

AN ENTERPRISE DECISION MODEL FOR
OPTIMAL VEHICLE DESIGN AND TECHNOLOGY VALUATION

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ABSTRACT

Design optimization traditionally has dealt with engineering design decisions. Yet it is well understood that optimal product decisions must be based on engineering as well as marketing and production considerations. An enterprise decision model attempts to link these aspects of the product development enterprise so that the value of the designed product to the enterprise can be assessed. The model also values new product technology in accordance with the enterprise's current operations to increase the likelihood of commercialization success before committing to a new strategy. The valuation technique uses comprehensive engineering simulation to provide a preliminary understanding of the technology's market and design potential. The model represents the enterprise in a mathematical formulation that simultaneously optimizes initial product design, product pricing, operating costs associated with capacity allocation and design decisions, and the value created by new products. The article demonstrates such a model for optimal vehicle design in a medium truck market experiencing hybrid penetration.

KEYWORDS: Technology valuation, optimal design, product development, analytical decision-making

NOMENCLATURE

C_H Initial hybrid component cost
 C_P Base production cost
 C_R Reduction in technology production cost
 CVC Conventional commercial truck
 D Diesel fuel price
 E_K Energy capacity of electrical components
 F Consumer fuel costs
 fe Fuel economy

HBC Hybrid commercial truck
 I_K Capacity investment cost
 K Available capacity
 K_a Additional monthly units of capacity
 K_0 Existing capacity
 L Learning curve costs
 M Truck mileage
 NPV Net present value
 P_{peak} Peak power of electrical components
 P Product price
 $\Delta P/\Delta C_R$ Portion of cost reduction passed
 $\Delta P/\Delta S$ Price to savings ratio
 Q^D Units demanded
 Q^P Units produced
 Q^{Rz} Cumulative units produced
 S Present value of fuel cost savings
 t_{0-55} Acceleration time 0-55 mph
 t_{30-50} Acceleration time 30-50 mph
 U Net utility threshold
 w_i Portfolio weight for technology i
 β Production cost coefficients
 Δt Monthly period
 η Speed of reversion
 μ Growth of historical data
 ρ Incremental capacity cost
 σ Volatility of historical data
 θ Demand-shift parameter

1. INTRODUCTION

The need for a product development process that links product design decisions with other enterprise decisions contributing to the market success of a product has been well recognized. Linking engineering design, marketing,

production allocation, and new product strategy decisions allows products to be optimized from a consumer need and an enterprise perspective. In a large organization this is often referred to as product planning but the design decisions included in these planning processes are usually limited to high-level product attributes. Optimizing these attributes through traditional planning is often driven by financial and marketing decisions and may not account for full technical feasibility, leading to product launch delays and increased cost. Similarly, product designers determine “optimal” designs considering technical performance and associated costs, but the design’s impact on the enterprise, i.e. product demand, pricing, and long-term effect on enterprise operations, such as production capabilities, are often overlooked.

In the design community there have been some recent efforts to address this issue quantitatively. Hazelrigg proposed an approach to link product design properties to the firm’s objectives using utility theory (1998). Gu *et al* expanded this work using a collaborative optimization framework with profit as an objective in the top-level of the product development hierarchy (2002). A complete hierarchical representation of the design process involves product attribute targets being set at the top level of the hierarchy and cascaded down through the hierarchy to determine optimal decisions considering both system and sub-system design (Papalambros, 2002; Cooper *et al*, 2003). Georgiopoulos *et al* (2002) proposed an enterprise-wide decision problem determining the net present value (NPV) resulting from design and portfolio decisions. Their work considered the re-design and allocation of resources to link product design properties with the enterprise’s business goals.

In the present work, we expand on the work of Georgiopoulos *et al* (2002) using an integrated decision-making approach across the organization to value the design capabilities of existing and new technologies over an extended time period using NPV analysis. An enterprise decision model determines proper re-alignment of the enterprise’s capacity based on future profitability and the design potential of new and existing technologies. The information flow of the enterprise decision model is shown in Figure 1. Potential cannibalization of the enterprise’s current business is also considered by valuing the tradeoff between advancing into a new, competing market versus continuing with only the established product.

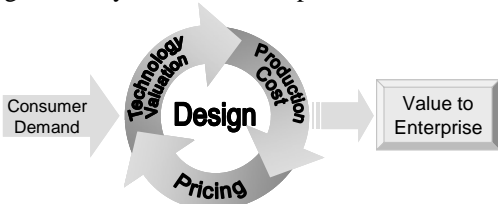


Figure 1. Information flow of enterprise decision model

An application of the enterprise decision model is presented for the medium truck market, which is experiencing hybrid technology penetration. The enterprise is modeled after International Truck Inc., one of the three leading manufacturers of medium and heavy trucks, because International historical sales data for medium trucks was publicly available (Navistar, 2002). Medium truck production is approximately 25% of International’s total business, which is operating in a mature industry with established demand from freight and small-package ground delivery services firms. The enterprise has already invested in developing hybrid technology and because demand penetration for hybrids is assumed gradual, the enterprise must decide how much of its existing capacity to allocate between current conventional trucks and new hybrid trucks. The enterprise decision model formulation for the case study is as follows.

$$\begin{aligned}
 & \text{maximize} && \text{Net present value} \\
 & \text{with respect to} && (\text{design})_{\text{Conventional}}, (\text{design})_{\text{Hybrid}}, \\
 & && \text{capacity allocation,} \\
 & && \text{technology pricing} \tag{1} \\
 & \text{subject to} && \text{product performance constraints,} \\
 & && \text{consumer’s technology threshold.}
 \end{aligned}$$

The model will be explained in further detail below. The case study considers product planning, strategy and development decisions for a 60-month production period as demand for hybrid trucks begins to penetrate.

In the following sections we develop the models that represent the enterprise’s product design process captured in Eq. (1). Application of these models is presented for a hybrid truck commercialization study, along with results and a discussion of our findings.

2. ENTERPRISE DECISION MODELS

The following sub-sections present the engineering, financial, and economic models used in the enterprise decision model. These models present theory and direct application to the case study.

2.1. Product design

Design capabilities of a product or product line provide insight to its market potential. Performance attributes of the design affect product demand and thus, pricing.

A high-fidelity engineering model is essential to appropriately link product performance with consumer preferences. The design for the conventional diesel trucks is represented using a previously validated, advanced powertrain simulation model called Vehicle-Engine-Simulation (VESIM) (Assanis *et al*, 2000). The vehicle simulation model integrates submodels of the engine, powertrain, and vehicle dynamics for a medium 3-axle truck. The vehicle simulation is structured to follow the

physical system layout. The hybrid truck design is represented using the Hybrid Electric version of VESIM (Lin *et al.*, 2001), which is configured as a parallel hybrid using a NiMH battery with an electric motor positioned after the transmission.

These high-fidelity vehicle simulation tools provide the relation between design characteristics and product performance. Using a combined Environmental Protection Agency (EPA) urban and highway driving cycle (see Figure 2), VESIM outputs acceleration performances and fuel economy fe .

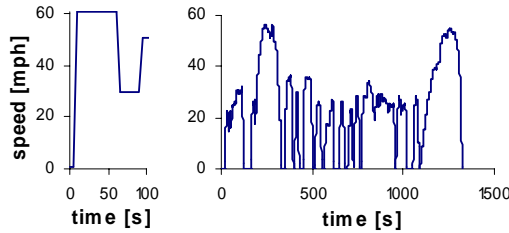


Figure 2. Driving cycles to determine acceleration performance (left) and fuel economy (right)

There are over 200 input parameters for the simulation that represent the truck design.

2.2. Life cycle considerations

The enterprise must recognize the important performance attributes that affect consumer demand. Creating this link allows marketers to reflect design changes into the product's price.

Consumers of the truck industry are most concerned with fuel costs during the life of the truck. Fuel costs F are a function of the diesel fuel price D , miles traveled M , and fuel economy [mpg], given by

$$F = \frac{D_t M_t}{fe} \quad (2)$$

The EPA defines a 20-year life-cycle for medium class trucks (EPA, 2002), shown in Figure 3.

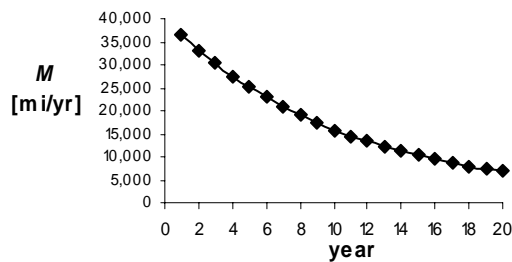


Figure 3. EPA life-cycle mileage of a medium truck (EPA, 2002)

To use diesel fuel price in Eq. (2), a forecasting technique must be implemented that incorporates fuel price uncertainty over time. The price of oil tends to revert to the marginal cost of production in the long run, despite short-term random variation. Therefore, it is appropriate to model the fuel price uncertainty using a mean-reverting process

(Dixit and Pindyck, 1994). The mean-reverting process, or the Ornstein-Uhlenbeck process, is given as

$$dx = \eta(\bar{x} - x)dt + \sigma dz, \quad (3)$$

where η is the speed of reversion, \bar{x} is the "normal" level to which x tends to revert, σ is the historical price data volatility and dz describes the stochastic nature of the process. These statistics are estimated using historical monthly diesel fuel price from March 1994 to November 2002 (DOE, 2002). A random walk for 240 monthly (20 years) diesel fuel prices is generated using Eq. (3). This process is repeated 100,000 times to account for many potential states of the oil market.

We now compute the fuel cost savings from an improved design across the time and probability space. Following from Eq. (2), the present value of the fuel cost savings S over 20 years is,

$$S = \int_0^{240} \left[\frac{D_t M_t}{fe_0} - \frac{D_t M_t}{fe'} \right] e^{-r_i t} dt \quad (4)$$

where fe_0 and fe' are fuel economies for the conventional baseline truck and proposed design, respectively. The discount rate in Eq. (4) is assumed to be static inflation rate r_i to account for the time value of money. Modeling of a dynamic interest rate is possible, but beyond the scope of this demonstration.

The fuel cost savings are discounted across the time dimension using Eq. (4) and averaged across the probability space of the 100,000 by 240 matrix.

2.3. Demand uncertainty

Product demand is the major driver of profits. Accordingly, it is important to use a demand model that reflects the product's past sales performance and cyclical tendencies and the market's potential response to new technologies.

Geometric Brownian motion is often used to predict a product's demand because it can forecast economic variables with stochastic processes (Dixit and Pindyck, 1994). Brownian motion uses the growth μ and volatility σ of historical enterprise sales data to forecast demand. Using the discrete-time version of the Brownian motion model (Hull, 2000),

$$\frac{\Delta Q}{Q} = \mu \Delta t + \sigma \varepsilon \sqrt{\Delta t} \quad (5)$$

where ΔQ is the change in sales Q , the enterprise's demand is forecasted over the 60-month production period. Equation (5) is used to simulate 100,000 random demand walks with random numbers of normal distribution, $\varepsilon \sim N(0,1)$. Each random walk represents a potential state of the economy. This demand model therefore incorporates market uncertainty in the valuation process.

In addition to historical sales' growth and volatility, the demand forecast must include the annual seasonality and

business cycle of the industry. The demand model includes the effect of annual seasonality using Winter's method for seasonality. The following steps outline Winter's method (Winston *et al*, 1997):

- i. Take average of sale units \bar{Q} per year of the historical data.
- ii. For each N period, calculate seasonal factor, $s_N = Q_N / \bar{Q}$.
- iii. Average seasonal factors for each month m (i.e. January), $s_m = \sum s_m / N$.
- iv. De-season the historical data: $Q_{t,deseasoned} = Q_t / s_m$.
- v. Calculate the growth rate and volatility from the de-seasoned data required for Brownian motion.
- vi. After forecasting the random walks, re-season the data using s_m .

The decision-maker must also decide if future demand will continue its long-term business cycle or breakout to a new cycle by continuing short-term trends. Copeland *et al* (2000) concluded it is important to account for each scenario by taking an equally weighted average. This is accomplished by first forecasting demand with Brownian motion using "zero-insight" into the business cycle or, in other words, using short-term trends as a measure of the future. Next, demand is predicted using "full-insight" into the business cycle; namely, assume demand will continue the trends of its existing cycle. The latter is achieved by "de-cycling" historical data using the previously described Winter's method with annual data in replace of monthly data. The 100,000 demand forecasts for each insight are generated simultaneously and averaged together for the final demand forecast.

2.4. Technology market penetration

We now consider market penetration of a new technology offering advanced performance. To value an emerging technology, decision-makers must predict the market's reaction to the technology's costs and benefits. The Utterback-Abernathy dynamic model of innovation suggests the evolution of a new technology entering a marketplace goes through a three-phase process in an S-shaped curve: emerging, growth, and maturity (Utterback and Abernathy, 1975; Afuah, 1998).

In the present study we focus on the emerging phase when the product is initially costlier to produce, with associated higher consumer prices, and prominent technical and market uncertainties exist. We assume consumers possess some utility threshold that describes, in part, the consumer's willingness to pay for the new technology. It is also assumed that during this phase, consumers expect prices to eventually decline from the initially high prices. Industry analyst's or enterprise expert's forecasts can be used to fit an S-curve penetration. Two points used for hybrid penetration into the truck market are 20% in year 4 and 70% in year 9 (Rockwell, 2000). Figure 4 shows

market penetration of past vehicle technologies that enhanced fuel efficiency (Ehlen, 1999) and a fitted S-curve

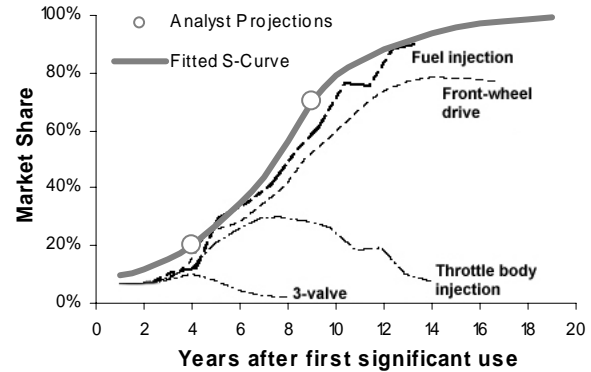


Figure 4. S-curve penetration of fuel efficiency enhancing technologies (Ehlen, 1999) with forecasted hybrid penetration

for the hybrid penetration of the medium truck market using the two analyst data points. The final demand model includes market uncertainty, using Brownian motion, and forecasted market penetration of the new technology.

2.5. Production and technology costs

Operating cost of each truck is divided into two categories, production and technology costs. Production costs are associated with the manufacturing of the product, including labor and materials. Technology costs describe the difference in operating costs among a product portfolio with different technologies.

Production costs C_p are closely connected to the level of production (Bollen, 1999) or capacity utilization (Morrison, 1993), which is the ratio of used capacity Q^p to available capacity K . Regression from the enterprise's historical cost data results in a quadratic cost equation, which is a standard assumption in capacity cost analysis (Pindyck, 1988; Trigeorgis, 1996), of the form

$$C_p = \beta_1 - \beta_2 \left(\frac{Q^p}{K} \right) + \beta_3 \left(\frac{Q^p}{K} \right)^2, \quad (6)$$

with β_1 , β_2 , and β_3 equal to 48201, 42253, and 25560, respectively. We assume the base cost structure remains the same for future production of the current and new technologies (An *et al*, 2000).

Production for each product depends on the available capacity and demand for each technology. The capacity for each technology is defined by an allocation decision w_i that divides the enterprise's current capacity K_0 . The available capacity K_i for technology i is,

$$K_i = w_i K_0. \quad (7)$$

Remaining capacity is used for the other technology. The capacity allocation decision in Eq. (7) is assumed fixed over the production period because it is unrealistic for a manufacturer to continually change capacity to match

growing demand (Morrison, 1993). Production of each technology is thus,

$$Q_i^p = \min(Q_i^D, K_i), \quad (8)$$

with the quantity demanded Q^D forecasted for each technology using the methodology outlined in Sections 2.3 and 2.4. Thus, the production cost in Eq. (6) depends on the capacity allocation and demand of each technology.

We now distinguish the costs for the new technology. To correspond with the S-curve technology penetration model in Section 2.4, the new technology's cost decreases as production volume increases. The standard learning curve theory, namely, cost per unit decreases as a function of cumulative production Q^{cum} (Argote and Epple, 1990), is used to describe this decrease in cost. The standard form of the learning curve is a power function:

$$L = C_H (Q^{\text{cum}})^{-b}, \quad (9)$$

where L is the learning curve cost, C_H is the initial cost of the hybrid design, and b is a parameter that measures the rate of cost reduction as output increases, which is estimated by combining the forecasted hybrid demand and predicted hybrid cost decline over time for parallel, NiMH medium trucks from An *et al* (2000).

Hybridization cost C_H is a function of the design of the hybrid system calculated using the following equation:

$$C_H = \alpha_0 + \alpha_1 E_K + \alpha_2 P_{\text{peak}}, \quad (10)$$

where E_K and P_{peak} are the energy capacity [kW-hr] and peak power [kW], respectively, of the electric components for the hybrid system. E_K and P_{peak} have a linear relation to the battery and motor size, respectively. Thus, the design decisions for the hybrid system, battery and motor size, translate directly to the cost of the hybrid system C_H . Coefficients α_0 , α_1 , and α_2 of Eq. (10) are estimated by product development engineers (EEA, 1998) and include the costs of battery replacement, inverter, and generator.

2.6. Technology portfolio implications

We next address consumer's reaction to a new technology in terms of performance attributes and effect on price. Consumer's willingness-to-pay (WTP) depends on product performance and the usefulness or utility of the product to the consumer.

Commonly, marketers use a rule-of-thumb metric to associate performance changes with pricing. For a new technology, however, the marketer should also consider the consumer's utility towards the new technology. A "net utility threshold" U captures the interaction between new technology performance and change in product price (Adner and Levinthal, 2001). This threshold helps define the consumer's WTP for a new technology. An example of this threshold used as a pricing constraint in the truck industry is that the change in fuel savings S of the hybrid truck must exceed any change in price by an amount U , or

$$S - \Delta P \geq U, \quad (11)$$

where U is estimated through marketing studies.

The enterprise must also consider the implications of competitors' reaction to the new technology. Competitive pressures exist and must be modeled to reflect competitive pricing. Reduction in technology cost C_R results as the enterprise progresses down the learning curve and is given by,

$$C_R = C_H - L_t. \quad (12)$$

with initial hybrid cost C_H and decrease in that cost L_t described by Eqs. (10) and (9), respectively. Competitive pressures force the enterprise to pass a portion of these cost reductions to consumers to ensure demand is not lost to competitors that lowered prices of the existing technology. The price change for the new technology due to competitive pressure is modeled as,

$$\Delta P_{C_R} = \left(-\frac{\Delta P}{\Delta C_R} \right) C_R. \quad (13)$$

The percent of cost reduction passed to customers, $\Delta P / \Delta C_R$, is estimated by the marketing department.

2.7. Product Price

Product price of course depends on the state of the market, but should also include the impact of design changes. Future market price P_t depends on the fluctuation of the enterprise's demand as well as the price elasticity ($\Delta Q / \Delta P$) consumers exhibit toward price changes. The inverse demand curve introduces this relation between price and quantity demanded Q^D ,

$$Q_t^D = \theta - \frac{\Delta Q}{\Delta P} P_t \rightarrow \quad (14)$$

$$P_t = \frac{\theta}{\Delta Q / \Delta P} - \frac{\Delta P}{\Delta Q} Q_t^D$$

where θ is the demand-shift parameter. Parameters for the inverse demand curve (see Table 1) can be estimated from historical price and sales data.

Table 1. Calculated parameters for inverse demand curve (Navistar, 2002)

Parameter	Value
$\theta / (\Delta Q / \Delta P)$	53,545.83
$\Delta Q / \Delta P$	2.27

The price elasticity for the truck market comprised of business consumers should be less than the personal light vehicle market. A price elasticity of 2.27 is reasonable considering the elasticity for the consumer vehicle market ranges from 3.1 to 6.8 (Berry *et al*, 1995). The price elasticity of demand is assumed the same for these

conventional and hybrid trucks because both are part of the medium truck market.

Equation (14) represents the inverse demand curve for the conventional product. Because of the new technology's advanced performance, specifically increased fuel savings, consumers are willing to pay more with some elasticity $\Delta P/\Delta S$ towards changes in fuel cost savings S . For the new technology, Eq. (14) becomes

$$P_t = \frac{\theta}{\Delta Q/\Delta P} - \frac{\Delta P}{\Delta Q} Q_t^D + \frac{\Delta P}{\Delta S} S \quad (15)$$

Equation (15) projects performance changes onto a third axis (see Figure 5). Initially, this information was aggregated in the $\theta/(\Delta Q/\Delta P)$ term of Eq. (14).

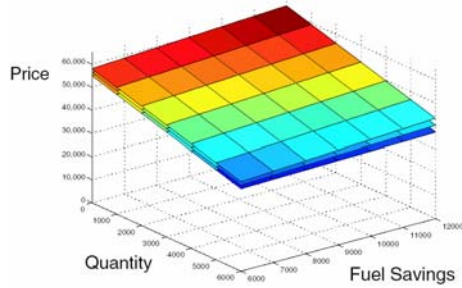


Figure 5. Demand curve for different price elasticities of fuel savings

The price-to-savings ratio $\Delta P/\Delta S$ is a pricing decision because the actual elasticity is unknown given the novelty of the technology.

2.8. Valuation

The enterprise decision model explores the value of the product or product line using net present value (NPV). NPV analysis uses expected profit cash flows to determine the worth of a new technology and proposed designs to the enterprise in today's terms. The NPV formulation has the form,

$$NPV = -I + \int_T E[\Pi] e^{-rt} dt, \quad (16)$$

where the expected profit from each product is the price minus per unit cost by the quantity produced:

$$E[\Pi] = (P - C)Q^P. \quad (17)$$

The discount rate r in Eq. (16) is the opportunity cost of capital of the enterprise's assets (Brealey and Myers, 2000). Estimating the weighted average cost of capital requires knowledge of the firm's debt and equity structure and can be calculated from publicly available data.

We assume the development period for the new products is 18 months. The development or investment cost I for new products is assumed fixed at \$350 million, which is 25% of International's average "engineering and research expenditures" accumulated over five years (Navistar, 2002). Operational expenditures such as marketing and sales are not taken into account.

3. HYBRID COMMERCIALIZATION CASE STUDY

The enterprise decision model is applied to a case study to determine the hybrid commercialization potential in the medium truck market. The enterprise, a truck manufacturer with established demand for conventional diesel trucks, is developing hybrid technology to include in its medium truck product line. Hybrid commercialization is defined here as the magnitude of resource allocation to hybrid trucks. The enterprise must assess potential cannibalization of switching production from the consistently profitable, conventional truck (CVC) to hybrid trucks (HBC), which possess technological and market uncertainty. This is an important consideration during the technology valuation process that is often overlooked.

The optimization framework for the EDM follows.

3.1. Decision variables

Product performance determined using high-fidelity engineering models is the backbone of the EDM. The variable design characteristics of the truck are represented by its engine and hybrid components. The design inputs for the engine are displacement [L], compression ratio, maximum intake pressure [atm], and wastegate activation speed [RPM]. The hybrid system is defined by the scaling of a baseline motor and battery size, which combine to determine E_K and P_{Peak} used in the hybrid cost equation (Eq. (10)). Battery size is the number of battery modules. These design variables are inputted into VESIM to determine acceleration performance and fuel economy.

Based on performance attributes and associated costs of each product, the enterprise must determine the amount of its existing capacity to re-allocate to hybrids. This decision, defined by w_{HBC} and used in Eq. (7), is assumed fixed once decided and is highly dependent on the forecasted market demand and hybrid penetration. Using the techniques described in Sections 2.3 and 2.4, the demand is forecasted (see Figure 6) using the growth, volatility, and cyclical behavior of International Truck's historical sales.

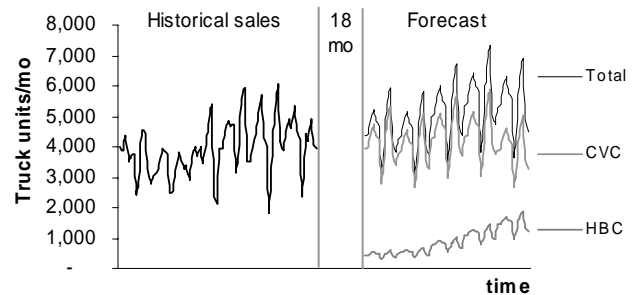


Figure 6. Enterprise historical sales and average demand forecast with hybrid penetration allowing 18-month development period

The final decision is the amount of fuel cost savings ($\Delta P/\Delta S$) to pass to consumers for hybrid trucks used in Eq. (15). The change in price of the conventional truck

from the market price determined in Eq. (14) is simply the rule-of-thumb for the medium truck industry:

$$S_{CVC}^3 = \Delta P_{CVC}, \quad (18)$$

where S^3 is the fuel cost savings for the first three years of the truck's life-cycle. This three-year payback is calculated using Eq. (4) over the first 36 months rather than the full 240-month life cycle.

3.2. Constraints

For both new products, conventional and hybrid, the designs are assumed to at least meet baseline acceleration performance. The acceleration performance constraints for both trucks (slightly relaxed to allow the optimizer to achieve feasibility more readily) are:

$$\begin{aligned} t_{0-55} &\leq 20 \text{ seconds} \\ t_{30-50} &\leq 10 \text{ seconds} \end{aligned} \quad (19)$$

The hybrid pricing decision in Eq. (15) is constrained by the utility threshold, determined from enterprise marketing studies to be \$5,000,

$$S_{HBC} - \Delta P_{HBC} \geq \$5,000. \quad (20)$$

That is, fuel savings from the hybrid design must exceed the change in hybrid price by at least \$5,000.

3.3. Optimization formulation

The enterprise decision model from Eq. (1) is summarized as follows.

$$\begin{aligned} \max \quad & NPV = -\$350M + \int_{18}^{78} (\Pi_{CVC} + \Pi_{HBC}) e^{-i_{wacc}t} dt \\ \text{wrt.} \quad & (\text{engine})_{CVC}, \\ & (\text{engine, scaled motor, battery size})_{HBC}, \\ & w_{HBC}, \Delta P/\Delta S \\ \text{s. to} \quad & (t_{0-55})_{CVC} \leq 20 \text{ seconds} \\ & (t_{30-50})_{CVC} \leq 10 \text{ seconds} \\ & (t_{0-55})_{HBC} \leq 20 \text{ seconds} \\ & (t_{30-50})_{HBC} \leq 10 \text{ seconds} \\ & S_{HBC} - \Delta P_{HBC} \geq \$5,000 \end{aligned} \quad (21)$$

The MATLAB sequential quadratic programming (SQP) algorithm (Coleman *et al*, 1999) is used as the optimizer.

The solution to the enterprise decision model in Eq. (21) determines the optimal vehicle design for a portfolio of medium trucks using two technologies and valuation of the new technology with respect to the enterprise's current operations.

4. RESULTS AND DISCUSSION

Design and performance results are shown in Table 2. The engine designs for the two trucks are very close and potentially could be shared. Advantage of component sharing is not explored here, but is detailed by Fellini (2003).

Table 2. Design and performance results from EDM

	Decisions and Responses	CVC	HBC
Design Decisions	displacement	9.5	9.5
	compres. ratio	22.0	22.0
	intake pressure	2.695	2.628
	wastegate RPM	2250	2250
	motor scaled	N/A	-11.4%
	battery size	N/A	36
Performance	C_H	N/A	\$9,414
	% Δf_e	12%	26%
	t_{0-55}	18.8	19.8
	t_{30-50}	9.0	8.9

Despite having the same engine design, the hybrid truck offers an additional 14% fuel economy improvement versus the conventional truck, at an additional cost of \$9,414 per truck. Employing this design information the enterprise makes informed technology allocation and pricing decisions, resulting in maximum value. These results are shown in Table 3.

Table 3. Enterprise decisions and value-created

	Decisions and Responses	CVC	HBC
Enterprise Decisions	w	83.8%	16.2%
	K [monthly units]	5,071	979
	$\Delta P/\Delta S$	N/A	69%
Enterprise Implications	Value [\$MM]	\$1,426	\$222
	NPV [\$MM]	\$1,298	

Note that the marketing constraint in Eq. (20) is proven to be active. This is expected since the enterprise has no incentive to offer consumers more than the utility threshold of \$5,000.

For the scenario in which the enterprise produces no hybrids, i.e. w_{HBC} is 0%, the NPV for the optimal CVC design in Table 2 is \$1,038 million. By evaluating the hybrid product's design and market capabilities in accordance with current operations, the enterprise increases the product line's value 25% to \$1,298 million.

Figure 7 shows the enterprise does not have sufficient resources to capture all demand, so it sets capacity for each technology in such a way that misses some demand for both

conventional and hybrid trucks to maximize total value. Once the enterprise recognizes its production capabilities are insufficient, it may consider investing in additional capacity. This capacity investment decision is addressed at the end of the section.

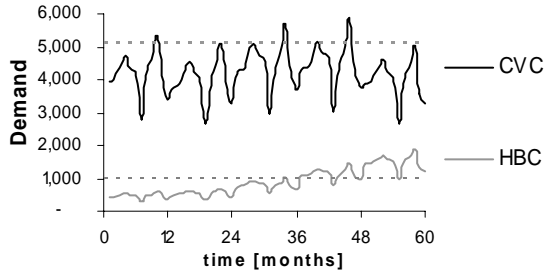


Figure 7. Capacity decision (dotted) and average demand for conventional and hybrid technologies

A key assumption in the enterprise decision model is the market penetration for hybrid technology. The following parametric study shows how this assumption may affect enterprise decision-making and value. Figure 8 shows decelerated, analyst (used in the original case study, see Figure 4), and accelerated forecasts for hybrid market penetration.

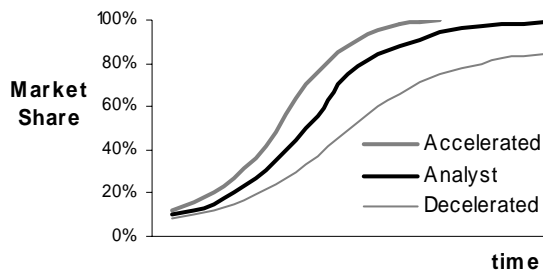


Figure 8. Parametric study for hybrid technology market penetration

The EDM in Eq. (21) is solved for each of these scenarios. The results are compared in Table 4.

Table 4. Comparison of results using decelerated, analyst, and accelerated hybrid penetration

Result	Decelerated	Analyst	Accelerated
NPV [\$MM]	\$1,305	\$1,298	\$1,284
$(\text{Value})_{CVC}$	\$1,484	\$1,426	\$1,343
$(\text{Value})_{HBC}$	\$171	\$222	\$291
w_{HBC}	12.5%	16.2%	21.6%
C_H	\$8,466	\$9,414	\$8,606
$(\% \Delta fe)_{HBC}$	23.9%	26.1%	24.2%

As expected, the hybrid allocation of the enterprise's capacity w_{HBC} increases with faster hybrid penetration.

Accordingly, the value created by the hybrid product (HBC) also increases rather substantially. The total value created (NPV) by the two products, however, decreases with greater penetration because the enterprise cannot produce as many profitable conventional trucks due to decreasing conventional demand. If the study were conducted during the growth phase of hybrid penetration, this trend might be different depending on the profitability of hybrid trucks.

Another important result of the parametric study is that design decisions, in particular the hybrid design that corresponds directly to C_H via Eq. (10), depends on the level of technology penetration, which obviously affects the enterprise's portfolio decision w_{HBC} . For the accelerated case, the enterprise chooses to produce a less expensive hybrid system despite lowering fuel economy improvement and thus decreasing selling price because the production costs for the steeply sloped accelerated penetration were substantially higher than the analyst case. Note that the engine design did not change significantly for either truck. Although the enterprise cannot influence the speed of hybrid penetration, decision-makers can use these results to make more informed design and strategic decisions that account for market uncertainties.

As previously mentioned, the enterprise decision model helps decision-makers recognize the sufficiency of its production resources. Following this, the enterprise may desire to invest in additional capacity to adequately meet growing demand during new technology penetration. An EDM can include a capacity investment decision using an additional capacity K_a decision variable (Cooper, 2003) to account for insufficient resources. This decision corresponds to a capacity investment cost I_K , modeled as:

$$I_K = \rho K_a, \quad (22)$$

which is a linear function to K_a with per-unit cost coefficient ρ (Dixit and Pindyck, 2000), approximated from previous enterprise capacity investments. This variable investment cost introduces the tradeoff between capturing future growing demand and incurring the cost today.

5. CONCLUSIONS

Although the enterprise decision model uses simplifying assumptions, it can still provide understanding of a product's design and market capabilities for existing and new technologies. Considering market uncertainty and design and production capabilities is essential for valuing a commercialization strategy of a new technology. Of course there are limitations when trying to incorporate all pertinent enterprise distributed decisions into a single decision model. We demonstrated through a practical application, however, that a reasonably simple but multifaceted approach can provide valuable insight to decision-makers for initial product design and technology valuation.

ACKNOWLEDGEMENTS

We gratefully acknowledge P. Georgiopoulos and M. Kokkolaras for ideas contributed during the execution of this work. The research was partially supported by the US Army TACOM through the Automotive Research Center and a Dual Use Science and Technology Project at the University of Michigan. This support is gratefully acknowledged. The views presented here are only those of the authors and do not necessarily reflect views of the sponsors or other individuals we consulted.

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