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A REAL OPTIONS APPROACH TO HYBRID ELECTRIC VEHICLE ARCHITECTURE DESIGN FOR FLEXIBILITY

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ABSTRACT

Manufacturers launch new product models at various time increments to meet changing market requirements over time. At each design period, product design and price may change. While price decisions can be made at product launching time, redesign decisions must be made in advance. Real options theory addresses such time gap decisions. This paper presents a real options approach with a binomial lattice model to determine optimal design and price decisions for hybrid electric vehicles (HEVs) that maximize expanded net present value of profit under gas price uncertainty over time. Results confirm that we can obtain changing vehicle attributes by changing gear ratios rather than the architectures themselves due to high cost of redesigning. A parametric study examines the impact of gas price volatility on option decisions and shows that larger volatility of gas price causes the change option to be selected more frequently.

NOMENCLATURE

$\mathbf{X}^{(t)}$ Design at time t
$P^{(t)}$ Price of a new design at time t
$P'^{(t)}$ Price of the current design at time t
$V^{(t)}$ Profit at time t
$PV^{(t)}$ Present value of profit at time t
$I^{(0)}$ Initial investment
$NPV^{(0)}$ Net present value of whole design project
n_i^t i-th node at time t
p Probability of gas price being increasing
u Proportional increase in gas price
d Proportional decrease in gas price
σ Volatility of gas price
G Initial gas price
r Risk-free interest rate
C Redesign cost
ρ Planetary gear ratio
FR Final drive ratio

1 Introduction

Product planning is affected by uncertainty in future market environments. Successful current designs may not succeed in the future due to market changes. For example, in the automotive market, customer preferences on vehicles are affected by external factors such as gas prices, government subsidies and taxes, and infrastructures. This study focuses on gas price changes. Market data shows that there is a positive correlation between gas prices and fuel efficiency in the market [1], i.e., customers may look for better MPG vehicles when gas prices are high. This assumption is validated by the consumer surveys in Section 3.1. Automobile manufacturers must develop new or modified vehicle models over time to meet such changing market needs.

When making design decisions for future product models, producers must decide whether and how to change the current product model and invest in new development at the present. In the real options investment strategies developed in finance, the decision maker does not commit to decisions in advance. Instead,

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the decision maker waits until uncertainty (or risk) is reduced (or "hedged") and commits to a decision at subsequent periods using the latest market information. Several studies have applied real options ideas to engineering design [2–10].

Design decisions differ from financial decisions such as setting a price, in that they cannot be implemented immediately. Cardin et al. [8] have accounted for a time lag between the time the decision to exercise the flexibility is made and the time this flexibility is actually operational. This is often referred as "time to build". In the automotive industry, the time between initial planning and production is at least two years [11]. Thus, vehicle model decisions must be made at least two years in advance of the expected sale time. Redesign cost can be high, especially in the automotive industry, making it difficult to change models frequently, as a new model's cost may exceed the additional profit it brings.

This paper presents an optimization model using a real options approach for product design, including time and cost considerations for redesigning future models under uncertain market conditions. The specific product implementation is the design of a plug-in hybrid electric vehicle (PHEV) powertrain architecture for a given time horizon under gas price uncertainty. This study focuses on powertrain design because the powertrain system has the largest impact on fuel economy and vehicle performance, although other systems can contribute. Powertrain architecture in a PHEV is the connection arrangement of powertrain components through planetary gears. Figure 1 shows the powertrain architecture of the Toyota Prius as an example where an engine and two motor/generators (MG) are connected through a planetary gear (PG) system to drive a vehicle output shaft. Design alternatives with different fuel economy and vehicle performance results can be created by changing this connection arrangement and the corresponding gear ratios. Previous work has shown that desirable vehicle attributes and duty cycles affect the choice of architecture [12].

The paper is organized as follows. Section 2 reviews relevant literature. Section 3 introduces the proposed decision making framework and model for PHEV architectures. Section 4 presents and discusses the optimization results. Section 5 concludes with limitations.

2 Related Work

The section presents a brief discussion of previous work in real options for design and in HEV architecture optimization.

2.1 Real options in design

In investment decision making, discounted cash flow (DCF) evaluates net present value (NPV) of projects and is used to evaluate potential investments. However, traditional DCF underestimates the value of having flexibility of decisions (option values)

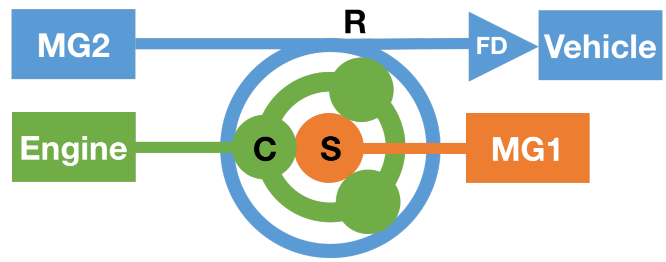


FIGURE 1. Connection arrangement in the Toyota Prius architecture. "R", "C" and "S" denote the ring, carrier and sun gears, respectively. "MG" denotes motor/generator and "FD" denotes the final drive.

and the real options approach was introduced to address this limitation of DCF [13, 14]. An option is the right (without being an obligation) to take action depending on the realization of future market environments. In general, there are five types of options: Deferment, abandonment, expansion, contraction, and switching options [14]. In real options, the Expanded Net Present Value (ENPV) is introduced by adding Real Option Values (ROV) to NPV: ENPV = NPV + ROV. The investor will choose to invest if ENPV is positive. So, even if NPV is negative, high ROV can result in an investment. ROV is obtained from the value of flexibility of decisions in each stage.

There are three widely-used methods to compute ROV: Black-Scholes model [15], binomial lattice model [16], and Monte Carlo simulation method [17]. The Black-Scholes model is representative of continuous time-based models, while the binomial lattice model is representative of discrete time-based models. The Black-Scholes model can yield a closed-form solution and was introduced in finance. The binomial lattice model provides an intuitive interpretation of results and is applicable to various options. It assumes that the value of an asset can change in one of only two directions over time, i.e. increase or decrease, so that the 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 time unit of minutes is used for the binomial lattice model, the result converges to that of the Black-Scholes model [18]. However, this model is sensitive to parameter inputs. The Monte Carlo (MC) simulation method randomly generates different scenarios and computes a profit distribution. The MC method computes option values from the initial time in chronological order in contrast to the binomial lattice model. This method is useful when it is difficult to define parameters for the Black-Scholes and binomial lattice models.

Real options have been used in a design context to value flexibility [19], and as a tool that can be used not "on" but "in" design projects [4]. Zhao and Tseng showed that valuing flexibility is important for infrastructure design such as parking garages [2]. Kalligeros and de Weck evaluated the value of flexibility in modularized office building design considering the contraction option of an office complex [3]. Silver and de Weck introduced the "Time-Expanded Decision Networks" to analyze the effect of lock-in and flexibility in space launch system design considering switching cost in choosing launch vehicle configurations [5]. Dong et al simulated a real options approach using the merge, substitute, and reject options for modules in modular product design, and randomly generated data sets rather than actual data [6]. Cardin and Hu designed a waste-to-energy system by using MC simulations [10]. They formulated and compared three methods: Inflexible decision making in deterministic markets, inflexible decision making in uncertain markets, and flexible decision making under uncertain markets, focusing on designing system flexibility early on, so that it can be exercised in operations within a short deployment time. Time lag was not modelled.

The extant literature generally treats price under uncertainty without addressing the time lag between price and design decision options. Most applications use MC simulations as the solution strategy, evaluating hundreds or thousands of random scenarios. While some models run within fractions of seconds, such as the examples in [7] and [10], MC simulations generally are not computationally tractable when using high fidelity engineering simulation models due to high computational cost [9]. In the present study we use the binomial lattice model as the most fitting to the problem.

2.2 Architecture design

Vehicle powertrain architecture design has been studied for both gasoline and hybrid electric vehicles (HEV). An example of the powetrain architecture design problem for gasoline vehicles with automatic transmissions is finding the optimal connectivity arrangement among powertrain components (internal combustion engine, planetary gears and vehicle output shaft), and the placement of clutches in the arrangement to obtain a desired set of gear ratios. Methods based on canonical graph representations have been used to enumerate all possible 4-speed [20] and 6-speed [21] automatic transmissions.

The powertrain architecture design problem for HEVs is more challenging than that for gasoline vehicles due to the variety of architecture alternatives and the additional need to account for the control strategy that manages power demand and supply for the engine and motor/generators (MG). There are three main classes of architectures for HEVs, namely, *series*, *parallel* and *power-split* architectures. Munzer and Shea studied the selection of an appropriate architecture among these options for a given vehicle application assuming a simple control strategy [22]. Liu and Peng [23], and Bayrak et al. [24] integrated optimal control strategies for power-split architectures since these offer the largest variety of alternatives. Using an architecture representation with a dynamic system matrix or bond graphs, respectively, these approaches generate all possible architecture alternatives and select candidates based on engineering performance metrics such as fuel economy, vehicle acceleration, or top speed. More generalized approaches add the design of gear ratios to the architecture design and control problem and solve the coupled problems together [12, 25, 26].

These previous studies focused only on optimizing the engineering performance of architectures. In the present study the optimization model is expanded to include a business perspective that accounts for future model offerings under under gas price uncertainty. The architecture representation and optimization solution approach used in this study follows closely that of [12,26].

3 Problem Formulation

In the proposed problem formulation there are two decisions available, design and price. To launch new product models sequentially over time, the decision maker has an option to stay with a current design and price or change them. Since redesigning a product takes time (e.g., a few years in new vehicle development), a decision on design should be made in advance depending on the new product development time frame, while price decisions can be made at the time of product launch.

A general process of computing NPV based on the decided design and price is shown in Figure 2, where t indicates time, $\mathbf{X}^{(t)}$ indicates a particular design (i.e., a vector including design variables), $P^{(t)}$ indicates price of product, $V^{(t)}$ indicates profit, and $PV^{(t)}$ is the present value of profit at time t. $I^{(0)}$ is the amount of initial investment, and $NPV^{(0)}$ is NPV of whole design project. At $t = 0$, a manufacturer must decide on product design, $\mathbf{X}^{(1)}$, to launch at $t = 1$ while the price decision $P^{(1)}$, for this product $\mathbf{X}^{(1)}$, is made at $t = 1$, i.e., right before launching the product. At the same time ($t = 1$), a manufacturer should begin redesigning product $\mathbf{X}^{(2)}$ to launch at $t = 2$. If we use the traditional DCF method, all designs and prices will be the same: $\mathbf{X}^{(1)} = \mathbf{X}^{(2)} = \mathbf{X}^{(3)} = \mathbf{X}^{(4)}$...; $P^{(1)} = P^{(2)} = P^{(3)}$..., because traditional DCF does not allow design flexibility over time.

In this study, we employ real options for a PHEV design problem. The design decision vector $\mathbf{X}$ consists of powertrain architecture (see Figure 1) and corresponding gear ratios. Following the study presented in [26], we model PHEV powertrain architectures using a graphical representation (based on bond graphs) that defines the connections among powertrain components through planetary gears denoted by $\mathbf{x}_c$, planetary gear ratios denoted by $\boldsymbol{\rho}$ and final drive ratio denoted by FR. Using that representation, we extract a quasi-static 2×2 kinematic matrix denoted by $\mathbf{C}_{conf}$ that defines the speed and torque relationships among an engine, two motor/generators (MGs) and vehicle output shaft to simulate the vehicle attributes such as range and vehicle performance including 0 to 60 miles per hour (mph) time

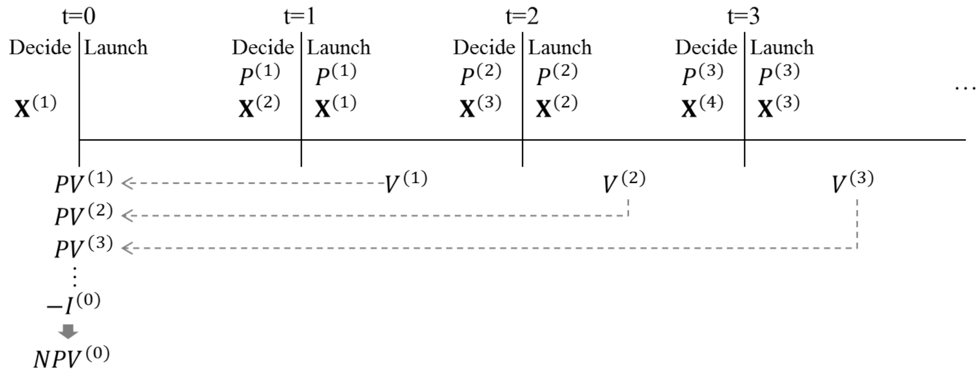


FIGURE 2. Time-series decision making

and top speed. We explain details of how these representations are used in the engineering model in Section 3.3.

Gas price is used to represent market uncertainty, where gas price volatility over time affects consumer demand. We discretize the time horizon in 2-year steps assuming that we redesign and launch a new product model every 2 years. Based on this setting, the binomial lattice model can be applied as shown in Figure 3. The paths in traditional binomial lattice model should be recombined. For example, nodes $n_2^{(2)}$ and $n_3^{(2)}$ should be the same node under the traditional binomial lattice model. However, the proposed model differs from the traditional model. It consists of three steps: (1) The gas price change is estimated by using recombinant paths like the traditional model as shown in Figure 4. (2) Consumer preferences are estimated for each gas price node. (3) Then, the product design decision is made by the binomial lattice model without recombining, because a product design is dependent on the previous design as shown in Figure 3. Note that a multinomial lattice methodology [27] can also be used considering multiple gas change scenarios.

In the engineering design problem at hand we do not follow the path independence assumption of the traditional binomial lattice model (i.e., a value is independent of the path followed, whether up-down, or down-up in a simple two stage sequence), because of the high redesign cost.

In this figure, n_i^t indicates the ith node at time t. p and $1-p$ indicate the probabilities of gas price being increasing and decreasing, respectively. Depending on these two scenarios, price and design decisions are made at subsequent periods. At $t=1$ we have two nodes where the decision maker decides on two separate optimal prices, $P_1^{(1)}$ and $P_2^{(1)}$, for the same design $\mathbf{X}^{(1)}$, corresponding to each scenario. This design decision was made at the previous time stage, $t=0$. The design option is whether to launch the design $\mathbf{X}^{(1)}$ or abandon it. In addition, a new design $\mathbf{X}_1^{(2)}$ for the increasing gas price scenario and another new design $\mathbf{X}_2^{(2)}$ for the decreasing gas price scenario should be made.

At $t=2$, we have four nodes. For example, in the first node, a decision maker has three options for product design: launching a new product $\mathbf{X}_1^{(2)}$ which was designed at $t=1$, selling the current product $\mathbf{X}^{(1)}$, or abandoning all. The price for a new design $P_1^{(2)}$ and the price for the current product $P_1^{'(2)}$ are decided at the same time. All other nodes work similarly. The design cost for the first product model is fixed, while the redesign cost for the next model depends on the degree of deviation from the previous model design. We assume that all costs are paid at the beginning of the year, and the profit for each year is earned at the end of each year.

To generate probability p, the following equations should be applied based on a Geometric Brownian Motion (GBM):

$$\begin{aligned} u &= e^{\sigma\sqrt{\triangle t}} \\ d &= e^{-\sigma\sqrt{\triangle t}} \\ p &= \frac{e^{r\triangle t}-d}{u-d} \end{aligned} \tag{1}$$

where u is the proportional increase in gas price, d is the proportional decrease in gas price, σ is the volatility of gas price over the time step, $\triangle t$, and p is the probability that gas price is increasing. Based on these parameters, it is assumed that the gas price changes over time as shown in Figure 4 where G is the initial gas price at $t=0$.

Based on the gas price, price decision, and vehicle design decision, consumer demand at each point in time can be estimated. This demand model will be explained in detail in Section 3.2. The profit at each point in time can be computed using price, demand, and redesign cost. Then the present value of profit at time t is

$$\begin{aligned} &PV^{(t)} = e^{-r\triangle t}[\\ &(p)\max\{V^{(t)}(P_k^{(t)},\mathbf{X}_j^{(t-1)},C_j^{(t-1)}),V^{(t)}(P_k^{'(t)},\mathbf{X}_i^{(t-2)},0),0\}+ \\ &(1-p)\max\{V^{(t)}(P_{k+1}^{(t)},\mathbf{X}_j^{(t-1)},C_j^{(t-1)}),V^{(t)}(P_{i+1}^{'(t)},\mathbf{X}_i^{(t-2)},0),0\}], \end{aligned} \tag{2}$$

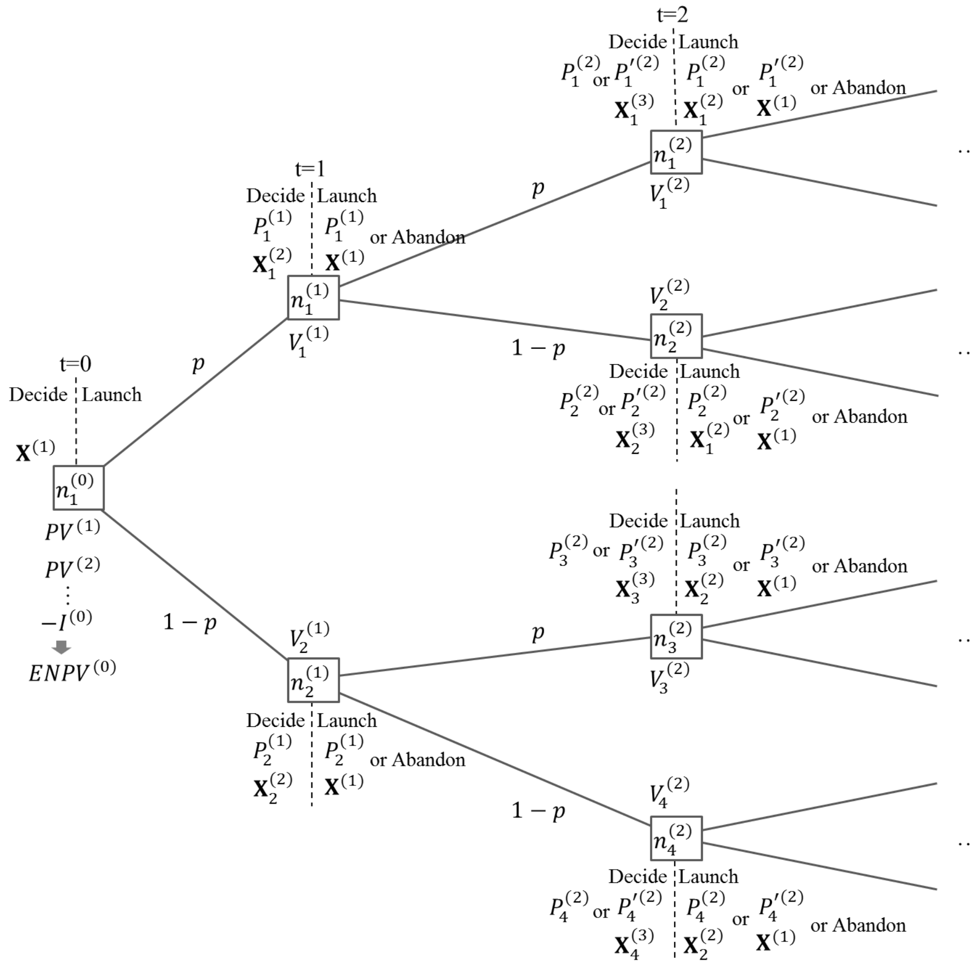


FIGURE 3. Binomial lattice model

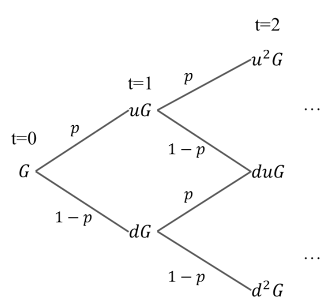


FIGURE 4. Gas price change as market uncertainty

where V is the profit function, C is redesign cost, r is the risk-free interest rate, i is the node index at $(t-2)$, j is the node index at $(t-1)$, and k is the node index at (t).

3.1 Optimization model

The overall optimization problem can be formulated as follows:

$$\begin{array}{cc} \max\limits_{\mathbf{X}_k^{(t)},\mathbf{P}_k^{(t)}} & ENPV^{(0)} = \sum\limits_{t=1}^{n} PV^{(t)} - I^{(0)} \\ \text{where} & \mathbf{X}_k^{(t)} = [[\mathbf{x}_{c,k}^{(t)}]^T, \boldsymbol{\rho}_k^{(t)}, FR_k^{(t)}]^T \\ & \mathbf{P}_k^{(t)} = [P_k^{(t)}, P_k^{'(t)}]^T \\ \text{subject to} & \boldsymbol{\rho}_{lb} \leq \boldsymbol{\rho} \leq \boldsymbol{\rho}_{ub} \\ & FR_{lb} \leq FR \leq FR_{ub} \\ & P_{lb} \leq P \leq P_{ub} \\ & \mathbf{x}_c : \text{technically realizable} \end{array} \tag{3}$$

The objective is to maximize the expanded net present value of profit over a given design period with respect to the design of vehicle powertrain architecture with gear ratios, and prices for each time (t) and node (k). The profit at each time and node is calculated by the marketing model using the vehicle attributes and redesign cost coming from the engineering model.

3.2 Marketing model

To compute profit, we need to model consumer demand. We define five vehicle attributes and four levels for each attribute as shown in Table. 1. Part-worths for attribute levels are estimated by Hierarchical Bayesian choice-based conjoint analysis [28].

TABLE 1. Vehicle attributes and levels for demand model

Attributes	Level1	Level2	Level3	Level4
Vehicle price	\$15K	\$25K	\$35K	\$45K
Range	100 miles	250 miles	400 miles	550 miles
MPG	30	60	90	120
Acceleration (0 to 60)	6 sec	9 sec	12 sec	15 sec
Top speed	70 mph	100 mph	130 mph	170 mph

Vehicle price is a decision variable in marketing, while range, MPG, acceleration, and top speed are product attributes determined by the design of vehicle powertrain architecture as described in Section 3.3. To incorporate gas price into the consumer demand model, we conducted three conjoint surveys with three different gas price scenarios of \$1/gallon, \$3/gallon, and \$5/gallon. 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 7 questions for each gas price scenario, and the order of three gas price scenarios were assigned randomly. A total of 226 subjects were surveyed using MTurk [29]. The relative importance of attributes is calculated using partworths, and the resulting attribute importance corresponding to each gas price is shown in Figure 5. This result shows that, when gas price increases, people care about MPG more and other attributes less. We use cubic splines to calculate interpolated values between discrete partworths calculated for each gas price in order to build continuous preference functions. For example, the preference function for MPG is shown in Figure 6. Finally, vehicle demand can be estimated by plugging utility (sum of partworths) into the multinomial logit model. Mathematical formulations and detailed information on how to use HB for design decision making can be found in [30–32].

3.3 Engineering model

The engineering model has two elements, powertrain redesign cost model and simulation of vehicle attributes. We represent the designs for each node in the binomial lattice model with a matrix of connectivity $\mathbf{x}_c$, PG ratios $\boldsymbol{\rho}$, and final drive ratio FR.

The redesign cost model computes the cost of making changes in the powertrain design based on the differences in connections and gear ratios. We compare $\mathbf{x}_c$ values of two subsystems i and j, and identify the number of different connections

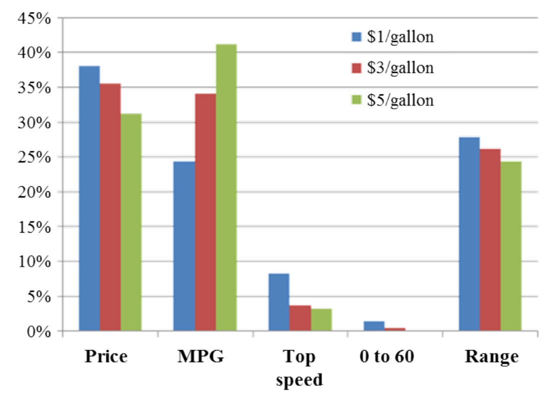


FIGURE 5. Attributes importance according to gas price

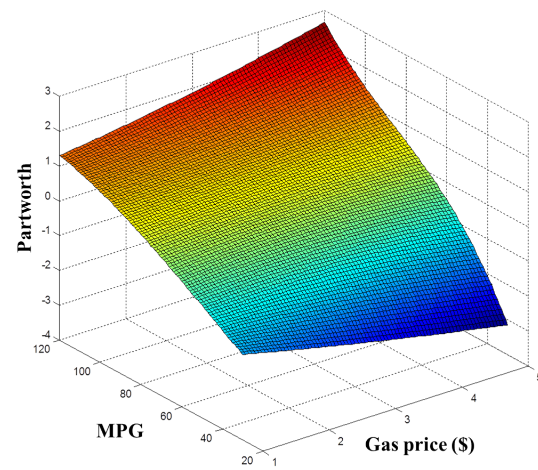


FIGURE 6. Preference surface function for MPG

denoted by $D_{i,j}$. This comparison is similar to the number of required clutch calculation described in [26]. Then, we build a linear cost model based on the number of different connections and gear ratio values. The redesign cost from design i to design j denoted by $c_{i,j}$ can be expressed as follows:

$$c_{i,j} = k_1 D_{i,j} + k_2 ||\boldsymbol{\rho}_i - \boldsymbol{\rho}_j|| + k_3 |FR_i - FR_j| \tag{4}$$

where k_1, k_2 and k_3 are linear cost coefficients.

Simulation of vehicle attributes, i.e., range, MPG, 0-60 mph time, and top speed, for demand estimation is done using a kinematic relationship matrix $\mathbf{C}_{conf}$ extracted from $\mathbf{x}_c$, $\boldsymbol{\rho}$ and FR as described in Section 3. When calculating the range of a PHEV, each design is evaluated with a power management (control) strategy with charge depleting or electric vehicle (EV) operation from 95% battery state of charge (SOC) to 15% SOC over one drive cycle period and charge sustaining (CS) operation keeping the SOC around 15% until the fuel tank is depleted completely.

This strategy is referred to as EV-CS strategy [33]. We prefer this control strategy for simplicity, although it is not optimal. Optimizing the controller is beyond the scope of this paper. Final range is calculated as an average of Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Driving Schedule (HWFET) ranges. Since range calculation is a computationally expensive process due to the power management strategy, we build a metamodel for range as a function of the elements of $\mathbf{C}_{conf}$ matrix.

We assume that all technically realizable connection possibilities ($\mathbf{x}_c$) are generated before the design process. In the present study we focus on only 2-PG hybrid configurations. Using [12], we generated 2124 feasible $\mathbf{x}_c$ values. Solving the optimization problem in Section 3.1 is computationally expensive, and so we reduce the number of architecture alternatives prior to optimization. We evaluate all generated $\mathbf{x}_c$ at discrete $\boldsymbol{\rho}$ values ranging from 2 to 4 and FR values ranging from 1 to 10 with respect to MPG, 0 to 60 mph time and top speed. Since range and MPG are both driven from fuel economy, we use only MPG in this process. All designs in the space of MPG, 0 to 60 mph time, and top speed form a Pareto curve. We eliminate dominated designs since they cannot be selected by the optimization problem in (3). Since we use a metamodel for the evaluations, the computational cost of this process is less than an hour.[1] We then pick unique $\mathbf{x}_c$ values on the Pareto surface of non-dominated solutions to be used in the optimization.

4 Optimization Results

This section presents results for the case study. We assume a 4-year time horizon discretized in 2-year steps and launch vehicles at $t = 1$ and $t = 2$. We originally make three design decisions ($\mathbf{X}^{(1)}$, $\mathbf{X}_1^{(2)}$, and $\mathbf{X}_2^{(2)}$) and ten price decisions ($P_1^{(1)}$, $P_2^{(1)}$, $P_1^{(2)}$, $P_1^{'(2)}$, $P_2^{(2)}$, $P_2^{'(2)}$, $P_3^{(2)}$, $P_3^{'(2)}$, $P_4^{(2)}$, and $P_4^{'(2)}$). However, by real options, final decisions are the values corresponding to the activated options. ENPV is calculated based on five profits ($V_1^{(1)}$, $V_2^{(1)}$, $V_1^{(2)}$, $V_2^{(2)}$, $V_3^{(2)}$, and $V_4^{(2)}$) with probabilities and interest rate. We used 5% as the risk-free interest rate. The market size is assumed to be 309,598, the total annual sales reported in 2015 of top selling vehicles of three different types: Toyota Corolla as a gasoline vehicle, Toyota Prius as an HEV, and Nissan Leaf as an EV [34, 35]. We model a new HEV manufacturer, assuming two competitors of Corolla and Leaf. Vehicle specifications used for the product to be designed are shown in Table 2. Vehicle attributes for two competitors used in this study are shown in Table 3.

We enumerate all selected architecture cases ($\mathbf{x}_c$) and then optimize prices and gear ratios ($\boldsymbol{\rho}$ and FR) for each case. We use the Sequential Quadratic Programming (SQP) algorithm of Matlab [36] for solving the continuous optimization problem. An optimization run on average takes 8.4 hours using parallel computing.[1]

TABLE 2. Vehicle specifications used for the case study

Specification	Value
Vehicle Body Mass	$1400[kg]$
Tire Radius	$0.3[m]$
Aerodynamic Drag Coefficient	0.29
Frontal Area	$2[m^2]$
Battery Voltage	$350[V]$
Battery Efficiency	$92[\%]$
Battery Capacity	$12.5[Ah]$
Fuel Tank Capacity	$36[L]$
Rated MG1 Power	$42[kW]$
Rated MG2 Power	$60[kW]$
Max MG Speed	12000 [rpm]
Max MG Torque	200 [Nm]
Rated Engine Power	$43[kW]$
Max Engine Torque	$102[Nm]$
Engine Displacement Size	$1.5[L]$

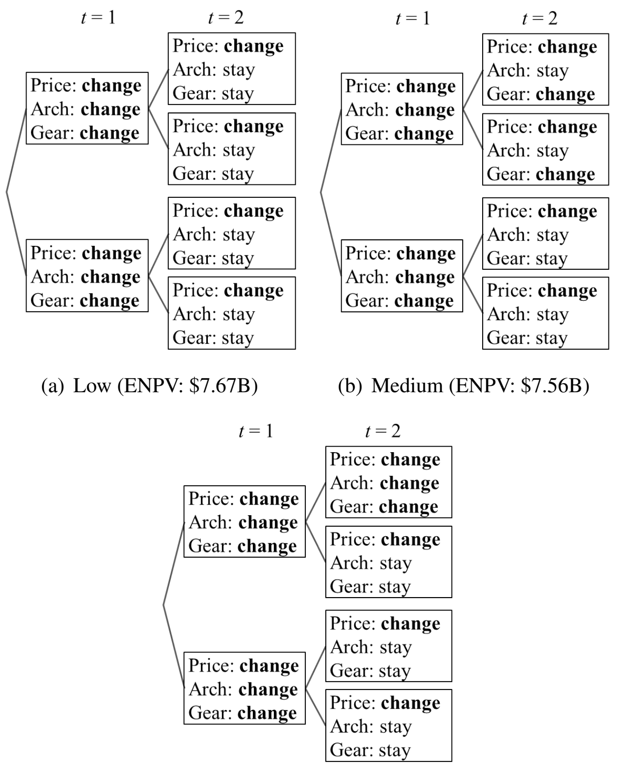
TABLE 3. Vehicle attributes of the competitors

Attributes	Gasoline	EV
Vehicle price	\$19.1K	\$36.8K
Range	100 miles	70 miles
MPG	36	114
Acceleration (0 to 60)	8.9 sec	10.2 sec
Top speed	150 mph	93 mph

For the volatility of gas price, we calculate the standard deviation of proportional change in gas price for each year from 2000 to 2015 [37]. Since estimating accurate volatility is difficult, we increase and decrease the value by 30% so that we have three volatility cases: low (σ=0.1182), medium (σ=0.1688), and high (σ=0.2194). We perform real options analysis with these three volatility cases and compare the results in Figure 7. From these results, we can see that as volatility increases, the option to change design is used more frequently. Especially, the architecture change option is used for only the high volatility case, because changing architectures is more costly than changing gear ratio values. The price change option is always used. It is shown that ENPV is lower when the market is more uncertain.

Next we examine the effect of high gas price volatility. The real options approach is illustrated in Figure 8. At the nodes $n_1^{(1)}$ and $n_2^{(1)}$, the option to change is selected so that the optimal design $\mathbf{X}^{(1)}$ is launched. For the node $n_1^{(2)}$, the option to change is selected so that new optimal design $\mathbf{X}_1^{(2)}$ is used. For the nodes

[1] On an Intel Xeon E5-2620 v2 @2.10 GHz CPU and 128 GB RAM



(a) Low (ENPV: \$7.67B) (b) Medium (ENPV: \$7.56B)

(c) High (ENPV: \$7.41B)

FIGURE 7. Real options approach results with different volatility of gas price

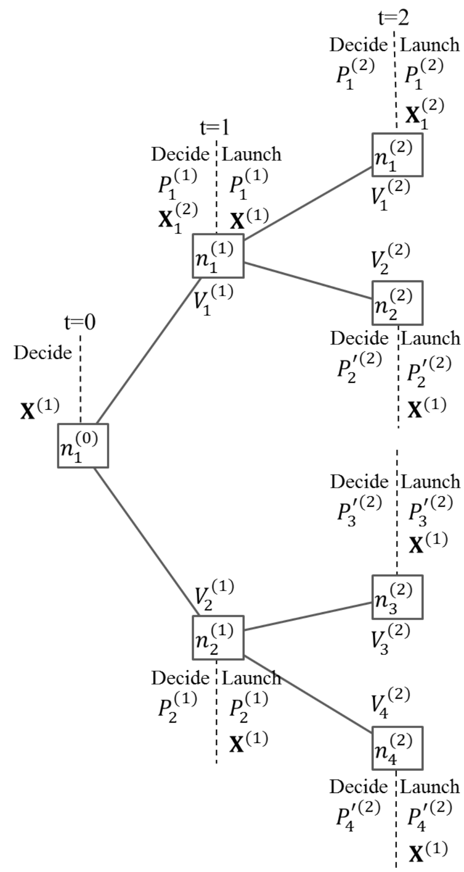
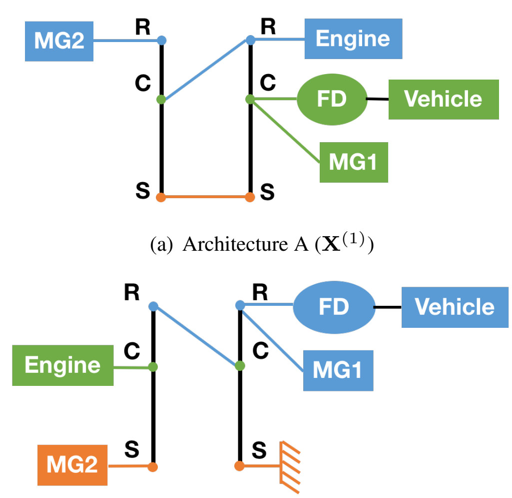


FIGURE 8. Real options approach result

$n_2^{(2)}$, $n_3^{(2)}$, and $n_4^{(2)}$, the option to stay with the current product is selected so that previous design $\mathbf{X}^{(1)}$ is used again. This means that if gas price increases at $t = 1$, the manufacturer should start redesigning the new model $\mathbf{X}_1^{(2)}$ from the previous design $\mathbf{X}^{(1)}$ in case the gas price increases again at $t = 2$. If the gas price decreases at $t = 1$, the manufacturer does not need to redesign a new model. Optimal prices and profits are summarized in Table 4. When gas price decreases, the optimal price also decreases because the advantage of HEV fuel efficiency decreases.

Optimal design decisions are summarized in Table 5. Design $\mathbf{X}_1^{(2)}$ has better fuel efficiency and range but worse top speed and acceleration than $\mathbf{X}^{(1)}$ and is preferred when gas price increases. The two designs have different architectures as shown in Figure 9. However, since the coefficient of the architecture in the redesign cost model given in Equation (4) has the highest weight, the desired vehicle attributes would be achieved by redesigning gear ratios with small or no change in the architecture design.

Since $\mathbf{X}^{(1)}$ does not have a predecessor, i.e., it is the first model, the cost for this design is set to the maximum cost. Since $\mathbf{X}_1^{(2)}$ is redesigned from $\mathbf{X}^{(1)}$ by changing architecture and gear ratios, design cost is lower than $\mathbf{X}^{(1)}$. In the medium volatility



(a) Architecture A ($\mathbf{X}^{(1)}$)

(b) Architecture B ($\mathbf{X}_1^{(2)}$)

FIGURE 9. Optimal architectures

TABLE 4. Optimal price decisions and profits

Price at t=1	Value	Price at t=2	Value
$P_1^{(1)}$	\$26.9K	$P_1^{(2)}$	\$28.7K
$P_2^{(1)}$	\$24.6K	$P_2^{'(2)}$	\$27.1K
		$P_3^{'(2)}$	\$27.1K
		$P_4^{'(2)}$	\$24.2K
Profit at t=1	**Value**	**Profit at t=2**	**Value**
$V_1^{(1)}$	\$4.46B	$V_1^{(2)}$	4.70B
$V_2^{(1)}$	\$3.42B	$V_2^{(2)}$	4.02B
		$V_3^{(2)}$	4.02B
		$V_4^{(2)}$	3.03B

TABLE 5. Optimal design decisions

Design	Variable values	MPG	Range	Top speed	0 to 60 mph time	Design cost
$\mathbf{X}^{(1)}$	$\rho_1^* = 3.61$ $\rho_2^* = 2.12$ $FR^* = 8.42$ Arch. A (Fig. 9(a))	56.7 [mpg]	541 [miles]	104 [mph]	9.8 [sec]	\$40M
$\mathbf{X}_1^{(2)}$	$\rho_1^* = 2.94$ $\rho_2^* = 2.02$ $FR^* = 6.22$ Arch. B (Fig. 9(b))	57.4 [mpg]	548 [miles]	95 [mph]	12 [sec]	\$17.4M

case, we can also obtain the desired vehicle attributes without any change in the architecture (see Figure 7(b)). As a future study, we plan to perform a parametric analysis on the redesign cost coefficients to understand the impact of these coefficients on the optimal results.

5 Conclusion

This research proposed a decision making framework based on real options when there is a time delay between design and price decisions. We adopted the binomial lattice model to design hybrid electric vehicle architectures. Choosing to create a new design, staying with the current design, and abandoning options were used as possible decisions. The purpose of this study was not to propose new architectures per se but rather to present a design methodology. The optimization results show that the high cost of redesigning architectures favors proportional changes in the existing design (such as gear ratios) over changes in the architecture. This is consistent with what one might expect. We also found that larger volatility in gas price results in selecting the change option more often.

Further parametric studies on the redesign cost coefficients to identify their impact on the decision results would be useful. It would be interesting to compare the results of the proposed methods with the results of MC simulations.

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