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ROBUST DESIGN FOR IMPROVED VEHICLE HANDLING UNDER A RANGE OF MANEUVER CONDITIONS

Wei Chen
Department of Mechanical Engineering
University of Illinois at Chicago
weichen1@uic.edu

Raman Garimella
Department of Mechanical Engineering
Clemson University

Nestor Michelena
Department of Mechanical Engineering
University of Michigan, Ann Arbor

ABSTRACT

In this article, a robust design procedure is applied to achieve improved vehicle handling performance as an integral part of simulation-based vehicle design. Recent developments in the field of robust design optimization and the techniques for creating global approximations of design behaviors are applied to improve the computational efficiency of robust vehicle design built upon sophisticated vehicle dynamic simulations. Our approach is applied to the design of a M916A1 6-wheel tractor / M870A2 3-axle semi-trailer. The results illustrate that the proposed procedure is effective for preventing the rollover of ground vehicles as well as for identifying a design that is not only optimal against the worst maneuver condition but is also robust with respect to a range of maneuver inputs. Furthermore, a comparison is made between a statistical approach and a bi-level optimization approach in terms of their effectiveness in solving robust design problems.

NOMENCLATURE

$\mathbf{x}$	Vector of design variables
$f(\mathbf{x})$	Objective function
$g_j(\mathbf{x})$	Constraint functions
k_j	Constant in worst case analysis
m_f	Mean of the objective function
s_f	Standard deviation of the objective function
C_{dk}, C_{dl}, C_{dk}	Design capability indices
LRL	Lower Requirement Limits
URL	Upper Requirement Limits
Δy	Variation from the mean
R	Rollover metric
C	Critical rollover condition
HH1	Height of hitch above ground (in)
KHX1	Hitch roll torsional stiffness (in-lb/deg)
LTS11	Distance between springs on axle 1 (in)
LTS123	Distance between springs on axles 2 & 3 (in)
LTS2123	Distance between springs on axles 4,5 & 6 (in)
M11	Laden load for axle 1 (lbm)
M123	Laden load for axles 2 & 3 (lbm)
M2123	Laden load for axles 4, 5 and 6 (lbm)
KT11	Axle 1 tire stiffness (lb/in)
KT123	Axles 2 & 3 tire stiffness (lb/in)
KT2123	Axles 4, 5 & 6 tire stiffness (lb/in)
SCFS11	Axle 1 spring stiffness scale factor
SCFS123	Axles 2 & 3 spring stiffness scale factor
SCFS2123	Axles 4,5 & 6 spring stiffness scale factor
start_brake	Start time of braking (sec)
brake_level	Level of braking pressure (psi)
end_brake	End time of braking (sec)
steer_level	Steering angle (deg)
start_steer	Start time of steering (sec)
end_steer	End time of steering (sec)

1. INTRODUCTION

Recent years have seen significant progress in developing simulation tools that can predict the performance of vehicle dynamic systems. Although the fidelity of these tools has been improved tremendously by introducing advanced control analysis and synthesis methodologies, high computational resources are still required even after the advent of inexpensive high-end workstations. This becomes a challenging issue especially while examining those vehicle behaviors where worst-case conditions must be evaluated over a range of operating conditions. An example is the study of vehicle handling performance in which the extreme maneuver conditions must be identified for a given maneuvering profile. Researchers have applied classical optimal control and game theory to obtain linear solutions analytically and used numerical methods for nonlinear situations in worst-case evaluations (Ma and Peng, 1996). Though useful, these procedures still require a significant amount of computations and are limited to the analysis, but not design, of vehicle systems. There is a need for a systematic design approach that can both utilize the capabilities of existing sophisticated vehicle simulation programs and optimize the vehicle performance by considering the extreme maneuvering conditions in a computationally efficient manner.

In this article, we propose to incorporate a robust design procedure as an integral part of simulation-based vehicle design. Foundational to this work is the Robust Concept Exploration Method (RCEM) developed in our research for designing complex engineering systems (Chen, 1995; Chen et al., 1996a; Chen et al., 1997). RCEM is a systematic design approach that can be used to quickly evaluate design alternatives and to develop design specifications with *quality* considerations. In particular, RCEM employs the principles of Design of Experiments (DOE) (Montgomery, 1991) to improve the computational efficiency in designing complex systems. This is achieved by creating surrogate global response surface models (Box et al., 1978) of the expensive simulation programs. The robust design concept (Phadke, 1989) is utilized to determine specifications that are *robust*, i.e., insensitive to adjustments in later stages of design or during operation, and *flexible*, i.e., allowed to vary within a range. RCEM has been tested for various engineering design problems (Chen et al., 1997; Simpson et al., 1996; Koch et al., 1996; Peplinski et al., 1996; Lautenschlager et al., 1996; Bailey et al., 1997). The type of analysis (simulation) programs used in these applications ranges from airframe and propulsion analyses in aircraft design, engine thermodynamic analysis, and finite element structural analysis, to manufacturing systems analysis. These applications illustrated that RCEM can be used to integrate multi-functional analyses across disciplines, to permit the introduction of downstream design considerations in the early stages of design and to provide flexibility to the design process.

In this work, the principles embodied in RCEM are utilized to achieve improved vehicle handling performance under a given range of maneuver conditions. Our focus is on studying the applicability of the robust design procedure embodied in RCEM to designs involving complicated evaluations of system dynamic performance, a domain that was not covered in previous RCEM applications. Significant computational resources are needed to evaluate dynamic behavior. Other challenges of this type of problems are associated with the existence of large number of design variables and parameters that are subject to variations (e.g., operating conditions). We will illustrate the effectiveness of our approach through the design of a M916A1 6-wheel tractor / M870A2 3-axle semi-trailer. Under certain maneuvers, the tractor-trailer model under consideration is subjected to rollover conditions, which can be quite detrimental and have been reported to be the cause of nearly one-third of all roadside crashes in the United States (Mohemedshah and Council, 1997). There is a need to determine vehicle and suspension parameters that can prevent this damaging behavior. Our approach is used to optimize vehicle and suspension parameters such that (i) extreme rollover conditions do not occur and (ii) variation of the rollover performance is minimized for the range of maneuver conditions. The computational efficiency is improved by using response surface models instead of ArcSim (ArcSim, 1997; Sayers and Riley, 1996), an integrated ground vehicle dynamics simulation program. We illustrate a sequential experimentation strategy for creating response surface models over a significant number of design variables using a limited number of simulations. We also demonstrate the effectiveness of two different strategies for robust design optimization, namely, the statistical approach and the bi-level optimization approach. The design capability index (Chen et al., 1997) is shown to be an effective tradeoff metric between the mean and variance attributes in robust design. Worst-case vehicle design studies using the full-blown ArcSim simulation have been presented by (Michelena and Kim, 1998) and are used in this work to further illustrate the advantages of the proposed robust design procedure.

The article is organized as follows. The adaptation of the robust design procedure embodied in RCEM for simulation-based vehicle design is presented in Section 2. This section is followed by a detailed description of the robust design metric used in the study (Section 3). The application of our approach to improving the handling behavior of a ground vehicle is presented in Section 4. Results and verification studies are also included. Section 5 is the closure of the article.

2. THE ROBUST DESIGN METHODOLOGY FOR SIMULATION-BASED VEHICLE DESIGN

The robust design principles in RCEM are employed in this work to develop a systematic and affordable approach for simulation-based vehicle design that involves sophisticated evaluations of dynamic behaviors. Figure 1 is a flow chart of the proposed procedure. The major components of this infrastructure include four processors (modules B, D, E and F) and a simulator (module C). The central slot, module C, is the high fidelity vehicle dynamic evaluation program. The different processors correspond to the three major steps of the proposed procedure.

In Step 1 (module A), based on the principles of quality engineering, vehicle parameters are classified as control factors (design variables), noise factors (uncontrollable variables), and responses (performance). Step 2 is used to build the response surface models used to replace the expensive vehicle dynamics evaluation program through a sequential experimentation strategy. Module B and the simulator C perform computer experiments in a systematic manner. The results are analyzed in module D and the response surface model is created in module E. Depending on the desired order of the response surface model, different types of experiments are chosen by module B to achieve the best accuracy of the surrogate models. Using the response surface models, in Step 3 the robust design method is applied to generate design solutions that are robust to potential design deviations (module F). The robust design formulation and the associated robust design metric are further explained in Section 3.

3. THE ROBUST DESIGN METRIC

A robust optimization problem can be formulated as the following multiobjective optimization problem,

given a range of **z** and the objective function $f(\mathbf{x}, \mathbf{z})$
find **x** that
minimizes (m_f , s_f)
subject to

$$g_j(\mathbf{x}, \mathbf{z}) + k_j \sum_{i=1}^{n} \left| \frac{\P g_j}{\P z_i} \right| \Delta z_i \leq 0, \quad j=1,2,\ldots J \qquad (3.1)$$

$$\mathbf{x}_L \leq \mathbf{x} \leq \mathbf{x}_U,$$

where m_f and s_f are the mean and the standard deviation of the objective function $f(\mathbf{x}, \mathbf{z})$, respectively. To study the variation of constraints under the deviation of noise factors **z**, we use the worst-case scenario, which assumes that all variations of system performance may occur simultaneously for the worst possible combination of design variables (Parkinson et al., 1993). k_j is a constant, chosen by the designer, that reflects the compensation of the error in estimating the worst case when using the first-order Taylor expansion. Depending on the computational resources, m_f and s_f can be obtained through simulations or analytical means such as Taylor expansions.

It can be noted from Eqn. (3.1) that the robust design objective involves two aspects, one is the optimization of the performance mean m_f and the other is the minimization of the performance variance s_f. When these two objectives need to be treated separately, the robust design problem can be modeled using a multiobjective optimization formulation (Chen et al., 1998; Iyer and Krishnamurty, 1998). However, when the conformation of the whole performance distribution with respect to the design requirement is the major concern, these two aspects are interrelated (Chen et al. 1997). In this case, a unified robust design metric is necessary to capture the tradeoffs between these two aspects. Note that the construction of this metric is strongly associated with designer's real needs.

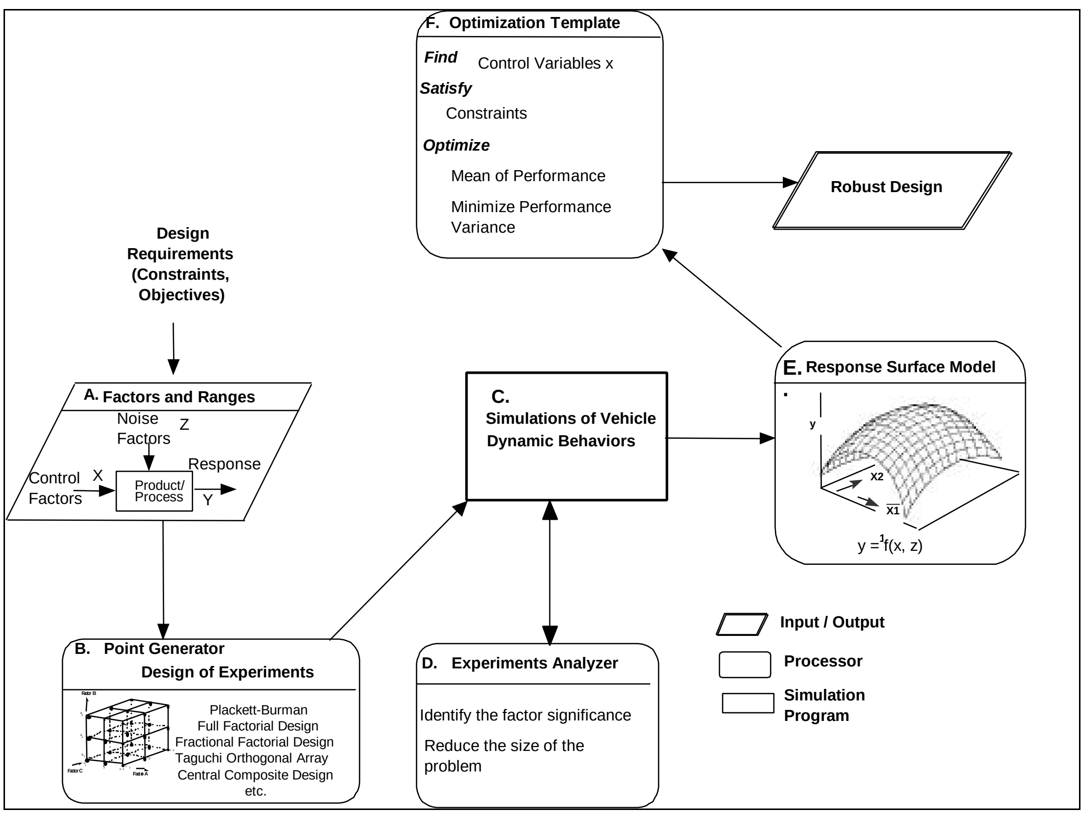


Figure 1 Schematic of Proposed Approach

In this work, we adopt the design capability index C_{dk} (Chen et al. 1996b) as the robust design metric for improving vehicle handling performance. The design capability index was developed as a metric to *measure the portion of the range of designs that satisfies the ranged design requirement*. Depending on whether the performance attribute is desired to be “the nominal the better,” “the smaller the better,” or “the larger the better,” C_{dk} is computed differently. For “the nominal the better”, C_{dk} is the minimum of C_{du} and C_{dl}, where

$$C_{dl} = \frac{\mu - LRL}{3\hat{s}}; C_{du} = \frac{URL - \mu}{3\hat{s}}, \qquad (3.2)$$

and LRL and URL stand for the lower and upper requirements, respectively. A value of C_{dk} greater than one indicates that the whole performance distribution will satisfy the design requirements. Statistically, the use of 3σ implies that when C_{dk} reaches 1, 99.865% of the performance distribution conforms to the requirements, assuming that the performance is normally distributed. An alternative to the statistical representation of the performance deviation in Eqn. (3.2) is the use of extremes of performance that occur in the worst and best possible combination of the noise factors. Correspondingly, the system performance varies between $\mu - \Delta y$ and $\mu + \Delta y$, and Eqn. (3.2) is modified as follows:

$$C_{dl} = \frac{\mu - LRL}{\Delta y}; C_{du} = \frac{URL - \mu}{\Delta y}, \qquad (3.3)$$

where μ is the center and Δy is the difference between the two extremes of performance, namely, the best and worst performance. In this research, we compare the effectiveness of two robustness evaluation strategies that use Eqns. (3.2) and (3.3) as the robustness measurements. The former strategy is called the *statistical approach* and the later is named the *bi-level optimization approach* in which the worst and best performances are identified using sublevel optimizations. Details of the implementation of these strategies for improved vehicle handling performance are provided in Section 4.3.

4. APPLICATION TO THE IMPROVEMENT OF VEHICLE HANDLING PERFORMANCE

The proposed approach is applied to vehicle design for improved handling, in particular for prevention of rollover. As mentioned in Section 1, rollover of ground vehicles is one of the major causes of highway accidents in the United States. Rollover generally occurs when a vehicle is subjected to extreme steering and braking inputs. To prevent rollover, there is a need to optimize those vehicle and suspension parameters that will make the design less susceptible to rollover under a range of maneuver conditions. In this project, the vehicle is assumed to be subjected to sudden steering to the left and to the right with the application of brakes, a scenario that often occurs for lane changing or obstacle avoidance.

4.1 The Simulator and Classification of Parameters

The simulator (Module C, Figure 1) for this design study is the integrated computer tool ArcSim (ArcSim, 1997; Sayers and Riley, 1996) developed at the University of Michigan for simulating and analyzing the dynamic behavior of 6-axle tractor-semitrailers. ArcSim can simulate responses to user-defined steering and braking inputs, on flat or inclined ground surfaces. The program contains a nonlinear 3D mathematical model with 91 state variables, a nonlinear tire model, and a detailed steering system model with major compliance effects. ArcSim considers solid-axle suspensions and major suspension effects. ArcSim is a computationally expensive program that includes more than one hundred input and output parameters. Each simulation takes more than three minutes to run on a Sun Ultra-1 workstation. The testing of an optimization scenario without robustness consideration takes at least five hours to converge (Michelena and Kim, 1998). When robustness considerations are introduced the total computational time needs to be multiplied by a factor of 2^n, where n is the number of noise factors, due to the evaluation of performance variance. The increase in computational demand for robust design becomes explosive when the number of noise factor increases.

In this study, fourteen ArcSim input parameters corresponding to suspension and vehicle parameters are chosen as design variables (control factors). A list of these variables and their ranges are given in Table 1. All the variables have a range of +/- 20 % from their nominal values (i.e., the values for the baseline design). Among the variables considered, suspension stiffness parameters are very likely to affect vehicle handling. These stiffness parameters are represented by spring stiffness scale factors (SCFS11, SCFS123 & SCFS2123), the vertical stiffness of the tires (KT11, KT123 & KT2123), and the hitch roll torsional stiffness (KHX1). Stiffness scale factors linearly scale the upper and lower envelopes of exponential spring models. The distances between the suspension springs (LTS11, LTS123 & LTS2123) and the height of the hitch (HH1) also influence the performance of the suspension system. Laden load distribution at the axes (M11, M123 & M2123) plays an important role for vehicle handling, in particular when the vehicle takes sharp turns.

In most cases, rollover occurs due to extreme steering and braking inputs. The steering and braking parameters are taken as the noise factors. Six noise factors are chosen, three corresponding to the braking inputs and three corresponding to the steering inputs. Their ranges are provided in Table 2. The ranges of start_brake and end_brake are +/- 15% from their nominal values to avoid overlap of the two parameters, whereas the other parameter ranges are +/- 20% from their nominal values. The level of braking is the amount of braking pressure applied. The level of steering is the angle the steering wheel is turned. The starting and ending times define total time of braking and steering.

Table 1 Design Variables and Their Ranges

Design Variable	Description	Low	High
HH1	Height of Hitch above ground	51.2 in	76.8 in
KHX1	Hitch roll torsional stiffness	8e5 in-lb/deg	1.2e5 in-lb/deg
LTS11	Distance between springs on Axle 1	30.4 in	45.6 in
LTS123	Distance between springs on Axles 2 & 3	30.4 in	45.6 in
LTS2123	Distance between springs on Axles 4,5 & 6	30.4 in	45.6 in
M11	Laden load for Axle 1	11540 lbm	17310 lbm
M123	Laden load for Axles 2 & 3	20358.4 lbm	30537.6 lbm
M2123	Laden load for Axles 4, 5 and 6	16274.4 lbm	24411.6 lbm
KT11	Axle 1 tire stiffness	5520.00 lb/in	8280.00 lb/in
KT123	Axles 2 & 3 tire stiffness	5520.00 lb/in	8280.00 lb/in
KT2123	Axles 4, 5 & 6 tire stiffness	4139.20 lb/in	6208.80 lb/in
SCFS11	Axle 1 spring stiffness scale factor	0.8	1.2
SCFS123	Axles 2 & 3 spring stiffness scale factor	0.8	1.2
SCFS2123	Axles 4,5 & 6 spring stiffness scale factor	0.8	1.2

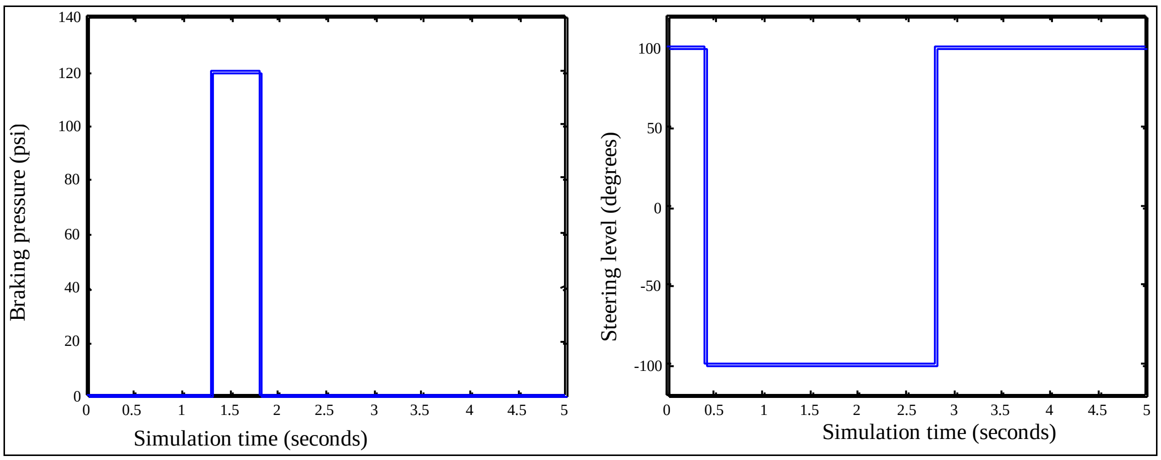


Figure 2 Braking and Steering Input Profiles

The plots in Figure 2 represent examples of maneuver profiles. Positive and negative angles stand for the direction of turn to left and right, respectively. In terms of the vehicle handling response, it is assumed that if the rollover angle becomes greater than 45^0, rollover will inevitably occur. A rollover metric is used as the response for which the response surface model is created. As shown in Eqn. (4.1), the rollover metric is defined as the square root of the integral of the square of the rollover angle in a 5-second period. Rollover angle versus simulation time is one of the outputs of ArcSim (Figure 3).

$$R=\sqrt{\int_0^5 roll\_angle^2\,dt} \qquad (4.1)$$

Five seconds was chosen as the upper limit of the integration, because it was observed that in all cases, when rollover occurs the simulation terminates before five seconds. Since the rollover angle takes up negative or positive values depending on whether rollover is to the left or to the right, the square of the rollover angle is used as the metric.

Table 2 Noise Variables and Their Ranges

Noise Variable	Lower Bound	Upper Bound
start_brake	1.02 sec	1.38 sec
brake_level	70 psi	100 psi
end_brake	1.53 sec	2.07sec
steer_level	60 deg	100 deg
start_steer	0.24 sec	0.36 sec
end_steer	2.16 sec	3.24 sec

Based on this definition, we note that the value of the rollover metric is desired to be as small as possible. For those situations in which rollover occurs before 5 seconds, the rollover metric is magnified by an additional area, from the stopping time to the end of the five-second period. Thus, a rollover metric for a simulation that terminates in less time almost always has a larger value.

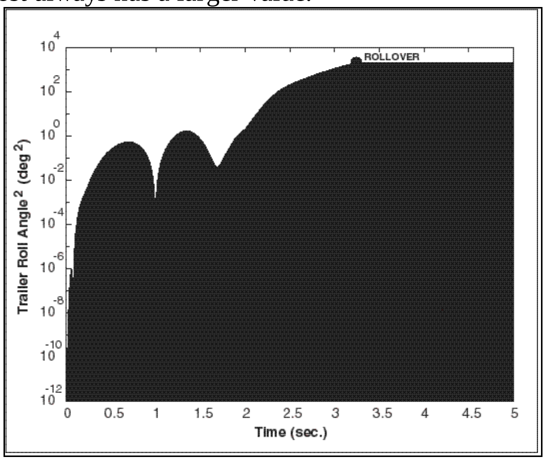


Figure 3 Integration of Rollover Angle vs. Time

4.2 Development of the Response Surface Model

Evaluation of the extreme condition for vehicle handling performance is a time consuming process as the worst maneuver must be identified among a set of possibly infinite number of combinations of steering and braking inputs. This problem becomes more significant in robust design as not only the worst performance but also the deviation of the whole performance must be identified. Hence, it is not practical to use ArcSim directly as the simulation module for optimization. A surrogate model for the ArcSim simulation program is therefore needed.

Following the procedure described in Section 4.1, the design variables and noise variables included in Tables 1 and 2 were chosen as the input factors in the screening experiments, whereas the rollover metric was taken as the output. The screening experiments were first performed to identify those factors that have a significant impact on the response. The Latin Hypercube design of experiments was chosen for the screening experiments. For Latin Hypercube design, the design space for each factor is divided by grid lines that are set equal to the number of inputs, and each input is randomly selected from within this grid. The Latin Hypercube design tends to be more uniform across the design space and thus ensures that a wide range of the design space be covered. The number of experiments performed was set at 350, which is above the minimum requirement of 231 experiments to fit a quadratic response surface models of 20 factors. Usually a greater number of experiments will ensure a better fit.

Through the experimentation, the data were analyzed and the contributions were ordered in terms of their significance. The chart in Figure 4 shows the contributions of the main factors[1] only. It is evident from this chart that 95% of the main effects is contributed by nine design variables and five noise variables, whereas the other parameters contribute only 5%. From these observations, it was decided that these fourteen variables would be used for further secondary experiments and the remaining would be maintained at their nominal values. In general, the main factors showed a greater significance than the interaction terms. From the chart it is noted that the noise variables brake_level, steer_level, and end_brake play a very significant role in the design. Only one noise variable, start_steer, does not make a significant contribution.

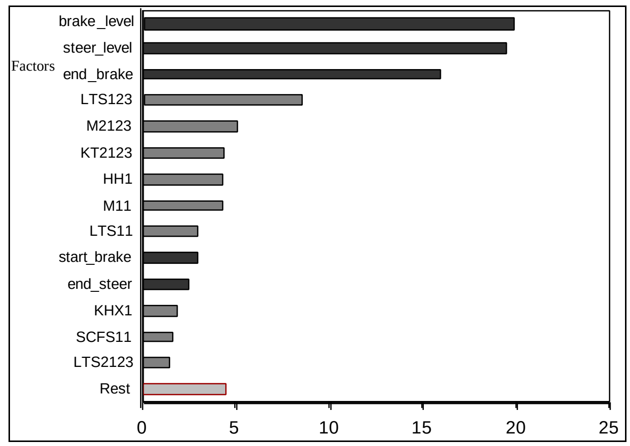
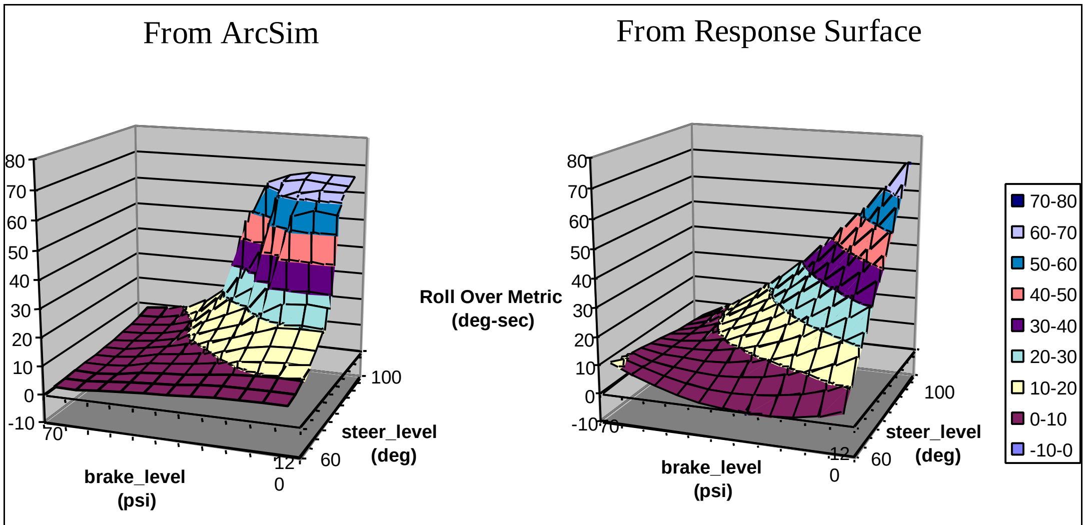


Figure 4 Contributions of Main Factors

Secondary experiments were performed to fit a quadratic response surface model on the reduced set of design factors (14 factors). In this case the minimum number of experiments required is 120 (14 x 13 / 2 = 91 for the interaction terms, 2 x 14 = 28 for the main effects and 1 for the constant term). As two to three times of the minimum number of experiments are often required to ensure a good fit, a total of 363 experiments were performed, which included 225 Latin Hypercube experiments, 121 grid experiments, and 17 Resolution III Fractional Factorial Experiments. These various types of experiments were performed to ensure a good fit representing the behavior across the whole design space. The grid experiments are those designs for which only the two most important factors (brake_level and steer_level) vary, and the remaining variables are maintained at their nominal values. They are performed to ensure that the behavior with respect to the most important factors is captured. The resolution III experiments are used to capture the main effects. As verification, the response from ArcSim and the response surface model is compared in Figure 5. These plots are obtained by performing 121 grid experiments for the two most important factors, while fixing the rest at their nominal levels. A regression coefficient of one ensures a perfect fit. The regression coeficients were R^2 = 0.8775, R^2_adj = 0.8175, and R^2_press = 0.504, thus indicating that there is room for

[1] Main factor effect refers to the contribution from an individual design variable that is independent from the rest of variables.



The regression coefficients are

R^2 = 0.8775 R^2_adj = 0.8175 R^2_press = 0.504

Figure 5 Comparison of RSM with the Actual Program

improvement in the model. However, the use of higher order polynomial models often increases the minimum number of experiments required. For 14 factors, the minimum number of experiments increases from 120 to 302 when changing from a quadratic polynomial to a cubic-order response (not considering three-factor interactions).

4.3 Robust Design Optimization

The design of the truck/trailer for improved handling under a range of maneuver conditions is modeled using the robust design formulation discussed in Section 3. The formulation is restated in Figure 6. Note that the design variables and the noise factors are the reduced set of variables identified based on the analysis of Section 4.2.

Since we aim at minimizing the rollover metric, the formulae of C_{dk} for "the smaller the better" scenario is used as the robust design metric. URL is the upper requirement limit, i.e., the critical rollover condition. The value of the rollover metric at which the rollover just occurs is considered as the critical rollover condition. In this work, this value is obtained empirically. Figure 7 is a plot of the rollover metric versus the simulation stopping time based on the results from both the preliminary and secondary simulations (Section 4.2). Only those data points from simulations where termination has occurred before the 5-second period are plotted. This curve is extrapolated to a stopping time of 5 seconds. It is observed that the critical rollover metric is around 45 deg-sec$^{1/2}$. This indicates that if the rollover metric is above this value, rollover will certainly occur.

Given
Range of noise factors (start_brake, brake_level, end_brake, steer_level, and end_steer)[2]

Find
The tire and suspension parameters (LTS123, M2123, KT2123, KT2123, HH1, M11, LTS11, SCFS11, LTS2123)[3]

Satisfy
M11 + 2*M123 + 3*M2123 = Constant
(The total sum of the laden loads needs to be maintained constant.)
LWB(2) - LXRL(1)/2 $\geq$ LXCGPL $\geq$ LXRL(1)/2
(The difference between the wheel base of the tractor and half the length of the box load should be greater than both the distance to the rear of the CG and half the length of the box load).

Boundaries of the variables

Maximize
Robust Design Metric
Statistical approach $C_{dk} = (URL-\mu_y)/3\sigma_y$
Bi-level approach $C_{dk} = (URL-\bar{y})/\Delta y$
y : rollover metric R; URL : critical roll over condition

Figure 6 Robust Design Formulation

[2] Refer to Table 4.2 for further information
[3] Refer to Table 4.1 for further information.

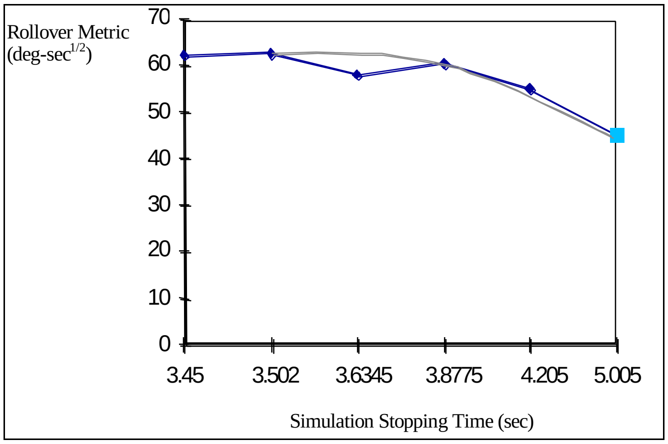
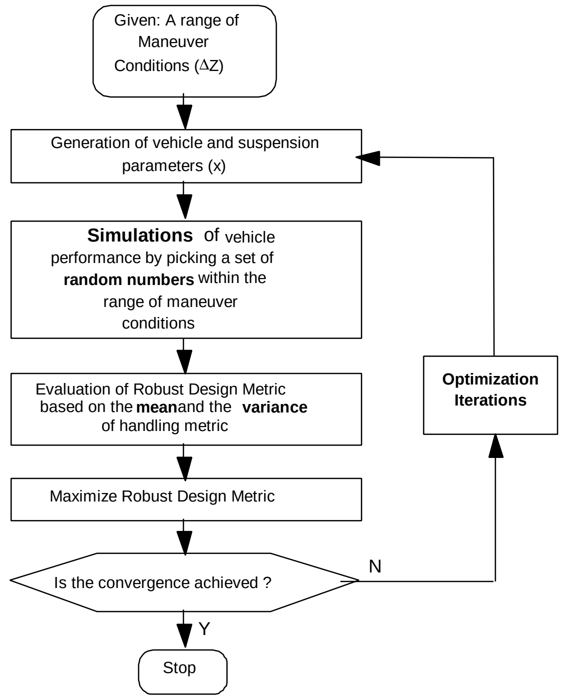


Figure 7 Determination of Critical Rollover Condition

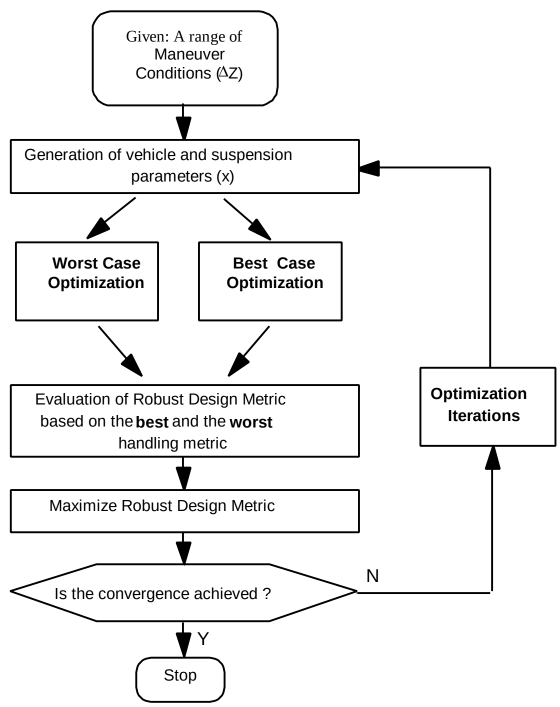
As discussed in Section 3, the robust design metric can be evaluated using either the statistical approach or the performance under extreme conditions. Correspondingly, two strategies, namely the *statistical approach* and the *bi-level optimization approach* can be used to solve the robust design problem. In the statistical method, an assumption of normal distribution for the response is made and the mean and standard deviation are obtained statistically. The bi-level optimization method is more conservative and the mean was assumed to be at the center of the worst and best design within the range of maneuver conditions. Figure 8 shows the flow charts of these two approaches.

When using the statistical approach, for a given range of maneuver conditions, sets of design variables, i.e., vehicle and suspension parameters, are generated by the optimizer. Vehicle performance is then evaluated by choosing the noise parameters from the range of maneuver conditions. If a 3-level full factorial design is used, 243 experiments are performed per iteration—since there are 5 noise variables. The statistical mean and variance of the rollover metric is obtained and the value of the robust design metric is calculated. This design metric is maximized and the process is repeated until convergence is achieved. In this particular case, the procedure involves 243 function calls in the inner loop for each iteration in the outer loop. The total number of function calls could be reduced by using fractional factorial design or Taguchi's orthogonal arrays.

When using the bi-level optimization approach, sets of design variables are also generated by the optimizer. In the inner sub-optimization routine, the noise variables are varied such that the worst (maximum) and the best (minimum) values of the robust design metric are obtained for a particular setting of the design variables. Thus, each iteration of the outer loop involves a maximization and a minimization problem at the sublevel. The robust design metric is calculated based on the extreme conditions and the metric is maximized until convergence is achieved. Depending on the number of function calls needed for the inner optimization loop, the total number of function calls for the bi-level approach can be less or more than for the statistical approach.



8a. Statistical Approach



8b. Bi-Level Optimization Approach

Figure 8 Flow Charts of Solution Strategies

4.4 Results and Discussions

To improve computational efficiency, the robust design model in Figure 6 is solved using the response surface model for the rollover metric. It is first noticed that the best C_{dk} obtained from both the statistical and the bi-level optimization methods is 0.7825. Since this value is less than one, it indicates that for the given range of maneuver conditions, it is likely that some combinations of noise variables will result in rollover. A design where the C_{dk} value is greater than one can be obtained by reducing the range of three of the noise variables, as show in Table 3.

Table3 The Reduced Range of Noise Variables

Variable	Low	High
end_brake	1.611	1.989
steer_level	66	94
brake_level	77.5	112.5

Graphical representations of the probability of the rollover under both the original range (full range) and the reduced range of noise variables are presented in Figure 9. The plot is obtained by running ArcSim, setting the vehicle and suspension design variables at the optimal values identified through robust design, and running a Central Composite Inscribed (CCI) design (43 experiments) for points within the range of the noise variables (steering and braking inputs). The optimal levels of vehicle and suspension variables are obtained from the statistical approach. The vertical axis stands for the frequency of occurrence. It is evident that under the original range, there are instances where rollover might occur (i.e., the rollover metric might be greater than 45 deg-sec$^{1/2}$). The probability of rollover occurrence is close to 5%. C_{dk} equals 2.559 for the reduced range. This implies that rollover is very unlikely for the reduced range of maneuver conditions, as shown by the picture at the bottom of Figure 9.

When comparing the results of the two robustness evaluation strategies, we found that the achieved C_{dk} is the same for the full noise range. For the reduced range, the design from the bi-level optimization method is marginally better since the C_{dk} value (2.795) is greater than that obtained from the statistical method. The robust design solution for the reduced range of noise factors is also compared to the baseline design peformance. Figure 10 shows the distribution of the rollover metric for the baseline design for the reduced range of noise variables. It is noted that probability of rollover occurrence is very high for this design. The standard deviation of the rollover metric for the baseline (17.9133) is much higher than the one obtained from the robust design formulation (4.80326). We observe that the distribution of the rollover metric is much more far away from the critical rollover condition when the robust design approach is applied. Thus, we can conclude that robust design optimization has resulted in improved vehicle handling performance.

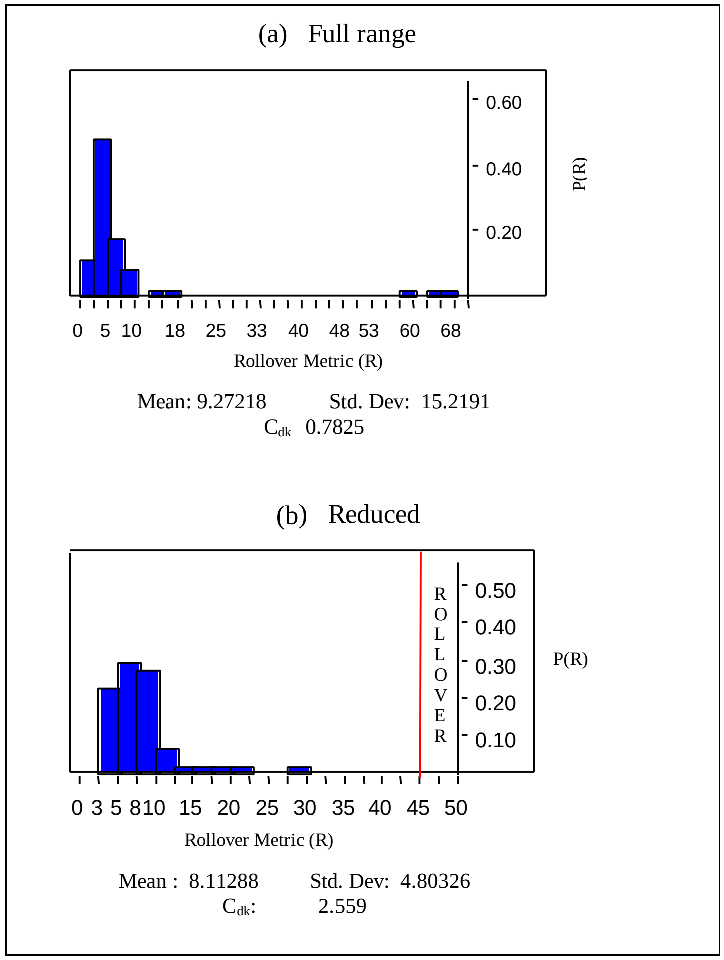


Figure 9 Rollover Metric Distributions from the Statistical Method

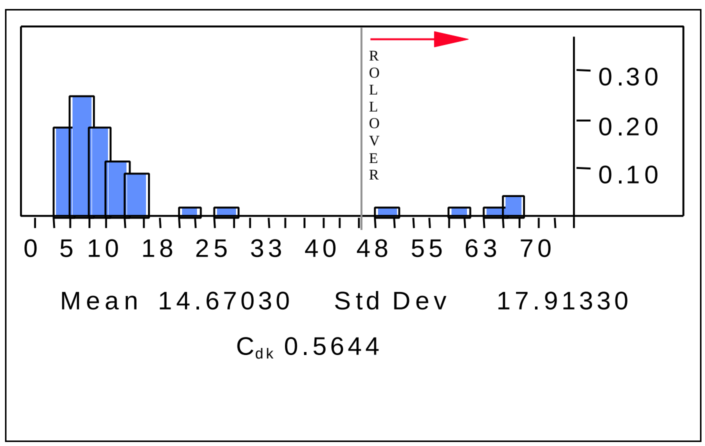


Figure 10 Distribution of the Rollover Metric for the Baseline Design (Reduced Noise Range)

In Figure 11, the baseline design is compared with the robust design in terms of deviation of the robust design solution from the baseline design. The central 0% line represents the baseline design values. The range from –20% to +20% was chosen for the design variables. We note that the robust design solution generally lies at the boundaries of the range of the design variables and a nearly four-fold improvement in the robust design metric. For variables such as hitch height, hitch roll torsional stiffness, distance between springs on axle 1 and axles 4, 5 & 6, laden load for axles 2 & 3 and 4, 5 & 6, and spring stiffness factor of axle 1, the final design values are at their lower bound, i.e., 20% below the baseline values. For the rest of the variables the design is at the upper bound, i.e., 20% above the baseline values.

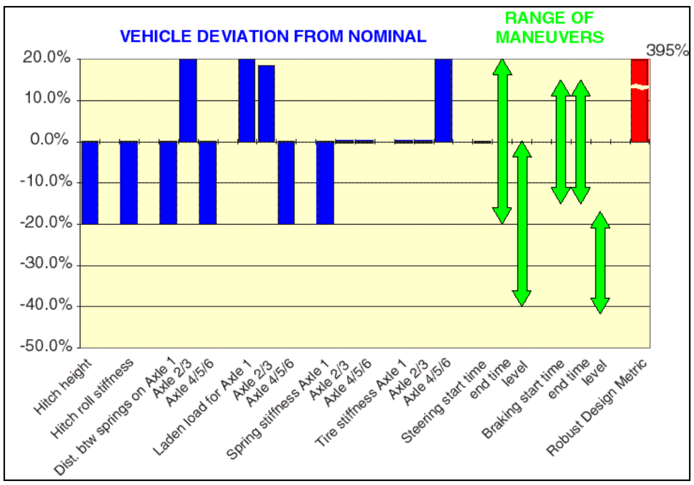


Figure 11 Comparison Between the Baseline Design and the Robust Design

5. CLOSURE

In this article, a robust design procedure is incorporated as an integral part of simulation-based vehicle systems design. It is illustrated through an example problem that this approach is very useful for designing a vehicle for improved handling performance. This is a type of problem that demands significant computational resources for system dynamics simulation and the evaluation of extreme operating conditions.

The first major advantage of our approach is the improvement of computational efficiency in vehicle systems design by using a response surface model (surrogate model) instead of the actual sophisticated simulation program. The surrogate model reduces significantly the computational time required for evaluation of performance distribution in robust design. For a robust optimization procedure that involves 243 function calls in the inner loop and 40 iterations in the outer optimization loop, robust optimization using ArcSim on a SUN Ultra-1 would require close to 500 hours, while it takes less than 2 minutes using the RSM. One may argue that the time spent on simulations for fitting the RSM should be considered. For this particular example, the total number of simulations employed in the sequential experimentation is 713 (a simulation time of 36 hours). The computational time required for fitting the response surface model is negligible at this level of comparison. This significant reduction of computational demand makes the optimal design of vehicle systems more tractable. Comparatively, worst-case vehicle design studies using the full-blown ArcSim simulation and involving fourteen design parameters and three maneuver parameters (Michelena and Kim, 1998) have shown to demand for simulation time in the order of 100 hours on a SUN Ultra-1. This approach models the problem as a semi-infinite programming problem in which the rollover metric is simultaneously maximized with respect to maneuver parameters and minimized with respect to design parameters.

Note also that the global response surface model obtained can be reused for design evaluations or optimizations with changed criteria. Therefore, the approach facilitates the exploration of design solutions through exercising different design scenarios.

The second major advantage of our approach is the introduction of the robust design concept into the design formulation of vehicle design problems in which certain operating parameters are subject to variations. This is superior to conventional worst-case evaluation in that the design is not only optimal against the worst maneuver condition but is also robust with respect to a range of maneuver inputs. Through the example problem, it is illustrated that both the statistical approach and the bi-level optimization strategy are useful for robust design. While the former may lower the total number of function evaluations using the reduced set of simulations based on the statistical principle, the later may generate over-conservative designs in many cases.

We have illustrated the use of a sequential experimentation strategy for problems with a large number of design variables. Problem size was reduced by conducting screening experiments. Although the response surface model using the quadratic function is not a perfect fit of the true behavior of the model, the design solution obtained using the RSM has been illustrated to be very close to the solution using the ArcSim program—because computer simulations were chosen such that the points selected belong to the most critical design region. For future improvement, approximation techniques such as Artificial Neural Networks (ANN) (Smith 1993) and the Kriging method (Cressie, 1988) could be used to replace the quadratic models. Since most of the design solution lies at the boundaries, it will be interesting to study whether relaxing the design range further improves the systems behavior. The same design principle illustrated in this article can be extended to considering multiple dynamic behaviors or other design requirements using multiobjective optimization formulations.

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