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RESEARCH PAPER

Solving multiobjective optimization problems using quasi-separable MDO formulations and analytical target cascading

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Abstract One approach to multiobjective optimization is to define a scalar substitute objective function that aggregates all objectives and solve the resulting aggregate optimization problem (AOP). In this paper, we discern that the objective function in quasi-separable multidisciplinary design optimization (MDO) problems can be viewed as an aggregate objective function (AOF). We consequently show that a method that can solve quasi-separable problems can also be used to obtain Pareto points of associated AOPs. This is useful when AOPs are too hard to solve or when the design engineer does not have access to the models necessary to evaluate all the terms of the AOF. In this case, decomposition-based design optimization methods can be useful to solve the AOP as a quasi-separable MDO problem. Specifically, we use the analytical target cascading methodology to formulate decomposed subproblems of quasi-separable MDO problems and coordinate their solution in order to obtain Pareto points of the associated AOPs. We first illustrate the approach using a well-known simple geometric programming example and then present a vehicle suspension design problem with three objectives related to ground vehicle ride and handling.

Keywords Multiobjective optimization · Quasi-separable MDO · Analytical target cascading

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1 Introduction

One approach to solving multiobjective optimization (MO) problems is to define a scalar substitute objective function that aggregates the components of the vector of objectives. This aggregate objective function (AOF) includes weight parameters so that the Pareto set of the original MO problem can be populated by solving the single-objective optimization problem for different values of these parameters. A popular and widely-used technique that follows this approach is to define a weighted sum of the objectives and vary the weights to obtain different Pareto points. It is also well known that linear combinations of the objectives may miss points on non-convex parts of Pareto sets (Athan and Papalambros 1996).

In this paper we consider MO problems in the design of large, complex engineering systems, where some of the objectives may not be under the control of the design engineer. For example, the system designer may not have access to the modeling and simulation models that evaluate these objectives because the analysis model may have been either distributed to subject matter experts or outsourced. Such situations are typical in multidisciplinary design optimization (MDO) problems, whose formulations are used to implement decomposition-based optimization strategies.

The main idea investigated in this paper is based on the observation that the objective function of quasi-separable MDO problems (Haftka and Watson 2005; Tosserams et al. 2007) can be viewed as a weighted sum of competing objectives of an MO problem with equal weights. Further, we assume that the use of MDO methodologies is required because the MO problem cannot be solved using an all-in-one approach. In this context, we propose solving the multiobjective optimization problem formulated as a quasi-separable MDO one using analytical target cascading (ATC) (Kim 2001). Specifically, we decompose the AOF by formulating a subproblem for each objective and use non-hierarchical ATC (Tosserams et al. 2010) to coordinate the solution of the decomposed problem.

The article is organized as follows. The proposed methodology is presented in Section 2. In Section 3, we use a simple geometric programming problem that can be viewed as a bi-objective problem to illustrate the proposed methodology. A more elaborate vehicle suspension design problem for optimizing ground vehicle ride and handling quality by considering multiple objectives for ride comfort, controllability and stability is presented in Section 4. Summarizing remarks are made in Section 5.

2 Quasi-separable MDO formulation for MO problems

The general MO problem is formulated as

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{f} = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_N(\mathbf{x})] \\ \text{subject to} \quad & \mathbf{g}(\mathbf{x}) \leq \mathbf{0} \\ & \mathbf{h}(\mathbf{x}) = \mathbf{0}. \end{aligned} \tag{1}$$

Note that the vector $\mathbf{x}$ represents a collection of all the variables that appear in all the functions of the MO problem and that vectors are assumed to be row vectors to avoid repeated use of transpose symbols. In reality, not all functions will depend on all of the variables in the vector $\mathbf{x}$; each function usually depends only on a subset of the variables included in the vector $\mathbf{x}$. The basic assumption is that every pair of objective functions will depend on at least one common variable; otherwise the problem can be completely or partially separated.

Let the subset of the variables included in $\mathbf{x}$, on which the j-th objective function depends, be denoted by $\hat{\mathbf{x}}_j = [\mathbf{y}, \mathbf{x}_j]$. Then the MO problem is reformulated as

$$\begin{aligned} \min_{\mathbf{y}, \mathbf{x}_j, \ldots, \mathbf{x}_N} \quad & \textstyle\sum_{j=1}^{N} w_j f_j(\mathbf{y}, \mathbf{x}_j) \\ \text{subject to} \quad & \mathbf{g}_j(\mathbf{y}, \mathbf{x}_j) \leq \mathbf{0} \quad j = 1, \ldots, N \\ & \mathbf{h}_j(\mathbf{y}, \mathbf{x}_j) = \mathbf{0} \quad j = 1, \ldots, N \end{aligned} \tag{2}$$

The AOF is defined by a weighted sum, where f_j denotes the j-th objective function and w_j is the associated weight ($j = 1, \ldots, N$). For simplicity and without loss of generality, we assume that all objective functions share the same number of variables $\mathbf{y}$ (the contrary merely makes bookkeeping and notation more tedious), while $\mathbf{x}_j$ denotes the "local" variables that only the j-th objective function depends on. The equality and inequality constraints of the MO problem can be separated according to local design variables. Again, for simplicity and without loss of generality, we assume that there exists at least one inequality and one equality constraint that depend on local design variables $\mathbf{x}_j$ and that they both depend on the same number of shared variables $\mathbf{y}$.

The weighted sum formulation of the MO problem shown in Eq. (2) is identical to the quasi-separable MDO problem considered by Tosserams et al. in (2007) if all the weights are set equal to 1. Therefore, the solution of a quasi-separable MDO problem is equivalent to the Pareto solution of the MO problem when all the weights are equal. Strictly speaking, the weighted sum method requires all the weights to sum up to 1; however, solving the MO problem with $w_j = 1 \ \forall\ j$ is equivalent to solving the MO problem with $w_j = 1/N \ \forall\ j$. Decomposition-based methodologies for MDO problems are motivated by the same reasons as for investigating decomposition-based approaches for MO: Either inability to solve the problem as "all-in-one" (AIO), or lack of control of some of the subproblems or disciplines involved. When the problem is decomposed, local variables that are copies of the shared variables are introduced into every subproblem and consistency constraints are formulated to ensure that all copies of shared variables are equal at feasible solutions. The functional dependency tables (FDT) of the AIO and decomposed MO problems are shown in Fig. 1 to illustrate the degree of separability of the two problem formulations.

2.1 Decomposition-based approaches to solve MO problems using quasi-separable MDO formulation

Tosserams, Etman and Rooda proposed a bi-level decomposition of the quasi-separable MDO problem that uses a master problem at the top level to coordinate the consistency constraints (Tosserams et al. 2007). Figure 2 depicts an MO example with three objectives that is treated as a quasi-separable MDO problem with three subproblems.

The non-hierarchical analytical target cascading formulation (Tosserams et al. 2010) enables us to solve the decomposed problem without the necessity of a master problem: The proposed methodology coordinates the auxiliary copies of the shared variables y_1, y_2 and y_3 directly among subproblems using penalty functions, eliminating the need to coordinate each auxiliary copy of the shared variables separately.

Fig. 1 Functional dependency tables for all-in-one (AIO) and decomposed multiobjective optimization problems (adapted from Tosserams et al. (2006, 2010)

(a) AIO problem

	$\mathbf{y}$	$\mathbf{x}_1$	$\mathbf{x}_2$	$\mathbf{x}_3$
$f_1, \mathbf{g}_1, \mathbf{h}_1$	•	•		
$f_2, \mathbf{g}_2, \mathbf{h}_2$	•		•	
$f_3, \mathbf{g}_3, \mathbf{h}_3$	•			•

(b) Decomposed problem

	$\mathbf{y}_1$	$\mathbf{x}_1$	$\mathbf{y}_2$	$\mathbf{x}_2$	$\mathbf{y}_3$	$\mathbf{x}_3$
$f_1, \mathbf{g}_1, \mathbf{h}_1, \mathbf{c}_1$	•	•				
$f_2, \mathbf{g}_2, \mathbf{h}_2, \mathbf{c}_2$			•	•		
$f_3, \mathbf{g}_3, \mathbf{h}_3, \mathbf{c}_3$					•	•

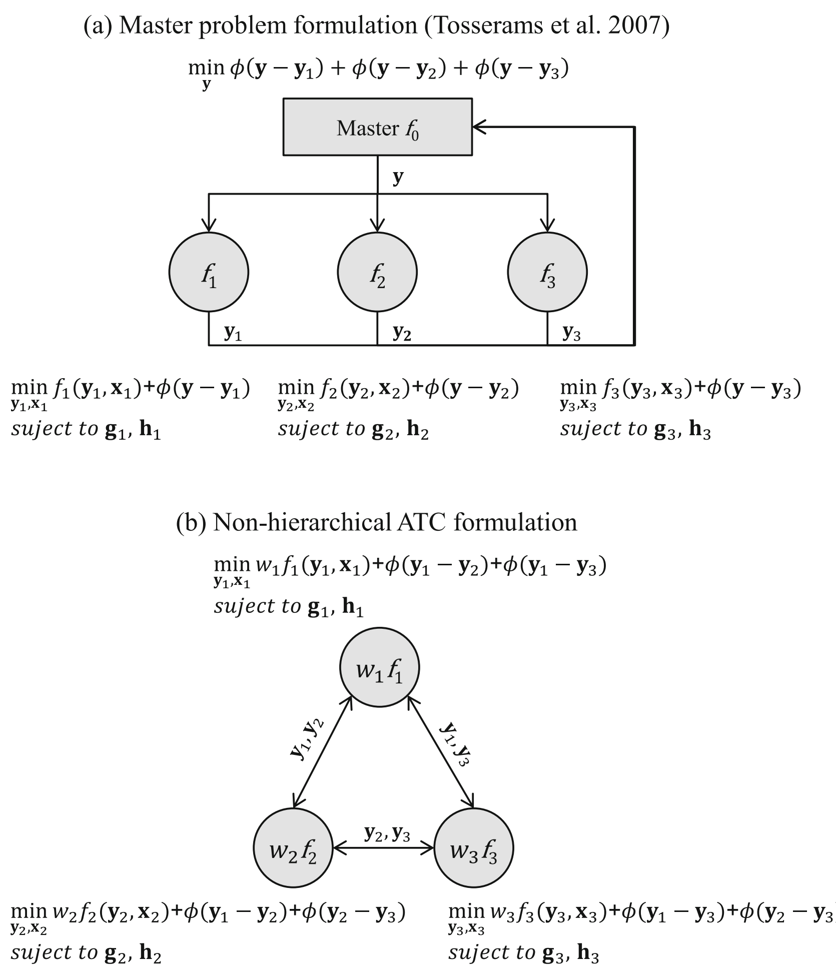
Synchronously (during the same conference) with the first presentation of the method proposed here (Kang et al. 2013), Guarneri et al. independently presented a similar "MultiObjective Decomposition Algorithm" (MODA) for bilevel multiobjective optimization (Guarneri et al. 2013). They also use an augmented Lagrangian approach to relax the equality constraints that coordinate the design optimization variables that are common among problems with different objectives. The main difference between the two methods is that while Guarneri et al. use a bilevel problem formulation for coordinating the subproblems of the decomposed multiobjective problem, we use a non-hierarchical ATC formulation to coordinate the subproblems corresponding to different objectives together with the traditional multi-level ATC formulation that coordinates the further decomposed subproblems.

2.1.1 ATC formulation

Using the Augmented Lagrangian Penalty Function approach of Tosserams et al. (2006), the general formulation for each subproblem is

$$\begin{array}{ll} \min\limits_{\mathbf{y}_j,\mathbf{x}_j} & w_j f_j(\mathbf{y}_j,\mathbf{x}_j) + \sum_{i\neq j}^{N} \phi(\mathbf{y}_j - \mathbf{y}_i) \\ \text{subject to} & \mathbf{g}_j(\mathbf{y}_j,\mathbf{x}_j) \leq \mathbf{0} \\ & \mathbf{h}_j(\mathbf{y}_j,\mathbf{x}_j) = \mathbf{0} \\ \text{with} & \phi(\mathbf{y}_j - \mathbf{y}_i) = \mathbf{v}_{ij}(\mathbf{y}_j - \mathbf{y}_i)^{\mathrm{T}} + \|\mathbf{w}_{ij} \circ (\mathbf{y}_j - \mathbf{y}_i)\|_2^2. \end{array} \tag{3}$$

Fig. 2 Decomposition-based approaches for solving MO problems using quasi-separable MDO formulations



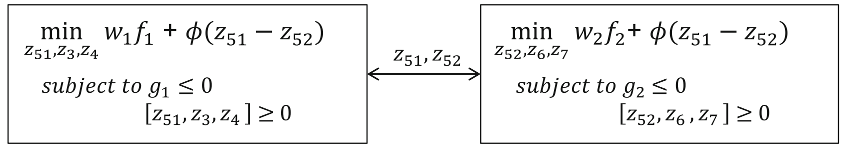


Fig. 3 Decomposition of the problem in Eq. (10)

Here $\mathbf{v}_i$ is the vector of Lagrange multipliers, $\mathbf{w}_i$ is the vector of penalty weights, and the Hadamard symbol $\circ$ is used to denote term-by-term multiplication of vectors. The iterative coordination algorithm used here is the method of multipliers as outlined in Tosserams et al. (2010): At every iteration q we solve all subproblems (in any sequence or in parallel), and then update the penalty weights according to

$$w_{ij,k}^{q+1} = \begin{cases} w_{ij,k}^{q} & \text{if } |(y_{j,k} - y_{i,k})^q| \le \gamma |(y_{j,k} - y_{i,k})^{q-1}| \\ \beta w_{ij,k}^{q} & \text{if } |(y_{j,k} - y_{i,k})^q| > \gamma |(y_{j,k} - y_{i,k})^{q-1}| \end{cases}, \tag{4}$$

where the subscript k denotes vector components. It is generally recommended that $\beta > 1$ and $0 < \gamma < 1$; we have used $\beta = 1.25$ and $\gamma = 0.4$ for the example in Section 3 and $\beta = 2.2$ and $\gamma = 0.4$ for the vehicle suspension design in Section 4.

The Lagrange multiplier estimates are updated using

$$\mathbf{v}_{ij}^{q+1} = \mathbf{v}_{ij}^{q} + 2\,\mathbf{w}_{ij}^{q} \circ \mathbf{w}_{ij}^{q} \circ (\mathbf{y}_j - \mathbf{y}_i)^q. \tag{5}$$

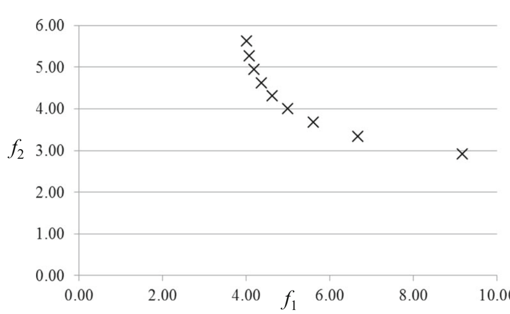
The iterative coordination algorithm is terminated when both of two conditions are satisfied. Let us denote the collection of all consistency constraints $(\mathbf{y}_j - \mathbf{y}_i)\ \forall\ j$ and i by a vector $\mathbf{c}$. The first condition requires that the change in the maximal consistency constraint value after two consecutive iterations is smaller than a user-specified small positive threshold ε_1

$$\|\mathbf{c}^k - \mathbf{c}^{k-1}\|_\infty < \varepsilon_1. \tag{6}$$

The second condition requires that the maximal consistency constraint violation is smaller than a user-specified small positive threshold ε_2

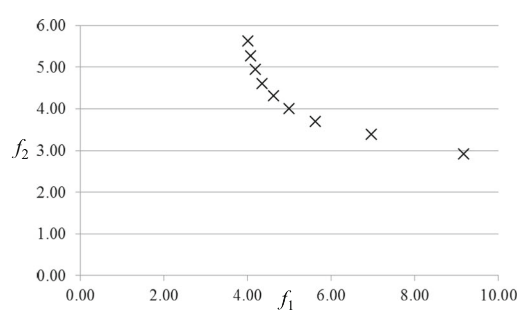
$$\|\mathbf{c}^k\|_\infty < \varepsilon_2. \tag{7}$$

Note that the decomposed problem can be solved with different weights to obtain different Pareto solutions of the MO problem. As mentioned before, if the Pareto set of a particular MO problem is not convex, the weighted method may not generate all parts of it because the AOF is a linear combination of terms. To generate points on non-convex parts of the Pareto set, the exponential weighted criterion



Weight w_1	w_2	Optimal values f_1	f_2	z_3	z_4	z_5	z_6	z_7
1.0	9.0	9.18	2.92	2.09	0.48	0.68	1.00	1.21
1.0	4.0	6.67	3.33	1.73	0.58	0.82	1.00	1.29
1.0	2.3	5.60	3.68	1.54	0.65	0.92	1.00	1.36
1.0	1.5	5.00	4.00	1.41	0.71	1.00	1.00	1.41
1.0	1.0	4.62	4.31	1.32	0.76	1.07	1.00	1.47
1.5	1.0	4.36	4.62	1.24	0.81	1.14	1.00	1.52
2.3	1.0	4.19	4.94	1.17	0.86	1.21	1.00	1.57
4.0	1.0	4.08	5.27	1.11	0.90	1.28	1.00	1.62
9.0	1.0	4.02	5.62	1.05	0.95	1.35	1.00	1.68

(a) AIO problem



Weight w_1	w_2	Optimal values f_1	f_2	z_3	z_4	z_5	z_6	z_7
1.0	9.0	9.18	2.92	2.09	0.48	0.68	1.00	1.21
1.0	4.0	6.96	3.38	1.77	0.56	0.82	1.00	1.31
1.0	2.3	5.62	3.68	1.55	0.65	0.92	1.00	1.36
1.0	1.5	4.99	4.00	1.41	0.71	1.00	1.00	1.41
1.0	1.0	4.62	4.31	1.32	0.76	1.07	1.00	1.47
1.5	1.0	4.35	4.60	1.23	0.81	1.14	1.00	1.52
2.3	1.0	4.19	4.94	1.17	0.86	1.21	1.00	1.57
4.0	1.0	4.08	5.27	1.11	0.90	1.28	1.00	1.62
9.0	1.0	4.02	5.62	1.05	0.95	1.34	1.00	1.68

(b) Decomposed problem

Fig. 4 Pareto solutions for the modified geometric programming problem

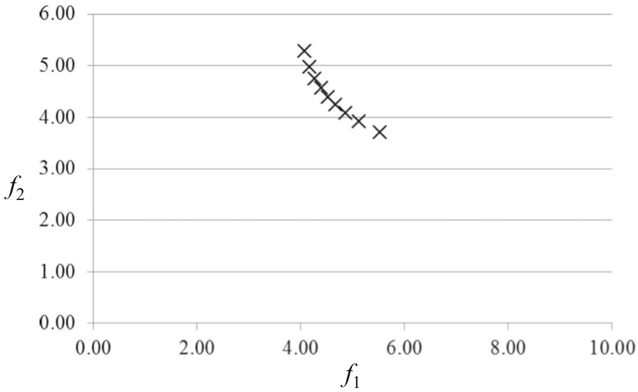


Fig. 5 Pareto solutions of the decomposed problem via the exponential weighted criterion

can be applied, replacing the objective function of Eq. (3) with

$$\min_{\mathbf{y}_j,\mathbf{x}_j} \; (e^{mw_j} - 1)e^{mf_j(\mathbf{y}_j,\mathbf{x}_j)} + \textstyle\sum_{i\neq j}^{N} \phi(\mathbf{y}_j - \mathbf{y}_i), \tag{8}$$

where m denotes a control parameter that can be selected as described in Athan and Papalambros (1996).

3 Illustration example

We apply the proposed method to a reduced version of the geometric programming problem, originally proposed in Kim (2001) and Kim et al. (2003), and used in Tosserams et al. (2007):

$$\begin{array}{ll} \min\limits_{z_1,z_2,\ldots,z_7} & f = z_1^2 + z_2^2 \\ \text{subject to} & g_1 = (z_3^{-2} + z_4^2) - z_5^2 \le 0 \\ & g_2 = (z_5^2 + z_6^{-2}) - z_7^2 \le 0 \\ & h_1 = z_1^2 - (z_3^2 + z_4^{-2} + z_5^2) = 0 \\ & h_2 = z_2^2 - (z_5^2 + z_6^2 + z_7^2) = 0 \\ & [z_1, z_2, z_3, z_4, z_5, z_6, z_7] \ge \mathbf{0} \end{array} \tag{9}$$

From a mathematical perspective, the equality constraints can obviously be used to reduce the size of the problem. In our case, we use the equality constraints to define two objective functions, add weights and view the problem as an MO:

$$\begin{array}{ll} \min\limits_{z_3,z_4,z_5,z_6,z_7} & f = w_1 f_1(z_3, z_4, z_5) + w_2 f_2(z_5, z_6, z_7) \\ \text{subject to} & g_1 = (z_3^{-2} + z_4^2) - z_5^2 \le 0 \\ & g_2 = (z_5^2 + z_6^{-2}) - z_7^2 \le 0 \\ & [z_3, z_4, z_5, z_6, z_7] \ge \mathbf{0} \\ \text{with} & f_1 = z_3^2 + z_4^{-2} + z_5^2 \\ \text{and} & f_2 = z_5^2 + z_6^2 + z_7^2. \end{array} \tag{10}$$

We first solve the problem in Eq. (9) using an AIO approach. Then the problem in Eq. (10) is decomposed into two subproblems as shown in Fig. 3, and solved using ATC. Note that the constraints are decomposed as mentioned above, i.e., by local design variables.

The two problems share variable z_5; we thus introduce auxiliary copies z_{51} and z_{52} to Subproblems 1 and 2, respectively, to replace the shared variable z_5. Matlab's implementation of the Sequential Quadratic Programming (SQP) algorithm (Matlab function `fmincon`) MathWorks (2012) is used to solve both the AIO and the decomposed problems. Figure 4a and b shows the Pareto solutions obtained for several sets of weights for the problem in Eqs. (9) and (10), respectively.

Note that we have not used weights that sum up to one; we are using weight ratios to emphasize one objective. For example, the second solution emphasizes objective f_2 4 times more than objective f_1; this is equivalent to using weights 0.2 and 0.8 in the weighted sum method where the weights have to add up to 1. The obtained results demonstrate that we can successfully solve the MO problem as a quasi-separable MDO problem using decomposition and non-hierarchical ATC coordination.

Figure 5 shows the Pareto solutions of the decomposed problem obtained by the exponential weighted criterion in Eq. (8) with m=1 and same weights as Fig. 4.

If the Pareto set of the geometric programming problem were not convex, we could have found all its parts by adjusting m. We now present a more elaborate design problem

Table 1 Design objectives and associated tests

Objective	Test	Description of test
Ride comfort	Bumpy ride test (ISO 13674-1 2003)	Measure the acceleration signal at the driver seat position at the moment of driving over bump
Stability	On-Centre handling test (ISO 2631 1997)	Measure yaw rate of a vehicle during straight-line driving and in negotiating large radius bends at high speeds but low lateral acceleration
Controllability	Roll control test on cornering (ISO 7401 1988)	Measure damping of roll movement with step steer input at constant speed and wide range of lateral accelerations

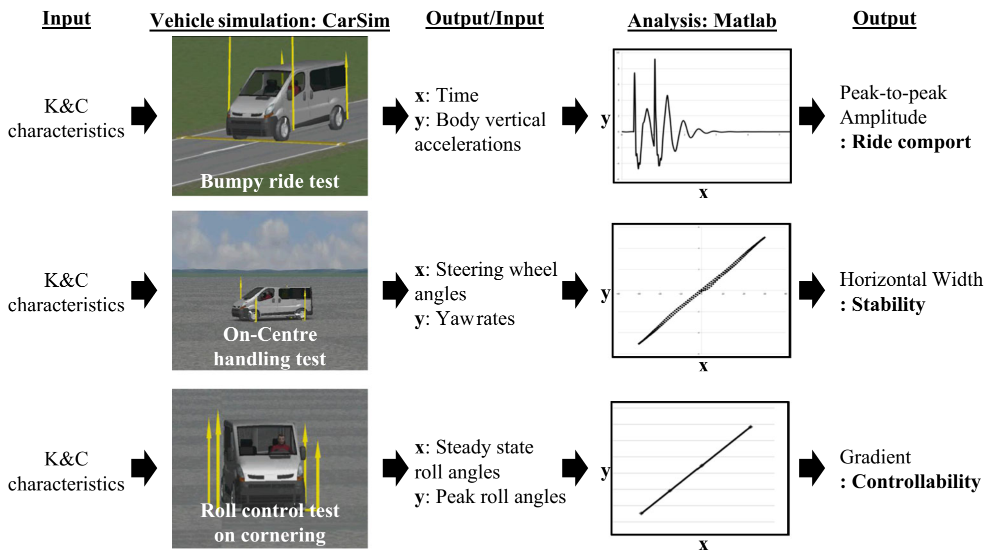


Fig. 6 Simulation and analysis models at the vehicle level

that motivates the use of their method in engineering design applications where the design engineer may not be able to solve the MO problem using an AIO approach.

4 Vehicle suspension design

4.1 Problem definition and simulation models

The problem involved a suspension design application for commercial vans considering ride and handling (R&H) quality. In general, R&H quality cannot be defined by a single aspect or attribute because it represents a complex qualitative "feeling" of the driver. It can be quantified in part using vehicle dynamic characteristics depending on driving situations. In this study, R&H quality is expressed through three objectives, ride comfort, controllability, and stability; three representative vehicle test methods are used to quantify each objective, as shown in Table 1.

To incorporate these vehicle test methods into simulation and analysis models for optimization, the models for two levels (i.e., vehicle and suspension system levels) are built as shown in Figs. 6 and 7.

At the vehicle level, the simulation models to test the vehicle are built using CarSim software (Mechanical Simulation 2006) and analysis models for test results are implemented in Matlab, as in Fig. 6. The three vehicle simulation models have kinematic and compliance (K&C) characteristics as inputs decided by the suspension system design. These characteristics will be explained below at the system level discussion. The simulation models generate vehicle movements such as acceleration, yaw rate, and roll. Analysis models to translate the simulation results into R&H quality follow the international standards of quantification methods published from the international organization for standardization (ISO) (ISO 2631 1997; ISO 13674-1 2003; ISO 7401 1988). For ride comfort, the bumpy ride simulation model generates body vertical accelerations with time, and we obtain peak-to peak amplitude from the wave graph with time as x-axis and body vertical accelerations as y-axis. The larger the amplitude is, the more impact drivers can feel when driving over a bump, and this magnitude of amplitude can be interpreted as a measure of vehicle ride comfort. For stability, the on-centre handling simulation model generates yaw rates with steering wheel angles, and these values show hysteresis loops with steering wheel angles as x-axis and yaw rates as y-axis. We obtain the hor-

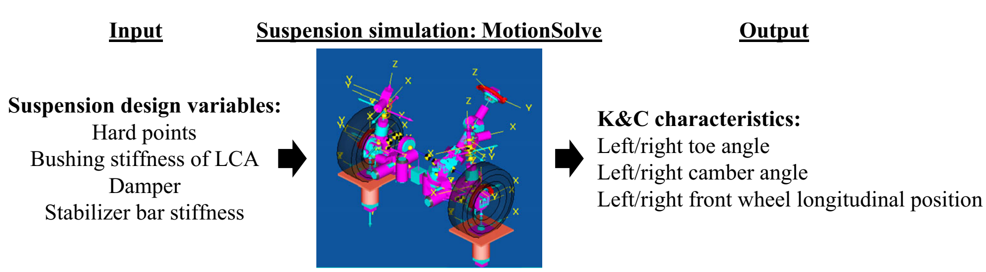


Fig. 7 Simulation models at the suspension system level

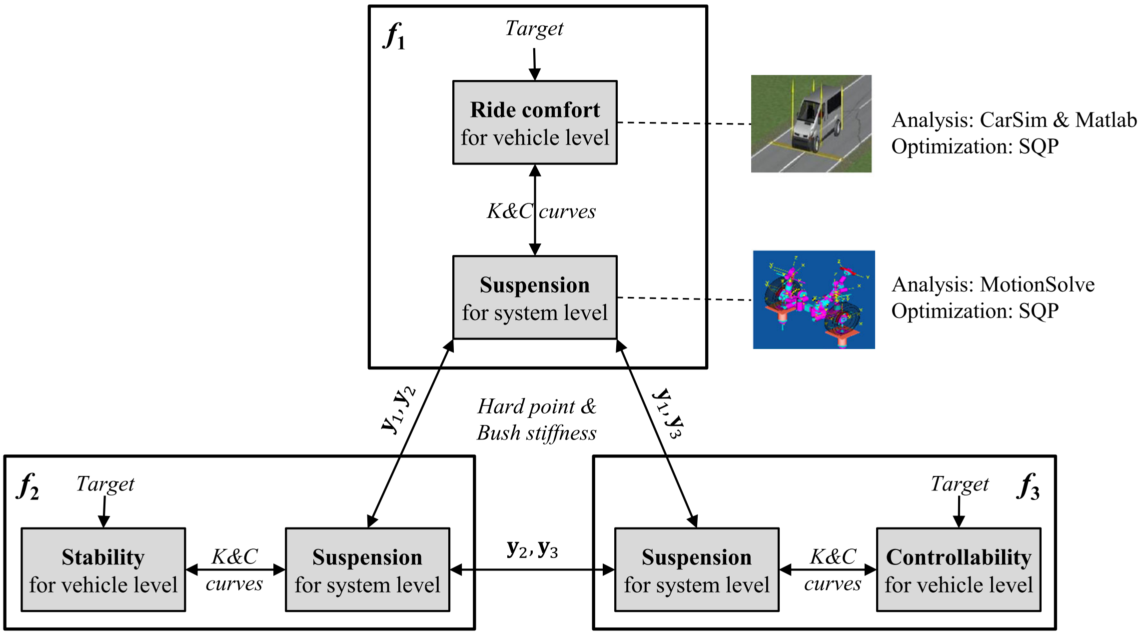


Fig. 8 Decomposition and information flow of the combined hierarchical and non-hierarchical ATC formulation

izontal width of the hysteresis loops at ordinate zero. The smaller the horizontal width is, the more sensitive is the vehicle reaction. This magnitude of sensitivity can be interpreted as a measure of vehicle stability. For controllability, the roll control simulation model generates steady-state roll angles and peak roll angles with step steer inputs. We obtain the gradient of the linear function with steady-state roll angles (i.e., average roll angles at each step steer input) as x-axis, and peak roll angles as y-axis. A larger gradient represents a larger lurch of the vehicle. The magnitude of gradient can be then interpreted as a measure of vehicle roll controllability.

There is a challenge in how to decide the target value for each objective. Since the magnitudes of outputs are related to the feelings of drivers, they cannot be simply maximized or minimized as other objective metrics. In our formulation, target values are set for these objectives based on test data from existing vehicles that have been reported

Table 2 Targets, responses, and variables for the suspension design problem

Level	Variables and parameters
Vehicle level	**Targets**
	T_i: Target of i-th subproblem
	(i = 1: ride comfort, 2: stability, 3: controllability)
	Responses
	R_i: Response of i-th subproblem
	Linking variables and parameters between vehicle and system levels (K&C curves)
	C_{ijk}: Coefficient of k-th order of j-th K&C curve for i-th subproblem
	(j = 1: left toe angle, 2: right toe angle, 3: left camber angle, 4: right camber angle, 5: left front wheel position, 6: right front wheel position) (k = 0, 1, 2)
System level	**Shared design variables among subproblems (suspension design variables)**
	$y_{ijk,hp}$: Coordinate of j-th axis of k-th hard point for i-th subproblem
	(j = 1: x-axis, 2: y-axis, 3: z-axis)(k = 1: LCA front bush, 2: LCA rear bush, 3: outer tie rod, 4: lower knuckle mounting)
	$y_{ijk,bs}$: Bush stiffness of j-th axis of k-th lower control arm (LCA) for i-th subproblem
	(j = 1: radial, 2: axial, 3: conical)(k = 1: front, 2: rear)
	$y_{i,d}$: Damper for i-th subproblem
	$y_{i,s}$: Stabilizer bar stiffness for i-th subproblem

Table 3 Targets and responses at the vehicle level

Response	Target value	Baseline value	Final value
Ride comfort	12.0146	11.8465	12.0141
Stability	1.4676	2.0526	1.4373
Controllability	0.9987	0.9998	0.9986

to have good reputation regarding R&H quality in the market place.

At the suspension system level, the simulation model is built using MotionSolve software (Altair 2012), as in Fig. 7. Suspension design variables such as hard points, bushing stiffness, damper, and stabilizer bar stiffness are used as inputs. The outputs are six main K&C characteristics, left and right side of toe angle, camber angle, and front wheel longitudinal position. These K&C characteristics link the simulation models of vehicle and suspension system, and we can see how the design variables of the suspension system affect R&H quality of the vehicle. Kinematic characteristics are represented by the relative motion of joined system elements such as lower control arm (LCA), outer tie rod, knuckle, etc. Compliance characteristics are based on observing displacements of bush, spring and stabilizer bar elements. From analysis of K&C characteristics, a suspension designer can decide the hard point and stiffness of elements.

However, the K&C characteristic cannot be used directly as design optimization variables at the vehicle level because they are not defined by a single-valued variable but by nonlinear functional relationships. The K&C characteristics can be represented by polynomials with respect to suspension characteristics such as camber, toe, caster, wheel position and wheel travel (Kang et al. 2012). Here, K&C characteristics are treated as second-degree polynomials, whose coefficients (i.e., c_0, c_1, c_2) are used as inputs to the vehicle simulation model. Based on communications with the suspension model developers and our own numerical experiments with the vehicle simulation model we treated c_1 as a design variable and c_0 and c_2 as parameters. All coefficients are cascaded to the suspension system level as targets. This will be described further in the ATC formulation and optimization results sections.

4.2 ATC formulation

Previous research on ATC application to suspension system design (Kokkolaras et al. 2004; Kang et al. 2012) did not consider R&H quality. Kang et al. addressed suspension design for R&H quality using a target cascading formulation (Kang et al. 2012), but without full coordination to achieve convergence between targets and responses. The present decomposition framework and detailed nomenclature are given in Fig. 8 and Table 2, respectively.

This framework is a combination of hierarchical and non-hierarchical ATC. The multiobjective optimization problem is decomposed into three single-objective optimization problems. The shared design optimization variables of the decomposed multiobjective problem are coordinated using the non-hierarchical ATC formulation. The single-objective problems are further decomposed into bi-level vehicle-system subproblems that are coordinated using the hierarchical ATC coordination.

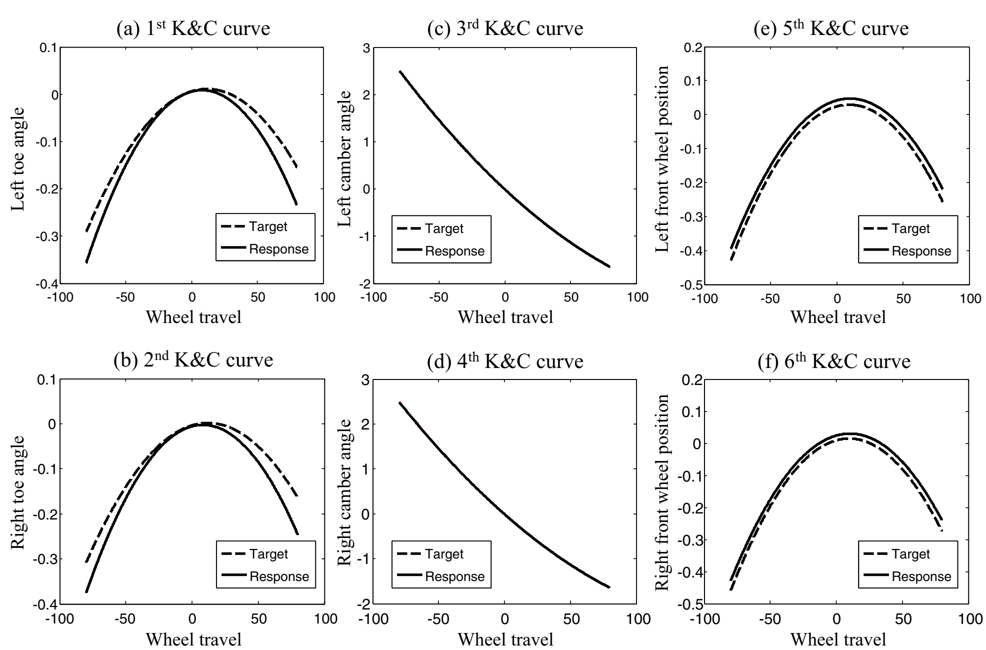


Fig. 9 Ride comfort target and response curves at the system level

Table 4 Optimal values of shared design variables at the system level

Type	Design variables	Axis	Baseline value	Optimal value
Hard point		x	-250.0	-280.0^{lb}
	LCA front bush	y	-413.0	-419.7
		z	-63.7	-52.1
	LCA rear bush	x	-119.7	-89.7^{ub}
		y	-413.0	-419.3
		z	-58.3	-52.7
	Outer tie rod	x	-131.0	-108.0
		y	-810.0	-775.0^{ub}
		z	-64.5	-84.4
	Lower knuckle moutnting	-	-116.6	-127.3
Bushing stiffness		Radial	1.00	2.00^{ub}
	LCA front bush	Axial	1.00	0.94
		Conical	572957	572957
	LCA rear bush	Radial	1.00	1.56
		Axial	581.0	581.0
		Conical	572957	572957
Others	Damper	-	1.00	0.97
	Stabilizer bar stiffness	-	23.5	25.2

The structure of the three subproblems of the decomposed multiobjective problem (see f_1, f_2, and f_3 in Fig. 8) was described in Section 4.1. At the vehicle level, the coefficients of six types of K&C curves are cascaded to the system level as targets. At the system level, the optimal hard points and bushing stiffness of the suspension system are calculated to satisfy the target coefficients of K&C curves from the vehicle level. All suspension levels share the suspension design variables in the non-hierarchical structure as shown in Fig. 2b, and these shared variables $[\mathbf{y}_1, \mathbf{y}_2, \mathbf{y}_3]$ converge to a single optimal value. An SQP algorithm is used for solving each optimization problem. The entire problem has total 72 design variables, with 18 design variables at the vehicle level (i.e., 1st order coefficients of 6 curves $\times$ 3 subproblems) and 54 design variables at the system level (i.e., 18 shared design variables $\times$ 3 subproblems).

The first subproblem for ride comport at the vehicle level is.

$$\begin{aligned} &\min_{\mathbf{C}_1^U} && \|T_1 - R_1\|_2^2 + \phi(\mathbf{C}_1^U - \mathbf{C}_1^L) \\ &\text{subject to} && lb \le \mathbf{C}_1^U \le ub \\ &\text{where} && R_1 = f_1(\mathbf{C}_1^U) \end{aligned} \tag{11}$$

The lower and upper bounds of the coefficients of the K&C curves were determined based on possible ranges given constraints on the suspension design variables. Response R_1 is obtained using the vehicle simulation and analysis model. Superscripts $(\cdot)^U$ and $(\cdot)^L$ indicate variables at the vehicle and system levels, respectively. To satisfy the target values obtained at the vehicle level, the design

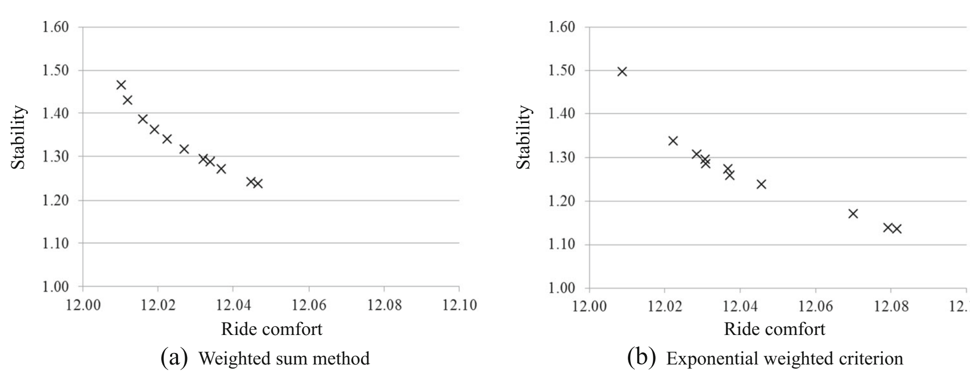


Fig. 10 Pareto sets obtained using the weighted sum method and the exponential weighted criterion

problem for suspension is formulated as.

$$\begin{aligned} \min_{\mathbf{y}_1} \quad & \phi(\mathbf{C}_1^U - \mathbf{C}_1^L) + \phi(\mathbf{y}_1 - \mathbf{y}_2) + \phi(\mathbf{y}_1 - \mathbf{y}_3) \\ \text{subject to } & lb \leq \mathbf{y}_1 \leq ub \\ \text{where} \quad & \mathbf{C}_1^L = f_c(\mathbf{y}_1) \end{aligned} \tag{12}$$

The lower and upper bounds of the shared design variables were determined by considering the feasible design space of current van design parameters. Coefficients for the K&C curves C_1^L are obtained using the suspension simulation model shown in Fig. 7.

4.3 Optimization results

A single optimal solution (one point of the Pareto set), corresponding to equal weights of the three objectives, was obtained after ten iterations of the ATC process. The obtained values for the responses at the vehicle level are listed in Table 3.

We could improve all objectives while it can be seen that the two of them (ride comfort and stability) are competing as shown in Pareto sets of Fig. 10. Note that while the value differences in Table 3 appear to be small, they represent significant differences in the drivers' expressed "feeling" regarding R&H quality.

Figure 9 depicts the target-response pairs of the K&C curves for ride comfort. It can be seen that most curves are in good agreement.

Table 4 lists the optimal shared design values at the system level.

Some optimal values are hitting lower or upper design variable bounds, which indicates that the design space or the configuration of the suspension system may need to be investigated further by means of parametric studies.

4.3.1 Pareto set generation for bi-objective problem

To demonstrate the generation of Pareto sets using the proposed method, we considered the bi-objective problem consisting of the ride comfort and stability objectives. Our motivation for omitting the controllability objective here is two-fold: 1) it was shown not to change much when solving for the single Pareto point discussed above and 2) to reduce computational cost and increase ease of results visualization.

Figure 10 shows the Pareto sets obtained by using both the weighted sum method and the exponential weighted criterion for pairs (w_1, w_2) = (1,0), (0.1,0.9), (0.2,0.8), (0.3,0.7), (0.4,0.6), (0.5,0.5), (0.6,0.4), (0.7,0.3), (0.8,0.2), (0.9,0.1), (0,1) and m=1. While both Pareto sets seem to be convex, it can be seen that the exponential weighted criterion can obtain slightly more extreme points than the weighted sum method.

5 Conclusion

We presented a methodology for solving multiobjective optimization problems when an all-in-one approach cannot be used either because of problem size and complexity or because of lack of control over all objectives and the analyses required for their evaluation. The work was motivated by two observations: The first one is that the above mentioned challenges are typical in multidisciplinary design optimization problems. The second one is that solving MO problems using an aggregate objective function results in problem formulations that are identical to quasi-separable MDO problem formulations, as noted also by Guarneri et al. (2013). The methodology we proposed uses the extension of analytical target cascading to non-hierarchical formulations. Specifically, non-hierarchical ATC is used to coordinate the shared design optimization variables of the decomposed multiobjective problem directly without the need for a master problem. The vehicle design problem features a hybrid ATC implementation that also utilizes a hierarchical formulation for coordinating subproblems nested within subproblems; it also demonstrates that ATC can solve large problems (72 variables) efficiently (10 iterations to convergence). Finally, we would like to note that the accurate and efficient generation of the entire Pareto set in simulation-based design engineering is a research problem in itself that is outside of the scope of this paper. The message we are trying to convey with this paper is that ATC can be a useful methodology to coordinate decomposed multiobjective problems when they can not be solved all-in-one.

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