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Analytical Target Setting: An Enterprise Context in Optimal Product Design

In this article the process of rigorously setting supersystem targets in an enterprise context is explored as a model-based approach termed "analytical target setting." Engineering design decisions have more value and lasting impact if they are made in the context of the enterprise that produces the designed product. Setting targets that the designer must meet is often done at a high level within the enterprise, however, with inadequate consideration of the engineering design embodiment and associated cost. For complex artifacts produced by compartmentalized hierarchical enterprises, the challenge of linking the target setting rationale with the product instantiation is particularly demanding. The previously developed analytical target cascading process addresses the problem of translating top level design targets into design targets for all systems in a multilevel hierarchically structured product, so that local targets are consistent with each other and top targets can be met as closely as possible. The effectiveness of linking analytical target setting and target cascading is demonstrated in a hybrid electric automotive truck vehicle example. The manufacturer introduces a new product (hybrid electric truck) in the market under uncertainty in fuel prices during the life cycle of the vehicle. The example demonstrates a clear interaction between the enterprise decision making and the engineering product development. [DOI: 10.1115/1.2125972]

Introduction

In modeling the product development process for the purposes of this article, the enterprise is defined as the organization that produces the designed artifact. The enterprise considers marketing, production, and engineering from the initial design phase through the final marketing and release of the product. For simplicity, marketing and production considerations are defined as product planning, and engineering design is defined as product development. Product planning determines the need for a product in the marketplace and attempts to communicate product attributes for market success to the development group. The development group conceptualizes a design and progresses towards the final design, while the planning group concurrently builds their strategy to market and produce the product based on the product attributes initially given to the engineers. Our hypothesis is that lack of proper interaction between the planning and development teams results in "suboptimal" enterprise decision-making. For example, as the two processes evolve independently, it is possible that the planning group prepares a marketing and production strategy suitable to a design that may not be achievable by the technical development team. The enterprise has then two choices: Proceed with the development team's design with the original marketing and production strategy or redesign the product with compromised performance while incurring costs and delays that may allow competitors to enter the market first.

In a hierarchical structure of the product design process, different decision levels within the enterprise can be identified, along with the appropriate fidelity of the design information used to make these decisions [1] Product planning works at a high (top) level and sets product design targets using high-level technical information. Decisions are economic ones based on expected revenues and current cost structure, and technical requirements are set to maximize profit. These top-level requirements are passed to the development team as targets to ensure technical feasibility more thoroughly and design the product embodiment. The development team uses target cascading to determine the "best" feasible design, i.e., a design with minimum deviation from the top-level targets achieved with proper coordination of system designs and associated local targets. A successful target cascading process will allow further development of systems to proceed independently and concurrently, as long as each system design team does not violate the agreed upon common decisions. Using the feasibility information provided by target cascading, the economic analysis in product planning can be repeated and initial business decisions can be updated. The methods used here are all based on analytical (meaning quantitative) models, and so the terms analytical target cascading (ATC) and analytical target setting (ATS) are used to describe the relevant decision models.

Analytical Target Cascading. In this work the engineering product development problem is viewed as a hierarchical process and solved using the Analytical Target Cascading (ATC) [2–5], a hierarchical multilevel optimization approach. In the context of hierarchical vs nonhierarchical decomposition, a key difference between ATC and many multilevel MDO formulations, including collaborative optimization (CO) [6], is that, in ATC, the original problem is cast into an object-based decomposition. Hierarchical MDO research (e.g., CO) has been concerned with decomposing a problem typically by aspect into a series of problems, all at a single level, that are connected through linking variables, and then imposing a hierarchical framework in order to coordinate the linking variables. In contrast, Kronsjo's dual formulation [7] and ATC impose a hierarchical decomposition first and then propose an algorithm (i.e., coordination) to solve the decomposed problem. Lassiter et al. [8] have placed ATC in the historical context of Lagrangian decomposition and coordination method for large-

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scale systems.

In the context of multidisciplinary model decomposition, most MDO formulations are dependent on the way *analysis* models (e.g., simulation codes) are decomposed and coordinated. In this article, an analysis model is differentiated from a design model. Analysis model is defined as a functional relation that takes input and generates output. For example, analysis models are simulations, closed form equations, or spreadsheet. Design model is defined as an optimization model that takes input parameters to optimize the objective and uses analysis models to evaluate objective and constraint functions. In CO, for each analysis model, a design problem is imposed and then the overall coordination problem is placed on top of these multiple design problems. The role of the top level problem is to coordinate differences of the linking variables among the lower level problems. In ATC *design* models are decomposed in a hierarchical manner. Analysis models evaluated by design models can be placed at different levels of the problem hierarchy. In a bilevel hierarchy the distinction between CO and ATC may not be as clear as it would be for multilevel hierarchies.

An advantage of ATC for product development is that it can model a multilayered organizational decision making infrastructure, where subsystems and components can be supplied by different organizational units or outsourced to independent companies. In an ATC-decomposed design problem, if more than one analysis model exist, a MDO formulation such as CO can be adopted to solve it. Thus, ATC and MDO methods are complimentary in that an MDO approach can be employed to solve the ATC-decomposed subproblems.

Before proceeding with individual problem formulations, some nomenclature and definitions are given. A vector of targets $\mathbf{T}_\nu$ is provided from product planning. The supersystem (i.e., the truck vehicle in the study presented later) and the systems it is composed of are referred to as the "elements" of the hierarchy. Each element is associated with an analysis model $\mathbf{r}$ used to estimate a vector of responses $\mathbf{R}$ that are assumed to be functions of local design variables $\mathbf{x}$ (associated exclusively with the element), linking design variables $\mathbf{y}$ (common with variables of other elements at the same level and having the same "parent" element), and responses of lower-level elements. Response and linking variable values are passed up and down during the ATC process for coordination and design consistency reasons; superscripts $(\cdot)^U$ and $(\cdot)^L$ denote values passed down and up from the upper and lower levels, respectively.

At the supersystem (vehicle) level, responses $\mathbf{R}_\nu$ must match desired product planning design requirements $\mathbf{T}_\nu$ from the analytical target setting phase. These responses are assumed to be functions of supersystem design variables $\mathbf{x}_\nu$ and system responses $\mathbf{R}_{s_i}$ for $i=1,\ldots,n_s$ systems, i.e., $\mathbf{R}_\nu=\mathbf{r}_\nu(\mathbf{x}_\nu,\mathbf{R}_{s_1},\ldots,\mathbf{R}_{s_{n_s}})$. To determine target values for system responses, values for supersystem design variables, and to coordinate system linking variables, a minimum deviation optimization problem is formulated as

$$\min_{\bar{\mathbf{x}}_\nu}\|\mathbf{R}_\nu-\mathbf{T}_\nu\|+\varepsilon_\nu^R+\varepsilon_\nu^y$$

$$\text{subject to } \sum_{i=1}^{n_s}\|\mathbf{R}_{s_i}-\mathbf{R}_{s_i}^L\|\leqslant\varepsilon_\nu^R$$

$$\sum_{i=1}^{n_s}\|\mathbf{y}_{s_i}-\mathbf{y}_{s_i}^L\|\leqslant\varepsilon_\nu^y$$

$$\mathbf{g}_\nu(\mathbf{R}_\nu,\mathbf{x}_\nu)\leqslant\mathbf{0}$$

$$\mathbf{h}_\nu(\mathbf{R}_\nu,\mathbf{x}_\nu)=\mathbf{0}, \qquad (1)$$

where $\bar{\mathbf{x}}_\nu=[\mathbf{x}_\nu,\mathbf{R}_{s_1},\ldots,\mathbf{R}_{s_{n_s}},\mathbf{y}_{s_1},\ldots,\mathbf{y}_{s_{n_s}},\varepsilon_\nu^R,\varepsilon_\nu^y]$ is the vector of optimization variables and $\|\cdot\|$ is some norm. The tolerance variable ε_ν^R coordinates system responses $\mathbf{R}_{s_i}$, determined at the supersystem level, with the vector of the ith system response values $\mathbf{R}_{s_i}^L$ passed up to the supersystem. The tolerance variable ε_ν^y coordinates system linking design variables for the ith system $\mathbf{y}_{s_i}$, determined at the supersystem level, with the vector of the ith system linking design variable values $\mathbf{y}_{s_i}^L$ passed up to the supersystem. Vector functions representing supersystem inequality and equality performance constraints are $\mathbf{g}_\nu$ and $\mathbf{h}_\nu$, respectively.

Once optimal values for the system responses $\mathbf{R}_{s_i}$ and system linking design variables $\mathbf{y}_{s_i}$, $i=1,\ldots,n_s$, are determined by Eq. (1) at the supersystem level, they are cascaded down to the system level as target values $\mathbf{R}_{s_i}^U$ and $\mathbf{y}_{s_i}^U$, respectively.

At the system level, n_s individual minimum deviation optimization problems are formulated to determine system design variables and system linking variables. System responses are assumed to be functions of system local design variables and system linking design variables, i.e., $\mathbf{R}_{s_i}=\mathbf{r}_{s_i}(\mathbf{x}_{s_i},\mathbf{y}_{s_i})$. Note that $\mathbf{R}_{s_i}$ is a vector of responses resulting from decisions at the ith system level, but a vector of decisions in the supersystem level. The optimization problem for each system s_i, $i=1,\ldots,n_s$, is

$$\min_{\bar{\mathbf{x}}_{s_i}}\|\mathbf{R}_{s_i}-\mathbf{R}_{s_i}^U\|+\|\mathbf{y}_{s_i}-\mathbf{y}_{s_i}^U\|$$

$$\text{subject to } \mathbf{g}_{s_i}(\mathbf{R}_{s_i},\mathbf{x}_{s_i},\mathbf{y}_{s_i})\leqslant\mathbf{0}$$

$$\mathbf{h}_{s_i}(\mathbf{R}_{s_i},\mathbf{x}_{s_i},\mathbf{y}_{s_i})=\mathbf{0}, \qquad (2)$$

where $\bar{\mathbf{x}}_{s_i}=[\mathbf{x}_{s_i},\mathbf{y}_{s_i}]$ is the vector of optimization variables, $\mathbf{x}_{s_i}$ is the vector of system design variables exclusively associated with the ith system, $\mathbf{R}_{s_i}^U$ is the vector of system response target values for the ith system passed down from the supersystem. The vector of system linking design variable values for the ith system passed down from the supersystem is $\mathbf{y}_{s_i}^U$ and vector functions representing inequality and equality design constraints for the ith system are $\mathbf{g}_{s_i}$ and $\mathbf{h}_{s_i}$, respectively.

Once optimal values for the system responses $\mathbf{R}_{s_i}$ and system linking design variables $\mathbf{y}_{s_i}$, $i=1,\ldots,n_s$, are determined by solving Eq. (2) at the system level, they are passed up to the supersystem as parameters $\mathbf{R}_{s_i}^L$ and $\mathbf{y}_{s_i}^L$, respectively.

Analytical Target Setting. In analytical target cascading the targets $\mathbf{T}_\nu$ are assumed to be given. In the statistics and operations research literature [9–13] there have been various attempts to model the target setting process but not in conjunction with a target cascading process. In the organizational behavior literature, target setting is being used as a means to increase employee performance [14–16]. More relevant to the work here is the use of a collaborative optimization framework by Gu et al. [17], where a profit utility stands as an objective at the top-level of the hierarchy. Other approaches in linking engineering to business decisions [17–40] use a nonhierarchical approach where net present value of future profits is directly linked to design variables. Both situations assume an integrated decision-making process across the organization.

In the approach presented here, a partitioned decision-making process is modeled: Decisions at the top-level of the hierarchy (ATS) are expected results from the lower levels (ATC). The linking of setting and cascading targets envisioned here is illustrated in Fig. 1.

The ATS problem is defined as

$$\max_{\mathbf{T}_\nu,\mathbf{x}_e}\pi(\mathbf{T}_\nu,\mathbf{x}_e)$$

$$\text{subject to } \mathbf{g}_e(\mathbf{T}_\nu,\mathbf{x}_e)\leqslant 0$$

$$\mathbf{h}_e(\mathbf{T}_\nu,\mathbf{x}_e)=0 \qquad (3)$$

where π is economic profit, $\mathbf{T}_\nu$ is a set of target values, $\mathbf{x}_e$ is the vector of local enterprise variables, and $\mathbf{g}_e$ and $\mathbf{h}_e$ are vectors of

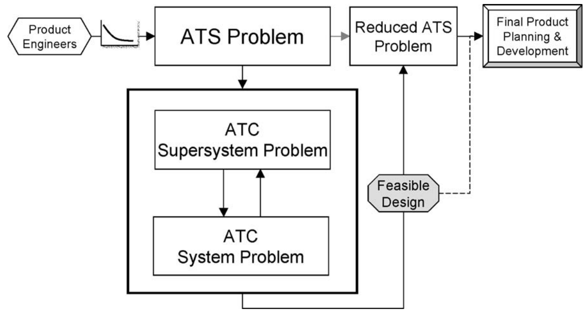

Fig. 1 Coordination and information flow in analytical target setting (ATS) and cascading (ATC) processes

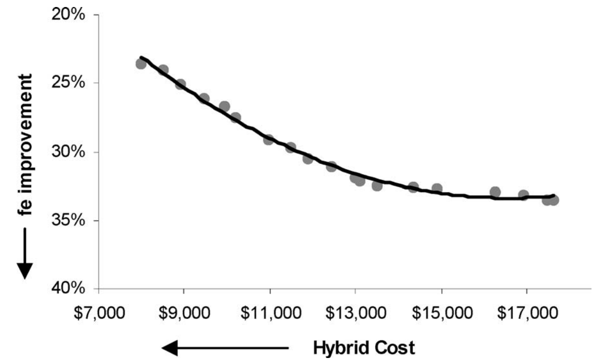

Fig. 3 Amount of dollars spent for fuel economy improvement

enterprise and high-level technical constraints. At this level of the hierarchy the engineering information is a high-level "abstraction" of the trade-offs among the technical decisions $\mathbf{T}_\nu$ provided by product engineers. Solution of the ATS problem provides optimal values for the targets $\mathbf{T}_\nu$, which are passed down as fixed parameters to the supersystem ATC problem. After the ATC process has converged, a feasible design is produced. A reduced ATS problem can then be solved, where the $\mathbf{T}_\nu$ are now fixed and set to $\mathbf{R}_\nu^*$, and the enterprise variables $\mathbf{x}_e$ are reoptimized.

$$\max_{\mathbf{x}_e} \pi(\mathbf{x}_e)$$

$$\text{subject to } \mathbf{g}_e(\mathbf{x}_e) \leq 0$$

$$\text{subject to } \mathbf{h}_e(\mathbf{x}_e) \leq 0. \tag{4}$$

This is one of several possible scenarios that can be used to link the ATS and ATC problems. At this stage, the mathematical properties of what is effectively a decomposition strategy are not being addressed.

Enterprise Design of a Medium-Class Truck. We will demonstrate Eqs. (1)–(3) for a commercial manufacturer of medium and heavy duty diesel trucks. This enterprise is operating in a mature industry with established demand from freight and small-package ground delivery services firms. Currently the truck manufacturer has undertaken the development of hybrid electric powertrains. Decision-makers must determine a product design and a production level that would lead to a profitable commercialization of the emerging technology.

This new product introduction calls for interaction of many decision-makers across the enterprise hierarchy (see Fig. 2). At the top level the product planning team will decide on the (i) level of production output and (ii) powertrain hybridization cost. Product planning decisions take the form of requirements for the next level, the product development.

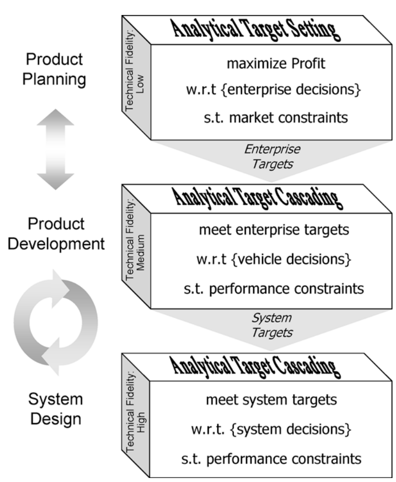

Fig. 2 Decision-making and technical information used at each level of the organization's hierarchy

The product development team uses high fidelity engineering information to determine the technical performance as well as feasibility of the design as specified by the performance requirements. Subunits within the powertrain team follow their own decision-making process to guarantee feasibility of suspension and transmission.

The next section describes in detail how the ATS problem Eq. (3) is constructed for the truck problem, by taking into account product demand information, cost estimates, and macroeconomic uncertainty. The implementation of a bilevel target cascading process for the truck vehicle is then presented, and results are discussed, justifying the value of the proposed approach.

Truck Design Study: Analytical Target Setting

The role of the engineering information involved at the ATS level is to augment the intuition of the decision-makers. The trade-off here is between powertrain hybridization cost and fuel economy improvement. Increasing the degree of hybridization increases the power the electric system provides for propulsion, improves the fuel economy, and increases cost. A rough approximation of expenditures due to powertrain hybridization for a percent improvement of fuel economy should answer the following question: How much does the enterprise need to spend for one percent improvement of fuel economy?

Hybridization cost C_H consist of battery and motor size costs calculated using the following equation:

$$C_H = c_{H0} + c_{H1} \times (\text{kW-hr}) + c_{H2} \times (\text{Peak kW}). \tag{5}$$

Coefficients c_{H0}, c_{H1}, and c_{H2} of Eq. (5) have been estimated [41] and include the costs of battery replacement, inverter and generator. Decision-makers during the target setting process treat C_H as a decision: They must decide on a target budget per truck for powertrain hybridization.

This relationship has been generated using the Hybrid Electric Vehicle-Engine-SIMulation (HE-VESIM) [42], an advanced vehicle simulation model. Using engine displacement, motor size and battery size as design decisions a Pareto optimum was generated to quantify the trade-off between fuel economy and hybridization cost (see Fig. 3).

Regressing on the values of fuel economy and hybridization cost we model the relation of fuel economy improvement (from the conventional baseline design) to hybridization cost:

$$\%\Delta\text{fe} = -0.053 + (4.67 \times 10^{-5})C_H - (1.41 \times 10^{-9})C_H^2. \tag{6}$$

Equation (6) is valid for hybridization costs from \$7,590 to \$18,000.

Next, the worth of fuel economy improvement in monetary value is modeled. Translating miles per gallon to dollars allows

Table 1 Historical product price and demand data points and demand values adjusted for expected new product penetration

Year	Price	Quantity	Adjusted quantity
1998	\$36,820	5230	523
1999	$(\$37{,}510)_{98}$	5020	502

the cost-benefit analysis of commercializing the technology. The relationship between fuel consumption and dollar value will be modeled with the assumption that the factors which influence customer's purchasing decision, other than fuel economy, will remain unchanged. In what follows we model how fuel economy improvements affect product demand.

Demand Curve. We draw the relationship between price P and quantity demanded q of conventional medium class trucks by assuming that the demand curve is linear and downward sloping. Both are standard assumptions in the microeconomic literature. Using two pairs of price and demand data points (see Table 1) from the last quarters of 1998 and 1999 of a U.S. publicly traded truck manufacturer, we estimate the price elasticity of demand to be equal to 2.269.

We assumed that between these two years there was no major change in consumer's income, product quality, product advertising, product information available to consumers, price and quality of substitutes and complementary goods, and population [43]. We also assume that hybrid electric medium class truck falls under the category of medium class trucks. Therefore, the price elasticity of demand would remain the same.

The enterprise has decided to allocate 10% of its existing capacity for the production of the new product. This allocation is based on a conservative estimation of hybrid electric truck demand penetration using industry knowledge [44]. Adjusting the quantity to this level of penetration (see Table 1) the demand curve $q=\theta-(\Delta q/\Delta P)P$, solved for P gives the "inverse" demand curve

$$P = \frac{\theta}{\frac{\Delta q}{\Delta P}} - \frac{\Delta P}{\Delta q}q \text{ or}$$

$$P = 53{,}545.83 - 31.96q. \tag{7}$$

Equation (7) represents the demand curve at 1999 with product quality that of the conventional medium class trucks. Now, the enterprise is considering an improvement in fuel economy by producing and marketing hybrid medium class trucks, translating to fuel cost savings S for the customers:

$$S = (\text{Fuel Expense})_C - (\text{Fuel Expense})_H \tag{8}$$

where $(\text{Fuel Expense})_C$ and $(\text{Fuel Expense})_H$ are the present values of future fuel expenses incurred during the lifecycle of a truck by the conventional and hybrid design, respectively.

From 1998 to 1999 there was no change in consumer fuel savings. It is expected that fuel cost savings S will shift the demand curve Eq. (7) as follows:

$$q = \theta - \frac{\Delta q}{\Delta P}P + \frac{\Delta q}{\Delta S}S \tag{9}$$

that assumes a linear relationship among quantity q, price P, and fuel cost savings S.

One could use Eq. (7), despite changes in consumer fuel savings by projecting changes from the fuel savings axis (see Fig. 4) to the two-dimensional demand curve of Eq. (7). This would aggregate θ and $(\Delta q/\Delta S)S$ from Eqs. (7) and (9). Equation (9) will be used to decide the level of fuel savings S that must be realized by the new design. Given that the enterprise is marketing a novel technology, a hybrid electric medium truck, Eq. (9) could only be

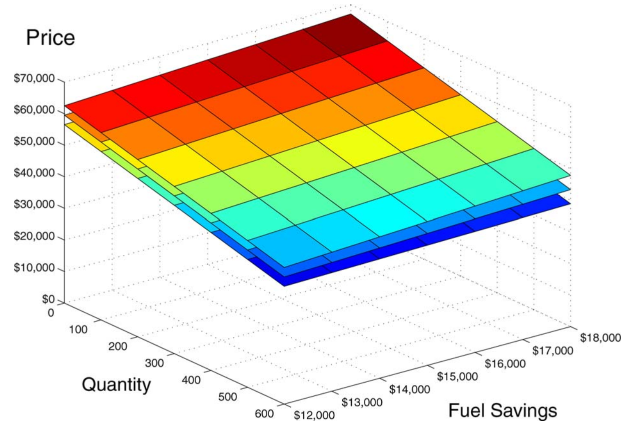

Fig. 4 The demand curve at different price elasticities of fuel savings

inferred from Eq. (7) by assuming that $(\lambda_S/\lambda_P)S$ will shift Eq. (7).

Solving with respect to price we have

$$P = \frac{\theta}{\frac{\Delta q}{\Delta P}} - \frac{1}{\frac{\Delta q}{\Delta P}}q + \frac{\frac{\Delta q}{\Delta S}}{\frac{\Delta q}{\Delta P}}S \Rightarrow$$

$$P = \frac{\theta}{\frac{\Delta q}{\Delta P}} - \frac{\Delta P}{\Delta q}q + \frac{\lambda_S}{\lambda_P}S. \tag{10}$$

The decision-maker seeks answer to the following question: What is the optimal fuel savings the new product should have to maximize profit? The answer is highly dependent on the amount of price premium ΔP the customer is willing to pay for one dollar improvement of fuel savings ΔS. Given the novelty of the technology and the potential for fuel economy improvement of the specific technology, the ratio λ_S is unknown. Marketing information is needed to understand consumer behavior towards the new technology.

Consumer Preferences. It is expected that the consumer will show aversion towards the new technology. A "net utility threshold" V is used to account for this aspect of consumer behavior [45]. From private discussions with industry experts we choose to define the "net utility threshold" for the truck industry as the difference between fuel savings from a hybrid powertrain and change in price. That is,

$$S - (P - \bar{P}_{98|99}) \geqslant V, \tag{11}$$

where S is the present value of fuel savings, P is the price of the hybrid truck design as defined by Eq. (10) $\bar{P}_{98|99}$ is the average of 1998 and 1999 market prices of the current conventional truck design, which is set at \$37, 165, and V=\$10,000. Since we have not validated the value of V, we will treat this number as a parameter in the optimization model and perform postoptimality studies to understand its importance.

A ratio of $\Delta P/\Delta S$ equal to unity means the customer is willing to pay an additional dollar for each dollar of fuel cost savings. Equation (11) shows that the customer is willing to accept the risk of buying a new product only for net gains of \$10,000. We will use Eq. (11) as a marketing constraint and the ratio $\Delta P/\Delta S$ as a decision variable in Eq. (25). Next we model the present value of fuel savings.

Modeling Fuel Savings Under Uncertainty. First we calculate the fuel expenses during the lifecycle of the truck. We define

Table 2 Lifecycle mileage of a medium class truck [46]

Age	Miles	Age	Miles	Age	Miles
1	36,493	8	19,012	15	10,228
2	33,203	9	17,359	16	9,397
3	30,221	10	15,861	17	8,644
4	27,519	11	14,502	18	7,962
5	25,069	12	13,271	19	7,342
6	22,849	13	12,155	20	6,782
7	20,836	14	11,145		

mileage over the lifecycle and forecast diesel fuel prices. The Environmental Protection Agency definition of lifecycle for a medium-class truck [46], see Table 2. The product of diesel fuel price D, miles traveled M and fuel consumption gives the total fuel expenses for the truck owner. However, it is common knowledge that diesel fuel price fluctuates across time. Quantification of this uncertainty follows.

While in the short-run the price of oil is expected to fluctuate randomly, in the long-run it is expected to revert to the marginal cost of producing oil [47]. The mean-reverting process will be used to model future diesel prices:

$$\Delta D_t = \alpha(\overline{D_t} - D_t)\Delta t + \sigma \Delta z$$

$$\Delta z = \varepsilon \sqrt{\Delta t}$$

$$\varepsilon \sim N(0,1). \quad (12)$$

Here α is the speed of reversion, $\bar{D}$ is the "normal" level of D, i.e., the level to which D tends to revert, σ is the volatility of diesel fuel price, estimated from historical monthly diesel fuel prices from March 1994 to November 2002 [48] (Table 3).

In the next step we use Eq. (12) to generate a random walk for 240 diesel fuel prices, which describes one possible future scenario of monthly fuel prices over the next 20 years. We repeat the same process 100,000 times taking into account multiple future scenarios. Multiplying each of the elements of the 100,000 by 240 matrix by the miles traveled and fuel consumption (assumed to remain constant across the lifecycle) we can estimate the fuel expenses of the consumer across time. Discounting back with a static interest rate r across time and averaging across the probability space we calculate the present value of future fuel expenses of the customer to be

$$(\text{Fuel Expense}) = \int (\text{Fuel Consumption}) \times (\text{Diesel Fuel Price})_t \times (\text{Miles Travelled})_t \times e^{-rt}. \quad (13)$$

Since

$$(\text{Fuel Consumption}) = 1/(\text{Fuel Economy}),$$

we have

$$(\text{Fuel Expense}) = \frac{\int D_t M_t e^{-rt} dt}{\text{fe}}. \quad (14)$$

where fe stands for fuel economy. Modeling of a dynamic interest rate is possible but beyond the scope of this demonstration.

At this point, we recall that the customers of the enterprise under consideration are freight and small-package ground delivery services firms. Their total fuel expenses would depend on the growth of the industry. In the current work we are not modeling uncertainty due to industry performance. However, one could select an appropriate discount rate that reflects the risk of the industry as it is observed in the financial markets. A 10-year average of the "beta," i.e., of various stock prices of freight and delivery firms is found to be 0.94. Using the Capital Asset Pricing Model [49] one could estimate a discount rate that captures the risk of the industry, and use it for the estimation of Eq. (14).

Table 3 Mean-reversion statistical parameters

Reversion speed (α)	0.041
Mean of reversion ($\overline{D_t}$)	\$1.235
Volatility (σ)	0.035

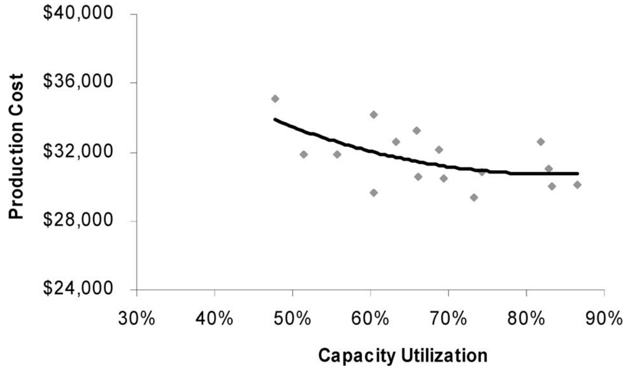

Fig. 5 A quadratic cost function links production cost with capacity utilization

Using Eqs. (8) and (14), fuel savings are expressed as follows, where D_t is a 100,000 by 240 matrix

$$S = \frac{\int D_t M_t e^{-rt} dt}{\text{fe}_C} - \frac{\int D_t M_t e^{-rt} dt}{\text{fe}_H}. \quad (15)$$

Profit Model. Profit equals revenues R minus costs C. Here we consider only production and hybridization costs, C_p and C_H, respectively. We are not taking into account operational expenses such as marketing and sales expenditures. Regressing on historical data of cost of goods sold for the same U.S. publicly traded truck manufacturer (see Fig. 5) we estimate the cost curve per truck to be

$$C_p = 48201 - 42253U + 25560U^2, \quad (16)$$

where U is the utilization of capacity. Note that minimum production cost is achievable at 83% utilization rate.

Quantity produced q and utilization of capacity U are linked as follows:

$$q = UK. \quad (17)$$

For an allocated monthly capacity of $K=600$ available units Eq. (16) becomes

$$C_p = c_0 - c_1 q + c_2 q^2$$

$$C_p = 48201 - 70.4q + 0.07q^2 \quad (18)$$

The assumption here follows from [50], namely, the main cost difference between hybrid and conventional trucks is the electric component cost. This hybrid component cost is modeled separately [i.e., C_H, Eq. (5)], and so the enterprise is assumed to maintain the same cost structure for the production of new trucks.

Using Eqs. (10), (15), and (18), profit π will be equal to:

$$\pi = R - C = Pq - C_p q - C_H q = \left(53{,}545.83 - 31.96q + \frac{\lambda_S}{\lambda_P}\left(\frac{1}{\text{fe}_C} - \frac{1}{H_0}\right) D_t M_t e^{-rt}\right) q - (48201 - 70.4q + 0.07q^2) q - C_H q. \quad (19)$$

Prior formulating the final (ATS) model of the planning process, we will make a first attempt to quantify the impact of engineering information on profitability.

Necessary Conditions of the Top Level Problem. Let us formulate the following optimal production problem for the enterprise-wide truck design problem,

$$\text{maximize } \pi$$

$$\text{with respect to} \{q\}$$

$$\text{subject to } q \leqslant K. \tag{20}$$

From Eqs. (10), (18), and (19) we have

$$\text{maximize } \pi = \left(\frac{\theta}{\lambda_P} - \frac{1}{\lambda_P}q + \frac{\lambda_S}{\lambda_P}S\right)q - (c_0 + c_1 q + C_2 q^2)q - C_H q$$

$$\text{with respect to} \{q\}$$

$$\text{subject to } q \leqslant K. \tag{21}$$

Let us now write the Karush-Kuhn-Tucker conditions for Eq. (21)

$$\frac{\theta}{\lambda_P} - \frac{2}{\lambda_P}q + \frac{\lambda_S}{\lambda_P}S - (c_0 + 2c_1 q + 3c_2 q^2) - C_H + \mu_1 = 0,$$

$$\mu_1(q-K) = 0,$$

$$\mu_1 \geqslant 0. \tag{22}$$

Rearranging the terms in the general form of the quadratic equation $ax^2+bx+c=0$ we have

$$(-3c_2)q^2 + \left(-\frac{2}{\lambda_P} - 2c_1\right)q + \left(\frac{\lambda_S}{\lambda_P}S + \frac{\theta}{\lambda_P} - c_0 - C_H\right) + \mu_1 = 0,$$

$$\mu_1(q-K) = 0,$$

$$\mu_1 \geqslant 0. \tag{23}$$

When the capacity constraint is active $\mu_1 \neq 0$ and $q=K$. When the capacity constraint is inactive $\mu_1=0$. From the quadratic formula $(-b \pm \sqrt{b^2-4ac})/2a$ (i.e., the solution of $ax^2+bx+c=0$) and given that q is strictly positive we have

$$q = \frac{\frac{2}{\lambda_P} + 2c_1 + \sqrt{\left(\frac{2}{\lambda_P} + 2c_1\right)^2 + 12c_2\left(\frac{\lambda_S}{\lambda_P}S + \frac{\theta}{\lambda_P} - c_0 - C_H\right)}}{-6c_2}. \tag{24}$$

The term $\lambda_S/\lambda_P S - C_H$ depends on engineering information due to Eqs. (5) and (14). Unless $\lambda_S/\lambda_P S = C_H$ then engineering information will drive the solution. Engineering information will be unimportant in the case where the firm can pass all the hybridization cost to the consumer.

Therefore, when the demand for product differentiation, as it is partly determined by the physical characteristics of the product, $\lambda_S/\lambda_P S$ equals the cost C_H of supplying differentiation then engineering decisions do not affect enterprise ones [51]. This observation agrees with the corporate strategy literature where the product design decision-making process involves matching customer's demand for differentiation with the firm's capacity to supply differentiation [52].

Analytical Target Setting Model. The objective of the enterprise is to maximize profit and the decision variables are hybridization of the truck, units produced, and increase in price for a dollar improvement in consumer fuel savings (price to savings ratio). The enterprise constraint is derived from the aforementioned marketing information. The mathematical model is thus posed as follows:

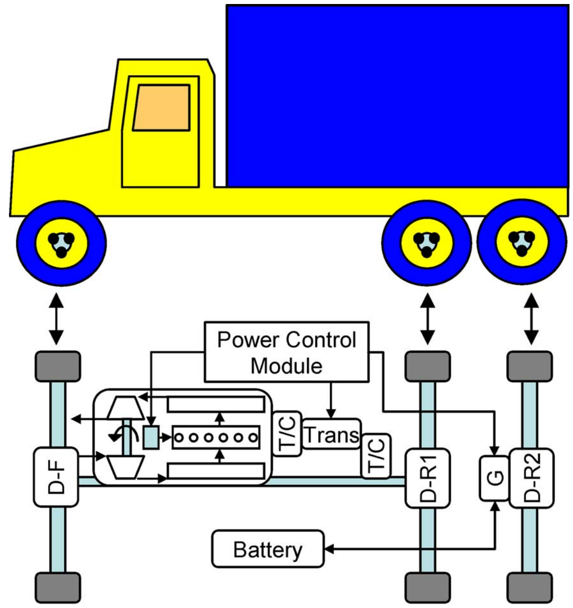

Fig. 6 Schematic of the integrated vehicle system

$$\text{maximize } \pi$$

$$\text{with respect to} \left\{C_H, \frac{\lambda_S}{\lambda_P}, q\right\}$$

$$\text{subject to } S - (P - \bar{P}_{98|99}) \geqslant V$$

$$q \leqslant K. \tag{25}$$

In the complete model λ_S/λ_P, C_H are decisions and S response of the decisions. Although λ_S/λ_P is known in the general case [51] in this case is treated as unknown. However, the constraint of Eq. (11) addresses this lack of information.

Profit estimation assumes that supply meets demand, and does not account for market demand uncertainty. One can incorporate uncertainty in Eq. (7) using historical price and demand panel data [53].

Truck Design Study: Bilevel Target Cascading

In this section the ATC formulation is tailored to the bilevel hierarchy of the present study. Design problems are formulated for each element at the two levels, as described below.

Vehicle Model. Appropriate vehicle and system analysis models that take design variables as input and compute responses as output are necessary to implement the target cascading process. At the vehicle level, the integrated system was represented using the HE-VESIM model [42] to predict responses corresponding to truck targets. The vehicle model contains submodels of the engine, powertrain, and vehicle dynamics. At the system level, higher fidelity models were used to predict responses of the transmission and suspensions.

The truck is configured as a parallel hybrid with the electric motor positioned after the transmission, see Fig. 6. The engine is connected to the torque converter, whose output shaft is then coupled to the transmission. The coupling at the transmission output side engages or disengages the electric motor depending on the operation mode of the hybrid. Hence, the transmission and/or

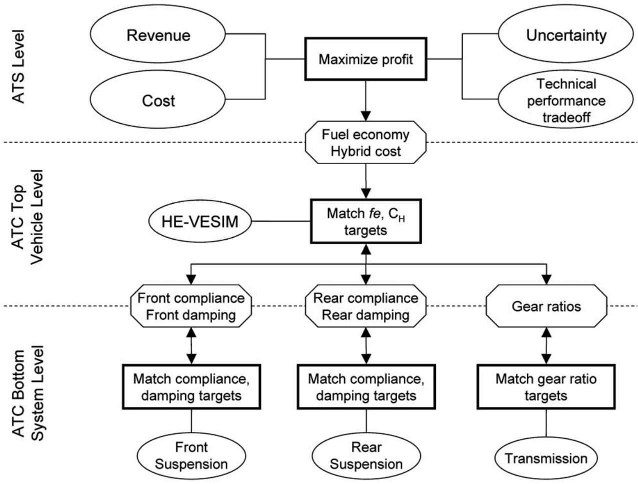

Fig. 7 Model description, coordination, and information flow in analytical target setting and analytical target cascading

Table 4 Summary of results (decisions indicated by boldface)

	Original ATS [Eq. (25)]	Reduced ATS [Eq. (27)]	Change
π	$1,572,593	$1,956,997	$384,404
$\%\Delta$fe	26.0%	27.5%	1.5%
$\frac{\lambda_S}{\lambda_P}$	**41.3%**	**45.7%**	4.4%
S	$15,929	$16,634	$705
$\frac{\lambda_S}{\lambda_P}S$	$6,578	$7,609	$1,031
q	**533**	**543**	10
P	$43,094	$43,799	$705
U	88.8%	90.5%	1.7%
C_p	$30,837	$30,896	$59
C_H	**$9,306**	$9,298	−$8

electric motor can be linked to the propeller shaft, differential and two driveshafts, coupling the differential with the driven wheels. The model was implemented in MATLAB/SIMULINK [54].

The local design variables $\mathbf{x}_\nu$ in the vehicle problem are engine displacement, compression ratio, maximum intake pressure, wastegate speed, electric motor scaling, and battery size. The system responses $\mathbf{R}_s$ are front and rear suspension compliance and damping, and four transmission gear ratios. Recalling Eq. (2) we set $[s_1, s_2, s_3]$ to correspond to $[f\text{susp}, r\text{susp}, \text{tra}]$, i.e., system responses for front suspension $\mathbf{R}_{f\text{susp}}$, rear suspension $\mathbf{R}_{r\text{susp}}$, and transmission $\mathbf{R}_{\text{tra}}$. Suspension and transmission responses are compliance and damping, and gear ratios, respectively. Lower and upper bounds for the optimization variables are set at ±20−33% of the baseline values depending on the variable. The sequential quadratic programming (SQP) algorithm of the MATLAB Optimization Toolbox [55] was used as an optimizer.

The driving cycle used to evaluate the fuel economy is a combination of EPA federal urban and highway cycles measured in miles per gallon and computed by dividing the traveled distance by the consumed fuel after completion of the driving cycle. This fuel economy calculation is averaged by simulating initial high and low energy states of charge for the hybrid propulsion.

System Models. The three elements at the system level include the transmission, front suspension, and rear suspension. Within the target cascading methodology, the system models are typically of higher fidelity compared to their counterparts within the vehicle model.

The transmission design model [4] at the system level is a planetary gear transmission that matches the gear ratios determined using the simplified transmission submodel at the vehicle level. Design variables are the number of teeth for the input sun, reaction sun, input ring, and reaction ring. Computed responses are the four gear ratios. The suspension design model [4] is a leaf spring suspension that matches the compliance and damping determined at the vehicle level. Design variables are the number, thickness, and width of leaves, and the curvature radius of the top leaf. Computed responses are compliance and damping of the suspension system. The local design variables are $\mathbf{x}_{\text{tra}}$, $\mathbf{x}_{f\text{susp}}$, and $\mathbf{x}_{r\text{susp}}$. Note that there are no system linking variables $\mathbf{y}_{s_i}$, i.e., none of the three system problems share any optimization variables. Due to the presence of integer variables, the derivative-free optimization algorithm DIRECT [56] was used for the two suspension and the transmission problems.

Decision-Making Process Information Flow. The model coordination and information flow is shown in Fig. 7. The objectives of each optimization problem are shown in rectangles and the analysis models are shown in ovals. The octagons depict the decision variables for a specific level of the decision-making hierarchy, which are also responses at the immediately lower level.

The ATS problem is solved first. Fuel economy and hybridization cost targets $\mathbf{T}_\nu$ are then set at the ATC vehicle level problem. The ATC problem is solved to match these targets with the minimum deviations. For both targets the deviation is defined as follows:

$$\max(\text{fe}^T - \text{fe}, 0) + \max(C_H - C_H^T, 0) \tag{26}$$

i.e., the deviation is nonzero when the targets are underachieved, otherwise, it is zero. In the enterprise context, Eq. (26) reflects the preference for overachievement when the targets are set for the ATC problem. Based on system level designs, the vehicle-level problem is solved again to complete one iteration of the target cascading process (the inner coordination block in Fig. 1). The updated system response values for front/rear suspension compliance and damping and transmission gear ratios are passed up to the vehicle level as constraint targets. If the matching of responses is not satisfactory the whole process is repeated in an iterative manner until convergence within some tolerance is achieved.

Global convergence properties of the analytical target cascading formulation, are discussed in [57]. One of the convergent solution sequences in [57] is implemented to solve the ATC problem here (Fig. 7). Once the ATC process is converged, vehicle response values fe^* and C_H^* are set as parameters to the reduced analytical target setting process problem, see Fig. 1. Equation (25) is then reformulated as follows:

$$\begin{aligned} &\text{maximize } \pi \\ &\text{with respect to } \left\{\frac{\lambda_S}{\lambda_P}, q\right\} \\ &\text{subject to } S - (P - \bar{P}_{98|99}) \geq 10000 \\ &q \leq 600. \end{aligned} \tag{27}$$

The solution of Eq. (27) determines the optimal output and increase in price per dollar of fuel savings.

Results

Results are shown in Table 4. The original ATS model Eq. (25) is solved first. The resulting targets are a hybridization cost budget of $9,306 and fuel economy improvement of 26.0%. Using finite

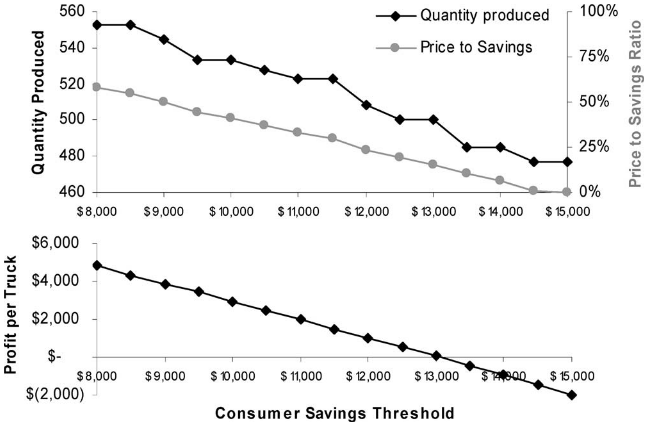

Fig. 8 Postoptimality analysis on consumer savings for the new technology

differences at the optimum of Eq. (25) the sensitivity of profit with respect to changes in fuel economy were found to be 8.5% and −1.9%, respectively. This stresses the importance of technical decisions to profitability.

Preference to overachievement of targets is allowable and modeled using Eq. (26) at the vehicle level of ATC, which is solved next. The ATC solution essentially matches the hybridization cost and overachieves fuel economy improvement by 1.5% from the top-level target. The reduced ATS problem, Eq. (27), is solved next, resulting in an increased price to savings ratio λ_S/λ_P, increased production volume q, and a 24% increase in profits π as detailed in Table 4. Recall that the reduced ATS problem Eq. (27) uses the ATC solution values as parameters.

At the vehicle level of ATC the final design is as follows: Displacement 9.5 L, compression ratio 22, maximum intake pressure 2.17 atm, wastegate speed 1420 rpm, base motor scaled down 25%, and 38 battery modules. The final design of the transmission has 56 and 45 teeth on the input and reaction rings, respectively, and 18 and 40 teeth on the input and reaction of the sun gears. This planetary system results in gear ratios of 6.87, 2.79, 1.48, 1.12. The front suspension system level has a final design with 11 leaf springs, 8.9 mm thickness, 0.58 m radius and 47 mm width for each leaf. This leads to compliance of 2.136×10^{-6} m/N and damping of 16405 N s/m. The rear suspension system final design, considered the same for both rear axles, has 15 leaf springs, a thickness of 10.2 mm, a radius of 1.17 m, and width of 40.4 mm. This leads to compliance of 1.804×10^{-6} m/N and damping of 15033 N s/m.

Discussion

Assumptions in the current case study fall under three categories: customer-, macroeconomic- and microeconomic-related. Key customer-related assumption was his/her preference towards the new technology and was modeled with the net utility threshold V, set at $10,000. Key macroeconomic assumption was the use of the mean-reverting process to simulate future market oil prices. Finally, key microeconomic assumption was the strategic decision of the firm to allocate 10% of its capacity mix.

First we performed a parametric study for the net utility threshold to fully understand its importance. A parametric study explored the effect of this parameter value on the original ATS decisions (without further exploration of possible influence on ATC results). The original ATS problem [Eq. (25)] was solved for consumer thresholds between $8,000 and $15,000. The price to savings ratio decreased in response to increased reluctance to pay for the new technology, see Fig. 8. Profitability per truck decreases as the consumer threshold increased due to significant decrease in the price to savings ratio from 58% to 0%, because the enterprise is unable to reap the benefits of commercializing the new technology. Increased reluctance leads to a decline in enterprise production. The study captured the relationship of consumer and enterprise preferences. The decision-maker can use the price to savings ratio to determine the marketing investment required to increase the likelihood of commercialization success of the new technology. At a utility threshold of $12,000 the price to savings ratio was 24% and the profit per truck was $1,000 (see Fig. 8). The profit per truck increased to $3,000 at a utility threshold of $10,000 with the price to savings ratio of 41%. This indicates that a combination of technology and marketing innovation is needed for a successful commercialization. A marketing campaign that increases technology awareness could decrease the aversion of the consumer towards the new technology and thus increase profitability. From the current example, reducing the reluctance of the consumer from $12,000 to $10,000 increased profit per truck threefold.

For the fuel price mean-reverting process it is important to update the price frequently to reflect current market conditions. As any other Markov process, current conditions will affect future random walks. Finally, the hybrid medium truck penetration assumption of 10% that translated to 10% hybrid production capacity allocation did not account for the effect of increasing hybrid capacity on the current product line of the enterprise. However, the valuation of a new technology depends heavily on the current business of the enterprise (i.e., conventional diesel trucks) and therefore the technology portfolio decision must consider the cannibalization effect of switching capacity. In the absence of this consideration, the enterprise may cannibalize the current product, potentially decreasing total profit (see Cooper and Papalambros [58]).

Conclusions

The ATS-ATC linking provides some interesting opportunities. The truck vehicle example demonstrated the effectiveness of a particular linking, via treating top targets as parameters. Other linking strategies are possible, corresponding to actual information flow in the enterprise. For example, the ATS problem could be combined with the top ATC into a single top-level model, addressing technical and enterprise issues simultaneously. Furthermore, the ATC formulation assumes essentially a weighted Pareto solution across all target-matching with equal weights. One can use the sensitivity of product attributes to profit from the ATS model to assign weights at the top-level ATC model, which reflect preference towards specific target achievement or overachievement. In any case, putting the design decisions in an enterprise context enriches the value and appeal of the engineering decisions made.

Acknowledgments

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Nomenclature

$(\cdot)^L$ = response/linking variable values passed up
$(\cdot)^U$ = response/linking variable values cascaded down
$(\cdot)_C$ = conventional vehicle design
$(\cdot)_H$ = hybrid vehicle design
c = cost coefficients
C = cost
C_H = powertrain hybridization cost per unit
C_p = cost of unit production

D = diesel fuel price
$\bar{D}$ = "normal" level of diesel fuel price
fe = fuel economy
$\mathbf{g}_e$ = vector of enterprise inequality constraints
$\mathbf{g}_\nu$ = vector of vehicle inequality constraints
$\mathbf{h}_\nu$ = vector of vehicle equality constraints
K = units of capacity per month
M = truck mileage
P = product price
q = quantity produced per month
R = revenues per month
$\mathbf{r}_\nu$ = vehicle analysis model
$\mathbf{r}_{s_i}$ = system analysis model for the ith system
$\mathbf{R}$ = vector of responses
$\mathbf{R}_\nu$ = vector of vehicle level responses
$\mathbf{R}_\nu^*$ = vector of "best" feasible responses
$\mathbf{R}_{s_i}$ = vector of system responses for the ith system
s = system
S = fuel cost savings
$\mathbf{T}_\nu$ = vector of targets
U = manufacturing capacity utilization
V = utility threshold
$\mathbf{x}_e$ = vector of local enterprise variables
$\bar{\mathbf{x}}_\nu$ = vector of vehicle optimization variables
$\bar{\mathbf{x}}_{s_i}$ = vector of ith system optimization variables
$\mathbf{x}$ = vector of local design variables
$\mathbf{y}$ = vector of linking design variables
α = speed of reversion
σ = volatility of diesel fuel price
Δt = monthly period
ε_ν^R = tolerance variable for system responses
ε_ν^y = tolerance variable for system linking design variables
λ = slope of the demand curve
λ_S/λ_P = price to savings ratio

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