Multilevel Optimization for Enterprise Driven Decision-Based Product Design

Deepak Kumar* and Wei Chen†
Northwestern University, Evanston, IL 60208 USA

Harrison M. Kim‡
University of Illinois at Urbana-Champaign, IL, 61801 USA

Research in Decision-Based Design (DBD) has traditionally modeled the interaction between enterprise product planning and engineering product development in a single optimization problem and solved it using an All-in-One (AIO) approach. Such an approach is not practical in a typical industry design environment, due to the organizational and computational complexities involved. In this paper, we present a hierarchical multilevel optimization approach, based on the principles of DBD and the concept of analytical target cascading (ATC), to integrate enterprise-level product planning with engineering-level product development. A disaggregate probabilistic demand modeling approach based on the Discrete Choice Analysis (DCA) is employed to capture the impact of engineering design on the choices of individual customers and to serve as the link between engineering product development and enterprise-planning. A search algorithm that coordinates the enterprise-level product planning and the engineering-level product development in a multilevel optimization solution process is presented. Such an algorithm systematically explores the engineering attribute space that may consist of a number of disconnected feasible domains due to engineering constraints. A case study that involves the design of an automotive suspension system is used to illustrate the effectiveness of the proposed approach.

Nomenclature

$\mathbf{A}$	=	Customer-product-selection attributes
$\mathbf{A}_{eng}$	=	Customer-product-selection attributes related to engineering performance
$\mathbf{A}_{ent}$	=	Customer-product-selection attributes related to enterprise product planning
AIO	=	All-In-One
ATC	=	Analytical target cascading
ATS	=	Analytical Target Setting
C	=	Total product cost
DBD	=	Decision-Based Design
DCA	=	Discrete Choice Analysis
$\mathbf{E}$	=	Engineering design attributes
$\mathrm{E}(U)$	=	Expected value of enterprise utility
$\mathbf{E}^*$	=	Utopia target of $\mathbf{E}$
$\mathbf{E}^D$	=	Achievable product performance
MDO	=	Multi-disciplinary Design Optimization
MNL	=	Multinomial Logit
P	=	Product price
Q	=	Product demand
RP	=	Revealed preference

* Graduate Student, Department of Mechanical Engineering, Email: k-dileep@northwestern.edu, AIAA Member.
† Corresponding author, Associate Professor, Department of Mechanical Engineering, Northwestern University, 2145 Sheridan Rd., Tech B224, Evanston, IL 60208-3111, USA, E-mail: weichen@northwestern.edu, AIAA Associate Fellow.
‡ Assistant Professor, Department of General Engineering, University of Illinois at Urbana-Champaign, Email: hmkim@uiuc.edu, AIAA Member.

$\mathbf{S}$	=	Customer demographic attributes
SP	=	Stated preference
$\mathbf{T}^{U}$	=	Targets of $\mathbf{E}$ set by the enterprise product planning problem
U	=	Enterprise utility
V	=	Selection criterion used by the enterprise (e.g., profit, revenues, etc.)
W_{in}	=	Deterministic part of the utility of choosing alternative i by customer n
$\mathbf{X}$	=	Design options
$\mathbf{X}_{\text{d}}$	=	Engineering design options
$\mathbf{X}_{\text{ent}}$	=	Enterprise planning options
$\mathbf{Y}$	=	Exogenous variables (represent sources of uncertainty in market)
t	=	Time interval for which demand/market share is to be predicted
u_{in}	=	True utility of choosing alternative i by customer n
ε_{in}	=	Random unobservable part of the utility of choosing alternative i by customer n

I. Introduction

There is a growing recognition in the design community of the need for a rigorous design approach that considers the enterprise goal of making profits and the decision maker's risk attitude, while also dealing adequately with engineering needs and various sources of uncertainty. Decision-Based Design (DBD)[1] is a collaborative design approach that recognizes the substantial role that decisions play in design and in other engineering activities. In recent years, we have seen many (DBD) related research developments in the field of engineering design (e.g., Thurston[2], Li and Azarm[3], Callaghan and Lewis[4], Scott and Antonsson[5], Roser and Kazmer[6], Marston et al.[7], Shah and Wright[8], Dong and Wood[9], Schmidt and Herrmann[10], Wassenaar and Chen[11], Wassenaar et al.[12,13], Lewis and See[14], Gu et al.[15], Dym et al.[16]). For profit-driven design under the DBD framework, ideally, all product design decisions, whether directly related to engineering or otherwise, are made simultaneously to optimize the enterprise level design objective, i.e., to maximize the expected utility, expressed as a function of net revenue (profit), subject to various sources of uncertainty. The existing implementation of the profit-driven DBD approach (Wassenaar and Chen[11], Wassenaar et al.[12,13]) seeks to integrate *enterprise product planning* and *engineering product development* by using an All-in-One (AIO) approach and solving as a single optimization problem. The enterprise is defined here as the organization that designs and produces an artifact to maximize its utility (e.g., profit). Marketing, production planning, and other enterprise-level activities are referred to as *enterprise-level product planning*; engineering-related design activities are referred to as *engineering product development*.

Designing a large-scale artifact typically involves multidisciplinary efforts in marketing, product design and production making. The AIO approach is often practically infeasible in such situations due to computational and organizational complexities. Optimization by decomposition, while alleviating the problem of having to deal with a large number of design variables and constraints at the same time, is made necessary by a number of factors. The decomposed approach helps enable simultaneous multidisciplinary optimization wherever possible and also addresses organizational needs to distribute the work over several groups of engineers/analysts. Historical evolution of engineering disciplines and the complexity of the Multi-disciplinary Design Optimization (MDO) problem suggest that disciplinary autonomy is a desirable goal in formulating and solving MDO problems. In MDO, several design architectures have been developed to support collaborative multidisciplinary design using distributed design optimization, e.g., Concurrent Subspace Optimization (CSSO)[17], Bi-level Integrated System Synthesis (BLISS)[18.19], Collaborative Optimization (CO)[15,20] and Analytical Target Cascading (ATC)[21-27]. A comprehensive review of the multidisciplinary design optimization architectures is provided by Kroo[28]. It should be noted that the choice of MDO formulations largely depends on whether the problem follows the hierarchical or non-hierarchical characteristics of decision flow. In most of the MDO approaches listed above, a complex engineering problem is non-hierarchically decomposed along disciplinary or other user-specified boundaries into a number of sub-problems. Then they are brought into multidisciplinary agreement by a system-level coordination process. In our opinion, the non-hierarchical MDO infrastructure is better suited to capture the interrelationships between multiple engineering disciplines in engineering-level product development; however, a hierarchical approach such as the Analytical Target Cascading (ATC) is more appropriate in an enterprise-driven product design scenario where the enterprise decision making is often done at a higher level to set up targets for engineering product development. To represent the organizational infrastructure in industry more accurately, the interrelationships between enterprise product planning and engineering product development, as well as the engineering product development itself at system, subsystem, and component levels, should be treated as hierarchical. Such a hierarchical framework, as will be detailed later, is more representative of the hierarchical decision making in industry.

In this paper, we present a DBD based hierarchical approach to enterprise-driven design that treats enterprise level product planning and engineering level product development as two interrelated but separate optimization problems in a multilevel optimization framework. To fully integrate business and engineering decision makings, we illustrate how a disaggregate probabilistic choice model can be used to establish the link between the decomposed enterprise product planning and engineering development models. Any hierarchical approach, like the one presented here, should ensure preference consistency. In other words the optimization of the engineering objectives at the product development level needs to correspond to the maximization of the utility objective function at the enterprise product planning level. This is to guarantee that the solution from the multilevel optimization procedure will be close, if not identical, to the one that is obtained by solving the AIO integrated enterprise and engineering problem. As will be discussed in Section III later, if the feasible domain imposed by the engineering product development is disconnected in the space of engineering performance attributes, achieving the design which corresponds to the maximum enterprise utility becomes more challenging. A search algorithm that can systematically explore attribute targets in the disconnected feasible domain to lead the engineering product design to feasible and optimal designs in the enterprise context is needed and such an algorithm is also presented here.

The organization of the paper is as follows. In Section II, a discussion on enterprise-driven design approaches that incorporate economic considerations and customer preferences is presented. The review in Section II outlines various approaches to establishing the link between engineering decisions and their business impact. Section II presents the transformation of an All-in-One DBD framework to a hierarchical optimization formulation which combines enterprise level planning and engineering product development efforts using a probabilistic choice modeling approach for demand modeling, The section also presents an optimization algorithm which enables designers to handle problems when the feasible design is not continuous in the space of engineering performance attributes. An automotive suspension design case study is used to illustrate the approach in Section IV. Conclusions and future work are presented in Section V.

II. Discussion of Contemporary Enterprise Driven Design Approaches

There have been a number of efforts in the design community[3,11-15,26,27,29-31,32-34] to integrate economic considerations with the engineering product development efforts. The primary goal in all these approaches remains the same, i.e., to arrive at a design that is optimal with respect to enterprise level objectives. While modeling the interaction between enterprise-level product planning and engineering-level product development, one widely used approach involves computing the net revenue of the enterprise based on the demand for the product as a function of product attributes; demand plays a critical role in assessing the profit as it contributes to the computation of both revenue and life-cycle cost. Among the various demand modeling approaches adopted by the design community, differences exist in the type of customer data used for the analysis, the modeling of uncertainty in customer preferences, and how the model uses customer preference data. Some models aggregate customer preferences while others examine this information at the individual level. Also, either Stated Preference (SP)[35] data or Revealed Preference (RP)[36] data may be used for demand modeling. RP data refers to actual choice, i.e., actual (purchase) behavior that is observed in real choice situations. SP surveys are used to learn about how people are likely to respond to new products or new product features through surveys. While a more detailed discussion of the Multinomial Logit (MNL) demand modeling approach is presented in section III, we provide below, a brief review of demand modeling approaches that have been used for engineering design applications.

Azarm et al.[3,32-34] employed a traditional Conjoint Analysis based demand modeling approach within a multi-attribute instead of single-criterion DBD framework. They subsequently introduced a customer-centric utility metric that formed the basis for product design selection. Their selection procedure considered the preferences of both the customers' and designers' utility, while also factoring in market competition and uncertainties in product life, market size, cost, etc.

Cooper et al. proposed a bi-level framework that links Analytical Target Cascading (ATC)[21-25,27] and Analytical Target Setting (ATS)[26]. In their approach, ATC is used for the hierarchical product development process, while the solution to the ATS problem optimizing enterprise-level objectives (e.g., profit), sets suitable targets for various engineering attributes. Under the ATS-ATC framework, initially, a simplistic linear model[26] was used to capture demand. A more sophisticated disaggregated choice modeling approach has been proposed in recent work[27], where a choice-based conjoint analysis approach is implemented within the multinomial logit (MNL) framework to analyze Stated Preference (SP) data. The "part worth" model[37.38] was used to model changing customer perceptions for different ranges of product attributes. Such an approach helps capture the nonlinearity in customer preference over the entire range of the product attribute. One limitation of the existing ATS-ATC framework is that the ATS formulation for enterprise planning has been a deterministic formulation that does not consider uncertainty or designer's risk attitude in decision making.

Wassenaar and Chen[11-13] employed disaggregated probabilistic demand models based on Discrete Choice Analysis (DCA) in a Decision-Based Design (DBD) framework. The DBD framework is a single-criterion and collaborative approach that can be used to obtain the optimal settings of product attributes at the enterprise level to maximize the net revenue of a firm with the consideration of uncertainty and risk attitude. They demonstrated the use of a MNL based customer choice model[36,39] to identify the optimal levels of relevant customer product selection attributes, i.e., product attributes that are of interest to customers. They showed how these attributes could be used to maximize the expected utility of a firm considering engineering needs, the socio-economic and demographic background of customers. A major feature of the DCA-based disaggregate demand models is the use of data of individuals instead of group averages. This enables a more accurate representation of the heterogeneity among individuals and avoids paradoxes associated with aggregating group preference. However, Wassenaar and Chen' implementation did not show how the optimal settings of product attributes should be further cascaded to the descriptions of engineering design options. Also, using the AIO approach to making simultaneous enterprise planning and engineering development decisions under the DBD framework is not practically feasible due to the reasons explained earlier. In this paper, we illustrate how the DBD approach can be implemented using a multilevel optimization approach that treats enterprise planning and engineering development as two separate but closely related optimization problems. Our approach utilizes the disaggregated probabilistic demand modeling approach introduced in Wassenaar and Chen[11] & Wassenaar et al.[12,13] for product design to establish the critical link between the enterprise planning and engineering product development models.

III. A Multilevel Optimization Approach to Decision-Based Design

Here, the Decision-Based Design (DBD) approach is implemented using an optimization approach that treats enterprise planning and engineering product development as hierarchical, but interactive activities. In this section, the AIO DBD approach is introduced first and the proposed hierarchical optimization formulation is presented later. Some important features of the demand modeling approach employed in this work are also presented here. Finally, we present a search algorithm that can lead the engineering product design to feasible and optimal designs in the enterprise context.

A. All-In-One DBD Framework

An AIO DBD framework, an extension of the DBD framework presented in Wassenaar and Chen[11-13], is presented in Fig. 1. Unlike the flow chart they proposed, we split the design options $\mathbf{X}$ into two groups here: the engineering design options $\mathbf{X}_d$ and the enterprise planning options $\mathbf{X}_{ent}$, to separate the decisions made in these two domains and to illustrate their impact separately. The engineering design options $\mathbf{X}_d$ represent engineering decisions made by product designers; while $\mathbf{X}_{ent}$ typically includes quantities like price P, warranty options, annual percentage rate (APR) of auto loan, which are determined at the enterprise level. The arrows in the flowchart (see Fig. 1) indicate the existence of relationships between the different entities (parameters) in DBD, instead of showing the sequence of implementation.

In our DBD framework, a distinction is made between customer-product-selection attributes $\mathbf{A}$ and engineering design attributes $\mathbf{E}$. The customer-product-selection attributes $\mathbf{A}$ are product features and financial attributes (such as service and warranty) that a customer typically considers, when purchasing the product. Engineering design attributes $\mathbf{E}$ are any quantifiable product properties that are used in the engineering product development process. They are described as performance functions of engineering design options $\mathbf{X}_d$ through engineering analysis. To estimate the effect of design changes on a product's market share and consequently on the firm's revenues, Discrete Choice Analysis (DCA)[36,39] is used for demand modeling that establishes the relationship between the customer-product-selection attributes $\mathbf{A}$, the socioeconomic and demographic attributes $\mathbf{S}$ of the market population, price P, time t, and the demand Q. From market analysis point of view, the input $\mathbf{A}$ to the demand model could be attributes with physical units (e.g., fuel economy) or without (e.g., level of comfort). However, to assist engineering decision-making, customer-product-selection attributes $\mathbf{A}$ related to the engineering performance, need to be expressed in terms of quantifiable engineering design attributes $\mathbf{E}$ in demand modeling. Engineering design attributes $\mathbf{E}$, apart from including the quantifications of some of the attributes $\mathbf{A}$, also include attributes that are of interest, only to design engineers, e.g., stress level of a structure. Likewise, some of the non-performance related attributes $\mathbf{A}$ are not influenced by the engineering design attributes $\mathbf{E}$, but by the enterprise planning options $\mathbf{X}_{ent}$. Therefore, $\mathbf{A}$ and $\mathbf{E}$ can be viewed as two sets that share a number of common elements.

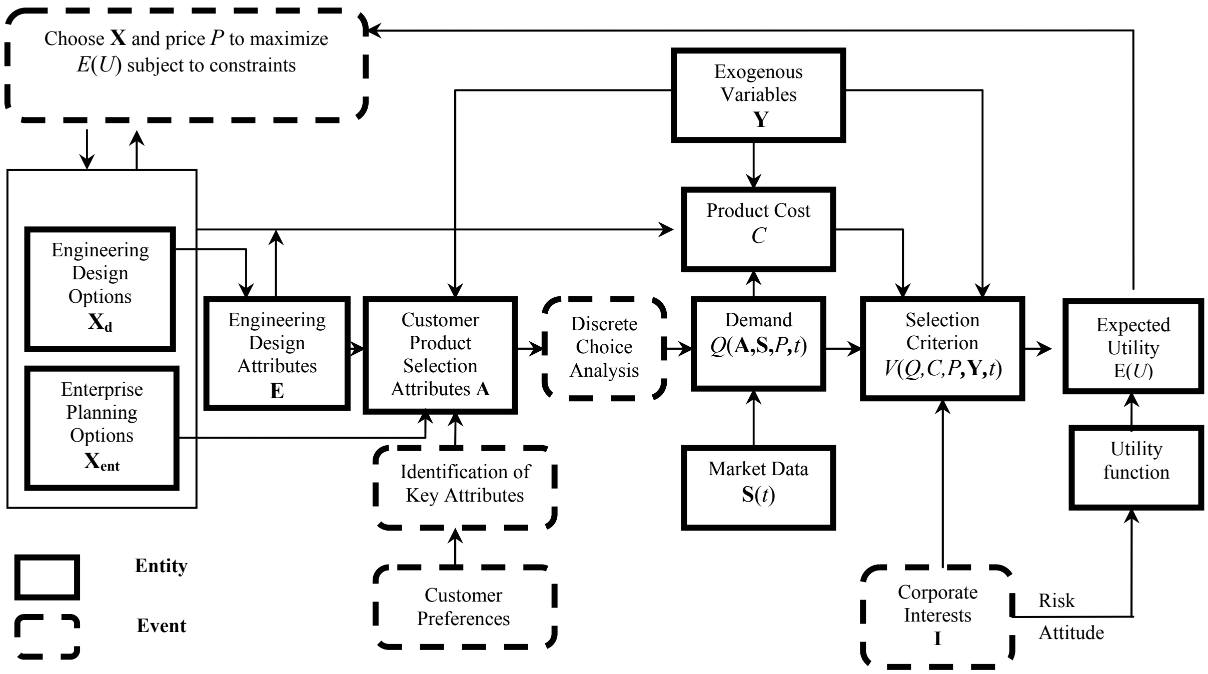


Fig. 1 All-In-One (AIO) DBD framework

The flow chart in Fig. 1 coincides with an optimization loop that identifies the optimal design options **X** (including both $\mathbf{X}_d$ and $\mathbf{X}_{ent}$) to maximize the expected utility E(U). It should be noted that uncertainty is considered explicitly and the enterprise goal is expressed as the maximization of expected utility. The enterprise utility U is expressed as a function of the selection criterion V (e.g., profits, revenues, etc.) and is designed to reflect the enterprise's risk attitude. In enterprise-driven design, the selection criterion V could be the net profit Π for the enterprise and expressed as a function of product demand Q, price P, cost C, exogenous variables **Y** (the sources of uncertainty in the market), and time t. Based on these relationships, as shown in (Eq. 1), demand Q, expressed as a function of customer-product-selection attributes **A**, customer demographic attributes **S**, price P, and time t, can be further expanded as a function of engineering design attributes **E**, enterprise planning options $\mathbf{X}_{ent}$, as well as **S**, P, and t.

$$\begin{aligned} V &= \Pi(Q, C, P, \mathbf{Y}, t) \\ &= Q(\mathbf{A}_{eng}(\mathbf{E}), \mathbf{A}_{ent}(\mathbf{X}_{ent}, \mathbf{Y}), \mathbf{S}, P, t) \times P - C(\mathbf{E}, \mathbf{X}_{ent}, \mathbf{Y}, Q, t) \\ &= V(\mathbf{E}, \mathbf{X}_{ent}, \mathbf{S}, P, \mathbf{Y}, t) \end{aligned} \tag{1}$$

Here we assume that the attributes **A** can be split into two groups, those related to product performance $\mathbf{A}_{eng}$ determined by engineering design attributes **E** and those non-engineering related attributes $\mathbf{A}_{ent}$ determined by enterprise planning options $\mathbf{X}_{ent}$ and exogenous variables **Y**. If we assume that the total product cost C can be expressed as a function of engineering design attributes **E**, enterprise planning options $\mathbf{X}_{ent}$, the product demand Q, as well as variables **Y** and t, we can then transform the selection criterion V into a function of (**E**, $\mathbf{X}_{ent}$, **S**, P, **Y**, t). This representation of the selection criterion V as a function of engineering design attributes **E**, instead of directly as a function of engineering design options **X**, greatly facilities the decomposition of the all-in-one DBD formulation into hierarchical enterprise planning and engineering product development as introduced next.

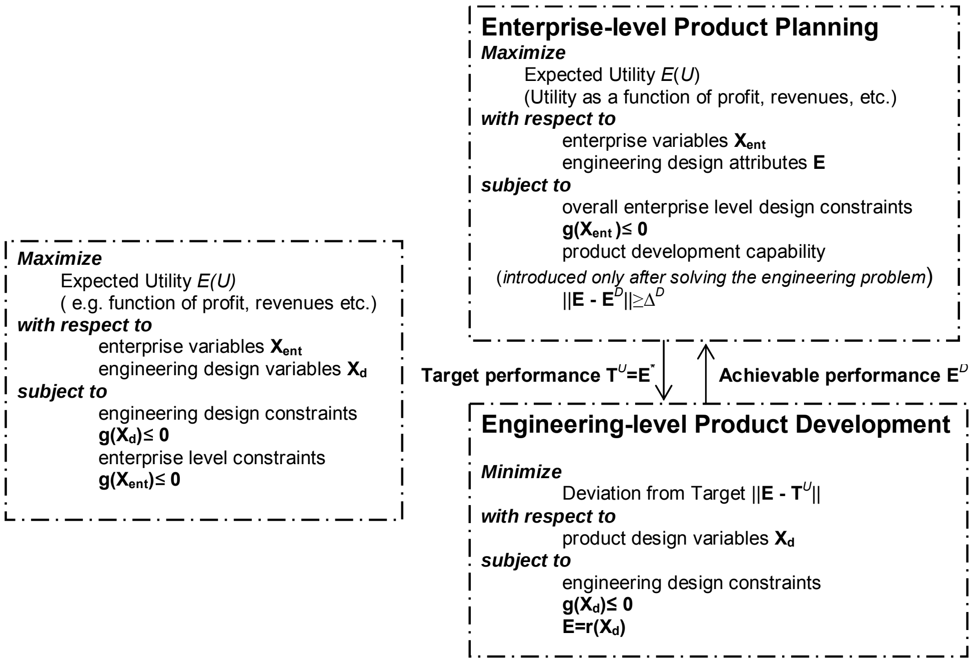
B. Multilevel Optimization Formulation to DBD

Fig. 2 illustrates the difference between the AIO approach and the proposed multilevel optimization formulation to DBD. The AIO approach in Fig. 2(a) treats the problem of maximizing the expected value of enterprise-level utility E(U) as a single optimization problem, where the decisions on product planning and product development are made simultaneously. Fig. 2(b) illustrates the proposed decomposed hierarchical framework, representing our view of the interaction between enterprise-level product planning and engineering product development. Following the "target cascading" paradigm[21-25,27] for hierarchical decision making in industrial settings, we view the engineering product development as a process for meeting the targets set from the enterprise level.

Using a multilevel optimization formulation, at the upper level, the enterprise-level product planning problem maximizes the expected utility E(U) with respect to the engineering design attributes $\mathbf{E}$ and the enterprise variables $\mathbf{X}_{\mathrm{ent}}$ subject to enterprise-level design capability. Decisions made on the optimal levels of engineering design attributes $\mathbf{E}$, represented as $\mathbf{E}^*$, are then used as targets or $\mathbf{T}^U$, passed to the lower level engineering product development process. The objective of the lower-level engineering product development is to minimize the deviation between the performance target $\mathbf{T}^U$ and the achievable product performance response $\mathbf{E}$ while satisfying the engineering feasibility constraints $\mathbf{g}$, with respect to engineering design options $\mathbf{X}_{\mathrm{d}}$. Restrictions on cost can be considered either as constraints or targets in engineering-level product development. The equation $\mathbf{E} = \mathbf{r}(\mathbf{X}_{\mathrm{d}})$ stands for the engineering analysis models that capture the relationship between engineering design attributes and design options. The achievable product performance $\mathbf{E}^D$ is then transferred to the enterprise level problem.

Under a multilevel design framework, an ideal product development scenario is when the targets corresponding to the optimal enterprise utility would lead to an engineering design matching the targets perfectly. Unfortunately such a match is rare due to constraints introduced at the product development level. This enforces the adjustment of the targets set at the enterprise level. This adjustment may shift the enterprise utility value away from its original optimal value. In return, however, a consistent feasible design that satisfies the engineering constraints may be now obtained. As will be detailed in Section III, in the iterative procedure of solving optimization problems at both enterprise and engineering levels, an additional constraint $\|\mathbf{E} - \mathbf{E}^D\| \geq \Delta^D$ is added at the enterprise level to enforce setting an alternative target for the engineering problem. Based on the minimum deviation Δ^D from the utopia target $\mathbf{E}^*$, the enterprise problem sets a geometric boundary constraint and a target outside the boundary. Then the engineering design problem is solved again based on a new target. An alternative target may guide to find an alternative engineering design in a disconnected feasible domain of attribute targets that corresponds to a better enterprise level utility. If the engineering product development comes up with the same design from the previous iteration, the radius Δ^D is expanded once again based on the slope information of the utility function and the engineering problem is solved once more. If the engineering problem continues to come up with the same feasible design, it means that there exists no disconnected feasible domain at least around the utopia utility design. The formulation shows that the targets identified for $\mathbf{E}$ serve as the critical link between the optimization problems at two levels.

It should be noted that the engineering product development typically involves the design of multiple engineering systems. Therefore, the optimization problem at the engineering development level can be further decomposed and solved using multilevel optimization. Based on the nature of decomposition, either non-hierarchical or hierarchical, different multilevel optimization formulations can be used. Most of the work considered up to this point in MDO research, e.g., BLISS[19] and Collaborative Optimization (CO)[20] had been concerned with decomposing a problem into a series of problems and solving them using bi-level optimization formulations. On the other hand, the Analytical Target Cascading (ATC) approach decomposes the original engineering problem hierarchically at multiple levels, and operates by formulating and solving a minimum deviation optimization problem (to meet targets) for each element in the hierarchy. Compared to the bi-level optimization formulations for engineering level product development, we believe that the multilevel hierarchical modeling facilitated by the ATC approach better represents a multi-layered organizational decision making infrastructure. In this hierarchical model, subsystems and components can be supplied by different organizational units or outsourced to independent companies. In the following subsection, we discuss the demand modeling approach that helps establish the link between enterprise planning and engineering product development in a multilevel optimization formulation.



(a) All-In-One approach (b) Hierarchical approach

Fig. 2 Comparison between all-in-one and hierarchical approach to DBD

C. Discrete Choice Analysis for Demand Modeling

In order to separate enterprise level product planning and engineering level product development efforts, it is important to develop a demand model that can predict the economic impact of design changes as a function of engineering design attributes **E**. As part of our hierarchical approach to the problem of maximizing the expected value of enterprise level utility E(U), demand modeling is used to capture the impact of quantitative engineering design attributes on customer choices, ultimately the product market share. Here, Discrete Choice Analysis (DCA) is used to model the choice behavior of customers. Each customer has to choose one alternative from a finite set of mutually exclusive and collectively exhaustive competitive alternatives. A key concept in DCA is the use of random utility to address unobserved taste variations, unobserved attributes, and model deficiencies. This entails the assumption that the individual's true utility u consists of a deterministic or observable part W and a random unobservable disturbance ε,

$$u_{in} = W_{in} + \varepsilon_{in} \tag{2}$$

The deterministic part of the utility can be parameterized as a function of observable independent variables (customer-product-selection attributes **A**, customer socioeconomic and demographic attributes **S**, and price P) and unknown coefficients $\boldsymbol{\beta}$, which can be estimated by observing choices respondents make. The idea behind including the demographic attributes of customers is to capture the heterogeneous nature of customers. The utility function terms are represented with the double subscript in, representing the n^{th} respondent, and the i^{th} choice alternative.

$$W_{in} = \mathrm{f}\left(A_i, P_i, \mathbf{S}_n : \boldsymbol{\beta}\right) \tag{3}$$

To provide the link between enterprise level product planning and engineering level product development, all attributes **A** in (Eq. 3) need to be converted to quantifiable engineering design attributes **E**, as well as non-engineering product attributes $\mathbf{A}_{\text{ent}}$ that are influenced by enterprise planning options. We now have

$$W_{in} = f\left(\mathbf{E}_i, \mathbf{A}_{\text{ent(i)}}, P_i, \mathbf{S}_n : \boldsymbol{\beta}\right) \tag{4}$$

Various multinomial market analysis techniques[36,39,40] can be employed to obtain the model in (Eq. 4) based on the collected market data. However, the multinomial logit (MNL)[36] model is used in this paper. The primary difference among the discrete choice approaches, (e.g., Nested Logit, Mixed Logit, etc.) is the degree of sophistication with which they model the unobserved error ε. More advanced techniques are also able to model heterogeneity better. In the MNL model, the coefficients of the utility function for the product attributes are identical across all customers. However, heterogeneity is modeled by considering demographic attributes (e.g., age, income, etc.) in the utility function. In an MNL model, any two customers, having at least one demographic attribute different from each other (e.g., one of them is older than the other or has a different income) are going to have different degrees of preference (i.e., choice probabilities) for the same product. In contrast, techniques such as Mixed Logit (see Ref. 40) address heterogeneity more effectively by modeling utility function coefficients as random variables. However, such techniques are limited by their prohibitive computational expense.

MNL is a popular choice, because it produces a closed form probabilistic choice model, and hence is more computationally tractable. Also, the error distribution, which is assumed to be Gumbel or extreme value, closely approximates the normal distribution, a more reasonable assumption for the error. The form of the choice probability for the multinomial logit model is shown below (Eq. 5), where $\Pr_n(i)$ is the probability that respondent n chooses alternative i and J_n is the choice set that is available to individual n.

$$\Pr_n(i) = \frac{e^{W_{in}}}{\sum_{j \in J_n} e^{jn}} \tag{5}$$

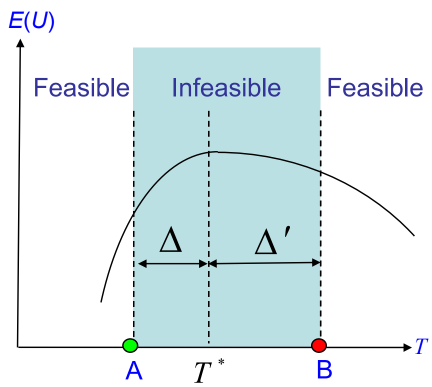
It should be noted that MNL is characterized by the Independence of Irrelevant Alternatives (IIA)[36] property which assumes that when one is choosing between two alternatives, all other alternatives are irrelevant, indicating that each alternative has the same unobserved error part ε in the utility. However, in many cases, choice alternatives from different market segments are likely to share common attributes. For example, to accurately model the entire automobile market, one would need to consider various market segments (e.g., mid-size, sports, luxury, etc.) together. In such a case, it is more reasonable to assume that customers are likely to consider cars from a particular segment, for example, SUV is to be more similar to each other and different from cars from another segment such as mid-size sedans.

D. Engineering Design Target Exploration Algorithm

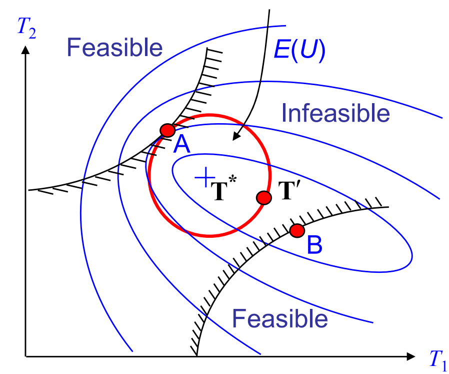
As shown in Fig. 2, our approach models the enterprise-level problem and the engineering-level problem as two separate problems in a multilevel optimization formulation. The enterprise product planning sets the targets for the engineering product development problem corresponding to the maximum utility. In most engineering design cases, it is uncommon to meet the utopia target perfectly due to the trade-off nature of multiple attribute target values or physical feasibility (i.e., no feasible design is available to meet the targets perfectly). If the engineering feasible domain is disconnected in the space of performance attributes (i.e., multiple, discrete feasible designs are available), the task becomes more challenging. Disconnected feasible performance domains often occur in the design of complex systems where multiple engineering disciplines are involved and each discipline seeks distinctly different design alternatives in down-stream engineering development. For example, the vehicle suspension design case study in Section IV illustrates a case where a vehicle manufacturer attempts to maximize the enterprise utility based on two disconnected feasible target performance domains imposed by suppliers of suspension components. In such cases where the feasible domain is disconnected, the engineering design with the minimum deviation from the attribute targets (i.e., the design which is a converged solution from the multilevel optimization) may not correspond to the maximum possible utility value and a new set of targets for the engineering problem need to be assigned. To explore this disconnected feasible target space, a search algorithm that can systematically explore attribute targets to lead the engineering product design process to finding a feasible and optimal design in the enterprise context should be employed. Here, we present an algorithm, first proposed by Kim et al.[25]. The proposed algorithm guides the enterprise-level decision maker to assign alternative targets so that the enterprise maximizes net revenue and the suppliers achieve targets as closely as possible. The adjustment of targets set at the enterprise level may shift the enterprise utility value away from its original utopia value. In return, however, a better (i.e., higher utility) feasible design can be obtained satisfying the engineering constraints that may exist in other disconnected feasible domain. While the details on the algorithm are available in Ref. 25, some of the important features are presented here. The original enterprise level utility optimization problem is

$$
\begin{aligned}
P_{ent}^{0}: &\quad \max_{\mathbf{X}_{\mathbf{ent}}} E\left[U(\mathbf{T}, \mathbf{X}_{\text{ent}})\right] \\
s.t. &\quad \mathbf{g}(\mathbf{X}_{\text{ent}}) \leq 0
\end{aligned} \tag{6}
$$

where the objective is to maximize the expected utility E(U), a function of engineering design attributes **E** and enterprise level variables $\mathbf{X}_{\text{ent}}$. The optimal value of engineering design attributes $\mathbf{E}^*$ obtained from model (Eq. 6) are assigned as the utopia targets $\mathbf{T}^*$ for engineering development. The engineering problem then finds an optimal response to the utopia target with the minimum deviations (see formulation in Fig. 3(b)). Fig. 3 illustrates one-dimensional and two-dimensional cases where the (feasible) minimum deviation from the utopia target does not match the best available utility. Points A and B are both engineering local optima with the minimum deviation from the target in each of the feasible space. The deviation for the point A is smaller, but the corresponding utility is not higher than that of point B. Note that these plots represent the engineering target (attributes **E**) domain instead of the design option space.



(a) One-dimensional case



(b) Two-dimensional case

Fig. 3 Utilities with engineering feasible domain imposed. Points A and B are both engineering local optima with the minimum deviation from the target. The deviation for the point A is smaller, but the corresponding utility is not higher than that of point B

To enable the move from one feasible domain to another, a circular inequality constraint (see Fig. 3(b)) is imposed in the enterprise problem based on the achievable engineering response $\mathbf{E}^D$, and the enterprise DBD problem is re-solved, as shown in (Eq. 7). The physical meaning of the additional constraint is that it imposes a minimum geometric distance from the utopia target so that the enterprise problem is forced to find an alternative target for the engineering problem. The idea of adding the constraint is to explore targets at new domain that may potentially lead to feasible designs with a better value for expected utility. The points inside the circular constraint are ruled out because they are infeasible (otherwise they should be identified as solution in the previous iteration as their deviations from the utopia target is less). Note that, for the discussion on the solution of the enterprise level product planning problem, engineering design attributes **E** are referred to as targets **T**. The modified enterprise problem P'_{ent} (Eq. 7) based on the engineering design $\mathbf{E}^D$ generates a new target $\mathbf{T}'$ for the engineering problem. Based on the new target, the engineering problem finds point B as the optimum with the minimum deviation from the new target $\mathbf{T}'$. Point B is farther from the original utopia target; however the corresponding utility is higher than that of point A. As a result, point B is selected as the optimal engineering design that has a better utility value.

$$
\begin{aligned}
&P_{ent}^{'}: \max_{\mathbf{T}, \mathbf{X}_{\mathbf{ent}}} E\left[U(\mathbf{T}, \mathbf{X}_{\text{ent}})\right] \\
&\text{subject to} \\
&C_{aux}: \left\|\mathbf{T} - \mathbf{E}^D\right\| \geq \left|\frac{\alpha}{\phi}\right| \Delta \text{ where } \Delta = \left\|\mathbf{T}^* - \mathbf{E}^D\right\|
\end{aligned} \tag{7}
$$

To avoid returning to the previous solution, additional slope information is utilized to adjust the radius of the restricted feasible domain in the enterprise problem. Hence, $\left|\frac{\alpha}{\phi}\right|\Delta$ is used instead of Δ Here, α and ϕ are the gradients of the utility function with respect to the current response $\mathbf{E}^{D}$ and new target $\mathbf{T}'$. The reader is referred to Kim et al.[25] for analytical case studies and a more detailed explanation of the algorithm. The proposed iterative procedure is terminated as soon as an engineering level design is found with a better utility; the goal of the algorithm is to explore the target space of engineering design attributes **E** until a feasible engineering design with a better enterprise utility is identified. The proposed algorithm does not attempt to find the global optimum; instead it explores the engineering feasible domain to find alternative feasible design with a better utility if it exists in a disconnected feasible domain.

The hierarchical framework presented in Fig. 2(b) shares a number of features with the ATC representation of the product planning and product development subproblems in Michalek et al[27]. However, there are some important differences. While the ATC formulation in Michalek et al[27] treats the enterprise problem as deterministic, we incorporate uncertainty and designer's risk attitude into the formulation by using expected utility $E(U)$ as the optimization criterion for the enterprise problem. In Michalek et al.[27], the product planning problem not only considers the optimization of the enterprise level objective (e.g., profit) but also attempts to minimize the deviation between achievable engineering design attributes and targets set by marketing. In our approach, enterprise and engineering objectives are treated separately in product planning and product development problems. Expected utility is the only optimization criterion at the enterprise level and the ATC approach is used only for the engineering product development problem. Such an approach not only preserves the essential distinction between product planning and product development functions but also results in far fewer iterations between the enterprise and engineering level problems, compared to Michalek et al.[27]. In fact, the engineering level problem needs to be resolved only if the design space is disconnected and the enterprise level targets are adjusted by the product planning problem.

IV. Suspension Design Case Study

An automotive suspension system design problem is used to demonstrate our approach. The assumptions made for the case study and the rationale behind including the various engineering design attributes **E** to represent customer-product-selection attributes **A** in the demand model are first explained. Also, details on the interpretation of the obtained demand model, and the examination of the suspension design obtained using the multilevel optimization framework are provided.

A. Hierarchical Approach to Suspension Design Problem

Here, we demonstrate the enterprise-driven Decision-Based Design approach to suspension system design of a mid-size car. We demonstrate in this case study: (1) how the problem can be solved using a multilevel optimization formulation; (2) how the demand model is created to provide linking between enterprise planning and engineering development; and (3) how the new optimization algorithm is used to explore the targets of engineering design attributes that correspond to the disconnected feasible design space.

While treating the enterprise product planning of vehicle and engineering product development of the suspension system as hierarchical decision making activities (Fig. 3(b)), we view the suspension design in engineering product development as a hierarchical design problem by itself and solve it using the ATC approach. The ATC formulation used here is based on the one in Kim et al.[23]. The schematic of the multilevel Decision-Based suspension design model is illustrated in Fig. 4. Here, targets for front and rear suspension stiffnesses ($\mathbf{T}^{U}$=$\mathbf{E}^{*}$, the top level suspension system attributes), are set by solving the enterprise level DBD product planning problem. These targets are then used to guide the subsystem engineering development of front and rear suspensions. By solving the problems at the subsystem level, the targets for front and rear coil spring stiffness are identified to guide the engineering development at the component level (i.e., front and rear coil spring designs).

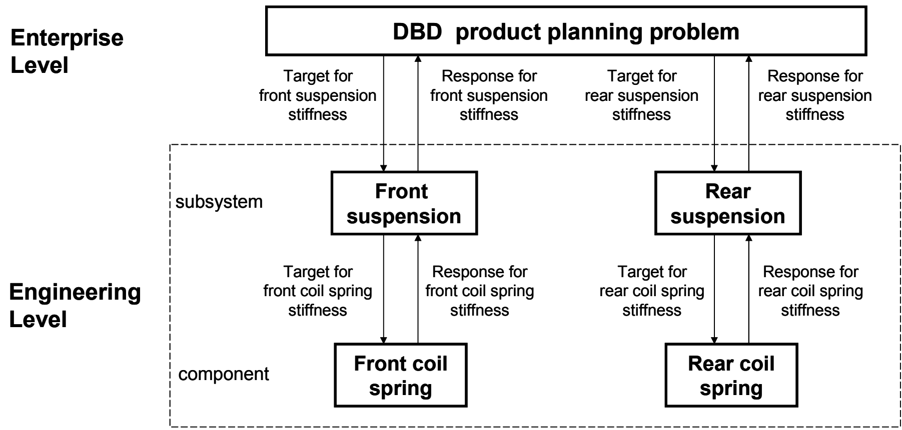


Fig. 4 Schematic of multilevel Decision-Based Suspension Design model

B. Demand Model for Mid-Size Car Segment

To formulate the demand model that is useful for profit and cost estimations in the enterprise-level DBD problem, Discrete Choice Analysis is applied to study the impact of front and rear suspension characteristics and other important vehicle level product attributes (e.g., engine performance, ride quality, and comfort) on customers' choices of a mid-size car. This case study is developed using market data provided by the Power Information Network group (PIN) at J.D. Power & Associates. Data on the vehicle attributes are from Wards Automotive Yearbook[41]. The statistical software package STATA[42] is used to estimate the multinomial choice model coefficients based on the maximum likelihood criterion. For choice set selection in demand modeling, twelve vehicles (seven models and twelve trims) from the mid-size segment are used to represent the entire market for mid-size cars. The assumption is that customers only consider vehicles from the midsize car segment, and specifically the twelve vehicle trims, when making their decisions.

Examples of customer-product-selection attributes **A** and engineering design attributes **E** considered in the suspension design case study, are presented in Fig. 5. Customer-product-selection attributes **A** belong to system level attributes. They are grouped into engineering-related customer attributes $\mathbf{A}_{eng}$ and non-engineering or enterprise-related customer attributes $\mathbf{A}_{ent}$. Examples of $\mathbf{A}_{eng}$ considered for demand modeling in the case study are performance, quality, comfort and handling. Relationship between $\mathbf{A}_{eng}$ and engineering design attributes **E** is illustrated in Fig. 5. Fuel economy and horse power are examples of engineering design attributes that are related to performance while vehicle length and suspension stiffnesses are related to handling. Front and rear suspension stiffnesses also influence customers' view of comfort. In this work, to facilitate engineering decision making, the engineering design attributes **E** at the system level are modeled directly as the inputs of the demand model. Fig. 5 also illustrates the cascading of engineering design attributes from vehicle system level to subsystem level, then to component level in suspension design. It should be noted that transfer relationships need to be established between the performance attributes at different levels of the hierarchy. For example, front/rear suspension stiffness is a performance attribute at the subsystem level and its target is identified as a design variable in vehicle system level optimization. Front/real coil spring stiffness is a performance attribute at the component level; its target is identified through optimization at the subsystem level. The demand model also considers various non-engineering design attributes $\mathbf{A}_{ent}$. APR of auto loan and Resale Value, which are grouped under $\mathbf{A}_{ent}$ coincide with the enterprise planning options $\mathbf{X}_{ent}$ for our case study. It should be noted that all design attributes unrelated to the suspension design (e.g., horsepower and fuel economy) are assumed to be constant.

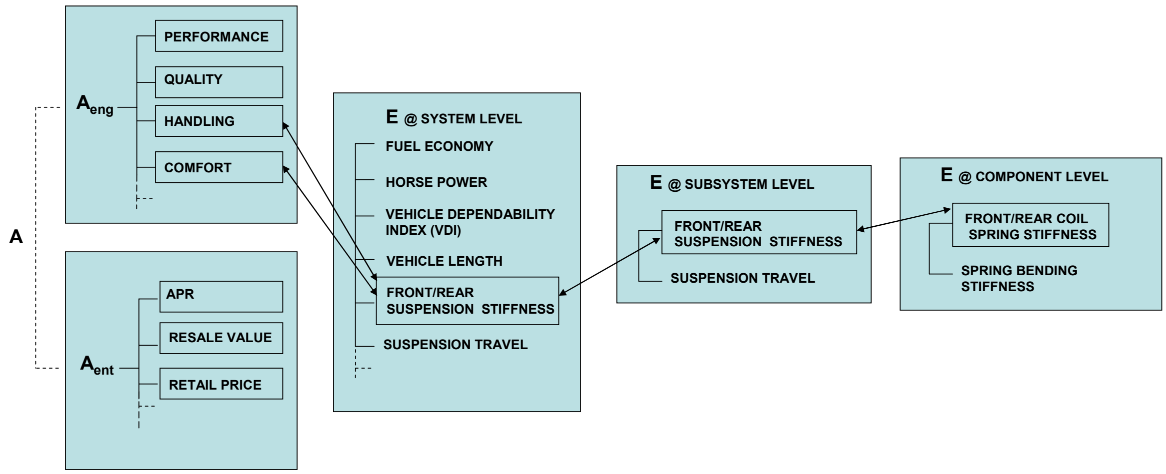


Fig. 5 Examples of customer-product-selection attributes (A) and engineering design attributes (E) in automotive suspension design case study
(**Note**: The arrows represent the correlations utilized in the current case study)

As a result of multnomial logit analysis, demand Q (Table 1) is expressed as a function of demographic and product attributes such as income, age, retail price, resale value, vehicle dependability index (VDI: a quality measure, expressed in terms of defects per 100 parts), annual percentage rate (APR) of loan, fuel economy, vehicle length, front suspension stiffness, and rear suspension stiffness. For the estimation of the demand model, (customer) utility biases (Eq. 2) due to excluded variables are measured using alternative specific constants and alternate specific variables[36]. They measure the "average preference" of an individual relative to a "reference" alternative. One important consideration when evaluating MNL models is that demographic variables related to the customer's age and income can only be included as alternative specific variables. In our model, the income terms capture the interaction of the customer's income with different vehicle alternatives. Eleven income variables were estimated; each corresponding to a particular vehicle alternative, and income variable 1, corresponding to vehicle alternative 1, was used as reference. It is anticipated that the income variables corresponding to more expensive cars will have positive signs since people with higher incomes are likely to view expensive cars more favorably.

Table 1 includes results of the demand model estimation and observations on the model estimation results follow. Negative signs of retail price, VDI, APR and vehicle length mean that customers prefer lower values for these variables, i.e., customers prefer cheaper cars, lower interest rates, fewer defects and cars that facilitate easy parking. Positive sign for fuel economy means that customers prefer higher gas mileage and positive signs for the suspension stiffnesses mean that stiffer suspensions are preferred. Typically, a stiffer suspension generally translates to better handling and load-carrying abilities but also results in a harsher ride. Hence, the current choice model indicates that customers (in the present data set) "value handling characteristics more than ride quality". Also, since we are dealing with variables normalized with respect to their extreme values, the magnitude of the coefficients should reflect their relative importance. The statistical goodness of fit of the different MNL models developed for this purpose is evaluated using likelihood estimates. While choosing the final model, it is necessary to not only compare the statistical goodness of fit measures, but also pay attention to the signs and magnitudes of the different terms in the utility function.

C. Solution to the Suspension Design Problem Using Multilevel Optimization

Even though our focus in this study is on suspension system design, it is necessary to compute the net profit of producing the whole vehicle to formulate the utility optimization model at the enterprise level. In this work, the net profit in (Eq. 8) is used for this purpose. Price of a vehicle P is assumed to be constant or unchanged from the current design, C_{susp} represents the unit cost for the suspension system and C_0 the unit cost for the rest of the vehicle system, respectively. In this work, C_0 is assumed to be constant, since changes in only suspension parameters will be made. The suspension system cost is assumed to be linearly proportional to the suspension stiffnesses (Eq. 9). In the context of design, among the engineering design attributes in the demand model, only front/rear suspension stiffnesses are considered as variables, while the rest of vehicle attributes are set constant at the baseline values. We also assume that the competitors will not change their designs. Uncertainty is captured in the cost variables a_f and a_r, considered as the exogenous variables **Y** in the DBD framework (see Fig. 1). The suspension cost variables a_f and

a_r are both defined as normally distributed variables, with the mean $\mu_a = 0.05\left[\$/k\mathrm{N}m^{-1}\right]$ and standard deviation $\sigma_a = 0.005\left[\$/k\mathrm{N}m^{-1}\right]$. For the current study, values for a mid-size sedan, $P = \$20{,}000, C_0 = \$18{,}100$ are used.

$$\Pi = Q \times (P - C_{susp} - C_0) \tag{8}$$

$$\Pi = Q \times (P - a_f k_f - a_r k_r - C_0) \tag{9}$$

Also, a logarithmic function of profit Π, consistent with the principles of utility theory (Keeney and Raiffa[43]), is used as the enterprise utility U(Π), to account for the risk averse nature of the firm. Then the enterprise level objective is to maximize the expected utility E(U) where

$$\mathrm{E}(U) = \int U f(a) da \tag{10}$$

In this work, the enterprise planning problem is considered as an unconstrained optimization problem. The expected utility function indicates that softer front suspension and stiffer rear suspension lead to the highest utility (see Fig. 6). In Fig. 6, the shaded regions in the target performance space indicate a disconnected feasible domain for the suspension design. The two shaded regions in the Fig.6 represent two suspension design options (i.e., softer vs. stiffer front/rear suspension designs) available to the designer. For example, the suspension manufacturing supplier provides two alternatives for suspension design and the vehicle producer adjusts their product planning decision based on the availability of engineering designs. When applying the proposed multilevel optimization algorithm in Section III(D), utopia targets $\mathbf{T}^*$ ($k_f = 30.2\left[k\mathrm{N}/m\right], k_r = 19.5\left[k\mathrm{N}/m\right]$, corresponding to an expected utility 14.27 and average profit \$80,460), are assigned for the suspension design problem after solving the original DBD at the enterprise level. Design A with the minimum deviation ($k_f = 25\left[k\mathrm{N}/m\right], k_r = 19.5\left[k\mathrm{N}/m\right]$ with expected utility 14.215 and average profit -\$8,935, i.e., loss) is found after solving the multilevel optimization using ATC at the engineering development level. Based on the design A, additional geometric constraint is added at the enterprise level (Eq. 7), which assigns an alternative target $\mathbf{T}'$ ($k_f = 30.2\left[k\mathrm{N}/m\right], k_r = 24.83\left[k\mathrm{N}/m\right]$ with expected utility 14.241 and average profit \$26,722) to the suspension design problem. Based on the new target $\mathbf{T}'$, the ATC finds design B ($k_f = 30.2\left[k\mathrm{N}/m\right], k_r = 26\left[k\mathrm{N}/m\right]$ with the improved expected utility 14.218 and average profit \$23,064) with the minimum deviation. The corresponding expected utility for design B is higher than that of design A. Design B is selected as the final design with a better enterprise level utility value.

Table 2 summarizes the iteration process using the proposed multilevel optimization algorithm. Detailed suspension designs at the subsystem and component level are summarized in Table 3–Table 6. For example, front suspension design model takes coil spring stiffness, spring free length, and torsional stiffness as inputs to the suspension model and returns suspension stiffness and suspension travel as outputs. Among the inputs, coil spring stiffness is cascaded to the front coil spring design model as a target. Based on the coil spring target from the suspension model, the coil spring design at the component level takes wire diameter, coil diameter and pitch as inputs and returns actual coil spring stiffness and spring bending stiffness as outputs.

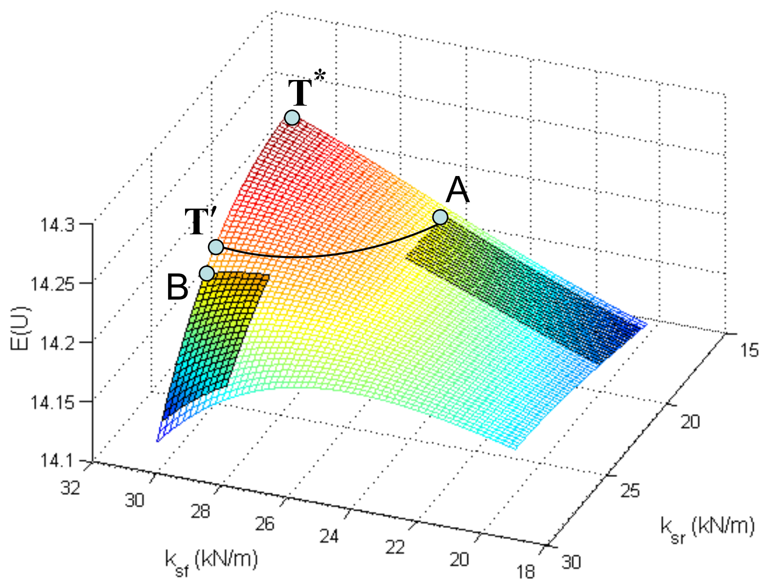


Fig. 6 Vehicle demand model: profit change with respect to suspension stiffness changes
(**Note:** The shaded areas represent disconnected feasible suspension design domain. After the engineering design A is found, a geometric limiting constraint (solid circle) is added in the utility space to find an alternative target $\mathbf{T}'$ to explore another disconnected feasible space)

Table 1. Results of estimation of the multinomial logit model

Attribute type	Description	β Coefficient	t-value	95% Confidence Interval
Demographic Attributes (Income variables capture the interaction between customers' income and vehicle type. (e.g. income × vehicle 2 captures the interaction between income and mid size vehicle 2)	Income × vehicle 2	0.13	6.41	(0.09, 0.18)
	Income × vehicle 3	0.01	0.48	(-0.03, 0.05)
	Income × vehicle 4	0.06	2.57	(0.01, 0.11)
	Income × vehicle 5	-0.10	-4.20	(-0.15,-0.05)
	Income × vehicle 6	-0.08	-3.37	(-0.13,-0.03)
	Income × vehicle 7	0.07	2.99	(0.02, 0.11)
	Income × vehicle 8	0.08	3.22	(0.03, 0.12)
	Income × vehicle 9	0.08	3.25	(0.03, 0.14)
	Income × vehicle 10	0.19	9.38	(0.15, 0.23)
	Income × vehicle 11	0.05	2.29	(0.01, 0.10)
	Income × vehicle 12	0.04	1.18	(-0.02, 0.10)
Demographic Attributes Variable captures interaction between age and country of origin of product.	Interaction between customers' age and country of origin of product	0.13	12.37	(0.11,0.15)
Product Attributes	Retail Price	-1.57	-4.14	(-2.31,-0.82)
	Resale Value	2.15	2.54	(0.49,3.80)
	Vehicle Dependability Index	-1.69	-1.49	(-3.92,0.53)
	Annual Percentage Rate (APR)	-1.05	-1.34	(-2.58,0.49)
	Fuel Economy	0.64	1.51	(-0.19,1.46)
	Vehicle Length	-0.60	-0.5	(-2.95,1.74)
	Front Suspension Stiffness	1.75	3.11	(0.65,2.85)
	Rear Suspension Stiffness	0.88	1.28	(-0.47,2.24)

Table 2. Iteration history: maximizing expected utility with vehicle suspension design change (see Fig. 6). Here the value of profit has been computed for the mean values of a_f and a_r.

Iteration	Target for front suspension stiffness (N/mm) T_1^*	Target for rear suspension stiffness (N/mm) T_2^*	Desired Profit ($)	Desired $E[U]$	Response for front suspension stiffness (N/mm)	Response for front suspension stiffness (N/mm)	Profit achieved ($)	$E[U]$
1	30.2	19.5	80460	14.272	25.0 (point A)	19.5 (point A)	-8935	14.215
2	30.2	24.83	26722	14.241	30.2 (point B)	26 (point B)	23064	14.218

Table 3. Front suspension design

Front suspension subsystem design	Type	Optimal value	Lower bound	Upper bound
Coil spring stiffness (N/mm)	Input	117.53	30	160
Spring free length (mm)	Input	372.9	300	650
Torsional stiffness (N-m/deg)	Input	30.0	20	85
Suspension stiffness (N/mm)	Output	30.2	19	30.2
Suspension travel (m)	Output	0.1	0.05	0.1

Table 4. Rear suspension design

Rear suspension subsystem design	Type	Optimal value	Lower bound	Upper bound
Coil spring stiffness (N/mm)	Input	80.1	30	160
Spring free length (mm)	Input	410.3	300	650
Torsional stiffness (N-m/deg)	Input	58.7	20	85
Suspension stiffness (N/mm)	Output	25.8	19	30.2
Suspension travel (m)	Output	0.1	0.05	0.1

Table 5. Front coil spring design

Front coil spring design	Type	Optimal value	Lower bound	Upper bound
Wire diameter(m)	Input	0.014	0.005	0.03
Coil Diameter(m)	Input	0.074	0.05	0.20
Pitch	Input	0.04	0.04	0.10
Coil spring stiffness (N/mm)	Output	124.9		
Spring bending stiffness (N-m/deg)	Output	16.1		

Table 6. Rear coil spring design

Rear coil spring design	Type	Optimal value	Lower bound	Upper bound
Wire diameter(m)	Input	0.02	0.005	0.03
Coil Diameter(m)	Input	0.14	0.05	0.20
Pitch	Input	0.05	0.05	0.10
Coil spring stiffness (N/mm)	Output	84.5		
Spring bending stiffness (N-m/deg)	Output	33.2		

V. Conclusions and Future work

In this paper, a multilevel optimization approach that integrates enterprise-level product planning with engineering-level product design based on the principles of Decision-Based Design and the concept of Analytical Target Cascading is presented. The hierarchical approach presented provides a systematic way to resolve the organizational and computational complexities involved in integrating design efforts across the enterprise. Based on the review of various existing demand modeling approaches in engineering design, a disaggregate probabilistic demand modeling approach is selected to model customer choices at the enterprise level. It is shown how customer preferences for product attributes can be translated into the market share of a product and used to guide the engineering product development process by setting up the targets for engineering design attributes. An effort is made to clearly distinguish between the various types of product attributes that are commonly used in an enterprise-driven design situation; some attributes are more relevant to customer desires, while others are used by engineers alone; some depend on engineering design options while others are more related to enterprise planning options. Conventionally the product development tries to match the utopia target with the minimum deviation. In cases where the utopia target is unattainable, the minimum deviation design may not correspond to the highest possible enterprise utility if the design space is disconnected. The target exploration algorithm employed for the hierarchical product development scenario in this work sets alternative targets for the product development with higher corresponding enterprise level utility. An automotive suspension design case study was presented to demonstrate the effectiveness of our approach. The case study uses the customer data for the mid size sedan market and obtains a demand model that studies the impact of the suspension variables on customer choices. Our approach explores the enterprise-level preference target space to assign the suspension design targets for higher utility and the ATC successfully cascades the targets at the subsystem and component levels to achieve a design consistent with enterprise-level goals.

The proposed multilevel optimization model is potentially the most useful during the early stages of a design process when the iterative process can be used to revise, negotiate and validate design targets by engineering design and the enterprise-planning groups. In an actual implementation, some targets may be more loosely specified than others. Future formulations should accommodate the setting of a range of targets. It should be noted that while cost is not one of the targets set by the enterprise planning problem in our case study, it could be a target or modeled as a constraint in the engineering-level problem. Since complex systems design involves the design of a number of subsystems and components, and each of these designs may have different computational requirements for design evaluations due to the different nature of analysis models, future implementation should consider the optimal allocation of computational resources as a part of the multilevel optimization solution algorithm.

Future work will also involve introducing uncertainty in engineering product development and expanding the use of the multinomial logit model to incorporate the use of both stated and revealed preference data. Such models can be more effectively incorporated to model multilevel decision making scenarios as well as heterogeneous market segments (e.g., considering sedans with sport utility vehicles in the same choice set). In this work, the role of manufacturing on decisions made during the product planning and development processes is mainly reflected in the product cost modeling. Most industrial design problems involve manufacturing decision making as a part of the engineering product development. To separate manufacturing and product design decision makings, the manufacturing aspects of the product development process need to be investigated further and their relationship with product design needs to be modeled more rigorous.

Acknowledgments

The specialists at the Power Information Network group (PIN) at J.D. Power & Associates are gratefully thanked for their thoughtful contributions and their efforts to gather data for the vehicle demand model. The support from the NSF grant DMI0335880 and Ford University Research Program are also acknowledged. The engineering development model of the suspension system design was created during Dr. Harrison Kim's PhD study, supported by the Optimal Design Laboratory at University of Michigan.

References

[1]Hazelrigg, G., *Systems Engineering: An Approach to Information-Based Design*, Prentice-Hall, Inc., Upper Saddle River, NJ, 1996.

[2]Thurston, D.L., "Real and Misconceived Limitations to Decision Based Design with Utility Analysis", *Transactions of ASME: Journal of Mechanical Design*, Vol. 123, pp. 176-182, June, 2001

[3]Li, H., and Azarm, S., "Product Design Selection under Uncertainty and with Competitive Advantage", *Transactions of ASME: Journal of Mechanical Design*, Vol. 122, pp. 411–418, 2000.

[4]Callaghan, A.R. and Lewis, K.E., "A 2-Phase Aspiration-Level and Utility Theory Approach to Large Scale Design", *Proceedings of DETC 2000 ASME Design Engineering Technical Conference*, Baltimore MD, 2000.

[5]Scott, M.J. and Antonsson, E.K., "Arrow's Theorem and Engineering Design Decision Making", *Research in Engineering Design*, Vol.11 No. 4, pp. 218-228, Springer, 1999.

[6]Roser, C. and Kazmer, D., "Flexible Design Methodology", *Proceedings of DETC 2000 ASME Design Engineering Technical Conference*, Baltimore MD, 2000.

[7]Marston, M., Allen, J., and Mistree F., "The Decision Support Problem Technique: Integrating Descriptive and Normative Approaches in Decision Based Design", *Engineering Valuation & Cost Analysis, special edition on "Decision-Based Design: Status & Promise*, Vol. 3, No. 2/3, pp. 107-130, 2000.

[8]Shah, J.J. and Wright, P.K., "Developing Theoretical Foundations of DfM", *Proceedings of DETC 2000 ASME Design Engineering Technical Conference*, Baltimore, MD, 2000.

[9]Dong, H. and Wood, W.H., "Integrating computational synthesis and decision-based conceptual design", *Proceedings of ASME 2004 Design Engineering Technical Conference*, Salt Lake City, Utah, 2004.

[10]Schmidt, L.C. and Herrmann, J.W., "Viewing Product development as a decision production problem", *Proceedings of ASME 2002 Design Engineering Technical Conference*, Montreal, Canada, 2002.

[11]Wassenaar, H. J. and Chen, W. , "An approach to Decision-Based Design with Discrete Choice Analysis for Demand Modeling", Transactions of ASME: Journal of Mechanical Design, Vol. 125, No. 3, pp. 490-497, September, 2003.

[12]Wassenaar, H.J., Chen, W., Cheng, J., and Sudjianto, A., "Enhancing discrete choice demand modeling for Decision-Based design", *Transactions of ASME:Journal of Mechanical Design*, Vol. 127, No. 4, pp.514-523, 2005.

[13]Wassenaar, H.J., Chen, W., Cheng, J., and Sudjianto, A., "An Integrated Latent Variable Modeling Approach for enhancing Product Demand Modeling", *Proceedings of DETC 2004 ASME Design Engineering Technical Conference*, Salt Lake City, Utah, 2004.

[14]Lewis, K. and See, T-K, "Multiattribute Decision making using Hypothetical Equivalents", *Transactions of ASME: Journal of Mechanical Design*, Vol. 26, No. 6, pp. 950-958, 2004.

[15]Gu, X., Renaud, J., Ashe, L., Batill, S., Budhiraja, A., and Krajewski, L., "Decision-Based Collaborative Optimization", Tr*ansactions of ASME: Journal of Mechanical Design*, Vol. 124, No. 1, pp. 1–13, 2002.

[16]McAdams, D.A. and Dym, C.L., "Modeling and Information in the Design Process", *Proceedings of DETC 2004 ASME Design Engineering Technical Conference*, Salt Lake City, Utah, 2004.

[17]Stelmack, M.A. and Batill, S.M., "Concurrent Subspace Optimization of Mixed Continuous/Discrete Systems", *AIAA/ASME/ASCE/AHS/ASC 38th Structures, Structural Dynamics and Materials Conference*, Kissimmee, Florida, 1997.

[18]Sobieszczanski-Sobieski, J., "Optimization by Decomposition: A Step from Hierarchic to Nonhierarchic Systems", T*ech. Rep. NASA CP-3031*, NASA Langley Research Center, Hampton, VA, 1988.

[19]Sobieszczanski-Sobieski, J., Agte, J., and Sandusky, R., "Bi-Level Integrated System Synthesis (BLISS)", *Technical Memorandum TM-1998-208715,* NASA Langley Research Center, Hampton, VA, 1998.

[20]Braun, R., "Collaborative optimization: architecture for large-scale distributed design", *Ph.D. thesis*, Stanford University, Stanford, CA, 1996.

[21]Michelena, N., Kim, H.M., and Papalambros, P.Y., "A System Partitioning and Optimization Approach to Target Cascading", *Proceedings of the 12th Int. Conf. on Engineering Design*, Vol. 24, pp. 1109–1112, Munich, Germany, 1999.

[22]Kim, H.M., "Target Cascading in Optimal System Design", *Ph.D. thesis*, The University of Michigan, Ann Arbor, MI, 2001.

[23]Kim, H.M., Rideout, D.G., Papalambros, P.Y., and Stein, J.L., "Analytical Target Cascading in Automotive Vehicle Design", *Transactions of ASME: Journal of Mechanical Design*, Vol. 125, No. 3, pp. 481–489, 2003.

[24]Kim, H.M., Michelena, N.F., and Papalambros, P.Y., "Target Cascading in Optimal System Design", *Transactions of ASME: Journal of Mechanical Design*, Vol. 125, No. 3, pp. 474–480, 2003.

[25]Kim, H.M., Kumar, D., Chen, W., and Papalambros, P.Y. "Target Feasibility Achievement in Enterprise-Driven Hierarchical Multidisciplinary Design", *Proceedings of the 10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Aug. 30 - Sept. 1, Albany, NY, 2004.

[26]Cooper, A.B., Georgiopoulos, P., Kim, H.M., and Papalambros, P.Y., "Analytical target setting: An enterprise context in optimal product design", *Proceedings of the 2003 ASME Design Automation Conference*, Chicago, IL, 2003.

[27]Michalek, J., Feinberg, F. and Papalambros, P.Y., "Linking marketing and engineering product design decisions via analytical target cascading", *Journal of Product Innovation Management*, Vol. 22, No. 1, pp. 42-62, 2005.

[28]Kroo, I., "Multidisciplinary Optimization Applications in Preliminary Design - Status and Directions"*, Proceedings of the 38th AIAA/ASME/ASCE/HS/ASC, Structures, Structural Dynamics and Materials Conference*, Kissimmee, FL, 1997,

[29]Donndelinger, J. and Cook, H.E., "Methods for analyzing the value of vehicles", Society of Automotive Engineers, February 1997.

[30]Cook, H.E., *Product Management: Value, Quality, Cost, Price, Profit and Organization,* Chapman and Hall, 1997.

[31]Monroe, E.M. and Cook, H.E., "Determining the Value of Vehicle Attributes using a PC based tool", *SAE Technical Paper Series 970763*, International Congress and Exposition, Detroit, Michigan, 1997.

[32]Besharati, B., Azarm, S., and Farhang-Mehr, A., "On the aggregation of preferences in engineering design", *Proceedings of DETC 2001 ASME Design Engineering Technical Conference*, Pittsburgh, PA, 2001.

[33]Besharati, B., S. Azarm, and A. Farhang-Mehr, "A customer-based expected utility metric for product design selection", *Proceedings of DETC 2002 ASME Design Engineering Technical Conference*, Montreal, Canada, 2002.

[34]Besharati, B., Luo, L. and Azarm, S. and Kannan, P.K., "An Integrated Robust Design and Marketing Approach for Product Design Selection Process", P*roceedings of DETC'04, ASME Design Engineering Technical Conferences and Computers in Engineering Conference*, Salt Lake City, Utah, 2004.
[35]Louviere, J.J., Hensher, D.A., Swait, J.D., *Stated Choice Methods, Analysis and Application*, Cambridge University Press, 2000.
[36]Ben-Akiva, M. and Lerman, S.R., *Discrete Choice Analysis*, The MIT Press, Cambridge, MA, 1985.
[37]Green, P. and Wind, Y., "New way to measure consumers' judgments", *Harvard Business Review*, Vol. 53, pp. 107–117, 1975.
[38]Green, P. and Srinivasan, V., "Conjoint analysis marketing: New developments with implications research and practice", *Journal of Marketing*, 1990.
[39]Koppelman, F. and Sethi, V., "Closed Form Discrete Choice Models" In D.A. Hensher and K.J. Button, editors, *Handbook of Transport Modeling*, pp. 211–228. Pergamon Press, Oxford, 2000.
[40]Train, K., *Discrete Choice Methods with Simulation*, Cambridge University Press, 2003.
[41]Ward's Automotive Yearbook, *Ward's Communications*, Detroit, 2000.
[42]STATA Corporation, *Stata Programming Reference Manual*, ISBN 1-881228-73-8, 2003.
[43]Keeney, R.L., Raia, H., *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*, Wiley, New York, 1976.