ANALYTICAL TARGET CASCADING

Target cascading is a key challenge in early product development: How to propagate desirable product characteristics, defined by product's specifications, to the various subsystems and components in a consistent and efficient manner. Consistency means that all parts of the designed system should end up working well together, while efficiency means that the process itself should avoid iterations at later stages, which are costly in time and resources.

Analytical target cascading (ATC) is formalized in a process modeled as a multilevel optimal design problem. Design targets are cascaded down to lower levels by partitioning the overall design problem into a hierarchical set of subproblems. For each design subproblem at a given level, a rigorous optimization problem is formulated to minimize deviations from the propagated targets and thus achieve intersystem compatibility. A coordination strategy links all subproblem decisions so that overall product performance targets are met.

ATC requires a hierarchical decomposition of the product and the underlying models into systems, subsystems and components, collectively referred to as elements. An element's design response **R** is a function of the element's own design variables **x** as well as of the responses of (sub)elements making up the element. For each level and for each element in the model hierarchy, a design optimization problem is formulated to match responses dictated by elements above in the hierarchy and to satisfy the element's design constraints. ATC is general enough to account for multiple levels and for interactions between elements at the same level by means of linking design variables.

To illustrate the concept we describe how ATC is applied to the design of an advanced heavy tactical truck. Novel technologies (e.g., series hybrid and electric propulsion systems, in-hub motors, and variable height suspensions) are introduced with the intention of improving both civilian and military design attributes within the framework of a dual-use philosophy. Emphasis is given to fuel economy, ride, and mobility characteristics. A two-level target cascading hierarchy is defined, and five design subproblems are formulated. At the top level, design targets for the truck are matched; at the bottom level, suspension characteristics, cascaded down from the top level, are matched using a detailed model of the suspension system. A schematic of the vehicle configuration is shown in Figure A. Left and right tires are combined into one tire because of symmetry.

The vehicle is powered by a diesel engine that is connected to the generator through a speed reduction gearbox. The electrical power of the generator, through the power bus, is fed to eight in-hub motors that drive the wheels through a gearbox at each wheel. Additional power may be taken from the battery modules connected to the power bus. Distribution of power and charging and discharging of the batteries are managed by the power control module based on instantaneous power requirements.

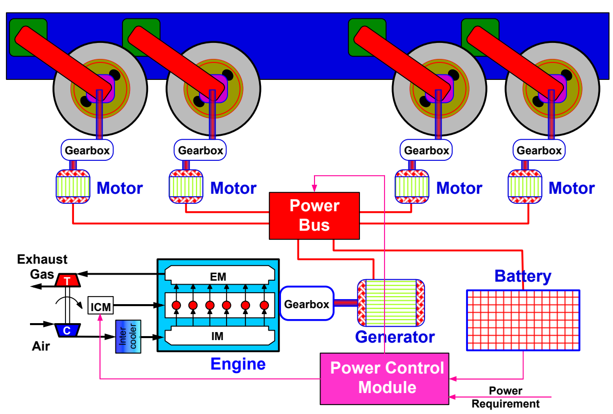

Figure A: Vehicle model configuration(hierarchical bi-level)

Models are developed to simulate the transient response of both a series hybrid and an electric-driven truck at the top (vehicle) level, and the response of variable height suspensions at the bottom (system) level. The models at both the vehicle and system levels are tailored to fit the target cascading process. Automated modeling techniques are used to develop vehicle dynamics models that are computationally efficient, accurate, and described by physical parameters. Baseline designs are chosen to be consistent with current practice, whereas vehicle targets are defined commensurate with desired advanced performance.

At the vehicle level, responses $\mathbf{R}_v$ must match desired design specifications $\mathbf{T}_v$. These responses are assumed to be functions of vehicle design variables $\mathbf{x}_v$ and system responses $\mathbf{R}_{s_i}$, for $i = 1,\ldots,n_s$ systems, i.e., $\mathbf{R}_v = \mathbf{r}_v(\mathbf{x}_v, \mathbf{R}_{s_1},\ldots, \mathbf{R}_{s_{ns}})$. To determine target values for system responses $\mathbf{R}_{s_i}$ and vehicle design variables $\mathbf{x}_v$ a minimum deviation optimization problem is formulated as follows:

$$\begin{aligned}
&\text{Min} \quad \left\| \mathbf{R}_v - \mathbf{T}_v \right\| + \varepsilon_v^R \\
&\text{with respect to} \\
&\mathbf{x}_v, \mathbf{R}_{s_1}, \cdots, \mathbf{R}_{s_{n_s}}, \varepsilon_v^R \\
&\text{subject to} \\
&\sum_{i=1}^{n_s} \left\| \mathbf{R}_{s_i} - \mathbf{R}_{s_i}^L \right\| \le \varepsilon_v^R \\
&\mathbf{g}_v(\mathbf{R}_v, \mathbf{x}_v) \le 0 \\
&\mathbf{h}_v(\mathbf{R}_v, \mathbf{x}_v) \le 0
\end{aligned}$$

where $\mathbf{x}_v$ is the vector of design variables exclusively associated with the vehicle, $\mathbf{R}_v$ is the vector of vehicle responses, $\mathbf{R}_{s_i}$ is the vector of responses for the *i-th* system making up the vehicle, ε_v^R is a tolerance variable for coordinating system responses, $\mathbf{T}_v$ is the vector of vehicle design targets or specifications, $\mathbf{R}_{s_i}^L$ is the vector of system response values passed up to the vehicle from the *i-th* system, and $\mathbf{g}_v$ and $\mathbf{h}_v$ are vector functions representing vehicle design constraints.

Once the optimal values of the system level responses $\mathbf{R}_{s_i}$, $i = 1,\ldots,n_s$, are determined by solving the vehicle-level design problem shown above, they are cascaded down to the system level as target values $\mathbf{R}_{s_i}^U$. At the system level, n_s individual minimum deviation optimization problems are formulated to determine the system design variables $\mathbf{x}_{s_i}$. System responses are assumed to be functions of system design variables alone, i.e., $\mathbf{R}_{s_i} = \mathbf{r}_{s_i}(\mathbf{x}_{s_i})$, given the two-level hierarchy assumption. The minimum deviation optimization problems for the $i = 1,\ldots,n_s$ systems are formulated as follows:

$$\begin{aligned}
&\text{Min} \quad \left\| \mathbf{R}_{s_i} - R_{s_i}^U \right\| \\
&\text{with respect to } \mathbf{x}_{s_i} \\
&\text{subject to} \\
&\mathbf{g}_{s_i}(\mathbf{R}_{s_i}, \mathbf{x}_{s_i}) \le 0 \\
&\mathbf{h}_{s_i}(\mathbf{R}_{s_i}, \mathbf{x}_{s_i}) \le 0
\end{aligned}$$

The analytical target cascading process iterates between the vehicle- and system-level design problems. At each iteration, values of $\mathbf{R}_{s_i}^L$ and $\mathbf{R}_{s_i}^U$ determined at the system and vehicle levels, respectively, are passed up and down to the other level design problem(s).

For target cascading, the models are decomposed into an integrated vehicle model at the top level and four copies of a suspension system model at the low level, see Figure B. The top level vehicle model predicts the vehicle responses $\mathbf{R}_v$, whereas the suspension model predicts the system responses $\mathbf{R}_{s_i}$, $i = 1, 2, 3, 4$.

Two sets of targets were used for a new concept truck design study. In the first part of the study, the goal was to achieve a fuel efficiency that would be better by at least 50% than the baseline. Fuel economy was computed at both the Gross Vehicle Weight (GVW, truck weight plus payload) and the Gross Combined Vehicle Weight (GCVW, GVW plus trailer). Performance metrics were to be maintained at the same levels as those of the baseline. In the second part of the study, specific numerical values were not defined as targets; instead, it was attempted to improve all metrics as much as possible.

Attributes of interest for both the series hybrid and the electric drive are compared in Figure C for the first set of targets. Results are normalized such that 1.0 represents the target values. The first three targets are achieved. The last three responses are improved compared to the baseline design but do not achieve the targets. The maximum speed

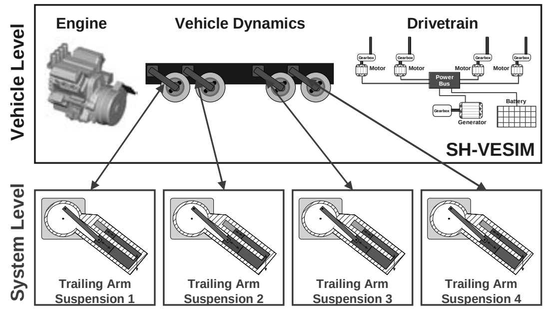

Figure B: Hierarchy of models for target cascading

degradation for the series hybrid configuration comes very close to the target. Note that responses that achieve or exceed their targets become “neutral” to the optimizer, i.e., they do not contribute to the objective

Thus, responses estimated for GVW achieve their targets, while responses estimated for GCVW do not. One can deduce that performance targets at GCVW were too stringent. The same trend is observed for the second set of targets presented in Figure D. Results are normalized with respect to the first set of targets for the sake of comparison. In this case the optimizer tries to improve all responses as much as possible without limits. This leads to a dramatic increase of the ride quality. Hybrid vehicle fuel economy shows more modest, but tangible further improvements over the conventional at both GVW and GCVW. Performance metrics of the hybrid are maintained at about the same level as in the previous case. For the electric drive propulsion system only the ride quality displays significant further improvement compared to the optimization performed for the specific targets, while all other responses remain about the same.

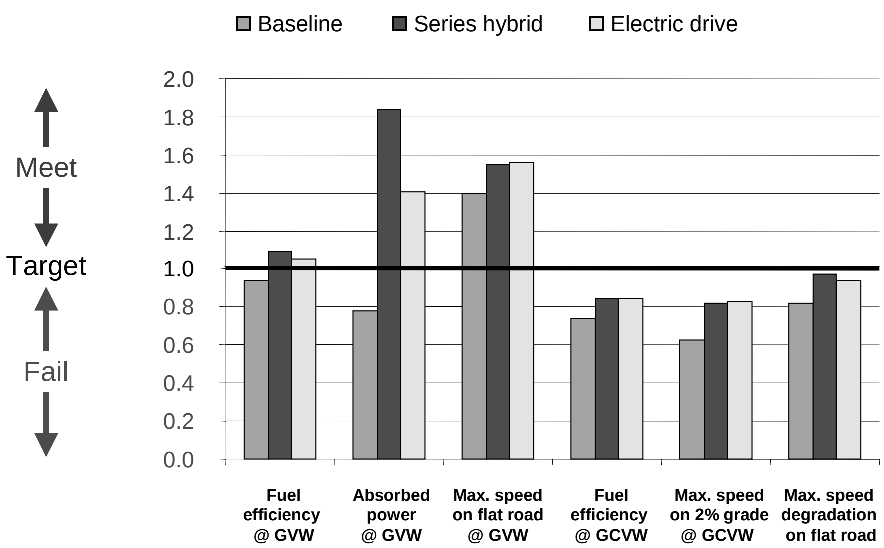

Figure C: Achievement of specific targets

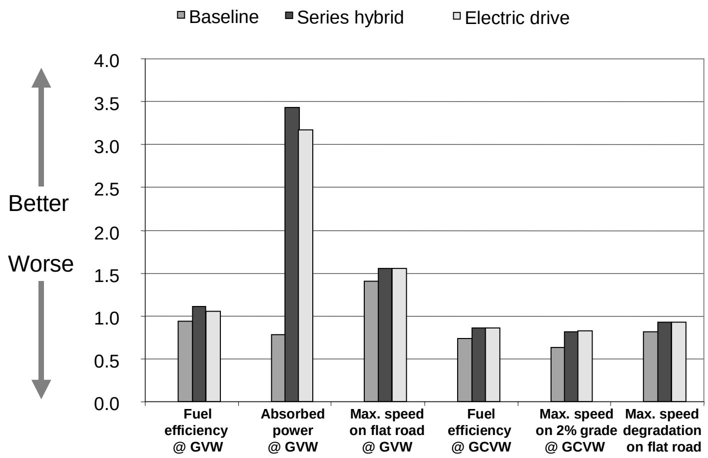

Figure D: Achievement of maximal improvement targets