# ANALYTICAL TARGET CASCADING IN PRODUCT DEVELOPMENT

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ABSTRACT

*Setting and achieving appropriate product targets is the most critical element of the product development process from both a managerial and technical viewpoint. Target cascading is a systematic process that propagates the desired top-level design targets to appropriate specifications for a product's subsystems and components in a consistent and efficient manner. Design of modern complex artifacts utilizes performance analyses based on computer simulations or "virtual protoyping." If such analysis models are available to evaluate the outcomes of the relevant design decisions, analytical target cascading can be formalized as a hierarchical multilevel optimization problem. The mathematical formulation of the analytical target cascading process is reviewed along with some case studies from automotive vehicle product development. The generality of the approach is shown through an extension to the design of product families.*

## INTRODUCTION

Designing products is always an exercise in predicting the future. During product development we make decisions based on our ability to predict how these decisions will affect the future performance of the product from a technical or market viewpoint. Our design intent is manifested through the setting of targets that we believe the product must achieve. Target setting has long preoccupied both active managers and organizational management theorists (see, e.g., Carroll and Tosi 1973, Locke and Latham 1990, Welch 1996).

A complex product is an assembly of systems, subsystems, components, etc., which we can collectively call the product's elements. Once some overall (performance) targets are set, the challenge is how to translate these targets into specifications or targets for all of the product's elements. A hierarchy is typically assumed in the synthesis of complex products, and so this target translation can be seen as a cascading of targets down the hierarchy. Such cascading must be done so that the individual targets are compatible with each other and, if met, they guarantee that the overall product

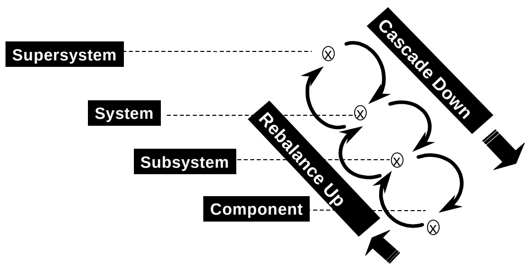


Figure 1. The target cascading process

targets are also met. This is shown schematically in Figure 1 with a four-level hierarchy. If such a task is accomplished, each element of the product can be further designed independently, while local element targets are met. A concurrent design process is thus enabled.

Most product architectures support some sort of hierarchical partitioning. Yet linking among the various elements is clearly present, which is what makes the problem really difficult. Such quantities shared by one or more elements are called linking variables. Values for them must be also set during the target cascading process and preserved during subsequent local design work, so that consistency and concurrency can be maintained. In the earlier formulations of the target cascading problem we will assume a hierarchical structure where linking variables exist only among "children" from the same "parent," as in Figure 2. In the final section on product families we will see how this assump-

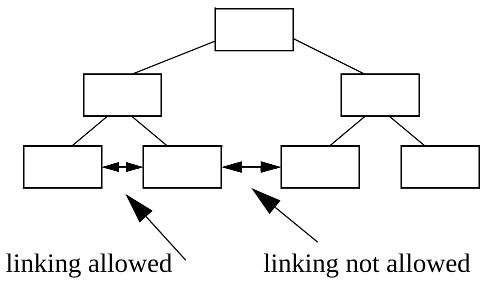


Figure 2. Product hierarchical structure assumption

tion can be relaxed.

When the design decisions can be modelled analytically, the process can be formalized in a multilevel optimization problem referred to as Analytical Target Cascading (ATC). The solution of such a partitioned multilevel problem is obtained by solving the individual subproblems and matching their solution in a process referred to as a coordination strategy. The overall ATC process then has the following steps:

- Assemble models
- Set targets
- Define system hierarchy (partitioning)
- Formulate ATC problem
- Solve ATC problem (coordination)
- Examine target achievement tradeoffs

The last bullet point above is an important one: Targets are set at the top level along with constraints on design feasibility for each element. There is no guarantee that the targets can be physically met under the given constraints. At the conclusion of a successful ATC study one may have to see what targets have not been met and what prevents them from being met. Tradeoffs among top targets may be necessary or design constraints may have to be relaxed. Part of the appeal of the ATC process is that such conflicts and tradeoffs can be quantified early and addressed rationally.

In the remainder of this article we will present the mathematical formulation of ATC as a hierarchical optimization process along with two ATC studies in automotive vehicle product development. We will then show how the concept can be extended to multiple product variants within a family. The exposition is condensed and more details can be found in cited sources. The most comprehensive treatment to date can be found in Kim (2001).

## ANALYTICAL TARGET CASCADING AS A HIERARCHICAL OPTIMIZATION PROCESS

Analytical target cascading is based on the premise that the performance of a system element can be modelled analytically. The term "analytically" here means any functional representation that computes responses for some given values of the element's design variables. Models can be explicit equations, simulations, data-fitting or other surrogate models. The complexity and fidelity of the required analysis models depends on the stage of the product development process that the ATC formalism is used. We should try to implement ATC as early as possible. Then the models needed should be the simplest possible that relate targets to design decisions and that account for the important interactions among the product's elements. .

In the modeling hierarchy of the ATC process two types of models are identified: *optimal design models* P and *analysis models r* (see also, Papalambros and Wilde 2000). An optimal design model requires analysis models to evaluate its functions. The analysis models take values of design variables and parameters, as well as of lower level responses, and return values of responses for design problems at a given level. A response is defined as an output from an analysis model, and a linking variable is defined as a design variable common between two or more design problems.

The following symbols and associated terminology is used to define this process formally.

$P_o$ original design optimization problem
$P_S$ supersystem level ATC optimization problem
$P_s$ system level ATC optimization problem
$P_{ss}$ subsystem level ATC optimization problem
$\mathbf{R}^L$ target values of **R** from a lower level
$\mathbf{R}^U$ target values of **R** from an upper level

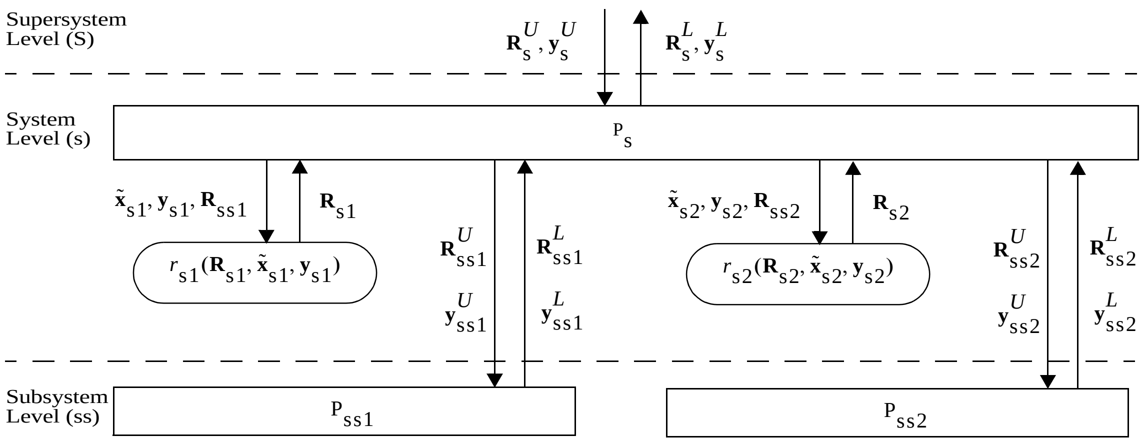


Figure 3. Flows from and into the system-level design problem (one system and two subsystems).

| | |
|---|---|
| **R** | responses computed by analysis models |
| **T** | design targets |
| $f$ | objective for the design problem |
| **g** | inequality constraints for the design problem |
| **h** | equality constraints for the design problem |
| $r$ | response function |
| **x** | vector of all design variables $(\tilde{\mathbf{x}}, \mathbf{y})$ |
| $\tilde{\mathbf{x}}$ | local design variables |
| $\mathbf{x}^{min}$ | lower bound of **x** |
| $\mathbf{x}^{max}$ | upper bound of **x** |
| **y** | linking design variables |
| $\mathbf{y}^L$ | target values of **y** from a lower level |
| $\mathbf{y}^U$ | target values of **y** from an upper level |
| $\varepsilon_{\mathbf{R}}$ | target deviation tolerance for responses |
| $\varepsilon_{\mathbf{y}}$ | target deviation tolerance for linking variables |

Figure 3 shows interactions between analysis models (rectangles with rounded corners) and design models (rectangles with sharp corners) at the system level. Targets for system responses and system linking variables $\mathbf{R}_s^U$ and $\mathbf{y}_s^U$ are passed down from the supersystem level. After solving the system design problem, target values for system responses and system linking variables $\mathbf{R}_s^L$ and $\mathbf{y}_s^L$ are passed up to the supersystem level. Likewise, for subsystem 1, $\mathbf{R}_{ss1}^U$ and $\mathbf{y}_{ss1}^U$ are passed down as targets from the system-level design problem, whereas $\mathbf{R}_{ss1}^L$ and $\mathbf{y}_{ss1}^L$ are returned to the system level. Responses from subsystem 1, $\mathbf{R}_{ss1}$, system local design variables $\tilde{\mathbf{x}}_{s1}$, and system linking variables $\mathbf{y}_{s1}$ are input to the analysis model $r_{s1}$, whereas system responses $\mathbf{R}_{s1}$ are returned as output.

The original target problem $P_0$ can be stated as follows: Find a design that minimizes the deviations between the overall design targets and responses, while satisfying all constraints, Eq. (1). The objective function is the discrepancy between targets **T** and responses **R** obtained from analysis models $\mathbf{r}(\mathbf{x})$; **g** and **h** are inequality and equality design constraint vectors with sizes $m_i, m_e$, and the design variables **x** are defined within lower and upper bounds, $\mathbf{x}^{min}$ and $\mathbf{x}^{max}$.

$$
\begin{aligned}
P_0:\ & \underset{\mathbf{x}}{\text{Minimize}} \quad \|\mathbf{T}-\mathbf{R}\| \\
& \text{where} \quad \mathbf{R} = \mathbf{r}(\mathbf{x}) \\
& \text{subject to} \\
& g_i(\mathbf{x}) \le 0 \qquad\qquad i = 1, \ldots, m_i \\
& h_j(\mathbf{x}) = 0 \qquad\qquad j = 1, \ldots, m_e \\
& x_k^{min} \le x_k \le x_k^{max} \qquad k = 1, \ldots, n
\end{aligned} \tag{1}
$$

This model is now partitioned into a hierarchical form that accounts for linking variables. Note again that linking is allowed only between elements of the same parent in order to preserve the hierarchy assumption. At each level $i$, we define a set $E_i$ in which all the elements of the level are included. For each element $j$ in the set $E_i$, a children set $C_{ij}$ is defined, which includes the elements of the set $E_{i+1}$ that are children of the element. The generic target matching problem $P_{ij}$ for the $j$-th element at the $i$-th level is then formulated as follows.

$$
\begin{aligned}
& \underset{\bar{\mathbf{x}}_{ij}}{\text{Minimize}} \quad \|\mathbf{R}_{ij}-\mathbf{R}_{ij}^U\| + \|\mathbf{y}_{ij}-\mathbf{y}_{ij}^U\| + \varepsilon_{\mathbf{R}_{ij}} + \varepsilon_{\mathbf{y}_{ij}} \\
& \text{subject to} \\
& \sum_{k \in C_{ij}} \|\mathbf{R}_{(i+1)k}-\mathbf{R}_{(i+1)k}^L\| \le \varepsilon_{\mathbf{R}_{ij}} \\
& \sum_{k \in C_{ij}} \|\mathbf{y}_{(i+1)k}-\mathbf{y}_{(i+1)k}^L\| \le \varepsilon_{\mathbf{y}_{ij}} \\
& g_{ij}(\mathbf{R}_{ij}, \mathbf{x}_{ij}, \mathbf{y}_{ij}) \le \mathbf{0} \\
& h_{ij}(\mathbf{R}_{ij}, \mathbf{x}_{ij}, \mathbf{y}_{ij}) = \mathbf{0}
\end{aligned} \tag{2}
$$

The symbols in this equation are defined below.

$C_{ij} = \{k_1, \ldots, k_{C_{ij}}\}$

$\mathbf{R}_{ij} = r_{ij}\left(\mathbf{R}_{(i+1)k_1}, \ldots, \mathbf{R}_{(i+1)k_{C_{ij}}}, \mathbf{x}_{ij}, \mathbf{y}_{ij}\right)$

$\bar{\mathbf{x}}_{ij} = \left[\mathbf{x}_{ij}, \mathbf{y}_{ij}, \mathbf{y}_{(i+1)k_1}, \ldots, \mathbf{y}_{(i+1)k_{C_{ij}}}, \mathbf{R}_{(i+1)k_1}, \ldots, \mathbf{R}_{(i+1)k_{C_{ij}}}, \varepsilon_{\mathbf{R}_{ij}}, \varepsilon_{\mathbf{y}_{ij}}\right] \in \Re^{n_{ij} + l_{ij} + 2 + \sum_k l_{(i+1)k} + \sum_k d_{(i+1)k}}$

is the vector of all (optimization) variables,

$\mathbf{x}_{ij} \in \Re^{n_{ij}}$ is the vector of local variables,

$\mathbf{y}_{ij} \in \Re^{l_{ij}}$ is the vector of linking variables,

$\mathbf{R}_{ij} \in \Re^{d_{ij}}$, is the vector of local responses; as shown above, and it is a function (e.g., the result of a simulation) of local, linking, and children response optimization variables: $r_{ij}: \Re^{n_{ij} + l_{ij} + \sum_k d_{(i+1)k}} \to \Re^{d_{ij}}$,

$\varepsilon_{\mathbf{R}_{ij}}$ is the tolerance for coordinating the response optimization variables of the children of the element,

$\varepsilon_{\mathbf{y}_{ij}}$ is the tolerance for coordinating the linking optimization variables of the children of the element,

$\mathbf{R}_{ij}^{U} \in \Re^{d_{ij}}$ is the vector of response values cascaded to the element from its parents, and at the top level $(i, j = 0)$, $\mathbf{R}_{ij}^{U} = \mathbf{T}$ is defined as the overall system target,

$\mathbf{y}_{ij}^{U} \in \Re^{l_{ij}}$ is the vector of linking variable values cascaded to the element from its parent,

$\mathbf{R}_{(i+1)k}^{L} \in \Re^{d_{(i+1)k}}$ is the vector of response variable values cascaded to the element from its *k*-th child,

$\mathbf{y}_{(i+1)k}^{L} \in \Re^{l_{(i+1)k}}$ is the vector of linking variable values cascaded to the element from its *k*-th child,

$g_{ij}:\Re^{d_{ij}+n_{ij}+l_{ij}} \to \Re^{v_{ij}}$ and $h_{ij}:\Re^{d_{ij}+n_{ij}+l_{ij}} \to \Re^{w_{ij}}$ are vector functions representing inequality and equality design constraints, respectively, and

$\| \ \|$ is some norm, for example the Eucledian one.

This elaborate mathematical statement is necessary for describing the entire problem in a very general way that includes cascading targets across multiple products, as will be shown later below.

Some brief comments on this mathematical formulation are in order. Multilevel systems engineering concepts are well developed (see, e.g., IEEE 1998) and multilevel optimization methods have been well studied (see, e.g., Sobieski et al. 1987, Cramer et al. 1994). The ATC has a strong resemblance to collaborative optimization (Braun 1996, Braun et al. 1996, Tappeta and Renaud 1997) in using deviation norms as objectives. Happily, ATC does not suffer from some theoretical difficulties of collaborative optimization (Alexandrovand Lewis 2000) and can be shown to be a special case of overlapping hierarchical coordination that has proven global convergence (Michelena et al. 1999, Park et al. 2001, Kim 2001).

## CASCADING VEHICLE RIDE AND HANDLING TARGETS

We will now employ the ATC process to the chassis system of a typical sport-utility vehicle (SUV) to establish ride and handling targets. The study is described more fully in Kim et al. (2001). Figure 4 gives a schematic of the information flow. The "super-system" is here the vehicle design problem, which contains a "half-car" analysis model and a "bicycle" analysis model. System-level analysis models for the front and rear suspensions are multibody-dynamics models of short-long arm suspensions. The tire models call the tire stiffness equations described in Wong (1993)

The vehicle-level targets to be met are: First natural frequency of front and rear suspension ($\omega_{sf}$, $\omega_{sr}$); second natural frequency (wheel hop frequency) of front and rear suspension ($\omega_{tf}$, $\omega_{tr}$); pitch natural frequency ($\omega_{p}$); and understeer gradient ($k_{us}$). These quantities are the target vector for which the half-car and bicycle analysis models generate responses. The computed variable values are cascaded to the system-level design problem as targets. For example, the front suspension stiffness is changed to achieve the desired first natural frequency for the front suspension.

Once an optimal value of the stiffness is found at the vehicle level, that value becomes a *target* at the system-level design problem, where the suspension design variables (coil spring stiffness and free length) are adjusted to achieve a suspension configuration with a stiffness as close to the cascaded target value as possible. The computed value of, say, the coil spring stiffness that gives the optimal suspension stiffness is cascaded to the subsystem level as target. The spring subsystem variables are optimized to achieve minimal deviation from the target assigned for the coil spring stiffness. Similarly, optimal tire stiffness and cornering stiffness calculated at the vehicle level become targets at the system level, where system-level variables (tire inflation pressure) are changed to meet the stiffness targets. In the tire design models for vertical and cornering stiffnesses, the inflation pressure is common, i.e., the inflation pressure is a linking variable

After vehicle design targets are cascaded down to the lowest level, the resulting design decisions are passed back up. Matching target values and computer responses exactly in one "down-and-up" cycle will not happen except by coincidence. Thus an iterative process working in both a top-down and a bottom-up fashion is needed to lead to a consistent design or to uncover potential incompatibilities among targets and design constraints.

In the models that follow we will show how the general model of Eq. (2) is implemented at the different levels.

The following symbols are used for the physical quantities involved in the models.

$C_{\alpha f}$ tire lateral cornering stiffnesses for front
$C_{\alpha r}$ tire lateral cornering stiffnesses for rear
$K_{sf}$ stiffness of front suspensions
$K_{sr}$ stiffness of rear suspensions
$K_{tf}$ stiffness of front tires
$K_{tr}$ stiffness of rear tires

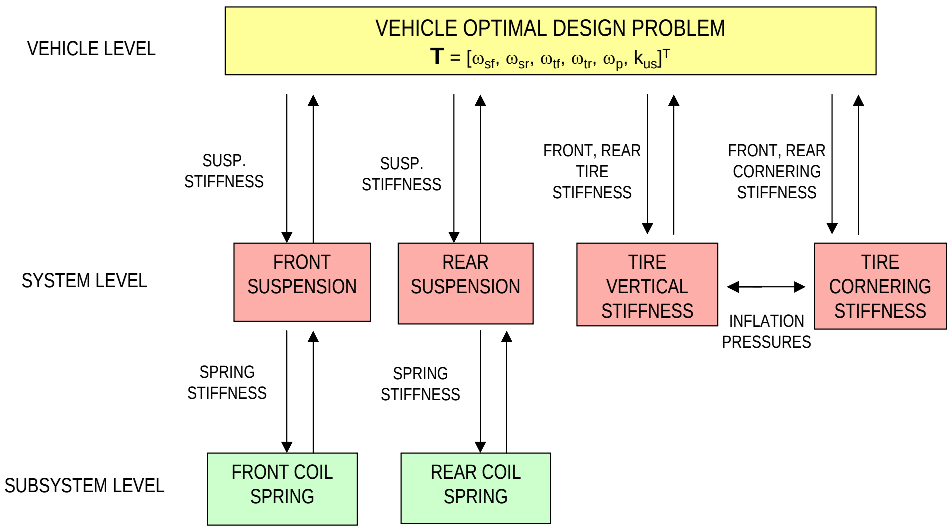


Figure 4. SUV chassis design problem structure

| | |
|---|---|
| $P_{if}$ | front tire inflation pressure |
| $P_{ir}$ | rear tire inflation pressure |
| $a$ | distance from vehicle center of mass to front axle |
| $b$ | distance from vehicle center of mass to rear axle |
| $k_{us}$ | understeer gradient |
| $u$ | vehicle forward velocity |
| $\omega_p$ | pitch natural frequency |
| $\omega_{sf}$ | first natural frequency of front suspension |
| $\omega_{sr}$ | first natural frequency of rear suspension |
| $\omega_{tf}$ | second natural frequency (wheel hop frequency) of front suspension |
| $\omega_{tr}$ | second natural frequency (wheel hop frequency) of rear suspension |
| $zsmax$ | suspension deflection at jounce bumper contact |

Vehicle Level Models

At the top level of the vehicle hierarchy the problem is stated as follows:

$$P_v: \ \text{Minimize}_{\tilde{\mathbf{x}}_v, \mathbf{y}_s, \mathbf{R}_s, \varepsilon_\mathbf{R}, \varepsilon_\mathbf{y}} \ \|\mathbf{R}_v - \mathbf{T}_v\| + \varepsilon_\mathbf{R} + \varepsilon_\mathbf{y}$$

$$\text{where} \quad \mathbf{R}_v = r_v(\mathbf{R}_s, \tilde{\mathbf{x}}_v)$$

subject to

$$\|\mathbf{R}_s - \mathbf{R}_s^L\| \le \varepsilon_\mathbf{R}, \quad \|\mathbf{y}_s - \mathbf{y}_s^L\| \le \varepsilon_\mathbf{y} \tag{3}$$

$$\mathbf{g}_v(\mathbf{R}_v, \tilde{\mathbf{x}}_v) \le \mathbf{0}, \ \mathbf{h}_v(\mathbf{R}_v, \tilde{\mathbf{x}}_v) = \mathbf{0}$$

$$\tilde{\mathbf{x}}_v^{min} \le \tilde{\mathbf{x}}_v \le \tilde{\mathbf{x}}_v^{max}$$

In this implementation we define

$$\|\mathbf{y}_s - \mathbf{y}_s^L\| \equiv \frac{1}{p}(\|\mathbf{y}_s - \mathbf{y}_{s1}^L\| + \ldots + \|\mathbf{y}_s - \mathbf{y}_{si}^L\| + \ldots + \|\mathbf{y}_s - \mathbf{y}_{sp}^L\|). \tag{4}$$

where $\Psi$ is an averaging function and $\mathbf{y}_{si}^L$ is a system linking variable calculated at the system optimal design problem $i$.

The five ride quality targets involve the half-car model of Figure 5. The target frequencies can be calculated in closed form as functions of sprung mass ($M_s$), front and rear unsprung masses ($M_{usf}$, $M_{usr}$), and suspension stiffnesses. The sprung and unsprung masses are assumed to be prescribed *a priori*, and are fixed design parameters. The vehicle body is treated as a single rigid body mass.

Table 1 summarizes the vehicle-level variables, responses, and the system-level linking variables and responses corresponding to the ATC formulation at the vehicle level. The handling target is the understeer gradient $k_{us}$, a measure of the magnitude and direction of the steering input for a vehicle to track a curve of constant radius $R$ with forward velocity $u$. For the purpose of understeer analysis, it is convenient to represent the vehicle by the bicycle model shown in Figure 6. The understeer gradient is a function of $a$ and $b$ and of the front and rear tire lateral cornering stiffnesses $C_{\alpha f}$ and $C_{\alpha r}$.

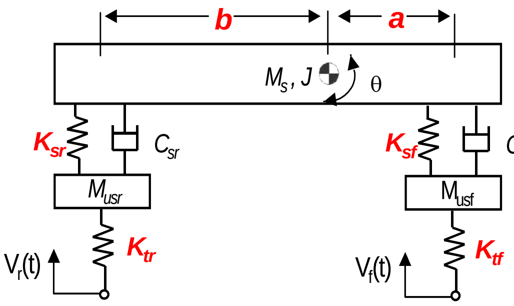


Figure 5. Half-Car model

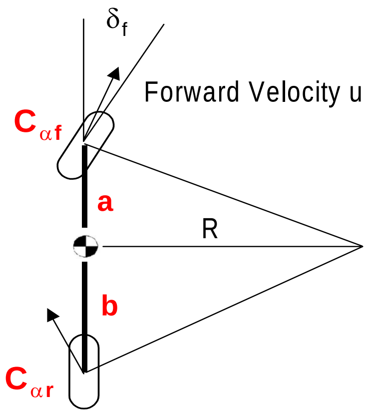


Figure 6. Cornering of a bicycle model

Table 1: Responses and variables at the vehicle level

| Design problem | $P_v$ |
|---|---|
| Responses ($\mathbf{R}_v$) | $\omega_{sf}, \omega_{sr}, \omega_{tf}, \omega_{tr}, \omega_p, k_{us}$ |
| Local variables ($\tilde{\mathbf{x}}_v$) | $a, b$ |
| System-level linking variables ($\mathbf{y}_s$) | $P_{if}, P_{ir}$ |
| Responses from system level ($\mathbf{R}_s$) | $K_{sf}, K_{sr}, K_{tf}, K_{tr}, C_{\alpha f}, C_{\alpha r}$ |

The TC design problem at the vehicle level is stated in Eq. (5).

$P_v$:

$$\text{Minimize} \left\|\omega_{sf} - \omega_{sf}^U\right\| + \left\|\omega_{sr} - \omega_{sr}^U\right\| + \left\|\omega_{tf} - \omega_{tf}^U\right\| + \left\|\omega_{tr} - \omega_{tr}^U\right\| + \left\|\omega_p - \omega_p^U\right\| + \left\|k_{us} - k_{us}^U\right\| + \varepsilon_{\mathbf{R}} + \varepsilon_{\mathbf{y}}$$

with respect to

$$(\omega_{sf}, \omega_{sr}, \omega_{tf}, \omega_{tr}, \omega_p, k_{us}, a, b)$$

$$(K_{sf}, K_{sr}, K_{tf}, K_{tr}, C_{\alpha f}, C_{\alpha r}, P_{if}, P_{ir})$$

$$(\varepsilon_{\mathbf{R}}, \varepsilon_{\mathbf{y}}) = (\varepsilon_{R1}, \varepsilon_{R2}, \varepsilon_{R3}, \varepsilon_{R4}, \varepsilon_{R5}, \varepsilon_{R6}, \varepsilon_{y1}, \varepsilon_{y2})$$

where

$$\omega_{sf} = \sqrt{\frac{K_{sf}}{M_{sf}}} \quad \omega_{sr} = \sqrt{\frac{K_{sr}}{M_{sr}}}$$

$$\omega_{tf} = \sqrt{\frac{K_{tf}}{M_{usf}}} \quad \omega_{tr} = \sqrt{\frac{K_{tr}}{M_{usr}}}$$

$$\omega_p = \sqrt{\frac{K_p}{J}} \quad k_{us} = \frac{Mb}{LC_{\alpha f}} - \frac{Ma}{LC_{\alpha f}}$$

$$K_p = \frac{2(a+b)}{\dfrac{(K_{sf}+K_{tf})}{aK_{sf}K_{tf}} + \dfrac{(K_{sr}+K_{tr})}{bK_{sr}K_{tr}}} \tag{5}$$

subject to

$$\left\|K_{sf} - K_{sf}^L\right\| \le \varepsilon_{R1}, \ \left\|K_{sr} - K_{sr}^L\right\| \le \varepsilon_{R2}$$

$$\left\|K_{tf} - K_{tf}^L\right\| \le \varepsilon_{R3}, \ \left\|K_{tr} - K_{tr}^L\right\| \le \varepsilon_{R4}$$

$$\left\|C_{\alpha f} - C_{\alpha f}^L\right\| \le \varepsilon_{R5}, \ \left\|C_{\alpha r} - C_{\alpha r}^L\right\| \le \varepsilon_{R6}$$

$$\frac{1}{2}\left(\left(P_{if} - P_{if}^L\Big|_{vert}\right)^2 + \left(P_{if} - P_{if}^L\Big|_{corn}\right)^2\right) \le \varepsilon_{y1}$$

$$\frac{1}{2}\left(\left(P_{ir} - P_{ir}^L\Big|_{vert}\right)^2 + \left(P_{ir} - P_{ir}^L\Big|_{corn}\right)^2\right) \le \varepsilon_{y2}$$

$$a^{min} \le a \le a^{max}$$

$$b^{min} \le b \le b^{max}$$

System Level Models

The system-level problem is given in Eq. (6).

$$\begin{aligned}
\mathbf{P}_s:\quad & \text{Minimize} \quad \left\|\mathbf{R}_s - \mathbf{R}_s^U\right\| + \left\|\mathbf{y}_s - \mathbf{y}_s^U\right\| + \varepsilon_{\mathbf{R}} + \varepsilon_{\mathbf{y}} \\
& \text{with respect to} \quad \tilde{\mathbf{x}}_s, \mathbf{y}_s, \mathbf{y}_{ss}, \mathbf{R}_{ss}, \varepsilon_{\mathbf{R}}, \varepsilon_{\mathbf{y}} \\
& \text{where} \quad \mathbf{R}_s = r_s(\mathbf{R}_{ss}, \tilde{\mathbf{x}}_s, \mathbf{y}_s) \\
& \text{subject to} \\
& \left\|\mathbf{R}_{ss} - \mathbf{R}_{ss}^L\right\| \le \varepsilon_{\mathbf{R}}, \quad \left\|\mathbf{y}_{ss} - \mathbf{y}_{ss}^L\right\| \le \varepsilon_{\mathbf{y}} \\
& \mathbf{g}_s(\mathbf{R}_s, \tilde{\mathbf{x}}_s, \mathbf{y}_s) \le \mathbf{0}, \quad \mathbf{h}_s(\mathbf{R}_s, \tilde{\mathbf{x}}_s, \mathbf{y}_s) = \mathbf{0} \\
& \tilde{\mathbf{x}}_s^{min} \le \tilde{\mathbf{x}}_s \le \tilde{\mathbf{x}}_s^{max}, \mathbf{y}_s^{min} \le \mathbf{y}_s \le \mathbf{y}_s^{max}
\end{aligned} \tag{6}$$

The objective function minimizes the discrepancy between current system level responses $\mathbf{R}_s$ and the targets set at the upper (vehicle) level $\mathbf{R}_s^U$, as well as between system linking variables $\mathbf{y}_s$ and the targets set at the vehicle level $\mathbf{y}_s^U$. Therefore, $\mathbf{R}_s^U$ and $\mathbf{y}_s^U$ are determined by solving Eq. (3). Target deviation tolerances are minimized to achieve consistent design with minimum discrepancies between the subsystem level responses $\mathbf{R}_{ss}$ and the target responses $\mathbf{R}_{ss}^L$ from the lower (subsystem) design problem, as well as between the subsystem level linking variables $\mathbf{y}_{ss}$ and the target values $\mathbf{y}_{ss}^L$ from the subsystem design problem.

In the chassis problem there are four design models at the system level: front and rear suspension models, and tire models for vertical and cornering stiffness. The design problem for the front suspension model is as follows.

$$\begin{aligned}
& \mathrm{P}_{s1}: \\
& \text{Minimize} \quad \left\|K_{sf} - K_{sf}^U\right\| + \varepsilon_{R1} + \varepsilon_{R2} + \varepsilon_{R3} \\
& \text{with respect to} \quad (zsmax_f, K_{Lf}, K_{Bf}, L_{0f}, \varepsilon_{R1}, \varepsilon_{R2}, \varepsilon_{R3}) \\
& \text{where} \quad K_{sf} = \mathrm{AutoSim}(zsmax_f, K_{Lf}, K_{Bf}, L_{0f}) \\
& \text{subject to} \\
& \left\|K_{Lf} - K_{Lf}^L\right\| \le \varepsilon_{R1} \qquad K_{Lf}^{min} \le K_{Lf} \le K_{Lf}^{max} \\
& \left\|K_{Bf} - K_{Bf}^L\right\| \le \varepsilon_{R2} \qquad K_{Bf}^{min} \le K_{Bf} \le K_{Bf}^{max} \\
& \left\|L_{0f} - L_{0f}^L\right\| \le \varepsilon_{R3} \qquad L_{0f}^{min} \le L_{0f} \le L_{0f}^{min} \\
& zsmax_f^{min} \le zsmax_f \le zsmax_f^{max}
\end{aligned} \tag{7}$$

For a given target value for suspension stiffness from the vehicle problem in Eq. (5), the objective is to minimize the discrepancy between target and response. As there is no linking variable at the subsystem level, the term for minimizing the linking variable deviation is not included in the objective function. Besides the original variable bound constraints for suspension design, additional deviation constraints from the subsystem level are included in the constraint set. Deviations for subsystem level responses $K_{Lf}^L, K_{Bf}^L, L_{0f}^L$ are constrained within tolerance.

The rear suspension design model $\mathrm{P}_{s2}$ is the same as for the front except that it has different variable bounds. The tire is represented as a single spring in the half-car model at vehicle level. At the system level, two different aspects of the same tire analysis model, vertical and cornering, are considered, and for each aspect a design problem is formulated. These models are shown in Eq. (8) and Eq. (9).

$$\begin{aligned}
& \mathrm{P}_{s3}: \\
& \text{Minimize} \quad \left\|K_{tf} - K_{tf}^U\right\| + \left\|K_{tr} - K_{tr}^U\right\| \\
& \text{with respect to} \quad (K_{tf}, K_{tr}, P_{if}, P_{ir}) \\
& \text{where} \quad K_{tf} = 0.9((0.1839P_{if} - 9.2605)F_m + 110119) \\
& \qquad K_{tr} = 0.9((0.1839P_{ir} - 9.2605)F_m + 110119) \\
& \qquad F_m = \frac{9.81Mb}{a+b} \\
& \text{subject to} \quad P_{if}^{min} \le P_{if} \le P_{if}^{max} \\
& \qquad P_{ir}^{min} \le P_{ir} \le P_{ir}^{max}
\end{aligned} \tag{8}$$

$$\begin{aligned}
& \mathrm{P}_{s4}: \quad \text{Minimize} \quad \left\|C_{\alpha f} - C_{\alpha f}^U\right\| + \left\|C_{\alpha r} - C_{\alpha r}^U\right\| \\
& \text{with respect to} \quad (C_{\alpha f}, C_{\alpha r}, P_{if}, P_{ir}) \\
& \text{where} \\
& C_{\alpha f} = \\
& F_m\left(-2.668\times10^{-6}P_{if}^2 + 1.605\times10^{-3}P_{if} - 3.86\times10^{-2}\right)\frac{180}{\pi} \\
& C_{\alpha r} = \\
& F_m\left(-2.668\times10^{-6}P_{ir}^2 + 1.605\times10^{-3}P_{ir} - 3.86\times10^{-2}\right)\frac{180}{\pi} \\
& F_m = \frac{9.81Mb}{a+b} \\
& \text{subject to} \\
& P_{if}^{min} \le P_{if} \le P_{if}^{max} \qquad P_{ir}^{min} \le P_{ir} \le P_{ir}^{max}
\end{aligned} \tag{9}$$

Table 2: Responses and variables at the system level

| Design problem | $P_{s1}$ | $P_{s2}$ | $P_{s3}$ | $P_{s4}$ |
|---|---|---|---|---|
| Responses ($\mathbf{R}_s$) | $K_{sf}$ | $K_{sr}$ | $K_{tf}, K_{tr}$ | $C_{\alpha f}, C_{\alpha r}$ |
| Local variables ($\tilde{\mathbf{x}}_s$) | $zsmax_f$ | $zsmax_r$ | N/A | N/A |
| System-level linking variables ($\mathbf{y}_s$) | N/A | N/A | $P_{if}, P_{ir}$ | $P_{if}, P_{ir}$ |
| Responses from subsystem level ($\mathbf{R}_{ss}$) | $K_{Lf}, K_{Bf}, L_{0f}$ | $K_{Lr}, K_{Br}, L_{0r}$ | N/A | N/A |

All responses and variables at the system level are summarized in Table 2.

Subsystem Level Models

The subsystem level problem is stated in Eq. (10).

$$
\begin{aligned}
&P_{ss}: \\
&\text{Minimize}_{\tilde{\mathbf{x}}_{ss}, \mathbf{y}_{ss}} \left\|\mathbf{R}_{ss} - \mathbf{R}_{ss}^U\right\| + \left\|\mathbf{y}_{ss} - \mathbf{y}_{ss}^U\right\| \\
&\text{where} \quad \mathbf{R}_{ss} = r_{ss}(\tilde{\mathbf{x}}_{ss}, \mathbf{y}_{ss}) \\
&\text{subject to} \\
&\quad \boldsymbol{g}_{ss}(\mathbf{R}_{ss}, \tilde{\mathbf{x}}_{ss}, \mathbf{y}_{ss}) \le \mathbf{0}, \quad \boldsymbol{h}_{ss}(\mathbf{R}_{ss}, \tilde{\mathbf{x}}_{ss}, \mathbf{y}_{ss}) = \mathbf{0} \\
&\quad \mathbf{x}_{ss}^{min} \le \mathbf{x}_{ss} \le \mathbf{x}_{ss}^{max} \qquad \mathbf{y}_{ss}^{min} \le \mathbf{y}_{ss} \le \mathbf{y}_{ss}^{max}
\end{aligned}
\tag{10}
$$

At the bottom of the model hierarchy, subsystem design variables are input to the analysis models $r_{ss}$ returning responses to the subsystem level as output. Target deviation tolerance constraints are not used because there are no lower level design models that need to be coordinated.

At the subsystem level below the suspension model, the front and rear coil spring design models minimize the difference between target coil spring stiffness and the response generated by the spring design analysis model. The coil spring design model attempts to minimize an objective function that is a weighted sum of the difference between target and actual linear spring stiffness, bending stiffness, and free length, while satisfying the typical spring design constraints (Shigley and Mischke 1989): maximum shear stress limit, fatigue life limit, bounds on coil and wire diameters, wire diameter must be greater than the pitch, ratio of wire diameter to coil diameter must be limited, and the spring must not be fully compressed at maximum suspension travel.

The detailed model is given in Eq. (11).

$$
\begin{aligned}
&P_{sub1}: \\
&\text{Minimize} \quad \left\|K_{Lf} - K_{Lf}^U\right\| + \left\|K_{Bf} - K_{Bf}^U\right\| + \left\|L_{0f} - L_{0f}^U\right\| \\
&\text{with respect to} \quad (D, d, p) \\
&\text{where } K_{Lf} = \frac{Gd^4}{8D^3\left(\frac{L_{0f} - 3d}{p}\right)} \quad K_{Bf} = \frac{EGd^4}{16D(2G+E)} \\
&\text{subject to} \\
&\quad (F_a + F_m) \times \left(\frac{8D}{\pi d^3} + \frac{4}{\pi d^2}\right) - \frac{S_{su}}{n_s} \le 0 \\
&\quad n_f - \left(\frac{S_{su} S_{se} \pi d^3}{8D}\right) \Big/ \left(\left(\frac{4D}{d} + 2\right) \Big/ \left(\frac{4D}{d} - 3\right) F_a S_{su} \right. \\
&\quad \left. + \left(\frac{2D}{d} + 1\right) \Big/ \left(\frac{2D}{d}\right) F_m S_{se}\right) \le 0 \\
&\quad p - d \le 0 \\
&\quad D^{min} \le D \le D^{max} \qquad d^{min} \le d \le d^{max}
\end{aligned}
\tag{11}
$$

where $L_0$ is spring free length, $G$ is modulus of rigidity of spring material, $n_s$ is the factor of safety in shear, $S_{su}$ is the maximum allowable shear stress, $S_{se}$ is fatigue endurance limit, and $F_a$, $F_m$ are alternating and mean component of spring load.

All models in the ATC formulation have now been determined and the multilevel solution strategy (coordination) can be commenced.

The computational process used was the following. First, the top level vehicle design problem was solved and system level targets were cascaded. Second, four system-level problems were solved independently based on the targets assigned from the top level. Third, subsystem-level problems for the front/rear coil spring design were solved. Based on the subsystem-level responses, system-level design problems for front/rear suspension design were solved again and all the system

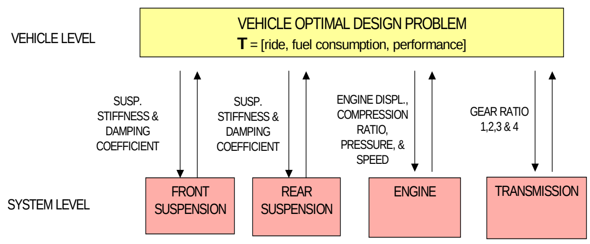


Figure 7. Model hierarchy for Class VI truck.

level responses and linking variables from the four system design problems were fed back to the top level, completing one iteration. Iterations were terminated when the deviation terms became smaller than the tolerances—typically within ten iterations.

Several design scenarios were studied, with different target values, weights on the vehicle targets, and bound values for some of thee constraints. The results are extensive and can be found in the cited reference (Kim et al. 2001). In principle, the final results upon convergence of the target cascading algorithm depend on the relative weights assigned to the targets, on the target values themselves, and on the constraint bounds. Our purpose here was to demonstrate how the ATC models can be assembled in the hierarchical structure postulated in the earlier section.

## "CLASS VI" TRUCK REDESIGN

The ATC methodology is applied to the redesign of an existing medium size truck of "Class VI" in the US market. The baseline configuration consists of a V8 210 HP, direct injection, turbocharged, intercooled diesel engine, a four-speed automatic transmission, leaf-spring suspension systems, and a two-axle rear wheel drive. The truck has 7950 kg gross vehicle weight (GVW), 3.7 m long wheelbase, 5 $m^2$ frontal area, and 0.8 aerodynamic drag coefficient. Vehicle targets are set for fuel efficiency, ride quality, and performance.

### Model Hierarchy

The model hierarchy is defined at vehicle and system levels as in Figure 7. At the vehicle level, the truck is modelled using the Vehicle-Engine SIMulation (VESIM) model (Assanis et al. 1999), which makes possible the evaluation of the overall truck behavior in terms of vehicle dynamics and powertrain fuel efficiency.

Vehicle-level variables include vehicle mass moment of inertia, location of the axles with respect to center of gravity, tire characteristics, suspension characteristics, transmission gear ratios, and engine map (torque as a function of fuel and speed). For the ATC study engine maps within VESIM were computed by a simplified surrogate model based on an artificial neural network that was created keeping displacement, compression ratio, boost engine speed, and inlet manifold pressure as the only design variables.

At the system level, more detailed models represent engine, transmission, and suspension. The engine is modeled using the Turbocharged Diesel Engine Simulation (TDES) code (Assanis et al. 1999). The local engine variables are the same as in the neural net model above. The transmission is modeled as a planetary configuration with the number of teeth for each of four planet gears as design variables. The leaf-spring suspension model accounts for nonlinear stiffness and damping based on Coulomb friction. The design variables are the number of leaves and the width, thickness and curvature radius of each leaf. All system models were implemented in MATLAB.

### Target Cascading Implementation

The computational process is illustrated in Figure 8. The optimizers used are the Sequential Quadratic Programming (SQP) algorithm from the MATLAB Optimization Toolbox (Grace 1994) and the global optimization algorithm DIRECT (Jones et al. 1993) used when discrete variables are present.

Targets are set to improve fuel economy, ride quality, and performance characteristics by at least 20% relative to the existing baseline design, except for the vertical acceleration metric.The driving cycle used for assessing performance and computing fuel economy is

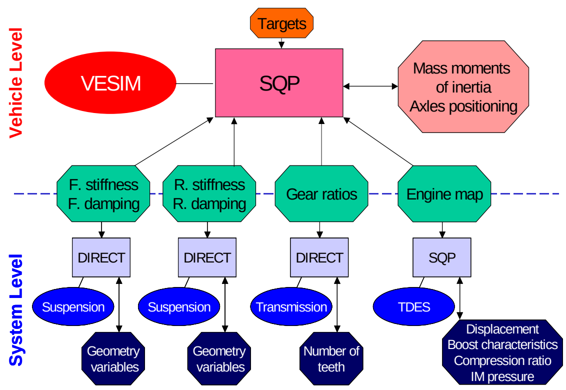


Figure 8. Coordination and information flow for Class VI truck ATC

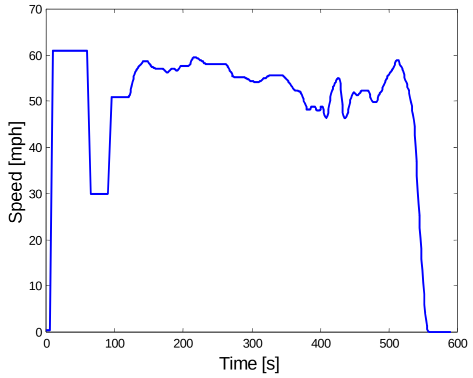


Figure 9. Driving cycle for Class VI truck.

depicted in Figure 9, and is based on US federal highway standards. The design space is also constrained to be within +/-20% of the baseline values. Baseline, target, and final values for the metrics of interest are given in Table 3. Only the vertical acceleration target is achieved and slightly surpassed, but this target was already close to the baseline value. The desired 20% improvement across the board appears too aggressive for the given values and constraints. Nevertheless, significant improvements can be realized with only minor deterioration in the horizontal acceleration. These target achievements can be visualized in the simple chart of Figure 10.

Table 3: Targets and responses for class VI truck

| Metric | Baseline value | Target value | Final value | Improvement |
|---|---|---|---|---|
| Fuel economy [mpg] | 12.27 | 15.5 | 14.42 | 17.5 % |
| Horizontal acceleration [ m/s2] | 44.57 | 35.0 | 45.13 | -1.23 % |
| Vertical acceleration [m/s2] | 1.53 | 1.5 | 1.36 | 12.7 % |
| 0-60 mph time [s] | 35.66 | 29.0 | 34.38 | 3.7 % |
| 30-50 mph time [s] | 16.12 | 13.0 | 15.32 | 5.2 % |

The actual target cascading process is illustrated in Figure 11. The solutions obtained for the cascaded responses after solving the optimization problems at the vehicle and system levels are coordinated in order for the final design to be consistent. While the mismatches for the transmission and suspension characteristics are more visible, the engine maps lie on top of each other. The transmission problems provides a quite interesting example of how an initially inconsistent design becomes consistent: The third gear ratio obtained by solving the initial vehicle level design problem is smaller than the fourth one; this is then corrected at the system level by solving the individual transmission optimal design problem, and so the final design, obtained by solving the top level optimization problem once more, is consistent.

.

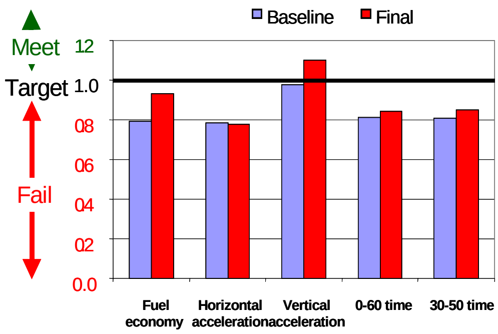


Figure 10. Class VI truck target achievement.

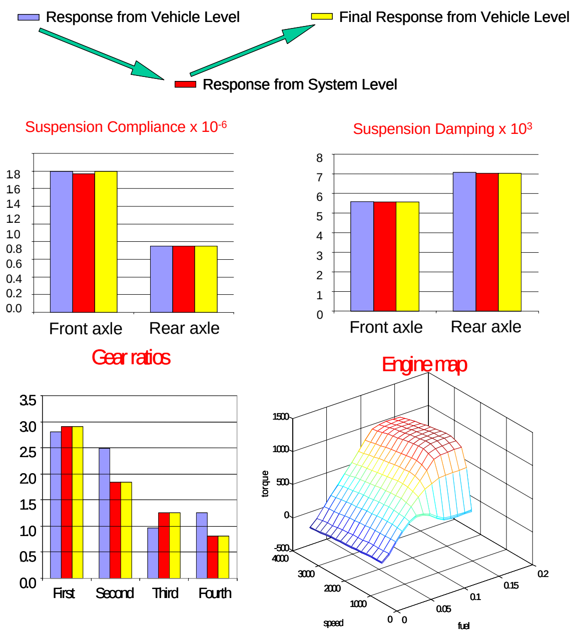


Figure 11. Class VI truck target cascading process

In the next section we will briefly show how the ATC formulation can be extended to families of products.

TARGETS FOR PRODUCT FAMILIES

The ATC formulation of Eq. (2) can be extended to the design of product families. A product family is defined as a collection of products that share some common elements. Since commonality is an additional constraint, one expects that designing the products as a family will require some tradeoff in individual performance. A Pareto representation of such tradeoffs allows a rigorous exploration of when commonality is desirable (Nelson et al. 1999).

To apply the ATC process to product families the restriction shown on Figure 2 must be removed, namely, some parents may share the same child as in Figure 12. Removing this restriction would seem to destroy the hierarchical structure we had required for the target cascading process. However, there are possible remedies that can address this difficulty. One way is to simply move the linking among common children of different parents to the grandparents, so that the relevant linking variables are included at the design problem that is two levels up rather than the level just above the one where the linking is present.

In order to allow for elements to be shared (i.e., have multiple parents), the parents set $\Pi_{ij}$ is defined for each element $j$ of the set $E_i$ at every level $i$; it includes the elements of the set $E_{i-1}$ that are its parents. The general optimization problem $\mathrm{P}_{ij}$ for product platform design is then formulated as

$$
\begin{aligned}
\underset{\bar{\mathbf{x}}_{ij}}{\text{Minimize}} \quad & \left\|\tilde{\mathbf{R}}_{ij} - \mathbf{T}_{ij}\right\| + \sum_{q \in \Pi_{ij}} \left\|\mathbf{R}_{ij} - \mathbf{R}^{U}_{ijq}\right\| \\
& + \sum_{q \in \Pi_{ij}} \left\|\mathbf{y}_{ij} - \mathbf{y}^{U}_{ijq}\right\| + \varepsilon_{\mathbf{R}_{ij}} + \varepsilon_{\mathbf{y}_{ij}} \\
\text{subject to} \quad & \sum_{k \in C_{ij}} \left\|\mathbf{R}_{(i+1)k} - \mathbf{R}^{L}_{(i+1)k}\right\| \le \varepsilon_{\mathbf{R}_{ij}} \qquad (12) \\
& \sum_{k \in C_{ij}} \left\|\mathbf{y}_{(i+1)k} - \mathbf{y}^{L}_{(i+1)k}\right\| \le \varepsilon_{\mathbf{y}_{ij}} \\
& g_{ij}(\mathbf{R}_{ij}, \mathbf{x}_{ij}, \mathbf{y}_{ij}) \le \mathbf{0} \\
& h_{ij}(\mathbf{R}_{ij}, \mathbf{x}_{ij}, \mathbf{y}_{ij}) = \mathbf{0}
\end{aligned}
$$

with $\Pi_{ij} = \{q_1, \ldots, q_{p_{ij}}\}$ and $\mathbf{T}_{ij}$ is the local target for individual product with $i, j \ge 1$ .

We illustrate these ideas on a multi-vehicle design problem, see Figure 13. The individual vehicles are modeled using the half-car model of the previous section. A vehicle body and a suspension model providing responses to the half-car model from a lower "sub-

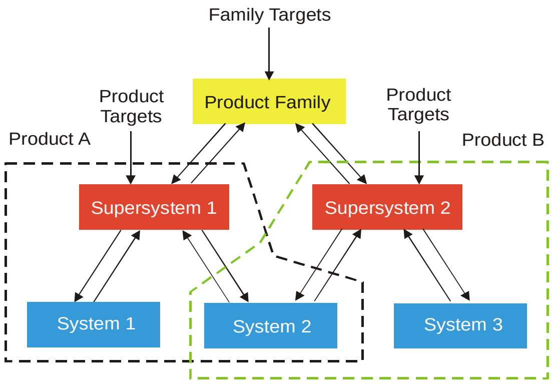


Figure 12. Partitioning of a product family optimal design problem

assembly" level. The body is modeled in a finite element model consisting of ten elements representing eight members of a two-dimensional body including the A pillar, B pillar, hinge pillar, etc. (Kikuchi, 1997). Each member is described by its cross-sectional area and moment of inertia, which are functions of shell thickness. The joint linking elements are modeled as radial springs. The suspension model duplicates stiffness for suspension attributes that make up the sprung stiffness rate in the half-car model.

The family problem formulation is initiated by allowing the bodies of two vehicle variants to share some members, in this case the roof, rocker, and hinge pillar—collectively called the vehicle platform. For the study, the two vehicles based on this platform are a sports car and a luxury car. At the vehicle level, targets are set for the ride of each variant. The ride is defined as a vector of six responses: Front and rear ride frequency, front and rear wheel hop frequency, pitch frequency, and under-steer gradient. The sports car is targeted to have a more stiff and sporty ride, whereas the luxury car should have a softer ride.

At the subassembly level targets for body and suspension must be set. For the body we set targets to maximize the stiffness of the structure, while for the suspension we simply require a design consistent with the spring rates in the half-car vehicle model. At the family level an objective should be defined for the family as a whole that depends on responses from both vehicles. In this study a combined mass objective is set at the family level, with 80% emphasis placed on minimizing the mass of the sports car and 20% placed on the luxury car.

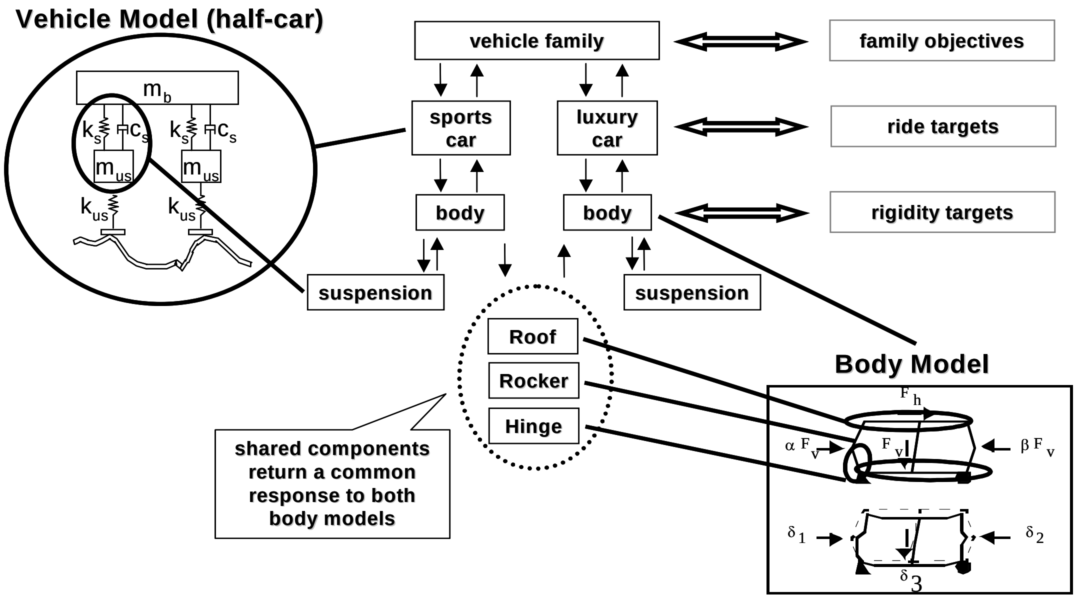


Figure 13. Parts sharing in the vehicle family.

Given the hierarchical structure and modified target cascading formulation, there are various ways that the problem can be configured to include the component sharing. One possible configuration is to model the shared pillars as components that return a common response to more than one body model. This is accomplished by having a pillar model that has shell thickness as input and returns cross sectional properties as output. For each shared pillar, these responses are then passed to both sports car and luxury car bodies. The complete formulation can be seen in Figure 14. . Another possible configuration is to formulate the shared pillar(s) as linking variables between the individual body models. This idea is the linking at "grandparent level" discussed at the beginning of this section. Coordination would be from the family level to the level where sharing is

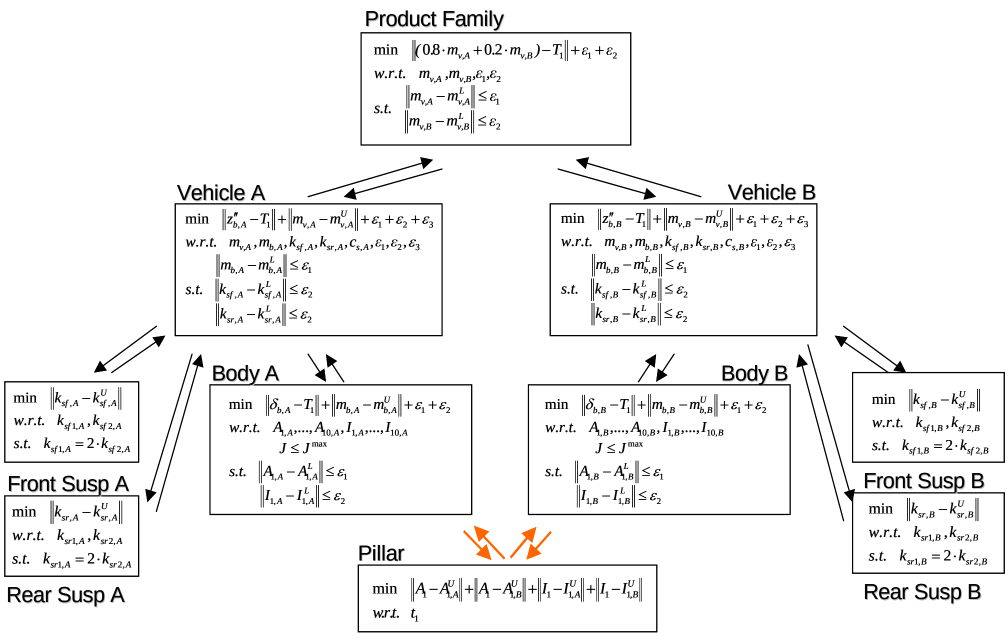


Figure 14. Shared pillar responses are passed to both sports car and luxury car bodies

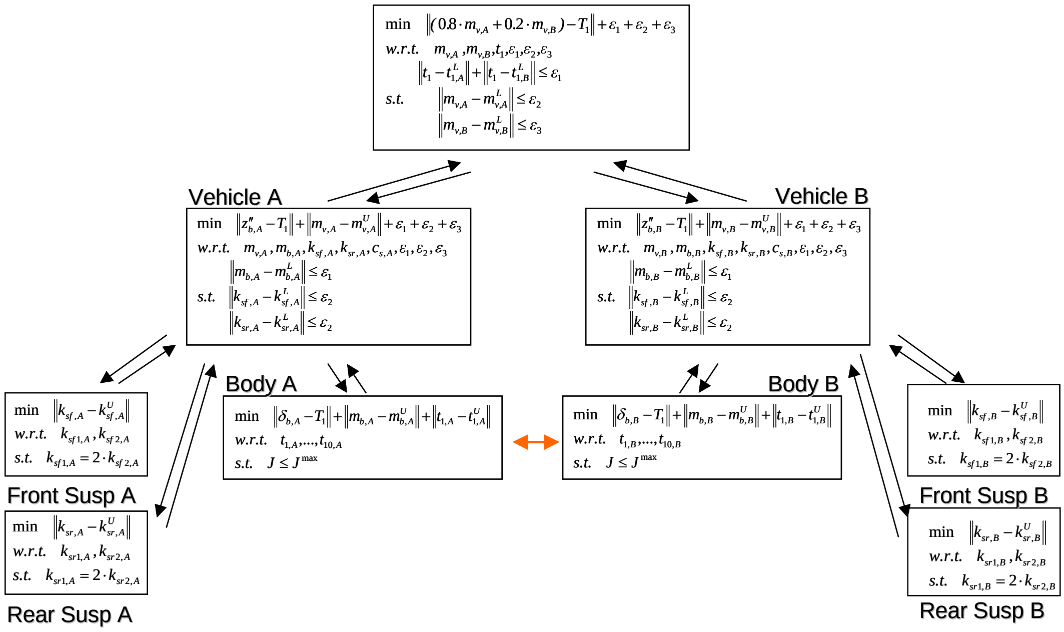


Figure 15. Shared pillars are treated as the linking variables and coordinated at the family level.

occurring. The formulation for this configuration can be seen in Figure 15.

To solve the target cascading problem, a generic coordination strategy is implemented starting at the top level. Each level is solved in sequence, and then the problems are solved once again by returning to the top level problem. This process is counted as one iteration and convergence is accepted if deviation terms have been sufficiently reduced.

Some sample results for this study are shown in Figure 16.

| Platform Targets | Vehicle A | Vehicle B |
|---|---|---|
| front ride frequency (Hz) | 8.000 | 6.000 |
| rear ride frequency (Hz) | 10.000 | 10.000 |
| front wheel hop frequency (Hz) | 65.000 | 65.000 |
| rear wheel hop frequency (Hz) | 65.000 | 60.000 |
| pitch frequency (Hz) | 3.140 | 3.000 |
| under-streer gradient (rad/m/s^2) | 0.007 | 0.007 |
| delta | 0.000 | 0.000 |
| deflection | 0.000 | 0.000 |

| | Vehicle A Initial Values | Vehicle B Initial Values | Vehicle A Optimal Values | Vehicle B Optimal Values |
|---|---|---|---|---|
| front ride frequency (Hz) | | | 7.209 | 5.962 |
| rear ride frequency (Hz) | | | 9.672 | 9.833 |
| front wheel hop frequency (Hz) | | | 63.527 | 64.306 |
| rear wheel hop frequency (Hz) | | | 64.308 | 59.523 |
| pitch frequency (Hz) | | | 5.134 | 4.510 |
| under-streer gradient (rad/m/s^2) | | | 0.007 | 0.007 |
| sprung mass (lbs) | 2282 | 2282 | 2140 | 2060 |

| | Body A Initial Values | Body B Initial Values | Body A Optimal Values | Body B Optimal Values |
|---|---|---|---|---|
| delta (in) | 0.353 | 0.353 | 0.365 | 0.381 |
| deflection (in) | 0.728 | 0.728 | 0.586 | 0.652 |
| sprung mass (lbs) | 2282 | 2282 | 2140 | 2060 |
| roof rail (in) | 0.100 | 0.100 | 0.053 | 0.054 |
| rocker (in) | 0.100 | 0.100 | 0.332 | 0.332 |
| a pillar (in) | 0.300 | 0.300 | 0.300 | 0.137 |
| hinge pillar (in) | 0.100 | 0.100 | 0.067 | 0.067 |
| b pillar above belt (in) | 0.100 | 0.100 | 0.400 | 0.329 |
| b pillar below belt (in) | 0.100 | 0.100 | 0.387 | 0.166 |
| c pillar above belt (in) | 0.100 | 0.100 | 0.400 | 0.067 |
| c pillar below belt (in) | 0.100 | 0.100 | 0.400 | 0.217 |

Figure 16. Sample results for the family problem.

## CONCLUSION

Analytical target cascading can contribute significantly to an efficient and successful product development process. From a management viewpoint, the benefits are reduction in product design cycle time, avoidance of design iterations late in the development process, and increased likelihood that physical prototypes will be closer to production quality. From an engineering viewpoint, the main difficulty is obtaining the appropriate analysis models. From a mathematical viewpoint, we can create several variants of the ATC formulation to enhance computational performance but the basic convergence issues pose largely benign difficulties. Perennial questions regarding the extent to which the solutions obtained are indeed global optima can only be answered as in other generic optimization situations: Unless we know otherwise the solutions are only local and perhaps not even true optima. But as in all engineering decisions, quantifying early enough that what we have is good enough is indeed good enough!

## ACKNOWLEDGMENTS

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