Decision Making under Uncertainty using a Vehicle Multilevel Model: Approaches for Target Allocation

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Nomenclature

C: Characteristic

VC, vc: Vehicle characteristic and target

VDP: Vehicle Development Process

VMM: Vehicle Multilevel Model

Abstract

In this paper, we consider setting performance targets for a vehicle design. The vehicle is modeled by a multilevel hierarchical tree structure. We have considered that each leaf of the structure may have several characteristics, and that for each characteristic a target is defined. Experts' opinions are expressed with uncertainty regarding the feasibility of achieving these targets. Experts' opinions are given in the form of intervals associated with their subjective beliefs for the possible values of characteristics. The collected information is propagated in the model to determine the plausibility and the belief for characteristics at the vehicle level. Using this information, five target allocation approaches are discussed which can be applied to three vehicle design strategies.

1 Introduction

In today's competitive environment, companies must respond quickly and effectively to consumers' expectations to maintain a competitive advantage in the market [1-3]. In the automotive industry, developing a new vehicle that satisfies consumer needs and wants is accomplished through a complex vehicle development process (VDP). This process requires continuous analyses and collection of relevant information from a wide variety of sources and is guided throughout by experts making crucial decisions regarding the competitiveness of the new vehicle.

At the early stages of the VDP, a set of characteristics desirable to the consumer are identified by the

planning team and passed to the engineering team to guide the development of the new vehicle. However, the initial utopian vehicle characteristics may evolve over time, and may be unattainable with the existing technologies, facilities and resources. In this context, the vehicle engineering experts must use analysis and experience to make two types of decisions:

- Allocation and modification of targets for each vehicle characteristic at the part, subsystem, system and vehicle level in accordance with the vehicle utopian characteristics and to resolve coupling among characteristics;
- Assignment of resources at all stages of the VDP consistent with high confidence to obtain a competitive vehicle.

Upon receiving a given target, the experts are asked to determine a range of characteristic values which are feasible and as close as possible to the target. Therefore, imprecise and uncertain estimates are provided, and the uncertainty must be managed during the VDP.

In this paper, we explore ways to reassign characteristic targets to the systems, subsystems and components of the vehicle based on the propagated uncertainties. Our strategy consists of formulating and solving single objective or multi-objectives optimization problems to obtain a vehicle design satisfying customer expectations with the highest confidence in feasibility. The resource assignment problem will be a subject for future work.

In section 2, the concepts and definitions of a vehicle multilevel model are briefly introduced. In section 3, the process of decision making under uncertainty in VDP is presented, followed by the vehicle design strategies and target allocation approaches discussed in section 4.

2 Vehicle multilevel model (VMM)

The VMM is based on the concept of decomposition of the vehicle in a hierarchical tree structure composed of systems, subsystems and parts of the vehicle (see Figure 1). The number of levels and the number of elements at each level are defined according to the complexity of the vehicle and the required level of details. Each leaf element of the structure (shaded boxes in Figure 1) can be associated with a set of characteristics as well as the experts' opinions regarding these characteristics. See Ref. [4] for details about previous work on the proposed vehicle multilevel model.

Figure 1. Example of a vehicle multilevel model

In the following subsections, we present the types of characteristics supported in the VMM, the propagation of characteristics, and the experts' opinions collected at the leaf elements of the tree structure.

2.1 Types of characteristics

In the vehicle multilevel model, two types of characteristics can be distinguished:

Engineering characteristics ($C_1, \dots, C_n$) are measures that represent physical specifications or characterize behaviour and/or response of the components of the vehicle. They directly or indirectly contribute to vehicle performances. These measures are controlled by engineers at system, subsystem and part levels. Examples are mass and torque.

Vehicle characteristics ($vc_1, \dots, vc_m$) appear only at the vehicle level. They represent various vehicle attributes that customers care about. Vehicle characteristics can be estimated using the engineering characteristics present in the elements of the VMM through functional relations. Examples are fuel economy and acceleration.

2.2 Experts' opinions

The experts' opinions are collected only at the leaf elements of the VMM. These opinions represent subjective evaluations of the feasibility of each characteristic. They are provided in the form of sets of intervals and their associated subjective beliefs for

each characteristic. Experts' opinions with respect to each characteristic usually encompass uncertainties due to lack of information about the technologies, design process, manufacturing process, and interactions among vehicle components.

An expert's opinion results from extensive experience and the team's work on a specific component based on the assigned characteristic target. The team must reach consensus about the feasibility of a characteristic target under timing constraints with limited engineering resources.

2.3 Uncertainty quantification and propagation

The information in the VMM is propagated along the branches of characteristic propagation trees. A propagation tree for one characteristic represents a specific tree structure made up of a subset of the elements of the VMM that participate in its composition. The bottom-up propagation of characteristics can be formalized by a functional relation between characteristics.

The propagation of uncertainties follows the same paths as the characteristics. Experts' opinions are collected at leaf nodes and propagated bottom-up in the vehicle multilevel model to support the decision making process. This will serve to determine whether the allocated targets are applicable for the feasibility of the vehicle as a whole or must be modified.

At each node of the VMM, the uncertainty is quantified by two measures, the belief (Bel) and the plausibility (Pl) in the interval $[0,1]$. By using intervals and subjective beliefs provided by experts, Evidence Theory allows the quantification of these two measures (see Ref. [4] for details).

The belief and plausibility measures can be viewed as the minimum and maximum likelihood of occurrence of an event A . We have considered events expressed with respect to a possible threshold value $x \in \mathbb{R}$ of characteristic C_i :

$$A = (C_i > x) \text{ or } A = (C_i < x)$$

Figure 2 provides an illustration of how belief and plausibility change when the threshold value x changes for a certain C_i .

3 Decision making under uncertainties

The vehicle development process alternates knowledge accumulation and decision making through a series of development stages with reviews or gates (one element is shown in Figure 3). There are

many parallel work streams and possible feedback loops.

Figure 2. Belief and plausibility curves

Figure 3. Stage/gate process representation

The vehicle development process starts with subjective and uncertain estimates of the characteristics. As the design matures, estimates are refined based on data generated from development activities such as analyses, simulations, prototypes, and demonstrations. Collected information on the engineering characteristics is transformed into information for the vehicle characteristics. Obviously, highly accurate assessments of the vehicle characteristics are possible only when the product is designed in detail and uncertainty has greatly diminished. However, design activities in the VDP must be conducted even with uncertain information. Decision makers must choose among alternative technical solutions and select characteristic targets and the engineering resources needed to achieve them. Ultimately and ideally, all decisions aim to design a vehicle with characteristics meeting all the customer expectations.

The estimates of vehicle and engineering characteristics become more accurate as the design matures due to the reduction of uncertainty. Our strategy of target allocation is based on this main idea. The allocation of targets consists of design decisions that occur during the vehicle development process at the gates (see Fig. 3). We presume that resources are required during development activities to produce information aimed at reducing uncertainty for the next

stage. We presume also that these decisions will guide the vehicle design towards its utopian targets. The decision making process at each stage of the vehicle development process can be guided by evaluating the ability to achieve the characteristics targets and the desirability, or the level of customer satisfaction. Accordingly, two measures are introduced: achievability and desirability.

3.1 Desirability and achievability measures

3.1.1 Desirability (utility) measure

We use the term desirability to describe the utility of a design with respect to customer expectations and desires for each vehicle characteristic.

From a set of values of the engineering characteristics (C_i) we can estimate each vehicle characteristic through a functional:

$$vc_j = F_j(C_1, \dots, C_n)$$

A utility functional provided by the marketing department allows the calculation of a desirability measure defined as a distance to the customer expectation for a given vehicle characteristic:

$$D_j : vc_j \rightarrow U_j(vc_j) \in [0,1]$$

Hence, the desirability depends implicitly on the

Figure 4. Higher is better utility function

Figure 5. Lower is better utility function

engineering characteristics ($C_1, \dots, C_n$). The desirability for each vehicle characteristic is non-dimensional. There are several ways to define these

functions but this is not the topic of this paper. We suppose that customers can express their preference for each characteristic as “higher is better”, or, as “lower is better” (see examples on Figure 4 and Figure 5).

3.1.2 Achievability measure

Achievability is defined as a measure of the confidence in achieving a given value of the vehicle characteristic (vc_j).

Experts’ opinions are provided as the confidence that a characteristic value will be within specific intervals, without additional information about the probability distribution. Hence, the confidence in achieving a given value or a narrow range of values is meaningless. Instead, we have considered the belief and plausibility that a variable will be larger or lower than a given value. This can be used to define four measures of achievability:

$$A_j^{Bel>} : vc_j \rightarrow Bel(VC_j > vc_j)$$

$$A_j^{Bel<} : vc_j \rightarrow Bel(VC_j < vc_j)$$

$$A_j^{Pl>} : vc_j \rightarrow Pl(VC_j > vc_j)$$

$$A_j^{Pl<} : vc_j \rightarrow Pl(VC_j < vc_j)$$

With such definitions, the achievability is between 0 and 1, independent of the unit of the characteristic being considered.

3.1.3 Allocation of characteristic targets

During the VDP, after each stage, a set of new engineering characteristic targets are obtained at the leaf nodes of the VMM. These targets map to a set of vehicle characteristics. Targets provide the experts a guide to what the vehicle should be. The determination of these new targets should take into consideration what the experts have reported as achievable. Full achievability is not always required because target selection should allow exploration throughout the design space when reasonable. However, a design close to full achievability should be attained while progressing through the vehicle development process.

Target selection can be directed toward high desirability, high achievability or a trade-off between the achievability and desirability of the design depending on the design strategy adopted and the corresponding target allocation approach.

The proposed approaches for target allocation involve solving optimization problems that maximize achievability and desirability. Several formulations of the target allocation problem are proposed below using

various combinations of the desirability and achievability measures.

4 Vehicle design strategies and target allocation approaches

The design of a new vehicle can be performed following many strategies. Wheelwright and Clark [3] consider several development processes which focus to different degrees on resource utilization, technical advancement, risk management, system solution, speed, and technical performance. Here, we consider three hypothetical design strategies: innovative design, imitative and/ or conservative design and iterative or evolutionary design. These strategies depend mainly on the company’s orientation, the intended consumers and the maturity of the developed product.

4.1 Vehicle design strategies

Innovative design strategy

The innovative strategy is characterized by speed and technical advancement. For a new competitive product, engineers aim at a utopian design that initially appears to be unachievable. Through the development process they strive to generate sufficient useful information to guide the design as close as possible to the utopian targets and to improve the confidence in achieving the design. When utopian characteristics are not too demanding, this approach may have the advantage of shortening the development process and may limit the risk of costly rework [2, 5].

Imitative and/ or conservative design strategy

The conservative strategy is characterized by risk management and technical performance with a focus on mature technologies. This strategy has the advantage that the confidence in achieving a design in progress is very high. However, evolving customer expectations may not be anticipated or satisfied [5].

Iterative or evolutionary design strategy

Under the iterative strategy, there is a focus on risk management and with technical advancement. Engineering targets and resources are adapted progressively to improve the desirability and achievability. However, if the starting design is far from the customer expectations, many design iterations may be required.

4.2 Approaches to target allocation

Target allocations must be driven with respect to achievability and desirability. At the end of the VDP, a vehicle is expected to be achievable and to match the utopian targets as close as possible. Prior to that, the

characteristic values reported in experts' opinions as intervals may or may not overlap the utopian targets, and are tainted with uncertainty. For any set of engineering characteristic values we can determine the achievability and desirability.

Target allocations can be directed toward high desirability, high achievability or a trade-off between the two. Target allocation approaches are proposed in the following two categories: single objective formulations and multi-objective formulations.

4.2.1 Single objective approaches

This category utilizes the formulation of a constrained single objective optimization problem [6]. These approaches can be adapted to different types of design strategies depending on a global measure of design merit. A unique solution that maximizes the design merit corresponds to a new set of characteristic targets for the next iteration of the VDP.

Global utility of design (GUD)

The global utility of design combines the achievability and the desirability of the different characteristics targets in a single measure of design merit:

$$GUD = \frac{1}{m} \sum_{j=1}^m w_j * D_j(vc_j) * A_j(vc_j)$$

The w_i serves to balance the importance of the different characteristics. Selecting the targets C_i by maximizing GUD is suitable for the progressive design strategy where designers aim to surpass the customer's expectations with a high level of confidence in realizing their design. GUD values close to unity indicate high desirability and achievability. However, since the GUD expression is based on multiplication of the achievability and the desirability for each vehicle characteristic, low values of GUD may correspond to low achievability, low desirability, or both.

Global desirability of design (GDD)

A global desirability measure of the design is defined as:

$$GDD = \frac{1}{m} \sum_{j=1}^m w_j * D_j(vc_j)$$

The GDD optimization problem is formulated as follows:

$$\begin{aligned} & \max_{(c_1, \dots, c_m)} GDD \\ & \text{subject to: } A_j(vc_j) \geq A_j^{min} \end{aligned}$$

with $j=1, \dots, m$

Where the parameters A_j^{min} are selected by the decision maker to control the minimal required achievability for each vehicle characteristic.

This formulation can be used when the design is highly focused on costumer expectations. However, achieving high desirability generally involves difficult to achieve utopian targets. The GDD formulation is suitable for the assertive design strategy but can also be used for the progressive design strategy.

A weakness of the GDD measure is that high desirability of each individual characteristic cannot be guaranteed. For example, a low desirability for a given characteristic may be compensated by a high desirability for another characteristic. Constraints may be added to insure minimum desirability.

Global achievability of design (GAD)

A global achievability measure of the design is defined as:

$$GAD = \frac{1}{m} \sum_{j=1}^m w_j * A_j(vc_j)$$

The GAD optimization problem is formulated as follows:

$$\begin{aligned} & \max_{(c_1, \dots, c_m)} GAD \\ & \text{subject to: } D_j(vc_j) \geq D_j^{min} \\ & \text{with } j=1, \dots, m \end{aligned}$$

Where the parameters D_j^{min} are selected by the decision maker to control the minimal required desirability for each vehicle characteristic.

This formulation can be used when high achievability is desired, as long as a certain level of customer satisfaction can be met. This approach is suitable for the conservative design strategy but also can be used in the case of the progressive design strategy.

A weakness of the GAD measure is that high achievability for each vehicle characteristic cannot be guaranteed because a low achievability for a given characteristic may be compensated by a high achievability for another characteristic. Constraints may be added to insure minimum achievability.

4.2.2 Multi-objective approaches

In most practical design situations, achievability and desirability are conflicting measures (see Figure 6). Without a priori knowledge of preference articulation all possible trade-offs between achievability and

desirability are equally valuable. A Pareto front of all the optimal trade-offs can be obtained by solving a multi-objective optimization problem. We have identified two formulations to obtain optimal trade-offs.

Figure 6. Trade-offs curve for achievability and desirability of a characteristic

Achievability and desirability of the design (ADD1)

The ADD1 formulation combines GDD and GAD:

$$\max_{(c_1, \dots, c_m)} (GAD, GDD)$$

This formulation is suited to all types of design strategies. Its major weakness comes from the possible compensation in desirability among vehicle characteristics and possible compensation in achievability among vehicle characteristics.

Achievability and desirability of the design (ADD2)

It is also possible to consider a product of achievability and desirability for each characteristic separately. The ADD2 formulation is given as follows:

$$\max_{(c_1, \dots, c_m)} (A_1(vc_1) * D_1(vc_2), \dots, A_m(vc_m) * D_m(vc_m))$$

Again, this formulation is suited to all types of design strategies. Its major weakness comes from the possible compensation between desirability and achievability for each vehicle characteristic.

4.2.3 Application of the GUD approach

As a first step in our work, a fully automated simulation of a hypothetical decision making process is desired without intervention of a human decision maker. Hence, a single objective optimization approach is preferred to return a unique set of characteristic targets. In this paper, the GUD optimization approach is considered.

For a vehicle having m vehicle characteristics which depends on a set of engineering characteristics $C = \{C_1, \dots, C_n\}$ obtained at different nodes of the

multilevel model, a general expression for the global utility of design (GUD) is given by:

$$GUD = \frac{1}{m} \sum_{j=1}^m w_j * D_j(vc_j) * ((1 - \varphi) A_j^{Pl}(vc_j) + \varphi A_j^{Bel}(vc_j))$$

where the achievability measure is determined by the belief and plausibility estimates. Belief and plausibility measures are weighted by a decision coefficient $\varphi \in [0, 1]$ which must be selected to fully define the GUD. The level of risk tolerance is defined by the value of φ . For $\varphi = 1$, we consider only the belief which represents the lowest probability for the event occurrence. For $\varphi = 0$, only the plausibility is considered which represents the highest probability for the event occurrence.

If a vehicle characteristic VC_j is identified as ‘higher is better’ then the achievability is based on plausibility $Pl(VC_j > vc_j)$ and belief $Bel(VC_j > vc_j)$ for achieving the target value vc_j . The two versions of achievability are noted $A_j^{Pl>}(vc_j)$ and $A_j^{Bel>}(vc_j)$. For such preference, the higher the vc_j value, the larger the corresponding utility and desirability of the vehicle; but higher vc_j values are harder to achieve, which corresponds to lower belief/plausibility and lower achievability value (see Figure 7). If a characteristic VC_j is identified as ‘lower is better’ then the achievability is based on plausibility $Pl(VC_j < vc_j)$ and belief $Bel(VC_j < vc_j)$ (see Figure 8). The achievability for plausibility and belief are noted $A_j^{Pl<}(vc_j)$ and $A_j^{Bel<}(vc_j)$.

Figure 7. Higher is better compromise

By maximizing the GUD objective function, a unique set of engineering characteristics $C = \{C_1, \dots, C_n\}$ will be obtained. However, a vehicle characteristic with high desirability and low achievability could have the same low value of ‘GUDness’ as a vehicle characteristic with low desirability and high achievability. Hence, the compromise may not be

acceptable for low values of GUD, but GUD values close to one always represent acceptable compromises.

Figure 8. Lower is better compromise

An example of a GUD function for a 2D characteristic design space is presented in Figure 9. Although discontinuous, the GUD function possesses a maximum that can be identified with a global search optimization algorithm. Discontinuities in the GUD function are caused by the discontinuities in the belief/plausibility estimates based on intervals of experts' opinions (see Fig. 2 as an example).

Figure 9. GUD measure in the design space of two characteristics

5 Conclusion

In this paper we have presented several target allocation approaches applicable to the design of a vehicle under uncertainty. Both single-objective and multi-objective optimization formulations are proposed, where desirability and achievability are components of the objective functions or constraints.

In the first stage of this project, an automated simulation for design decision-making under uncertainty is preferred. For this reason, the GUD

(Global Utility of Design) formulation is tested in a simple design space to demonstrate its appeal in target allocation.

In future work, we will proceed with in-depth investigations to demonstrate the applicability, the advantages and the limitations of all the proposed formulations.

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