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ROBUST SIMULATION-BASED DESIGN OF HIERARCHICAL SYSTEMS

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ABSTRACT

Hierarchical design scenarios arise when the performance of large-scale, complex systems can be affected through the optimal design of several smaller functional units or subsystems. Monte Carlo simulation provides a useful technique to evaluate probabilistic uncertainty in customer-specified requirements, design variables, and environmental conditions while concurrently seeking to resolve conflicts among competing subsystems. This paper presents a framework for multidisciplinary simulation-based design optimization, and the framework is applied to the design of a Formula 1 racecar. The results indicate that the proposed hierarchical approach successfully identifies designs that are robust to the observed uncertainty.

1 INTRODUCTION

Through multidisciplinary design optimization (MDO), complex engineering systems are decomposed by breaking the system into smaller, less complex subsystems. Mathematically, decomposition partitions relationships by discipline. Characteristic of most multidisciplinary design optimization problems is a coupling of disciplines or subsystems through design, function, and performance. Coupling variables, also called linking variables or shared variables, are those variables that are common to more than one subsystem or are shared by the system level with at least one subsystem. Equality constraints for coupling variables are added to the partitioned problem to ensure compatibility of the subsystem solutions. These shared variables must attain the same value in the final solution, while the equality constraints enforce system-level feasibility. Surveys of several approaches proposed to analyze MDO problems are provided in (Balling and Sobieszczanski-Sobieski 1996, Sobieszczanski-Sobieski and Haftka 1997).

Recent advances in MDO recognize the presence of uncertainty throughout the design process (Antonsson and Otto 1995, Bandte, et al. 1999, Chen and Yuan 1999, DeLaurentis and Mavris 2000, Du and Chen 2002, Gu and Renaud 2001, Lewis and Mistree 1998, Liu 2001, McAllister and Simpson 2001). Figure 1 illustrates the stages of design, where uncertainty is indicated by the symbol Δ to denote variation. During conceptual design (Medeiros, et al. 2000, Ruiz-Torres and Zapata 2000), the greatest source of uncertainty is within the requirements imposed on the design (e.g., *How big does it need to be; how fast should it travel; how much does it cost?*). As the design process evolves and matures to the preliminary and detailed design stages, the requirements become more refined and uncertainty in design variables (e.g., length, thickness, and diameter) and conditions of the environment (e.g., temperature, humidity, and air pressure) are the dominant sources of uncertainty. The evolution of the design is obviously affected by the decisions made in each stage of the design process, and these decisions have a considerable impact on the overall system cost. For instance, accurate decisions about the signal processing capability of an underwater vehicle may provide significant savings in performance analyses and design modifications. Explicitly modeling uncertainty within the design process is therefore critical to the identification of candidate designs that are robust to ambiguity and imprecision (Sanchez, 2000).

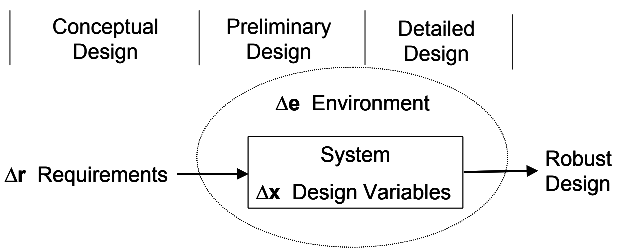

Figure 1: Uncertainty Encountered During Design Stages

The remainder of this paper is organized as follows. Section 2 develops the proposed hierarchical simulation-based design framework for robust design, which is applied in Section 3 to the design of a Formula 1 racecar. Results are provided in Section 4, and concluding remarks are offered in Section 5.

2 BACKGROUND

The simulation-based design (SBD) framework developed in this paper utilizes Collaborative Optimization (Braun, et al. 1996, Braun and Kroo 1997), Figure 2, a popular MDO approach that provides design flexibility by using a system-level optimizer to act on an overall design objective subject to the subsystem compatibility constraints (Braun, et al. 1997, Gu and Renaud 2001, Sobieski and Kroo 1996, Tappeta and Renaud 1997).

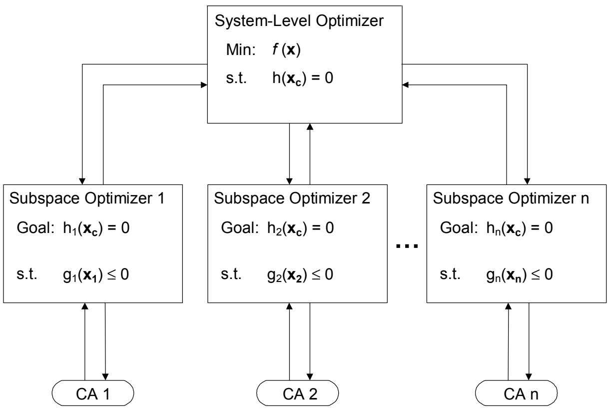

Figure 2: Collaborative Optimization

Applications of Collaborative Optimization include launch vehicle design (Braun, et al. 1997), aircraft wing design (Sobieski and Kroo 1996), lunar ascent trajectory (Braun and Kroo 1997), and the design of a racecar (McAllister, et al. 2002). Extensions to Collaborative Optimization include the multiobjective approach of Tappeta and Renaud (1997), which uses weighted sums for the system-level optimizer. The goal programming formulation of CO introduced in (McAllister, et al. 2000) extends the capabilities of the MDO framework to include multiple objectives at the system and subsystem levels.

The Collaborative Optimization framework is implemented using the compromise Decision Support Problem (DSP) to assess the impact of uncertainty encountered during simulation-based design of hierarchical systems. The compromise DSP is a multiobjective mathematical programming formulation used to determine the values of the design variables that satisfy a set of constraints and achieve a set of potentially conflicting goals as closely as possible (Mistree, et al. 1993). As depicted in Figure 3, system goals are modeled using two deviation variables (d_i^-, d_i^+), representing under-achievement or over-achievement of each goal with respect to individual target values (G_i). To handle tradeoffs, the objective is to minimize the deviation function, Z, which is a function of the relevant deviation variables. The deviation function can be formed by either weighted sums or a preemptive ordering of deviation variables. When a preemptive formulation is implemented, the lexicographic minimum (Ignizio 1985) concept is used to evaluate alternative designs. A comprehensive discussion of deviation variables, deviation functions, system constraints, goals, bounds, and the solution algorithm can be found in (Mistree, et al. 1993).

Given:
Assumptions used to model the domain of interest.
System parameters:
n — number of system variables
p — number of system equality constraints
q — number of system inequality constraints
m — number of system goals
$g_{i3}(\mathbf{x})$ — system constraint functions
$f_k(d_{i2})$ — function of deviation variables to be minimized at priority level k for the preemptive case.

Find: x_{i1} $i_1 = 1, \ldots, n$; d_{i2}^-, d_{i2}^+ $i_2 = 1, \ldots, m$

Satisfy:
System constraints (linear, non-linear):
$g_{i3}(\mathbf{x}) = 0$ $i_3 = 1, ..., p$
$g_{i4}(\mathbf{x}) \geq 0$ $i_4 = 1, ..., q$
System goals (linear, non-linear):
$A_{i2}(\mathbf{x}) + d_{i2}^- - d_{i2}^+ = G_{i2}$ $i_2 = 1, \ldots, m$
Bounds
$x_{i1}^{min} \leq x_{i1} \leq x_{i1}^{max}$ $i_1 = 1, \ldots, n$
$d_{i2}^-, d_{i2}^+ \geq 0$ $i_2 = 1, \ldots, m$
$d_{i2}^- \bullet d_{i2}^+ = 0$ $i_2 = 1, \ldots, m$

Minimize: *deviation function*:
$Z = [\, f_1(d_{i2}^-, d_{i2}^+), ..., f_k(d_{i2}^-, d_{i2}^+) \,]$

Figure 3: Mathematical Form of Compromise DSP (Mistree, et al. 1993)

Our approach to robust design follows the work of Chen and her coauthors (1996a, 1996b, 1999) who observed that the compromise Decision Support Problem (Mistree, et al. 1993) can be used to individually study the two competing objectives in robust design: (1) maximize the intensity of the signal on target and (2) minimize the variance of the response. Following their implementation of robust design in the compromise DSP, a probabilistic Collaborative Optimization (CO) formulation has been realized for robust design optimization of hierarchical systems. In general, the model is:

$$y = f(\boldsymbol{x}, \boldsymbol{u}), \tag{1}$$

where y is the response, $\boldsymbol{x}$ are the design variables, and $\boldsymbol{u}$ represents sources of uncertainty. The mean and variance of the response are determined by first-order Taylor expansion using the First Order Second Moment (FOSM) approach (Hasselman and Hart 1972, Kareem 1987, Solari

1997), assuming that variations are small and that the sources of uncertainty are independent.

$$\mu_y = f(\mathbf{x}, \mu_u) \qquad (2)$$

$$\sigma_y^2 = \sum_{i=1}^{k}\left(\frac{\partial f}{\partial x_i}\right)^2 \sigma_{x_i}^2 + \sum_{i=1}^{l}\left(\frac{\partial f}{\partial u_i}\right)^2 \sigma_{u_i}^2 \qquad (3)$$

Equations (2 and 3) are used to establish system-level objectives in the Collaborative Optimization framework to achieve robust designs. In a deterministic formulation, the objective is to either minimize, maximize, or meet a desired target, represented by Equation (2). Robust formulations also incorporate the variance of the response using Equation (3). The variance can effectively be included in a multiobjective formulation either combined with the mean in a weighted-sum approach or as a separate objective with preemptive priority lexicographically greater than or less than the mean (Du and Chen 2001). These objectives are readily implemented at the system level in the CO-DSP formulation as shown in Figure 4 and Figure 5 for the system and subsystem levels, respectively.

System Analysis
Given: $\mathbf{x}_u$ vector of n_u uncoupled design variables
$\mathbf{x}_c$ vector of n_s coupled design variables
$\mathbf{x} = [\mathbf{x}_u\ \mathbf{x}_c]$ vector of n design variables
$\mathbf{u}$ vector of v uncertainty sources
uncertainty in $\mathbf{x}$ and $\mathbf{u}$
$A_1(\mathbf{x}, \mathbf{u}) = f(\mathbf{x}, \mu_u)$

$$A_2(\mathbf{x}, \mathbf{u}) = \sum_{i=1}^{n}\left(\frac{\partial f}{\partial x_i}\right)^2 \sigma_{x_i}^2 + \sum_{j=1}^{v}\left(\frac{\partial f}{\partial u_j}\right)^2 \sigma_{u_j}^2$$

Find: $\mathbf{x}_c^0$, targets for coupled (shared) variables
Satisfy:
$\mathbf{x}_c^s - \mathbf{x}_c^0 = 0$
$A_1(\mathbf{x}, \mathbf{z}) + d_1^- - d_1^+ = G_1$
$A_2(\mathbf{x}, \mathbf{z}) + d_2^- - d_2^+ = G_2$
$\mathbf{x}_i^{min} \le \mathbf{x}_i \le \mathbf{x}_i^{max}$
Min: $f\,[d_2^-, d_1^-]$

Figure 4: Robust CO at the System Level

At the subsystem level, Figure 5, robust constraints are implemented assuming that the variations may simultaneously occur. The differences, Δx and Δu, correspond to the range of possible values that may be obtained about the current point due to uncertainty.

3 RACECAR DESIGN

As discussed by Kasprzak (2001), racecar design provides a rich environment in which to apply multidisciplinary

Subsystem Analysis
Given: $\mathbf{x}_c^0$, targets for shared variables
uncertainty in $\mathbf{x}$, $\mathbf{u}$
Find: $\mathbf{x}_c^s$, local values for shared variables
$\mathbf{x}_{i1}$, values for design variables unique to the subsystem
Satisfy:

$$g_{i4}(\mathbf{x},\mathbf{u}) + \left(\sum_{i=1}^{n}\left|\frac{\partial g_{i4}}{\partial x_i}\right|\Delta x_i + \sum_{j=1}^{v}\left|\frac{\partial g_{i4}}{\partial u_j}\right|\Delta u_j\right) \le 0$$

$\mathbf{x}_i^{min} \le \mathbf{x}_i \le \mathbf{x}_i^{max}$
Min: $(x_c^s - x_c^0)^2$
$f\,[d_i^+, d_i^-]$, local objectives of interest

Figure 5: Robust CO at the Subsystem Level

design optimization techniques. Racecar configuration and analysis involves knowledge of aerodynamics, structural mechanics, tire performance, and vehicle dynamics. This information is attained from disciplinary experts who have different opinions and control over the performance of the vehicle. The range of adjustment on the design variables may be limited during the racing season (e.g., center of gravity location), and sanctioning bodies limit the amount of on-track testing that can be conducted. As a result, vehicle simulations must be used to optimize a racecar before it is constructed. Advantages gained through simulation increase the vehicle's potential, and when combined with a talented driver, translate into an increase in on-track performance.

During a lap on a particular racetrack, a driver is faced with a number of different types of corners and straights. Designing a racecar to perform well across turns of all radii on a single track involves a set of conflicting tradeoffs. Each segment of the racetrack has its own optimal vehicle characteristics. The optimal racecar for tight cornering is vastly different than one for sweeping, large-radii curves. Kasprzak, et al. (2000) and Hacker, et al. (2000) use multiobjective optimization to maximize racecar performance across multiple tracks of different radii.

The racecar model is based on the classic bicycle model of Milliken and Milliken (Milliken and Milliken 1995), which has been expanded to include four individual wheels. Equations of motion are written for lateral acceleration, longitudinal acceleration, and yaw acceleration. The tires, which may be different for front and rear, are modeled using tabular tire data including representations of nonlinearities such as load sensitivity and slip angle saturation. Wheel loads are calculated based on static load, aerodynamic downforce, and lateral load transfer. Figure 6 illustrates a simplified sketch of the racecar model. There are three primary design variables: roll stiffness distribution (*K'*), weight distribution (*A'*), and aerodynamic downforce distribution (*C'*). All three design variables are normalized quantities between 0 and 1.

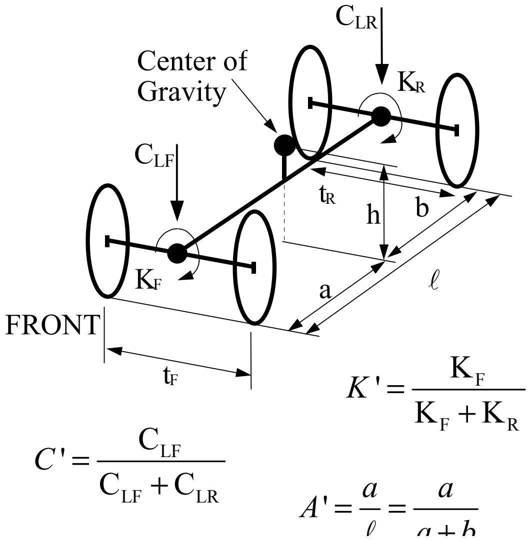

Figure 6: Sketch of the Racecar Model

3.1 Design Relationships

This section outlines the equations that govern racecar design. The analysis begins with the calculation of parameters and concludes with an iterative analysis to solve for lateral forces given the center of gravity and roll stiffness.

Table 1 presents the design variables under consideration for the racecar optimization. All design variables have lower and upper bounds of 0.3 and 0.6, respectively.

Table 1: Racecar Design Variables

Var.	Description	Init. Value
A'	Weight distribution	0.4
C'	Aero downforce distribution	0.4
K'	Roll stiffness distribution	0.3

Table 2 indicates the fixed racecar and track parameters used in this study. For instance, we considered a racecar with a wheelbase of 9.67 feet and mass of 41.7 slugs traveling on a 400-foot radius curve.

Table 2: Racecar and Track Parameters

Parameter	Value	Description
l	9.67 ft	Vehicle Wheelbase
mass	41.7 slug	Vehicle Mass
h	1.167 ft	Height of CG
tF	5.5 ft	Front Track
tR	5.25 ft	Rear Track
RefArea	10 ft^2	Frontal Area
Radius	400 ft	Skidpad Radius
CD	2.9	Drag Coefficient

Figure 7 illustrates the relationships between lateral forces and slip angles. As indicated, the center of gravity defines the origin of the coordinate system, and clockwise moments are positive.

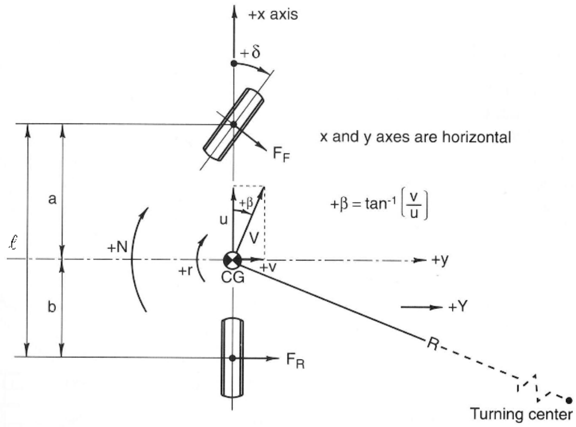

Figure 7: Racecar Dynamics

Equations (4 and 5) are used to compute the front and rear lift coefficients, *CLF* and *CLR*, respectively, based on the aerodynamic down-force distribution, *C'*.

$$CLF = -0.5 \times C' \quad (4)$$

$$CLR = -1 \times (5 + (-5 \times C')) \quad (5)$$

Equation (6) calculates half the weight of the car, *halfwt*, where *g* is the acceleration due to gravity.

$$halfwt = mass \times g/2 \quad (6)$$

Equations (7-9) determine the coefficients for front and rear downforce, *FDwnfc* and *RDwnfc*, and aerodynamic drag, *Dragc*, where *Den* is the atmospheric density.

$$FDwnfc = -(Den \times CLF \times RefArea)/2 \quad (7)$$

$$RDwnfc = -(Den \times CLR \times RefArea)/2 \quad (8)$$

$$Dragc = -(Den \times CD \times RefArea)/2 \quad (9)$$

Table 3 indicates the parameters that must be initialized before proceeding with the iterative analysis to solve for the lateral forces.

Table 3: Initialization of Lateral Force Loop

Parameter	Description	Init. Value
FyRF	Right front wheel load	0
FyLR	Left rear wheel load	0
FyRR	Right rear wheel load	0
FyF	Lateral force front axle	0
FyR	Lateral force rear axle	0
Fy	Lateral force	0
uOld	Velocity last iteration	0
MaxAlphaF	Max front slip angle	0
MaxAlphaR	Max rear slip angle	0

Equations (10-12) determine the aerodynamic forces, where positive quantities indicate downforce. The aerodynamic force acting on the front and rear wheels is represented by *AeroFzF* and *AeroFzR*, respectively. *AeroFx* is an aerodynamic force that opposes forward motion.

$$AeroFzF = FDwnfc \times uOld^2 \tag{10}$$

$$AeroFzR = RDwnfc \times uOld^2 \tag{11}$$

$$AeroFx = Dragc \times uOld^2 \tag{12}$$

Equation (13) indicates the required tractive effort, *FxReq*, which is always positive.

$$FxReq = AeroFx + |FyF \times \sin(MaxAlphaF)| + |FyR \times \sin(MaxAlphaR)| \tag{13}$$

Front and rear wheel loads, *FLT* and *RLT*, are given by Equations (14 and 15).

$$FLT = (Fy \times h/tF) \times K' \tag{14}$$

$$RLT = (Fy \times h/tR) \times (1\text{-}K') \tag{15}$$

Equations (16-19) determine the downforce on each of the four wheels. For instance, *FzRF*, is the downforce acting on the right front wheel.

$$FzLF = (1\text{-}A') \times halfwt + FLT + AeroFzF/2 \tag{16}$$

$$FzRF = (1\text{-}A') \times halfwt - FLT + AeroFzF/2 \tag{17}$$

$$FzLR = A' \times halfwt + RLT + AeroFzR/2 \tag{18}$$

$$FzRR = A' \times halfwt - RLT + AeroFzR/2 \tag{19}$$

Based on the installed tires with tabulated lateral forces due to normal load and slip angle, quadratic approximation is used to determine maximum slip angles, *MaxAlphaF* and *MaxAlphaR*, and lateral forces, *FyF* and *FyR*, for the front and rear axles. Equations (20 and 21) check the lateral forces on the rear wheels, *FyLR* and *FyRR*, and, if required, reduce these forces due to the friction ellipse effect.

$$FyLR = \begin{cases} 0 & \dfrac{FxReq}{2} > |FyLR| \\ \dfrac{FyLR}{|FyLR|}\sqrt{\left|FyLR^2 - \left(\dfrac{FxReq}{2}\right)^2\right|} & \text{else} \end{cases} \tag{20}$$

$$FyRR = \begin{cases} 0 & \dfrac{FxReq}{2} > |FyRR| \\ \dfrac{FyRR}{|FyRR|}\sqrt{\left|FyRR^2 - \left(\dfrac{FxReq}{2}\right)^2\right|} & \text{else} \end{cases} \tag{21}$$

Equation (22) calculates the total rear lateral force, *FyR*, as a sum of lateral forces acting on each of the two rear wheels.

$$FyR = FyLR + FyRR \tag{22}$$

Equations (23 and 24) determine the total yaw force, *YawBal*.

$$IDYaw = (FyRF\text{-}FyLF) \times tF \times \sin(MaxAlphaF) + (FyRR\text{-}FyLR) \times tR \times \sin(MaxAlphaR) \tag{23}$$

$$YawBal = [A' \times FyF \times \cos(MaxAlphaF)] - [B' \times FyR \times \cos(MaxAlphaR)] + IDYaw \tag{24}$$

Equations (25 and 26) are used to enforce yaw balance, $YawBal = 0$. If $YawBal < 0$, Equation (25) provides the necessary adjustment, while Equation (26) is used to correct for $YawBal > 0$.

$$FyF = \frac{\left((1\text{-}A') \times FyR \times \cos(MaxAlphaR)\right) - IDYaw}{A' \times \cos(MaxAlphaF)} \tag{25}$$

$$FyR = \frac{\left(A' \times FyF \times \cos(MaxAlphaF)\right) + IDYaw}{B' \times \cos(MaxAlphaR)} \tag{26}$$

Equation (27) calculates total lateral force, *Fy*, as a sum of front and rear lateral forces. Then, Equations (28 and 29) are used to determine the corresponding speed, *u*, and lap time, *et*, respectively.

$$Fy = FyF + FyR \tag{27}$$

$$u = \sqrt{\left|\frac{Fy \times Radius}{mass}\right|} \tag{28}$$

$$et = \frac{2\pi \times Radius}{u} \tag{29}$$

The analysis has converged if the difference in lap time between successive iterations does not exceed a small number, $|\, etOld\text{-}et \,| \le 0.005$. Otherwise, time and velocity estimates are updated, *uOld* = *u* and *etOld* = *et*, and the analysis loop returns to Equation (10).

3.2 Robust Hierarchical Formulation

Equations (4-29) establish the traditional optimization formulation for the racecar design problem. Formulating this as a robust multidisciplinary CO simulation-based design problem, Figure 8, two disciplinary subspaces are defined: (1) aerodynamics and (2) force analysis. Incorporated in the aerodynamic analysis are Equations (4-12) while the force analysis contains Equations (13-27). The system-level coordinator minimizes lap time, Equation 29, and establishes corresponding targets for design variables *A'*, *C'*, and *K'* and linking variables *AeroFzF*, *AeroFzR*, and *FxReq*. The goal of each subsystem is to minimize deviation from these established targets to ensure the compatibility dictated by a multi-level formulation.

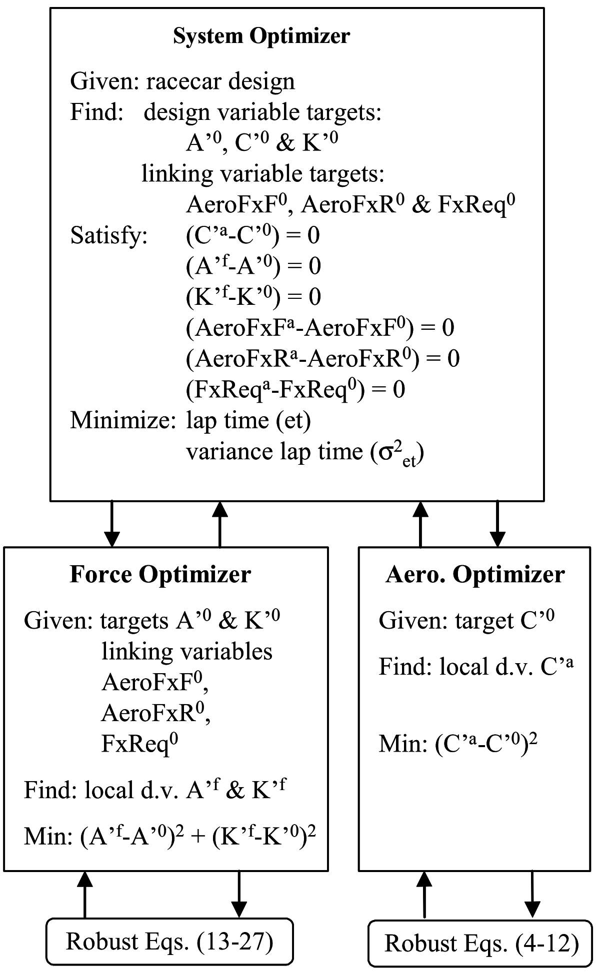

Figure 8: Robust SBD via Collaborative Optimization

To explore the impact of uncertainty, variability is included in the design variable (*C'*), normalized aerodynamic downforce, Table 4. Uncertainty in (*C'*) is represented as a normal distribution to reflect variability in the configuration of the racecar. Total lateral force (*Fy*) is modeled as a uniform distribution to reflect uncertainty arising from changes in tire properties throughout a particular race.

Table 4: Uncertainty in Racecar Design

Name	Type	Distribution
C'	Design variable	N(*C'*, 0.01)
Fy	Parameter	U(*Fy* - 50.0, *Fy* + 50.0)

The design scenarios were formulated as robust SBD instances of Collaborative Optimization, Figure 8, and solved using the compromise DSP software called DSIDES (Decision Support in the Design of Engineering Systems; (Mistree, et al. 1993)). The results are given and discussed in the next section.

4 RESULTS

Results for the simulation-based design optimization formulations are presented in Table 5, where cDSP represents a traditional (nonhierarchical) formulation, CO indicates a hierarchical formulation using Collaborative Optimization, and R indicates a robust design approach with preemptive priority to mean value, followed by variability about the mean. Solution times are given for a Sun Blade 150 with a 650 MHz processor. The CO columns show the expected agreement with the corresponding non-hierarchical columns. The increased computational expense of CO arises from the compatibility conditions that are difficult to meet as equality constraints. This increase is offset by (i) the value of representing the problem in the disciplinary format normally encountered in large-scale design problems and (ii) the ability to apply parallel computation. The robust design cases indicate a more conservative, slower racecar at 15.8 seconds vs. 14.92 seconds due to the observed uncertainty.

Table 5: Simulation-Based Design Optimization Results

Name	cDSP	RcDSP	CO	RCO
A'	0.30	0.40	0.30	0.40
C'	0.57	0.38	0.57	0.38
K'	0.30	0.30	0.30	0.30
et	14.92 s	15.80 s	14.92 s	15.80 s
Solution Time	2 min	3 min	90 min	100 min

Convergence plots for the robust formulations are provided as Figures 9 and 10. The model assumes all four wheels remain in contact with the track. Hence, negative wheel loads are penalized as evidenced by the vertical spikes. The cyclic behavior, with a period of approximately 70 iterations, evident in Figure 9 is largely avoided by the hierarchical formulation. In both cases, the Adaptive Linear Pro-

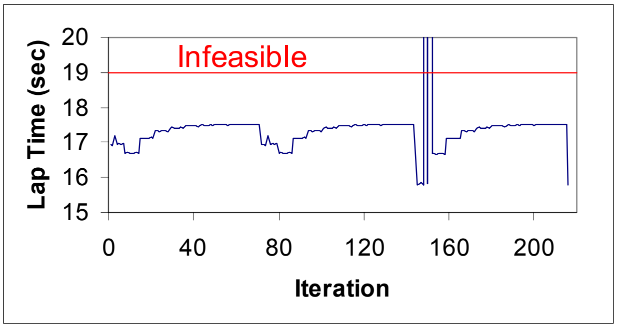

Figure 9: Robust Design Convergence (Nonhierarchical)

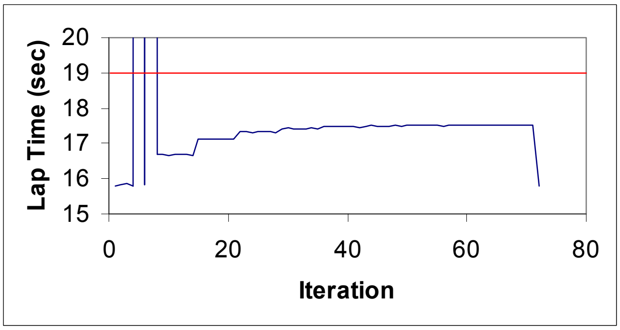

Figure 10: Robust Collaborative Optimization Convergence (Hierarchical)

gramming solution heuristic within the analysis software appears to converge toward a local optimum that is ultimately rejected in favor of a previously identified better point.

5 CLOSING REMARKS

The proposed approach for robust conceptual design optimization uses Monte Carlo techniques within simulation-based design to evaluate both the mean and variance of a response. Both nonhierarchical and hierarchical formulations attain identical optimum solutions. The effectiveness of Collaborative Optimization is offset by the increased computation time necessary to enforce the equality constrained system-level compatibility requirement. However, the Collaborative Optimization formulation more accurately represents the disciplinary organization encountered in conceptual design and facilitates parallel computation. Future investigations include the use of metamodels and data visualization to expedite the identification of design space tradeoffs for rapid exploration of alternative designs.

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