], and (4) FR within [2, 12] and battery size within [80, 200] for EV. The total number of variables varies depending on real options (i.e., when EV investment option is exercised to change the product mix).

We build a metamodel to calculate the energy consumption of HEV and EV as a function of the powertrain variables. We first use LHS with 2000 samples and train a neural network model using 90% of the samples with 15 hidden layers. Testing the metamodel with 10% of the samples gives 93% accuracy for HEV and 99% for EV.

Table 2. Vehicle attributes of the competitors and gasoline vehicle for the manufacturer

Attributes	(Competitor) Gasoline	(Competitor) HEV	(Competitor) EV	(Manufacturer) Gasoline
Vehicle price	\$19.6K	\$34.1K	\$31.5K	variable
Range	415 mi	436 mi	107 mi	416 mi
MPG	32	42	112	31
Acceleration (0 to 60)	6.9 sec	7.5 sec	10.4 sec	9.5 sec
Top speed	127 mph	102 mph	93 mph	111 mph

We define nine Scenario Groups (SGs) using the Cartesian product of three sets of gas price scenarios and three sets of the CAFE standard scenarios. All SGs consisting of 1,000 scenarios (see Fig. 1) are described as follows:

SG1: low gas price and low CAFE standard
SG2: low gas price and moderate CAFE standard
SG3: low gas price and high CAFE standard
SG4: moderate gas price and low CAFE standard
SG5: moderate gas price and moderate CAFE standard
SG6: moderate gas price and high CAFE standard
SG7: high gas price and low CAFE standard
SG8: high gas price and moderate CAFE standard
SG9: high gas price and high CAFE standard

We first present the results for $w_1 = 1$ and $w_2 = 0$. In this case, we run the optimization using the average values of 1,000 scenarios and validate the optimal decisions using 1,000 scenarios after optimization to reduce computational cost. In the low/moderate gas SGs, ENPV response has 0.2% difference between optimization and validation results, and in the high gas SG, this difference is 2.7%. This finding shows that using average value of scenarios is reasonable in this study. However, we used the original 1,000 scenarios when we run the multi-objective problem to include variance of NPVs. All results presented in this paper are the validation results using 1,000 scenarios. We used the sequential quadratic programming algorithm in Matlab [48] to solve the continuous optimization problem. An optimization run on average takes 1.4 hours on an Intel Core i7-6700K @4.00 GHz CPU and 32 GB RAM machine.

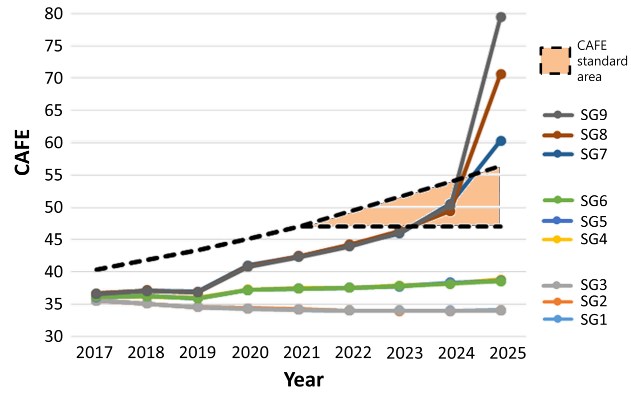

Fig. 3. CAFE results for nine SGs

Table 3 summarizes the key market responses for the nine SGs including EV investment decision and Market Share (MS) in 2025. When the gas price is not low, EV investment should be done in the first year (2017). In the low-gas price SGs, EV investment should not be done regardless of the CAFE standard. The higher the gas price and CAFE standard, the more EVs are produced. Table 4 shows the optimal vehicle design result in 2025 to compare nine SGs.

5 Discussion

We make several observations on the optimization results — under the assumptions made in the study.

1) Policymakers can adapt CAFE standards to account for gas prices.

CAFE standards should be relaxed when gas price is low and tightened when gas price is high. Fig. 3 shows the gap between CAFE standards and the optimized CAFE of the manufacturer in the nine SGs. The shaded area between dashed lines is the difference between maximum and minimum CAFE standard of the nine SGs. As seen in Fig. 3 and Table 3, when gas price is high, customers choose more fuel-efficient cars which gives the manufacturers more room to satisfy the CAFE standard by selling EVs. However, when gas price is low, even if the manufacturers launch EVs, customers do not choose EVs. Hence, the manufacturers cannot satisfy high CAFE standard without sacrificing profit. The

Table 3. Market responses for nine SGs

SG3 - Low gas and High CAFE std ENPV: $14.58B STD of NPVs: $0.29B CAFE Penalty: $1.20B Manufacturer's CAFE at 2025: 34.05 EV investment: None MS at 2025: EV(0.0%)/HEV(9.6%)/Gas(33.9%)	**SG6 - Moderate gas and High CAFE std** ENPV: $15.54B STD of NPVs: $0.34B CAFE Penalty: $0.97B Manufacturer's CAFE at 2025: 38.56 EV investment: 2017 MS at 2025: EV(2.8%)/HEV(16.1%)/Gas(27.4%)	**SG9 - High gas and High CAFE std** ENPV: $16.79B STD of NPVs: $0.51B CAFE Penalty: $0.28B Manufacturer's CAFE at 2025: 79.48 EV investment: 2017 MS at 2025: EV(27.6%)/HEV(12.3%)/Gas(11.9%)
SG2 - Low gas and Moderate CAFE std ENPV: $14.67B STD of NPVs: $0.29B CAFE Penalty: $1.12B Manufacturer's CAFE at 2025: 34.06 EV investment: None MS at 2025: EV(0.0%)/HEV(9.8%)/Gas(34.6%)	**SG5 - Moderate gas and Moderate CAFE std** ENPV: $15.63B STD of NPVs: $0.34B CAFE Penalty: $0.88B Manufacturer's CAFE at 2025: 38.64 EV investment: 2017 MS at 2025: EV(3.0%)/HEV(16.1%)/Gas(27.8%)	**SG8 - High gas and Moderate CAFE std** ENPV: $16.90B STD of NPVs: $0.52B CAFE Penalty: $0.26B Manufacturer's CAFE at 2025: 70.62 EV investment: 2017 MS at 2025: EV(24.9%)/HEV(12.9%)/Gas(14.5%)
SG1 - Low gas and Low CAFE std ENPV: $14.75B STD of NPVs: $0.29B CAFE Penalty: $1.04B Manufacturer's CAFE at 2025: 34.07 EV investment: None MS at 2025: EV(0.0%)/HEV(10.0%)/Gas(35.0%)	**SG4 - Moderate gas and Low CAFE std** ENPV: $15.73B STD of NPVs: $0.34B CAFE Penalty: $0.79B Manufacturer's CAFE at 2025: 38.82 EV investment: 2017 MS at 2025: EV(3.1%)/HEV(16.6%)/Gas(28.0%)	**SG7 - High gas and Low CAFE std** ENPV: $17.01B STD of NPVs: $0.52B CAFE Penalty: $0.23B Manufacturer's CAFE at 2025: 60.31 EV investment: 2017 MS at 2025: EV(20.5%)/HEV(13.5%)/Gas(18.1%)

Table 4. Optimal design of nine SGs for 2025

Scenario Groups	EV variables			EV performance				HEV variables			Gasoline variable
	Price	FR	# of battery	MPG	Range	Top speed	0to60	Price	PG	FR	Price
SG1	-	-	-	-	-	-	-	$27.4K	2.26	3.67	$23.1K
SG2	-	-	-	-	-	-	-	$27.6K	2.26	3.67	$23.3K
SG3	-	-	-	-	-	-	-	$27.8K	2.26	3.67	$23.5K
SG4	$41.1K	7.76	265	144	150	92	11.4	$28.2K	2.26	3.67	$24.1K
SG5	$41.6K	7.84	267	144	151	92	11.5	$28.5K	2.26	3.67	$24.2K
SG6	$42.2K	7.94	269	144	152	91	11.5	$28.5K	2.26	3.67	$24.4K
SG7	$39.0K	8.73	262	145	149	89	11.5	$29.6K	2.26	3.67	$27.2K
SG8	$38.1K	8.61	262	145	148	90	11.5	$30.0K	2.26	3.67	$28.6K
SG9	$37.8K	8.51	265	145	150	90	11.5	$30.0K	2.26	3.67	$29.8K

manufacturers increasingly suffer from higher CAFE standards in low gas price SGs, where the profit is more sensitive to the CAFE standard.

As shown in Fig. 4, at low- and moderate-gas price SGs (SG1-6), the CAFE standard does not have a big impact on the MS of EV and HEV. This means that higher CAFE standard is not a significant contributor to improving the market's eco-friendly status while high gas price is. Previous studies support this result. Shiau et al [49] show that manufacturers' design decisions are more sensitive to gas price than CAFE standards. CAFE standards and gas price taxing have been subjects of debate in the public policy research area [50–52]. Previous studies suggest that the combination of CAFE and other policies that incentivize customers to prefer eco-friendly cars including gas price taxing is more effective than CAFE policy alone [53, 54].

Fig. 3 shows that before 2024 the manufacturer in this study cannot meet the current CAFE standard. In high-gas price SGs, the manufacturer begins to satisfy the CAFE standard after 2024, and exceeds the CAFE standard in 2025.

Another policy alternative is to keep CAFE standards the same but control gas price fluctuation by adapting the

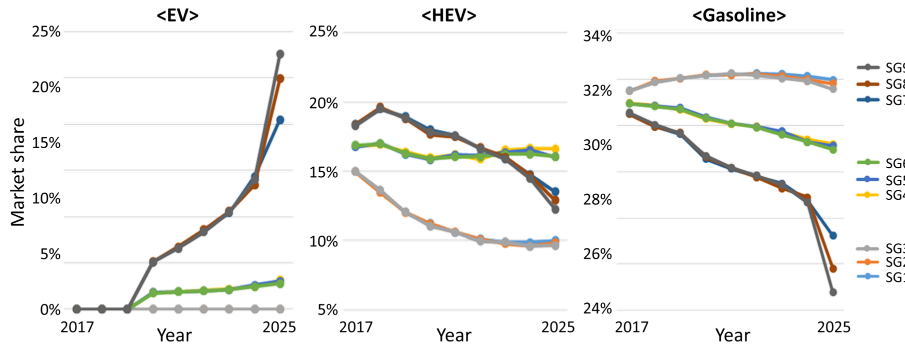

Fig. 4. Market shares for nine SGs

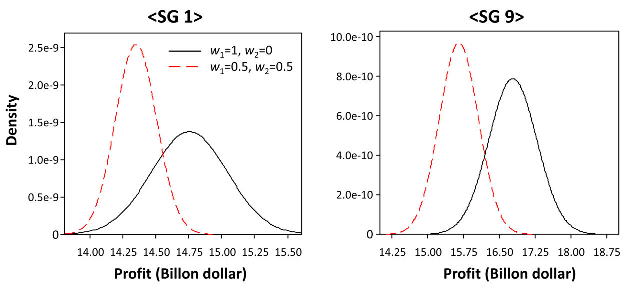

Fig. 5. ENPV vs. Robustness

Table 5. CAFE credit scenario results

Scenario	EV Profit	EV MS at 2025	EV price at 2025	Cafe credit (penalty)
SG9	$1.07B	27.6%	$37.8K	($0.28B)
SG9 + CAFE credit	-$3.69B	74.5%	$29.8	$19.4B

state tax on gasoline to keep gas prices high enough to induce the desired consumer behavior.

2) The credit market can be a promising way to encourage manufacturers to meet the CAFE standard. In this case, a manufacturer that over complies with the CAFE standard can sell credits to other manufacturers. We conduct additional simulations of the case where a manufacturer is compensated with money for the excess quantity of the CAFE standard. Optimization results for this case show that the manufacturer increases gasoline vehicle and HEV prices and decreases EV price to earn credits (see Table 5). We assumed credit and penalty can be exchanged one for one. In SG9 (high gas and high CAFE standard), the manufacturer sells EVs with lower price than the manufacturing cost. The profit from EV sales is negative, but compensation by CAFE credit surpasses the loss. Although it may seem odd at first glance that a manufacturer increases gasoline vehicle and HEV prices to decrease MS, this result means that an optimizing manufacturer does not want to sell those vehicles much. Previous research also showed that regardless of the incentives given to customers who buy fuel-efficient cars, manufacturers change their product mix only to satisfy the CAFE standards by increasing gasoline vehicle price and decreasing EV price [55].

3) Investment decisions (real options) should consider the trade-off between ENPV and robustness of NPVs.

EV investment can be delayed if a manufacturer wants to achieve robustness of NPVs. Optimal investment decisions differ based on the weights of the objectives in Eq. 1. We compare the ENPV maximizing approach and robust NPVs approach in Fig. 5.

When $w_1 = 1$ and $w_2 = 0$, only ENPV is maximized. We use $w_1 = 0.5$ and $w_2 = 0.5$ to balance between ENPV and robustness of NPVs. In the objective function, ENPV and standard deviation values are normalized before multiplying the weights. In low gas price SGs, the deviation of NPVs decreases by 45.9%, whereas the ENPV decreases by 2.8%. In moderate-gas price SGs, the deviation decreases by 17.4%, whereas the ENPV decreases by 0.7%. In high-gas price SGs, deviation decreases by 18.8%, whereas the ENPV decreases by 6.8%. This result shows that when the gas price is low, we can achieve more robustness with small sacrifice in ENPV than when the gas price is high.

Another important result is the change in the investment decision. In moderate-gas price SGs, investment at 2017 changes to no investment. In high gas price, investment at 2017 is delayed to 2020. If a manufacturer wants to improve robustness of profits, investment on EV should be delayed. In other words, when a manufacturer invests in EVs, the variance of NPVs increases because of increased business complexity.

As shown in Table 3, when the gas price is high, the NPV variance becomes high. This finding shows that NPVs was not robust even though meeting CAFE standards becomes easy in high gas price scenario.

4) Changing product mix is a solution to overcome the CAFE standard increases.

Redesigning vehicles is not enough to upgrade performance and does not enable adaptation to market changes flexibly. As shown in Fig. 3, a large increase in CAFE is observed at 2020 when EV is launched (three years after EV investment at 2017), even though the manufacturers cannot satisfy CAFE standard. This finding shows that investment in EVs is critical to meet the CAFE standards. In high-gas price SGs, the manufacturer meets the CAFE standard by increasing MS of EVs significantly (see Fig. 4).

No significant difference is observed among SGs in vehicle design. Especially in HEV design, optimal FR and PG ratio for all SGs are 2.26 and 3.67 respectively. Fuel economy, range, top speed, and 0-to-60 mph acceleration time are 52 mpg, 499 mi, 103 mph, and 13.8 sec. This finding shows that manipulating HEV gear ratios (FR and PG ratio) without fundamental changes in powertrain is not enough to improve adaption to market changes. Hence, only an investment on truly new fuel-efficient powertrains such as EVs can be a game changer.

5) Interest rate affects the investment decisions. A manufacturer should invest on EV immediately or never invest in all SGs, as shown in Table 3. However, when the interest rate is high, the effect of real options becomes significant [15]. A balance should be sought between the opportunity cost and the investment effect according to the interest rate. In our simulation of moderate-gas price SGs, the results show that investment should be made in the first year (2017) when we use a 10% interest. However, no investment provides increased profits when the interest increases to 15%. Interest rate can be another uncertainty to be considered in a future study.

6) Manufacturer profit increases with the gas price. Table 3 supports that observation. In our simulation, the profit increases by 6.6% from low-gas to moderate-gas SGs and by 8.1% from moderate-gas to high-gas SGs mainly due to the market demand for fuel-efficient and relatively expensive cars (i.e., EV and HEV) when gas price is high. When gas price is low, a manufacturer also pays more CAFE penalty. An average of \$1.12B penalty is paid in low-gas price SG, and in high-gas SG, an average of \$0.26B is paid corresponding to a decrease by 77%. The manufacturer can improve fuel economy by compromising other performance attributes such as acceleration, thereby reducing compliance cost to CAFE [56]. In future research, we plan to address how acceleration trade-offs influence expected product mix.

In our simulation, we assume that the manufacturer produces only sedans, excluding trucks from the analysis. If the manufacturer also produces trucks which are more profitable than sedans, in high-gas SG, the demand for trucks may be low which could ultimately decrease the manufacturer profit.

7) HEV is a bridge between gasoline and EV and its MS would decrease over time. HEV is favorable only when the gas price is moderate. MS fluctuates but remains sustained. When the gas price is low, EV is not launched, HEV shares decrease, and gasoline car shares increase annually. When gas price is high, the MS of EV increases fast and becomes sensitive to the CAFE standard while those of HEV and gasoline vehicle decrease. In 2018, the MS of HEV increases temporally because an optimized model year is launched for the first time.

6 Conclusion

We presented a decision-making framework using real options with RDO under gas price and CAFE standard uncertainties, and we examined the relationship between these uncertainties and the impact on investment decisions and their robustness. We applied time delay for R&D investment, redesign, and pricing in the real options approach and combined real options and RDO to explore the tradeoff between expected and robust NPVs. The results can help manufacturers to make decisions on product mix and assist policymakers to propose effective CAFE standards.

This study considered only passenger cars, though the methodology was general. We presented a particular illustration for a manufacturer producing a gasoline vehicle and an HEV, with EV investment as an option. We considered three competitors for a gasoline vehicle, an HEV and an EV. We obtained several insights from this illustrative study — subject to the modeling assumptions. First, policy makers should decide CAFE standard adaptively by considering gas price; they should relax CAFE standards when the gas price is low and tighten CAFE standards when the gas price is high. Second, the credit market could be a promising way to encourage for manufacturers to meet CAFE standard. Third, investment decisions (real options) should consider the tradeoff between ENPV and the robustness of NPVs; EV investment can be delayed if a manufacturer wants to achieve robustness of NPVs. Fourth, changing product mix is a solution to overcome CAFE standards increase; redesigning vehicles is not enough to upgrade performance and adapt to market changes. Fifth, interest rate affects investment decisions and manufacturers would balance opportunity cost and investment effect based on interest rates. Sixth, manufacturers make more money when the gas price is high. Lastly, HEV is a bridge between gasoline and EV, and its MS would decrease over time.

Future work can address how trading CAFE credit and interest rate affect market, and study additional cases such as manufacturers with only EVs, or manufacturers with a diverse mix including other vehicle classes such as SUVs. We have not addressed the issue of economies of scale in this paper.

Acknowledgement

The authors are grateful for the valuable feedback obtained by anonymous reviewers for earlier version of this manuscript that helped improve this work. This study was partially supported by the National Research Foundation of Korea grant N01170150, the Automotive Research Center at the University of Michigan, a US Army Center of Excellence in Modeling and Simulation of Ground Vehicle Systems, and a Graham Sustainability Institute Fellowship at the University of Michigan. This support is gratefully acknowledged. The third author acknowledges support by the Singapore University of Technology and Design - Massachusetts Institute of Technology International Design Center, and sabbatical leave support by the University of Michigan.

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