CROSS-DOMAIN OPTIMIZATION OF MOTORSPORTS TECHNOLOGIES IN MILITARY DESIGN

Lynn W. Bishop
Pratt & Miller Engineering
and Fabrication
New Hudson, MI

Kristian Houghton
Pratt & Miller Engineering
and Fabrication
New Hudson, MI

ABSTRACT

This paper addresses cross-domain optimization of lean technologies developed through motorsports as applied to military vehicle design. Optimization of performance objectives eliminates the reiterative assessments utilized in standard validation and verification of product development. This paper describes the enhancement of overall vehicle reliability, durability, and performance through utilization of front-loaded design, development, engineering, and prototyping activity. Cross-domain optimization, using a Design of Experiments approach (DOE) and the integration of CAE tools, predictably allows for the efficient and accurate solution of challenges prior to full scale prototype build and, congruently, eliminates the necessity for multiple variants often required throughout many testing phases. This paper illustrates, systematically, the reduction of build phases while introducing a new paradigm for military vehicle design.

INTRODUCTION

Warfighter and governmental demands are requiring that defense manufacturers bring products to the battlefield quicker, at reduced costs and with higher performance and quality. In addition, military mission profiles are changing at an ever increasing rate. These demands are requiring manufacturers to respond by accelerating product development and bringing to market faster the products that Warfighters want when they need them.

To respond to similar market demands and complexity, many automotive manufacturers have implemented and developed Lean Manufacturing and Lean Product Development practices to reduce costs and remain profitable. The success of Lean Product Development is illustrated by Toyota's implementation of its practices not only in manufacturing but throughout the entire product development and business enterprise. What is described as a socio-technical framework, Lean Product Development is defined as 'appropriately integrating people, processes and technology to add value to the customer and society'[1].

[1] *The Toyota Production Development System, Morgan, Liker, 2006*

A critical element of the Lean Product Development process is the implementation of Digital Design and Virtual Development technology to accelerate product development decisions with higher accuracy and reduced cost. By front-loading product development with Digital Design and Virtual Development, enterprises have eliminated the need for elaborate, expensive and time-consuming physical prototypes. Agile and robust motorsports companies have further developed and perfected the use of these Digital Design and Virtual Development toolsets to achieve accurate and robust design solutions that meet the rigorous requirements of 24 hour racing events. The technical systems implemented also allow the bi-modal mapping of the effects of component design changes on overall product requirements and vice versa, how changing requirements will cascade new system targets and component specifications.

This paper will describe how a scientific process called Response Surface Methodology (RSM) is developed to create a powerful enterprise model that integrates many of the corporate business systems to enable marketing, finance, product development and manufacturing to make better and faster decisions. This process allows a robust and agile system to evaluate the influences of product decisions and mission profile changes on cost, timing, quality and performance.

Defense industry participants have the opportunity to become more responsive and establish a competitive advantage and market leadership in the tactical wheeled vehicle defense industry by implementing automotive and motorsports Lean Product Development best practices.

METHODS

A significant advantage of Digital Design technology is the ability to model and simulate complete vehicle systems and evaluate the durability, performance, payload, and protection attributes without having to build expensive prototypes. More importantly, these digital design models are key elements in what is called the Product Target and Attribute Cascade Process.

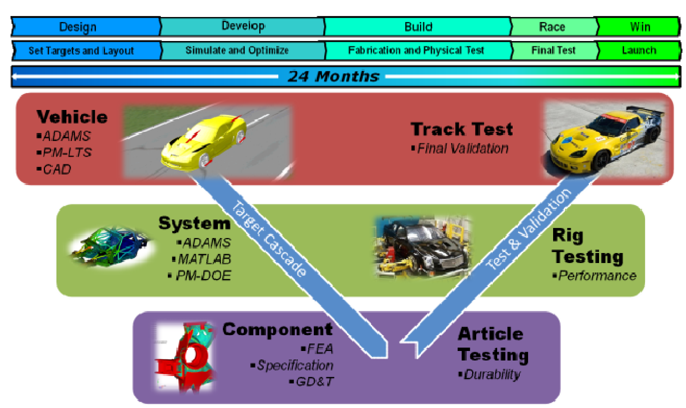


Figure 1 - Product Target Cascade

The process begins with overall program and customer requirements. Vehicle requirements are grouped into functional areas that include; mobility, performance, durability, safety, and C4ISR. Digital Simulation models are used to simulate the performance in each of these attributes by performing architecture Design of Experiments (DOE's). Modeling and Simulation (M&S) toolsets such as multi-body dynamics, finite element analysis, fatigue analysis, and blast simulation are used to synthesize and predict the performance of physical systems. The DOE's are used to cascade the system level targets (chassis, suspension, drivetrain, electronics, etc). System level modeling and simulation is used to then cascade the specifications for the component level design requirements.

As an example of this cascade process, this study will establish targets for Ride and Handling attributes (Absorbed power, RMS acceleration, understeer gradient, wheel lift) in an ADAMS multi-body simulation and cascade the requirements for spring rate, anti-roll bar rate, jounce bumper length, center of gravity height, weight distribution and tire pressure to optimize the performance of both ride and handling performance.

DOE

Experimental design (also called Design of Experiments) is a collection of procedures and statistical tools for planning experiments and analyzing the results.

Although experimental design techniques were originally developed for physical experiments, they also work very well in virtual environments. In the case of DOE, the experiments help increase the robustness of your conclusions, produce answers faster than trial-and-error or testing factors one at a time, and help to better understand and refine the performance of systems.

For simple design problems, you can explore and optimize the behavior of your system using a combination of intuition, trial-and-error, and discrete simulations. As the number of design options increase, however, these methods become inefficient in formulating answers quickly and systematically. The number of design combinations is $m \cdot n$, where m is the number of levels and n is the number of factors. Varying just one factor at a time does not give you information about the interactions between factors, and trying many different factor combinations can require multiple simulations that leave you with a great deal of output data to evaluate. To help remedy these time-consuming tasks, DOE provides you with the planning and analysis framework for running a series of experiments in an efficient and robust manner.

The experimental design process is summarized by the following procedure:

1. Determine the purpose of the experiment.
2. Define dependant variables or system responses of interest
3. Define independent variables or factors for the system that you are investigating and their experimental ranges
4. Define the analysis type depending on number of factors, type of factor (discrete or continuous), and levels of factor values. Common experimental design types include:
    a. Full Factorial
    b. Fractional Factorial
    c. Plackett-Burman
    d. Box-Behnken
    e. Central Composite Faced (CCF)
    f. D-Optimal
    g. Latin Hypercube
5. Define the order of the model to be fitted.

6. Generate design space or run order of factor variations.
7. Execute the experiments, recording the performance of the system at each run.
8. Fit the regression (response) model such that the error between the values predicted by the equation and the actual observed values is minimized.
9. Analyze the fit by evaluating R squared values
10. Refine the fit by removing outliers and/or terms or change the model order

RSM

A response surface is a mathematical surface represented by a series of polynomial equations. It gives an approximate value of the response (dependent variable or objective) as a function of the factors (independent variables or design variables). The techniques you use to create and analyze response surfaces are collectively called Response Surface Methodology (RSM). RSM is widely used for developing and optimizing processes and products of all kinds.

Common response surface models include:

Type:	Form:
Linear	$R = a_1 + a_2{*}F_1 + a_3{*}F_2 + e$
Interactions	$R = a_1 + a_2{*}F_1 + a_3{*}F_2 + a_4{*}F_1{*}F_2 + e$
Quadratic	$R = a_1 + a_2{*}F_1 + a_3{*}F_2 + a_4{*}F_1{*}F_2 + a_5{*}F_1^2 + a_6{*}F_2^2 + e$
Cubic	$R = a_1 + a_2{*}F_1 + a_3{*}F_2 + a_4{*}F_1{*}F_2 + a_5{*}F_1^2 + a_6{*}F_2^2 + a_7{*}F_1{*}F_2^2 + a_8{*}F_1^2{*}F_2 + a_9{*}F_1^3 + a_{10}{*}F_2^3 + e$

Table 1 - Common Response Surface Models

where:

- F1: Value of the first factor.
- F2: Value of the second factor.
- a1-a3: Coefficients computed by the regression analysis.
- e: The remaining error, minimized by the regression analysis.
- R: Response value.

RSM generates statistical models that allow the analysis of the significance and contribution of factors to the response magnitude. Depending on the order of the response model, one can also evaluate the interactions of factors to response values. The analysis of RSM models gives the analyst an empirical insight to what otherwise may be an overly complex closed-form numerical solution.

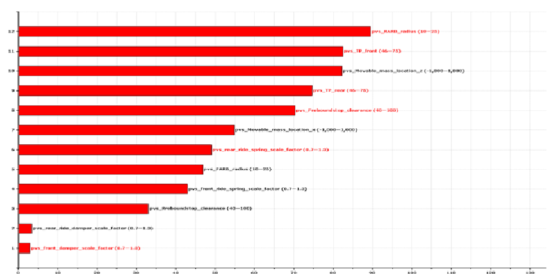


Figure 2 - RSM Pareto Diagram

You can use the response surface to estimate an optimal design. Because it is much quicker to evaluate a polynomial than run a full series of simulations, optimizing estimated response is a quick way to get an approximate optimum.

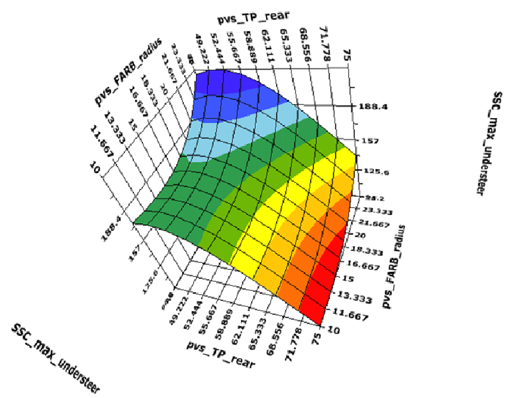


Figure 3 - Response Surface Contour Plot

OPTIMIZATION

Optimal designs are a class of experimental designs that allow parameters to be estimated without bias and with minimum statistical variance. The class of optimal design that is described in this paper is the D-Optimal design, which seeks to minimize $|(X'X)^{-1}|$, or equivalently maximize the determinant of the information matrix X'X of the design. A non-optimal design process would take hundreds or thousands of experiments to perform, evaluating each point, pertubating the factors to evaluate the gradient and come up with a new point of interest.

Conducting the optimization in the response surface reduces the effort required to perform the experiments. A few hundred tests can usually create a good response surface and once that response surface is created, optimizations are done on the response equations, not the underlying physical system. Each optimization only takes a few seconds and many different objective sets, factor sets, objective targets and target weights can be tested.
Visual inspection of the response surfaces and evaluating all responses can produce a global optimum or at least an optimum deemed well enough.

MULTI-DOMAIN OPTIMIZATION

Once the DOE and RSM formats have been established, the process can be extended to other attribute and simulation domains. Functional groups from chassis, suspension, powertrain, electronics and armor systems can perform simulations in their domain environments but all DOE results will be in the format of algebraic response equations. These response equations are now synchronize and can provide status, sensitivity, and interaction between various design components on program cost, weight, durability, protection, mobility, performance and fuel economy. In essence, engine designers, chassis designers, and suspension designers are all communicating in the same 'RSM' language.

Max_Ay = a1 + a2*SPR_K_FNT + a3*ARB_K_FNT + a4*SPR_K_FNT*ARB_K_FNT + a5*SPR_K_FNT2 + a6*ARB_K_FNT2 + a7*SPR_K_FNT*ARB_K_FNT2 + a8*SPR_K_FNT2*ARB_K_FNT + a9*SPR_K_FNT3 + a10*ARB_K_FNT3 + …….

The Pratt & Miller PM-DOETool™ utilizes Simple Constrained Optimization using the L-BFGS-B algorithm and Advanced Constrained Optimization using the Cobyla algorithm.

APPLICATION CASE #1 – Motorsports Event Performance Optimization

Motorsports presents unique challenges to engineering development teams in that the product development process is continuous, dynamic, and highly variable throughout the program life-cycle. Similar to military missions, motorsports missions, threats, and requirements change from week to week.

The motorsports mission-profile changes every event due to the complex nature of the racing circuits at which teams compete at. Top straight-line speeds, cornering speeds, track surface friction, ambient temperatures and pressures, number of competitors, and duration of races vary from one event to the next.

The nature of threat in motorsports comes in the form of 40 + drivers, crews, and engineers all competing against each other in wheel-to-wheel combat to maximize performance, strategy, and endurance to reach the finish line first. In addition to competitor threats, the driver and machine confront the laws of physics, with the consequences of going beyond the limits often being destructive and sometimes fatal.

Beyond large-scale requirements changes to the vehicle design between annual race seasons, teams are confronted with rules changes from series sanctioning bodies that mandate new weights, power limits, fuel consumption, aerodynamic features, and other restrictions between race events. This requires that the motorsports teams have a very robust, efficient, and accurate product development process to maximize the vehicle performance while maintaining reliability often without the opportunity to test physical hardware before the next event.

Pratt & Miller Engineering has developed and implemented a Lean Product Development process through its execution and support of a variety of motorsports programs through the use of Design of Experiments (DOE) and Response Surface Methodology (RSM) in the virtual and physical test environments.

This example will demonstrate the DOE/RSM process used during a race event for a Daytona Prototype racing vehicle in the Grand American Road Racing championship series in 2009.

<u>The Event</u>

A typical event begins with the development of a baseline setup based on full lap simulations using Pratt & Miller's PM-LTS™ software. The baseline model is generated from the previous year's event and updated with any new vehicle, track geometry or surface, and forecasted weather information.

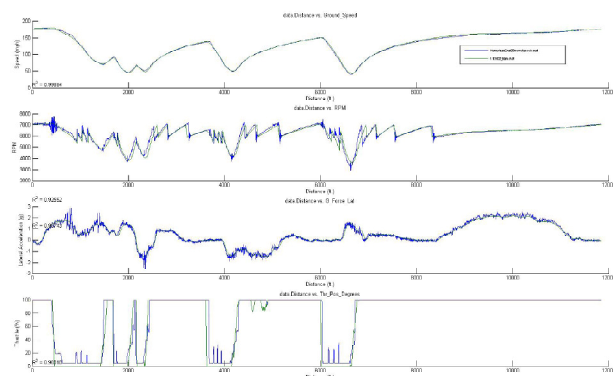


Figure 4 - Baseline PM-LTS™ model correlation

A number of DOE simulations are performed to optimize different sub-systems of the vehicle specific to the track event. These include:

- Engine torque curve
- Gear ratios
- Aerodynamic L/D (Lift/Drag)
- Chassis system settings

Once the initial DOE optimizations are performed, a general setup parameter DOE is executed to generate the event 'Engineering Playbook' which describes how various vehicle setup parameters will affect vehicle performance around the track. For this event, 19 vehicle setup parameters, or factors, were selected with appropriate variations.

The Event Factors

The factors for the race event generally include those vehicle setup parameters that are easily changed during an event. The 19 factors used for this event are illustrated below:

Experiment	Factor	Units	Min	Max
mid0906_doe	KSF	lb/in	450	1,500
mid0906_doe	KSR	lb/in	550	1,550
mid0906_doe	RideF	in	1.7	2
mid0906_doe	RideR	in	1.85	2.9
mid0906_doe	CamberFL	deg	-3.6	-2.2
mid0906_doe	CamberFR	deg	-3.6	-2.2
mid0906_doe	CamberRL	deg	-3.6	0
mid0906_doe	CamberRR	deg	-3.6	0
mid0906_doe	F_RC_H	in	-1.07	0.54
mid0906_doe	R_RC_H	in	-1.08	1.92
mid0906_doe	KAF	ft-lbs/deg	690	7,690
mid0906_doe	KAR	ft-lbs/deg	200	3,600
mid0906_doe	toeF	in	-0.06	0.06
mid0906_doe	toeR	in	0.03	0.13
mid0906_doe	crossW	lbs	0.49	0.51
mid0906_doe	Fwdist	lbs	0.39	0.48
mid0906_doe	Lwdist	lbs	0.49	0.52
mid0906_doe	weight	lbs	2,425	2,575
mid0906_doe	ackerman	%	0.7	1.3

Figure 5 - DOE Factor Matrix

The Response Objectives

Responses are various vehicle dynamics and powertrain metrics as well as driver and track segment times. In addition to overall laptime, the track is divided into straight and corner track segments to evaluate specific vehicle performance at each area of the track. For this DOE, over 150 responses were measured in the PM-LTS™ simulation.

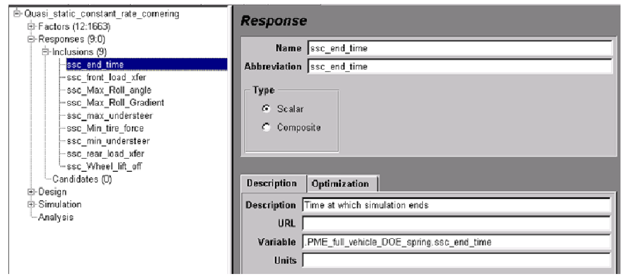


Figure 6 - DOE Response Matrix

DOE Model

Pratt & Miller Engineering generally uses the D-Optimal design model because of its ability to mix discrete and continuous factors and efficient design space matrix which minimizes simulation runs. A quadratic or cubic model is generally selected. For this DOE, a quadratic model was selected. The D-Optimal, quadratic model specified a minimum of 980 runs, but Pratt & Miller best practice dictates that 1.2x the specified minimum be used to ensure an adequate number of runs in the event outliers need to be removed during model refinement. The engineer specified 1175 runs and generated the work space.

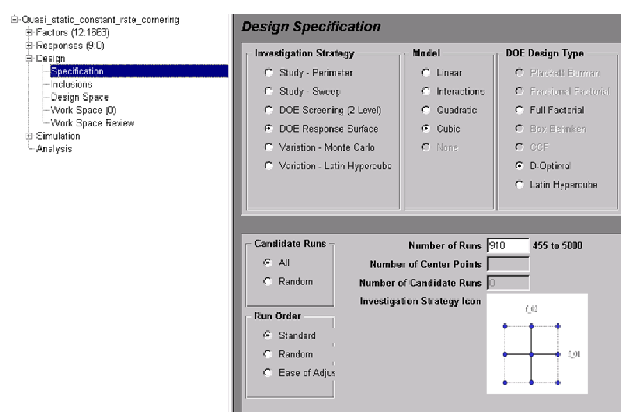


Figure 7 - DOE Design Specification

Simulation DOE

The Pratt & Miller PM-LTS simulation includes a DOE interface that automatically adjusts the model parameters based on the DOE run matrix and associated factor levels. PM-LTS simulations run at 1.5x real-time, so the 1175 DOE simulations were completed in approximately 17 hours.

The simulation responses were automatically generated and imported into the DOE workspace and the response equations were fitted using least-squares regression.

The goodness-of-fit of the responses was evaluated and outliers or simulation runs that did not converge were eliminated from the response fits. This is achieved by evaluating the studentized residuals of the responses and looking for run outliers.

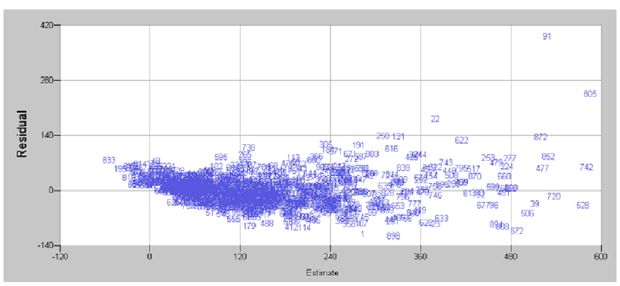


Figure 8 - Studentized Residuals

The engineer repeats the process and attempts to achieve an R^2 adjusted fit of greater than .90 for the majority of responses.

	end_time	floadXfer	MxRollAng	MxRollGrad	MxUnderStr	MnTireF	MnUnderStr	RloadXfer	WhlLiftOffG
R2	0.966	0.997	0.965	0.996	0.998	0.878	0.958	0.996	0.967
R2adj	0.947	0.996	0.982	0.994	0.996	0.778	0.936	0.995	0.951
P	7.2e-300	0	0	0	0	7.13e-077	1.38e-265	0	0
R/V	35.6	130	80.7	109	143	16.6	42.4	112	36.5

Figure 9 - Goodness of fit summary

Results Interpretation

During the initial practice session of the event, the engineer determines that the DOE response surface equations predicted accurately the actual vehicle laptime and segment metric performance. In cases where the current driver/vehicle performance does not correlate well with DOE response surface results, the engineer must correlate the model to the latest conditions and re-run the DOE overnight during the event. This is facilitated through the use of a five-node computer cluster installed in the race transporter.

Through evaluation of corner segment maximum lateral acceleration, understeer gradient, aerodynamic downforce, and straight segment top speed sensitivities to various setup adjustments, the engineer developed a 'baseline' setup to begin the event weekend with. This provided the engineer with a 'trackside playbook' to reference in diagnosing and improving the performance of the vehicle around segments of the track or adapting to changing track or weather conditions.

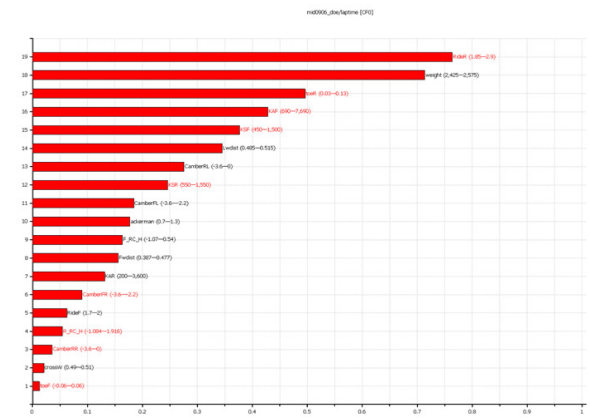


Figure 10 - Laptime Pareto Diagram

The above pareto diagram example of factor sensitivity to overall laptime indicates to the engineer that rear ride height, weight distribution, and rear toe angle have the dominant influence over laptime performance. The information provides directional and magnitude sensitivities to performance. This allows the engineer to focus on tuning parameters that will have the largest influence over the desired response.

Although overall laptime analysis is important, of greater significance to the engineer is how the minimum laptime is achieved over the distance of the track. The cascade of laptime to functional vehicle performance indicates in this example that reducing understeer gradient in the long-duration, high-speed corner segments was a significant metric to achieving minimum laptime. The pareto of understeer, defined in the data analysis metrics as steering-integral, indicates that weight distribution, front toe angle, and rear ride height are the dominant factors influencing understeer gradient.

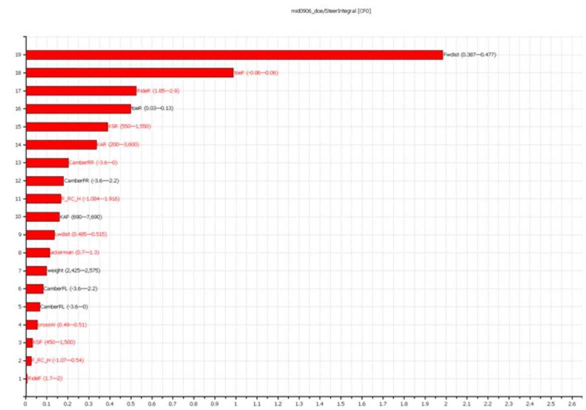


Figure 11 - Understeer Pareto Diagram

Additionally, the engineer can visualize the influence of factors on multi-dimension surface plots.

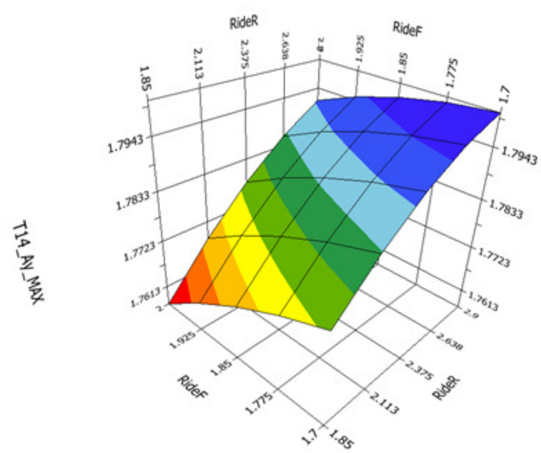


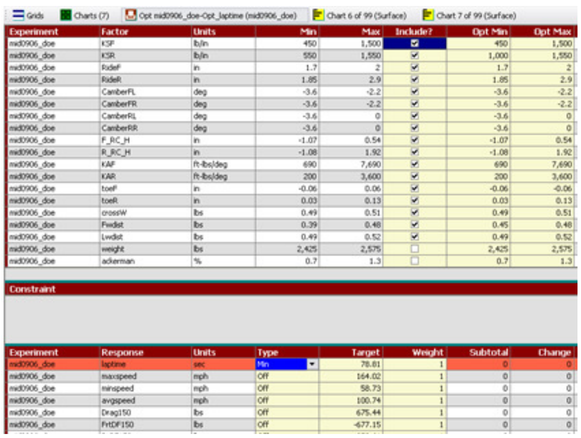
Figure 12 - Maximum Lateral Acceleration Surface Plot

The above example illustrates how front and rear ride heights influence the maximum lateral acceleration in a corner segment. This enables the engineer to evaluate the direction and gradient of response factors.

Throughout the event, subjective driver comments and real-time objective metrics from on-board data telemetry are used to identify areas for improvement in specific track segments.

Optimization

The engineer then performed an advanced constrained, multi-objective optimization using response constraints for segments where vehicle performance was desirable and optimization was performed on track segments needing improvement.



Grids | Charts (7) | Opt mid0906_doe-Opt_laptime (mid0906_doe) | Chart 6 of 99 (Surface) | Chart 7 of 99 (Surface)

Experiment	Factor	Units	Min	Max	Include?	Opt Min	Opt Max
mid0906_doe	KSF	lb/in	450	1,500	✓	450	1,500
mid0906_doe	KSR	lb/in	550	1,550	✓	1,000	1,550
mid0906_doe	RideF	in	1.7	2	✓	1.7	2
mid0906_doe	RideR	in	1.85	2.9	✓	1.85	2.9
mid0906_doe	CamberFL	deg	-3.6	-2.2	✓	-3.6	-2.2
mid0906_doe	CamberFR	deg	-3.6	-2.2	✓	-3.6	-2.2
mid0906_doe	CamberRL	deg	-3.6	0	✓	-3.6	0
mid0906_doe	CamberRR	deg	-3.6	0	✓	-3.6	0
mid0906_doe	F_RC_H	in	-1.07	0.54	✓	-1.07	0.54
mid0906_doe	R_RC_H	in	-1.08	1.92	✓	-1.08	1.92
mid0906_doe	KAF	ft-lbs/deg	690	7,690	✓	690	7,690
mid0906_doe	KAR	ft-lbs/deg	200	3,600	✓	200	3,600
mid0906_doe	toeF	in	-0.06	0.06	✓	-0.06	-0.06
mid0906_doe	toeR	in	0.03	0.13	✓	0.03	0.13
mid0906_doe	crossW	lbs	0.49	0.51	✓	0.49	0.51
mid0906_doe	Fwdist	lbs	0.39	0.48	✓	0.45	0.48
mid0906_doe	Lwdist	lbs	0.49	0.52	✓	0.49	0.52
mid0906_doe	weight	lbs	2,425	2,575		2,425	2,575
mid0906_doe	ackerman	%	0.7	1.3		0.7	1.3

Constraint

Experiment	Response	Units	Type	Target	Weight	Subtotal	Change
mid0906_doe	laptime	sec	Min	78.81	1	0	0
mid0906_doe	maxspeed	mph	Off	164.02	1	0	0
mid0906_doe	minspeed	mph	Off	58.73	1	0	0
mid0906_doe	avgspeed	mph	Off	100.74	1	0	0
mid0906_doe	Drag150	lbs	Off	675.44	1	0	0
mid0906_doe	FrtDF150	lbs	Off	-677.15	1	0	0

Figure 13 - Optimization Parameters

The engineer established limits on factors and constraints on acceptable response values.

The optimization process was completed in approximately 20 seconds and provided setup adjustment parameter values to the engineer.

Changes to the vehicle setup parameters were conducted between practice sessions by the mechanics. The performance of the vehicle was improved in the track segment areas without compromising the performance in other track segment. The total laptime performance improvement of .685 seconds correlated well to the .820 seconds predicted by the DOE optimization.

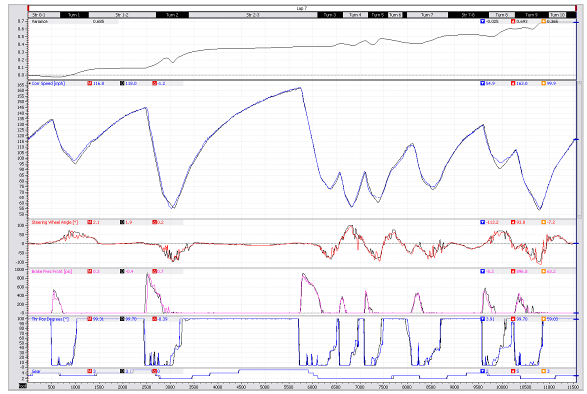


Figure 14 – Actual Vehicle Data Comparison of Optimized Setup Parameters

Over the course of the championship season, the team was able to win 4 races and claim the series Drivers and Manufacturers Championship in large part due to the implementation and execution of virtual Design of Experiments and optimal design through Response Surface Methodology.

APPLICATION CASE #2 – Light Tactical Vehicle Mobility Optimization

The same process that has been implemented by Pratt & Miller Engineering in motorsports has been applied to a number of defense related mobility projects.

This application case will illustrate the use of DOE and RSM in the multi-body dynamics simulation domain to improve the mobility of a Light Tactical Vehicle design. For purposes of confidentiality and ITAR restrictions, the customer, type of vehicle and parameter values are omitted or modified, but the overall process is as executed.

Design of Experiments (DOE) is used to optimize the mobility attributes for ride and handling of a light tactical vehicle. The ride and handling compromise is an example of the classic conflict of tuning suspension parameters to achieve the overall best balance between ride quality and handling stability. In general, the suspension attributes are tuned such that one attribute is compromised (i.e. ride) for the benefit of the other (i.e. handling). Suspension engineers who optimize ride quality typically like low spring, damping and anti-roll bar stiffness rates to reduce road input transmissibility and interior NVH. This often compromises handling attributes and transitional response due to high body roll and pitch velocities which cause excessive body side slip phase angle and overshoot. Conversely, suspension engineers who optimize handling typically increase spring, damping and anti-roll bar stiffness rates to optimize body side slip and reduce roll, pitch and yaw overshoots which compromises ride quality and interior NVH due to increased road input transmissibility to vehicle occupants.

The DOE process allows the vehicle team to robustly cascade system specifications and design requirements to the functional design teams establishing an important systems integration process. By analyzing the interactions and system responses, an overall balance that maximizes each ride and handling attribute can be achieved without having to perform expensive and time consuming testing of component combinations.

This structured modeling and simulation process is a more efficient use of computational resource and provides more inherent systems design knowledge than performing discrete, single-run simulations.

This example will illustrate the use of DOE and RSM in the development of targets for Ride and Handling attributes (Absorbed power, RMS acceleration, understeer gradient, wheel lift) in an ADAMS multi-body simulation and cascade the requirements for spring rate, anti-roll bar rate, jounce bumper length, center of gravity height, weight distribution and tire pressure to optimize the performance of both ride and handling.

<u>The Events</u>

The events simulated to describe the vehicle ride and handling requirements are summarized below. Four different events were selected to show the process of multi-experiment evaluation.

1. Ride Performance - 8” half-round at 40 km/h.
2. Constant radius cornering - 60 meter radius
3. Impulse steer event - Constant velocity of 80 km/h, steering wheel impulse of 45° length over 1 second
4. NATO double lane change standard AVTP 03-160W

The model was correlated to objective test data and a baseline configuration established to begin the DOE. Baseline simulation result examples are shown below:

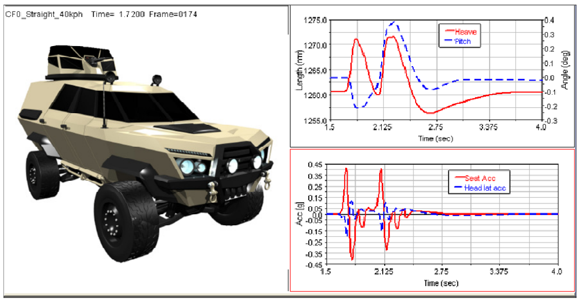


Figure 15 - 8" Half-Round Animation

Response	Units	Base / CR0
hf_pitch_frequency	Hz	0.64
hf_pitch_damping	-	0.41
hf_Max_roll_Rate	°/s	5.19
hf_Max_roll_angle	°	0.94
hf_max_pitch_angle	°	0.42
hf_Max_abs_dseat_acc	G	0.43
hf_heave_frequency	Hz	0.87
hf_heave_damping	-	0.35
hf_Head_Max_Lat_acc	G	0.20

Figure 16 - 8" Half-Round Results

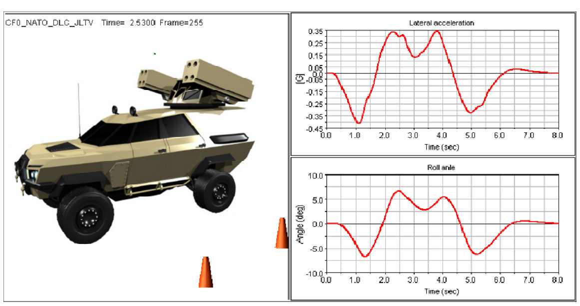


Figure 17 - NATO Lane Change Animation

Response	Units	Base / CR0
NATO_Head_Max_Lat_acc	G	0.37
Nato_margin_to_path	m	0.14
Nato_Max_lat_acc	G	0.41
NATO_Max_Roll_angle	°	6.89
NATO_Max_Roll_Rate	°/s	17.68
NATO_min_tire_force	N	3060.30

Figure 18 - NATO Lane Change Results

The Design Factors

The following design factors were selected as candidate examples to cascade component level specifications that influence the ride and handling requirements. The factors, factor nominal levels and factor ranges were simulated using discrete simulation events to determine the model robustness and accuracy across the range and combination of factor values. The table below represents the nominal value and range for each of the factors to be evaluated.

Factor	Min	Nominal	Max
Front spring scale factor	0.7	1	1.3
Rear spring scale factor	0.7	1	1.3
Front damper scale factor	0.7	1	1.3
Rear damper scale factor	0.7	1	1.3
Front ARB radius	10	17	25
Rear ARB radius	10	12	25
Front Rebound bumper free length	40	49.5	100
Rear Rebound bumper free length	40	40.9	100
Weight distribution (fore/aft)	-1000	0	1000
Weight distribution Vertical	-1000	0	1000
Tire pressure front (psi)		46,67,68,75	
Tire pressure rear (psi)		46,67,68,75	

Table 2 - DOE Factor Matrix

The Response Objectives

The following simulation results were used as the objective ride and handling response measures for which targets are evaluated.

Case	Description	Objectives	Units
1	Steady-state constant radius cornering	Lat acc at wheel lift-off	G
	60 meter radius	SWA Understeer gradient @ 0.3 G	°/G
	Increasing velocity	SWA Minimum understeer	°/G
		Roll gradient @ 0.3G	°/G
		Max Roll angle	°
		Min Tire force	N
		Front Load Transfer @ 0.3g	%
		Rear Load Transfer @ 0.3g	%
2	Impulse steer	Max roll angle	°
	45° steering wheel amplitude	Max abs roll rate	°/s
	Pulse length = 1 second	Roll frequency	Hz
	Velocity = 80 km/h	Roll damping	%
		max abs yaw rate	°/s
		yaw rate frequency	Hz
		yaw rate damping	%
		Yaw angle overshoot	%
		Max abs lat acc	G
		Min tire force	N
3	Right side half round	Max abs driver seat acc	G
	Half round height = 8"	Max pitch angle	deg
	Velocity = 40 km/h	Pitch frequency	Hz
		Pitch damping	%
		heave frequency	°
		heave damping	%
		Max Roll angle	°
		Max Roll Rate	°/s
		Head Max Lateral Accel	G
4	NATO lane change	Max lat acc	G
	NATO AVTP 03-160W	Max roll angle	°
	(also SAE J2014)	max roll rate	°
	Velocity = 45 mph	Min margin to path	m
		Min tire force	N
		Head Max Lateral Accel	G

Table 3 - DOE Response Objectives

Simulation DOE

A D-Optimal design type with a cubic response model was generated. This generated workspace of 910 runs for each simulation event. Response surface equations were generated for each objective of each event using least-squares multiple-regression. Each response model was refined to achieve a goodness-of-fit residual of .9 or above. An example of a fitted cubic response equation is below:

Max_Ay = a1 + a2*SPR_K_FNT + a3*ARB_K_FNT + a4*SPR_K_FNT*ARB_K_FNT + a5*SPR_K_FNT2 + a6*ARB_K_FNT2 + a7*SPR_K_FNT*ARB_K_FNT2 + a8*SPR_K_FNT2*ARB_K_FNT + a9*SPR_K_FNT3 + a10*ARB_K_FNT3 + …….

The response equations are then used to generate sensitivity analysis (ANOVA) and structure for cascading system level targets.

Results Interpretation

As can be seen from the Constant Radius Pareto analysis, Front Anti-Roll Bar rate and Rear Rebound Stop Clearance have the largest influence on maximum lateral acceleration. In addition to factor rank order, the vector magnitude and absolute value of rank can be determined. This allows attribute engineers to assign rank weighting of design variables to vehicle targets.

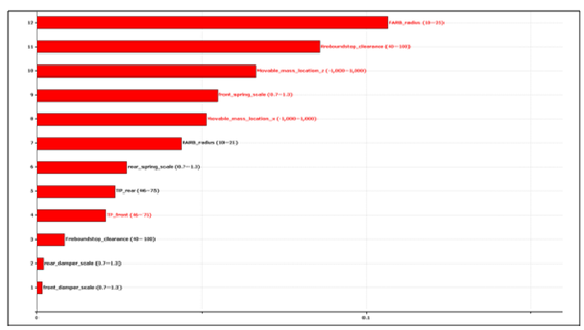


Figure 19 - Constant Radius Pareto Chart

An example of the Maximum Acceleration response surface plot of two independent variables, Rear Spring Rate and Front Rebound Stop Clearance is used to identify the local minima and maxima values that optimize the given response.

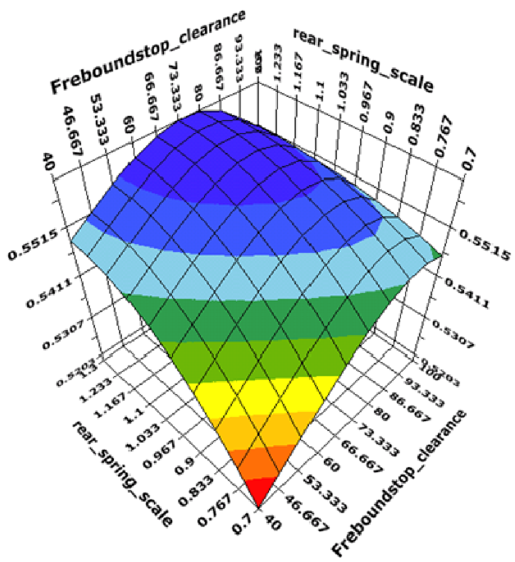


Figure 20 - Constant Radius Contour Plot

Single Event Optimization

The cascade of design specification values (i.e. factor settings) was performed for each response of each event. This is achieved through multi-variate, multi-objective optimization techniques that are easily facilitated through the algebraic response surface equations. The results of Constant Radius optimization and target cascade are summarized below:

Factor	Units	Base / CF0	CF1	CF2	CF3	CF4	CF5	CF6
TP_front	psi	68.00	50.12	50.12	46.00	75.00	75.00	75.00
FARB_radius	mm	17.00	10.00	10.00	16.34	11.76	10.00	25.00
Freboundstop_clearance	mm	49.50	40.00	40.00	40.00	40.00	40.00	40.00
TP_rear	psi	75.00	46.00	46.00	46.00	46.00	46.00	46.00
Rreboundstop_clearance	mm	40.90	57.76	57.76	40.00	40.00	40.00	89.97
RARB_radius	mm	12.00	23.06	23.06	10.00	10.00	10.00	10.00
Movable_mass_location_x	mm	0.00	0.00	0.00	0.25	0.10	-47.74	0.10
Movable_mass_location_z	mm	0.00	0.00	-1000.00	0.23	0.10	-7.71	0.10
rear_damper_scale	-	1.00	1.00	1.00	1.00	1.00	1.00	1.00
rear_spring_scale	-	1.00	0.70	0.70	0.70	0.70	0.70	0.70
front_spring_scale	-	1.00	0.98	0.98	0.70	0.70	0.70	1.10
front_damper_scale	-	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Response	Units	Base / CR0	CR1	CR2	CR3	CR4	CR5	CR6
ssc_end_time	G	0.55	0.62	0.64	0.54	0.53	0.54	0.39
ssc_front_load_xfer	-	0.75	0.67	0.65	0.77	0.77	0.76	0.85
ssc_Max_Roll_angle	°	7.40	7.60	7.33	8.46	8.28	8.36	5.69
ssc_Max_Roll_Gradient	°/G	18.15	15.42	14.09	21.66	21.89	21.73	14.33
ssc_max_understeer	°/G	23.39	21.35	20.79	45.95	70.05	70.95	61.61
ssc_Min_tire_force	N	3478.13	1497.13	1902.48	3560.42	3986.58	4062.67	1500.08
ssc_min_understeer	°/G	-14.69	-30.25	-33.72	3.32	51.84	70.54	-3.77
ssc_rear_load_xfer	-	0.72	0.78	0.75	0.71	0.72	0.72	0.61
ssc_Wheel_lift_off	G	0.54	0.60	0.63	0.52	0.52	0.52	0.38

Table 4 - Constant Radius Responses

Multi-Objective Optimization

The previous target cascade results were performed to optimize each handling and ride event to demonstrate the basic target cascade process within the stability and ride domains. This stage of target cascade is useful in understanding the sensitivities at the system attribute level but do not achieve total vehicle optimization. The following section demonstrates how to implement multi-domain optimization to achieve total vehicle requirement satisfaction across the design space.

The following table below summarizes the factor values established by the optimization to achieve the weighted response values:

Factor	Units	Base	CF1	CF2	CF3	CF4
TP_front	psi	68.00	68.00	75.00	68.00	75.00
FARB_radius	mm	17.00	13.34	10.67	10.67	25.00
Freboundstop_clearance	mm	49.50	40.00	61.17	61.17	54.27
TP_rear	psi	75.00	75.00	75.00	75.00	75.00
Rreboundstop_clearance	mm	40.90	40.14	60.21	60.21	40.00
RARB_radius	mm	12.00	10.00	10.69	10.69	10.00
Movable_mass_location_x	mm	0.00	0.00	0.00	0.00	0.11
Movable_mass_location_z	mm	0.00	0.00	0.00	0.00	0.12
rear_damper_scale	-	1.00	1.03	1.01	1.01	1.30
rear_spring_scale	-	1.00	0.70	1.05	1.05	1.18
front_spring_scale	-	1.00	0.83	0.82	0.82	1.18
front_damper_scale	-	1.00	0.91	0.90	0.90	1.30
		Estimates				
Response	**Units**	**Base**	**CR1**	**CR2**	**CR3**	**CR4**
hf_pitch_frequency	Hz	0.64	0.94	1.00	0.97	0.43
hf_pitch_damping	-	0.41	0.50	0.35	0.49	0.52
hf_Max_roll_Rate	°/s	5.19	4.59	5.06	4.95	7.00
hf_Max_roll_angle	°	0.94	0.94	1.03	1.00	0.76
hf_max_pitch_angle	°	0.42	0.40	0.39	0.41	0.41
hf_Max_abs_dseat_acc	G	0.43	0.38	0.42	0.40	0.50
hf_heave_frequency	Hz	0.87	0.57	0.95	0.92	0.83
hf_heave_damping	-	0.35	-0.14	0.37	0.34	0.25
hf_Head_Max_Lat_acc	G	0.20	0.20	0.21	0.20	0.18
ss_Max_abs_yaw_rate	°/s	10.34	10.32	9.92	10.34	9.97
ss_Max_lat_acc	G	0.23	0.23	0.22	0.23	0.23
ss_Max_Roll_angle	°	4.00	5.02	4.39	4.64	2.67
ss_Max_Roll_Rate	°/s	7.07	8.12	7.32	7.71	5.33
ss_min_tire_force	N	15415	14835	16388	15498	13954
ss_Roll_damping	-	0.49	0.44	0.44	0.45	0.61
ss_Roll_Frequency	Hz	0.37	0.34	0.35	0.35	0.36
ss_yaw_angle_overshoot	%	11.73	20.42	19.63	17.62	4.60
ss_yaw_rate_damping	-	0.55	0.47	0.48	0.50	0.60
ss_yaw_rate_frequency	Hz	0.47	0.53	0.41	0.47	0.66
NATO_Head_Max_Lat_acc	G	0.37	0.40	0.37	0.37	0.37
Nato_margin_to_path	m	0.14	0.14	0.16	0.15	0.15
Nato_Max_lat_acc	G	0.41	0.41	0.41	0.41	0.41
NATO_Max_Roll_angle	°	6.89	8.15	8.12	8.11	4.38
NATO_Max_Roll_Rate	°/s	17.68	20.50	21.21	20.89	11.25
NATO_min_tire_force	N	3060	559	1786	1902	4870
ssc_end_time	G	0.55	0.55	0.56	0.56	0.47
ssc_front_load_xfer	-	0.75	0.76	0.73	0.73	0.79
ssc_Max_Roll_angle	°	7.40	7.92	8.69	8.86	5.48
ssc_Max_Roll_Gradient	°/G	18.15	21.06	23.09	23.04	11.95
ssc_max_understeer	°/G	23.39	32.13	29.33	21.71	29.01
ssc_Min_tire_force	N	3478	3826	2593	2197	2154
ssc_min_understeer	°/G	-14.69	-0.47	0.06	-6.11	11.44
ssc_rear_load_xfer	-	0.72	0.72	0.77	0.77	0.65
ssc_Wheel_lift_off	G	0.54	0.54	0.55	0.56	0.47

Table 5 - Multi-Objective Optimization

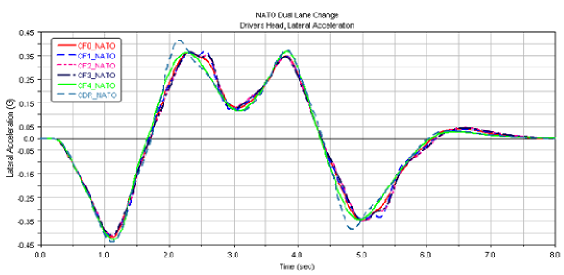


Figure 21 - NATO Lane Change Optimization

SUMMARY/FUTURE APPLICATIONS

This paper describes how Design of Experiments and Optimal Design through Response Surface Methodology are used to enable Lean Product Development processes in motorsports and defense applications.

A summary of the success in motorsports from such implementations of the DOE/RSM process include:

- NASCAR Sprint Cup - 100 wins in 187 races → 53% win rate
- Corvette Racing Le Mans GT - 6 24 Hours of Le Mans Victories → 60% win rate
- Team Cadillac World Challenge - 12 wins in 41 races → 30% win rate
- Pontiac Motorsports Grand Am - 26 wins in 59 races → 44% win rate

These Lean processes can be extended to other corporate enterprise organizations by which all technical decisions are evaluated against performance, cost and timing.

The same DOE techniques are available to other modeling and simulation domains including FEA, Blast, CFD, and system simulation using MATLAB/Simulink.

Key takeaways from implementation of Response Surface Methodology and Experimental Design are:

- Perform evaluation of design alternatives to cascade system & component targets
- Enhance knowledge of engineering systems through more efficient use of computational design
- Reduce time to develop new products and processes
- Improve performance of existing products and processes
- Improve reliability and performance of products
- Achieve product and process robustness

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