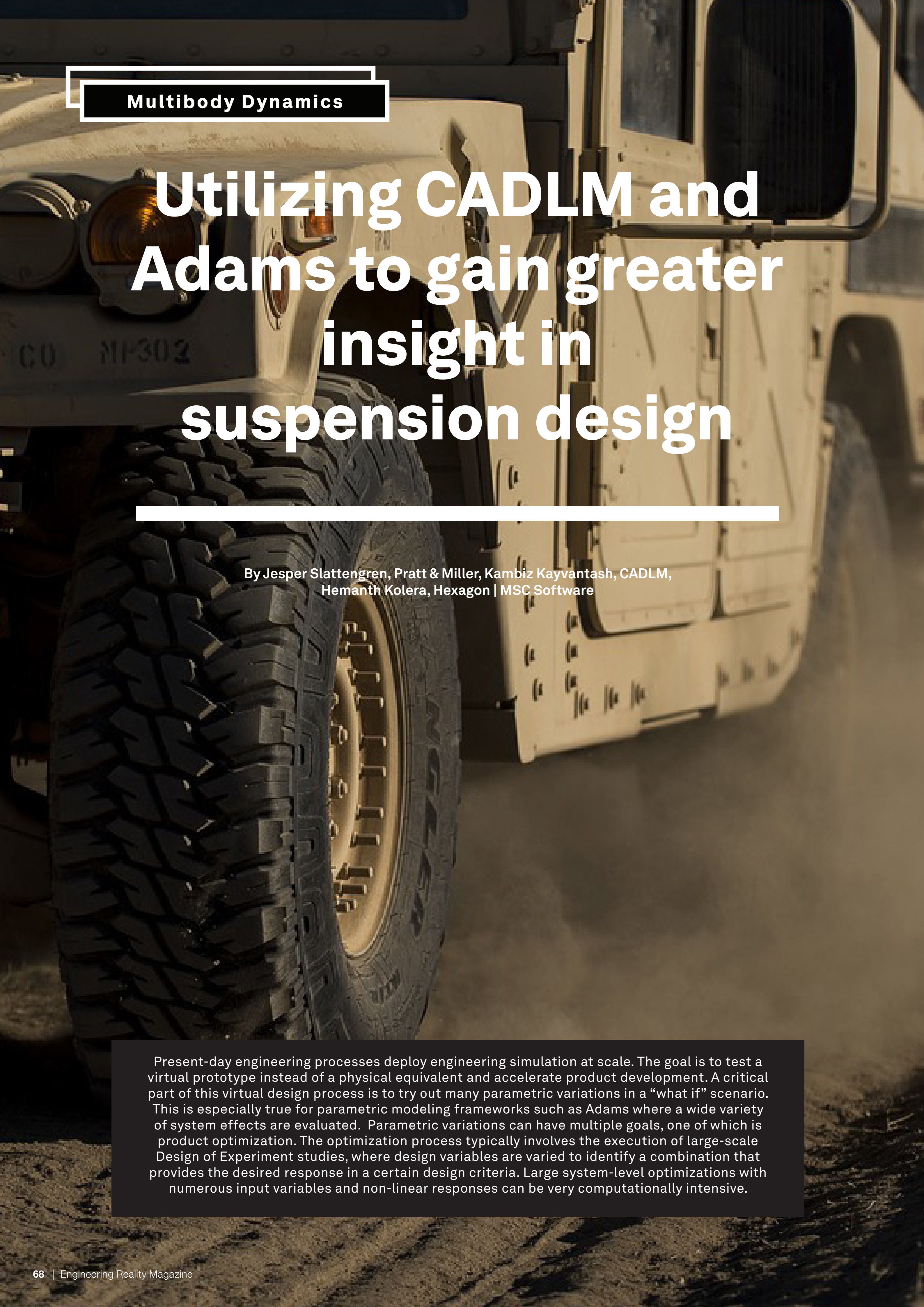

Multibody Dynamics

Utilizing CADLM and Adams to gain greater insight in suspension design

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Present-day engineering processes deploy engineering simulation at scale. The goal is to test a virtual prototype instead of a physical equivalent and accelerate product development. A critical part of this virtual design process is to try out many parametric variations in a “what if” scenario. This is especially true for parametric modeling frameworks such as Adams where a wide variety of system effects are evaluated. Parametric variations can have multiple goals, one of which is product optimization. The optimization process typically involves the execution of large-scale Design of Experiment studies, where design variables are varied to identify a combination that provides the desired response in a certain design criteria. Large system-level optimizations with numerous input variables and non-linear responses can be very computationally intensive.

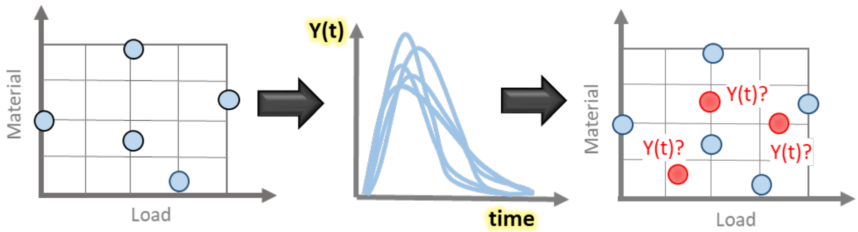

Figure 1 : Reduced order modeling

In a recent proof-of-concept, Adams, the gold standard in multibody dynamics simulations, and Lunar, the revolutionary supervised Machine Learning solution from CADLM, were used to create Reduced Order Models (ROMs) (Figure 1) of vehicle behavior and redefine the product optimization process at Pratt & Miller. The surrogate ROMs replicate time-series information from the parent Adams model using Machine Learning. ROM generation in Lunar is based on an Adams training dataset. The generated ROM is then validated against a set of new responses, not part of the initial training set. This validated ROM can then be used to explore the design space and find an optimal solution.

ROM based optimization is not the same as response surface-based (RSM) optimization which is the standard technique for parametric optimization in Adams. ROM replicates the entire time series unlike the scalar predictions using RSM. Additionally, while RSM methods are based on external or imposed "fitting" strategy where few selected points are exploited to identify an equation (e.g. polynomial) approaching as good as possible the real response (the output of DOE), a ROM method exploits decomposition techniques in order to evaluate physical "modal" participations of the response and exploit them to reconstruct new responses via non-linear superposition techniques.

The vehicle system under investigation is a military vehicle, and the particular response of interest is the total absorbed power with the design goal to minimize it as shown in Figure 2.

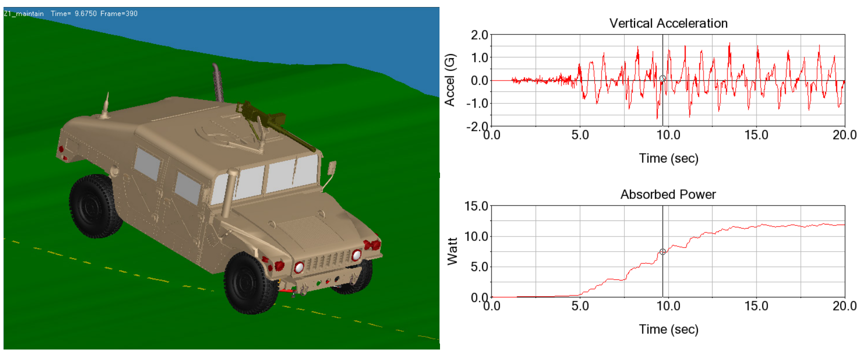

Figure 2 : System and responses of interest

The absorbed power increases with increasing vertical acceleration and transient vibrations. Minimizing the power absorbed by the vehicle during its operation leads to a better ride comfort experience for the occupants. The model parameters that were part of the optimization set are shown below.

Name	Short	Min	Nom	Max	Unit
Front Jounce Bumper Scale factor	F_JB_Scale	0.5	1	2	-
Front Jounce Bumper Clearance	F_JB_Clearance	20	38.1	50	mm
Front Damper Scale Compression	F_Da_Sc_Comp	0.5	1	2	-
Front Damper Scale Rebound	F_Da_Sc_Reb	0.5	1	2	-
Front Spring Scale	F_Spr_Sc	0.8	1	1.2	-
Rear Jounce Bumper Scale factor	R_JB_Scale	0.5	1	2	-
Rear Jounce Bumper Clearance	RF_JB_Clearance	20	30.48	50	mm
Rear Damper Scale Compression	R_Da_Sc_Comp	0.5	1	2	-
Rear Damper Scale Rebound	R_Da_Sc_Reb	0.5	1	2	-
Rear Spring Scale	R_Spr_Sc	0.8	1	1.2	-

Figure 3 : Parameter space under investigation

A DOE using the Latin HyperCube distribution was generated in Adams Insight. This DOE served as the training set for the LUNAR ROM. The DOE used to create the LUNAR ROM employed 60 runs. This is 10 times less expensive than an RSM based approach and is more robust as it captures the most dominant effects.

F_JB_Scale	F_JB_Clearance	F_Da_Sc_Comp	F_Da_Sc_Reb	F_Spr_Sc	R_JB_Scale	RF_JB_Clearance	R_Da_Sc_Comp	R_Da_Sc_Reb	R_Spr_Sc
0.5	20	0.5	0.5	0.8	0.5	20	0.5	0.5	0.8
1.25	35	1.25	1.25	1	1.25	35	1.25	1.25	1
2	50	2	2	1.2	2	50	2	2	1.2

Figure 4 : Validation runs

The generated ROM was validated using the three cases shown above. Users can use a variety of solver options to obtain a predictive ROM. Using the available set of solver options a highly predictive ROM was obtained. The comparison between ROM and the ADAMS predictions for the validated cases are shown (Figure 5) and show good agreement.

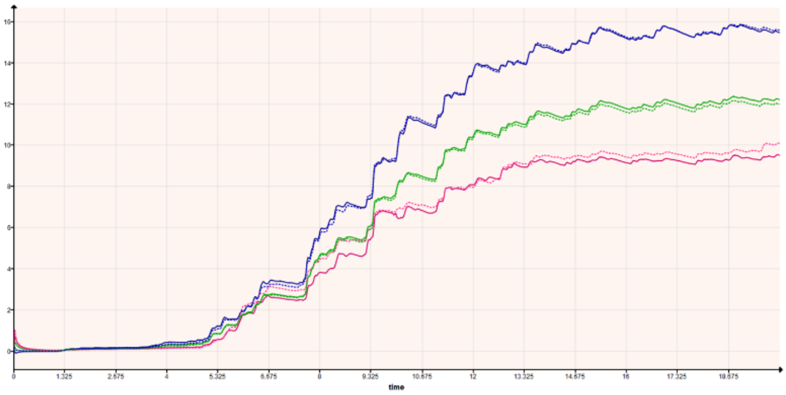

Figure 5 : Comparisons between ROM (solid) and Adams (dotted) predictions

The validated ROM can now be used in multiple ways. As an example, users can run sensitivity analysis at various temporal instances to gauge the effect of various design parameters on the absorbed power. As shown in Figure 6 there is a direct relationship between observed power and vertical acceleration. When vertical acceleration stays high for a longer time there is a jump in absorbed power. A single peak of the vertical acceleration does not impact absorbed power very much.

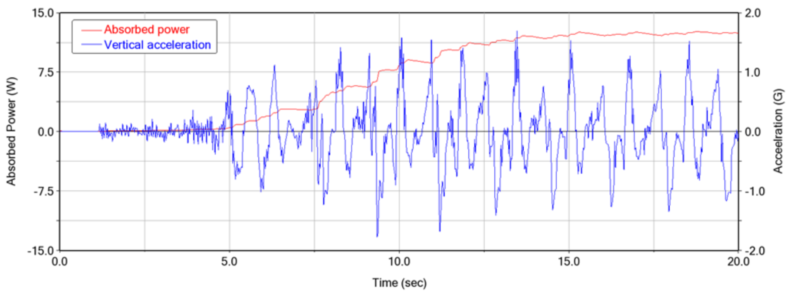

Figure 6 : Transient response of vertical acceleration and absorbed power

ODYSSEE Lunar can study the parameters influence on absorbed power peaks. The bar graph in Figure 7 shows the influence of each parameter at the peak at t=7 s.

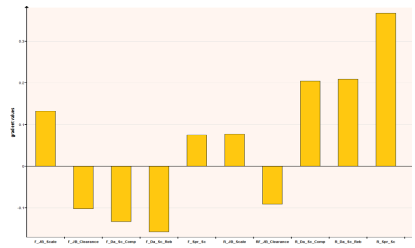

Figure 7 : Parameters sensitivity using Lunar

Since the overhead with executing a LUNAR run is minimal, optimization tasks can be performed very quickly. A set of parameters that minimized absorbed power was isolated in 53 seconds after 159 LUNAR evaluations of the ROM. The predicted optimal solution was then executed in Adams (Figure 8) with a step steer event. Lower lateral acceleration for the same steer input and higher roll velocity was observed using the optimized set as compared to the baseline.

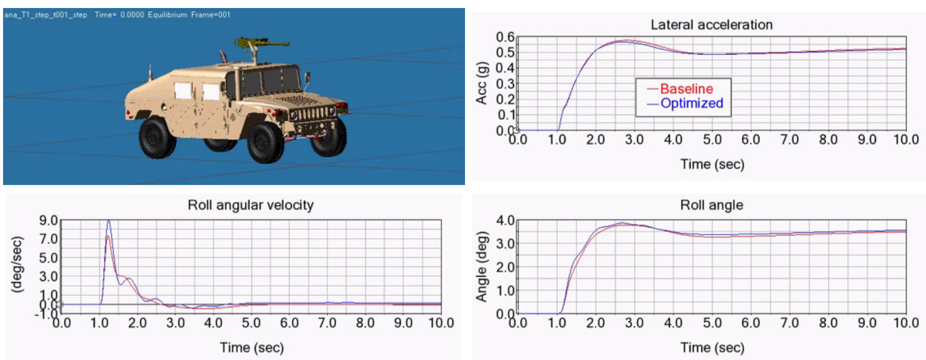

Figure 8 : Optimized vehicle responses using Lunar

This pilot study provides evidence that the CADLM approach reduces the number of runs as compared to a traditional RSM based DOE. The ROM can aid in an efficient understanding of parameter sensitivity and the rapid identification of optimal solutions.