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VULNERABILITY ASSESSMENT OF GROUND VEHICLE SYSTEMS ENABLED WITH ACTIVE PROTECTION SYSTEMS (APS) THROUGH SURROGATE MODELING

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ABSTRACT

Analytical performance assessment of Active Protection Systems (APS) and the vulnerability assessment of ground vehicles using classical physics-based modeling and simulations has many challenges. Also, modeling many of the factors involved in the interaction during Hard-Kill (HK) of the incoming threat with a countermeasure and the resulting outcomes are quite complex and have varied effects on the survivability of the vehicle. Therefore, relying only on deterministic solutions, are time consuming and computationally cost prohibitive.

This effort is focused on changing this paradigm by researching for a suitable machine learning algorithm which takes in simulation data from high fidelity physics-based models as training data. Through decomposition, interpolation and reconstruction techniques, surrogate models can be constructed using the simulation data. These surrogate models can then be used for a quick assessment (fraction of a second compared to a day per simulation) during Analysis of Alternatives (AoA), and Vehicle Protection Systems (VPS) trade studies.

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1. INTRODUCTION

The proliferation of advanced Rocket Propelled Grenades (RPGs) and Anti-tank Guided Missiles (ATGMs) have become popular with insurgents and non-state actors as they are readily available, inexpensive and require very little training [1]. Advances in technology has made these threats over matching the current state-of-the-art armor. These rapidly evolving threats have heightened the need to Active Protection

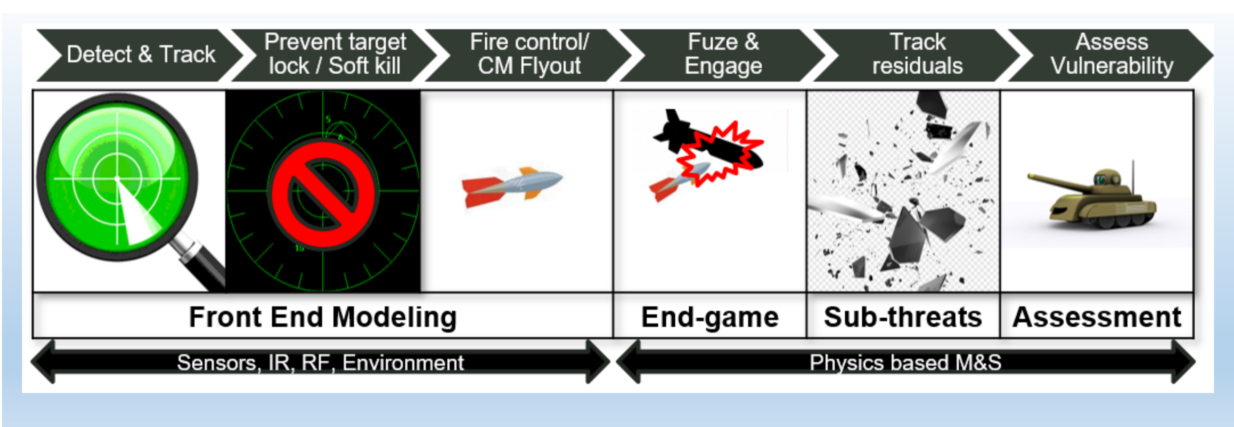
Systems (APS) for US military use more aggressively. Army is focused on expediting deployment and fielding of vehicle APS technology on ground combat vehicles.

Although many APS have been under development since 1950's, a fully self-contained yet affordable systems became available in the last decade. Performance assessment of these systems and the vulnerability assessment of ground vehicles equipped with APS using traditional physics-based modeling and simulations has many challenges. Relying only on deterministic solutions, which are time consuming and computationally cost prohibitive. To address some of these challenges, the many stages of APS hard-kill sequences such as detection, tracking, decision to deploy the countermeasure events must be modeled. Also, the myriad possible ways of a countermeasure can interact with the incoming threat and simulating every possible scenario is cost prohibitive.

This effort is focused on developing M&S framework using surrogate modeling techniques using the data generated from simulations using high fidelity physics-based models. Simulation data will be used to construct a surrogate model, which can be used for a quick assessment during AoA, and Vehicle Protection Systems (VPS) trade studies.

2. Why Surrogates APS M&S?

A surrogate model is a fast mathematical approximation to the long running physics-based high-fidelity model. It is a learning method or technique to establish dependency between a systems inputs and outputs from the supplied data from a known set of samples [2]. There have been some studies done to demonstrate modeling and simulation of APS systems and high energy armor piercing threats using classical FE methods showcasing various techniques and methods [3] [4] [5] [6] [7]. As there are many variables involved in an endgame scenario, in any given sample distribution, accurate assessment of all possible engagement scenarios using classical methods is almost impossible. Also, there is a need for quick assessment for various functional objectives of military ground vehicle survivability, while performing trade studies, design exploration and analytical performance assessments. Although there are a few tools available [8], created using empirical data gathered from coupled threat-countermeasure interactions and heuristics to make APS effectiveness and vulnerability assessments. As newer technologies being inserted at a rapid rate, it is essential to have a more robust physics-based assessment tools, yet with a faster turnaround time as an alternative to expensive physical testing.



A surrogate model is a fast mathematical approximation to the long running physics-based high-fidelity model. Surrogate models can be broadly classified in this study as scalar and full-field surrogate models.

3. M&S FRAMEWORK

Various stages of end-to-end APS – threat engagement modeling and simulation can be broadly broken down into six stages as shown in Figure 1. The first three stages of detecting, tracking, and initiating a soft-kill with the oncoming threat when feasible are collectively grouped under front-end modeling. Whenever soft-kill is infeasible and a hard-kill becomes necessary for survivability, modeling of APS-threat engagement, tracking residuals which in turn becomes sub-threats and the terminal ballistics can be grouped as end-game modeling and simulation. This stage often referred to as the endgame is the most computationally intensive and time-consuming aspect of end-to-end APS hard-kill M&S. This paper is focused on modeling the endgame where high fidelity finite element models of APS system engaging with the threat mid-flight and determining the potential outcome to assess vulnerability.

Two types of armor piercing threat types are considered in this study. Kinetic Energy (KE) threats such as a long rod penetrator and Chemical Energy (CE) threats such as Rocket Propelled Grenade (RPG). A notional blast-only countermeasure, a type similar to Elbit Systems' Iron Fist Light Decoupled (IFLD) APS is modeled for simulating end game scenarios.

3.1. APS-KE threat engagement model

A notional kinetic energy long rod penetrator is modeled as shown in Figure 2. A finite element model of the long rod penetrator is modeled using solid elements in the foreground mesh (Lagrangian) with about 120K DOF and the countermeasure and the surrounding domain was modeled as the background mesh (Eulerian) with about 100M DOF. The interaction is simulated using the Arbitrary Lagrangian Eulerian (ALE) method using the commercially off the shelf (COTS) software LS-DYNA®, capturing the nonlinear structural response amidst shockwaves from the countermeasure munitions. Turnaround time for a typical simulation on a high-performance computer using 12 processors in parallel takes about 12 CPU hours.

Figure 2 Model of an endgame scenario using notional countermeasure against a notional KE threat.

A total of ten parameters describing the quality of APS design features and the quality of engagement are chosen to perform a design of experiments. Due to sensitive nature of these technologies, these parameters are hidden and they are simply referred to as x_{01} .. x_{10}. Similarly, their domain ranges are normalized. The quality of engagement is parametrized through characteristic features of APS, the relative position, orientation and velocities of the threat and APS. Figure 3 shows a sample scatter plot of two variables showing the distribution of 140 training and 35 verification points.

3.2. APS-CE threat engagement model

A notional chemical energy penetrator is modeled as shown in Figure 4. A finite element model of a notional Rocket Propelled Grenade (RPG) is modeled using solid elements in the foreground mesh

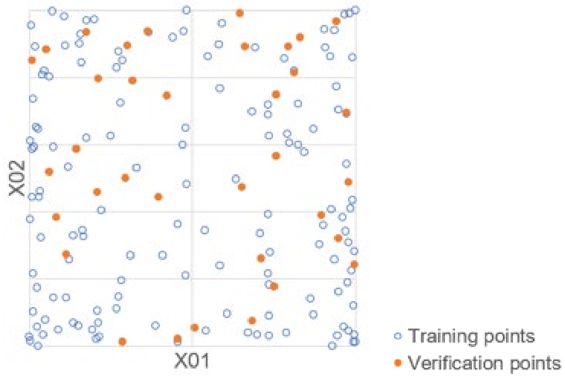


Figure 3 Sample scatter plot showing training and verification points plotted against two variables.

(Lagrangian) with about 16.5M DOF and the countermeasure and the surrounding domain was modeled as the background mesh (Eulerian) with about 17M DOF. The interaction is simulated using the Structural Arbitrary Lagrangian Eulerian (S-ALE) method using the commercially off the shelf (COTS) software LS-DYNA [9], capturing the nonlinear structural response amidst shockwaves from the countermeasure munitions. Turnaround time for a typical simulation on a high-performance computer using 12 processors in parallel takes about 8 CPU hours.

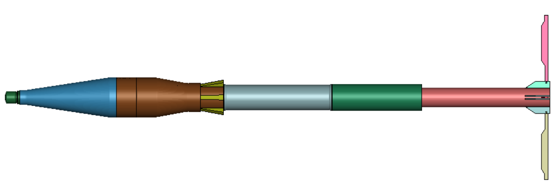


Figure 4 Model of a notional CE threat (Rocket Propelled Grenade).

A total of four parameters describing the quality of APS design features and the quality of engagement are chosen to perform a design of experiments [10]. Due to sensitive nature of these technologies, these parameters are also hidden and they are simply referred to as *x02* .. *x05*. Similarly, their domain ranges are normalized. The quality of engagement is parametrized through the relative position, orientation and velocities of the threat and APS. Figure 5 shows a sample scatter plot of two variables showing the distribution of 24 training and 6 verification points.

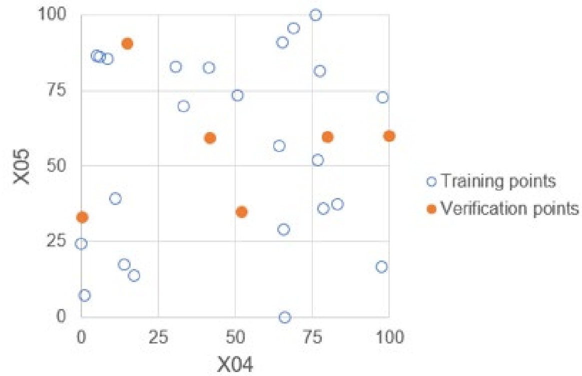


Figure 5 Sample scatter plot showing training and verification points plotted against two variables.

4. LEARNING FROM DATA

Machine learning techniques enable deployment of sophisticated algorithms on datasets to find relationships between input parameter or design variable combinations and their corresponding output responses. These output responses can be represented in the form of scalar quantities, transient field data or complete animation visualizations. These powerful data-driven techniques have proven to closely represent high-fidelity Finite Element (FE) simulation models to perform faster design exploration studies with high accuracy, thus significantly cutting down computing cost. The machine learning techniques used in this research vary from regression and classification algorithms like Kriging, RBF (Radial Basis Function), InvD (Inverse Distance), neural networks and SVM (Support Vector Machines) that can handle scalar quantities and class labels to Proper Orthogonal Decomposition (POD), Clustering and Fast-Fourier Transform (FFT) that can handle transient field data and animations.

4.1. Standard machine learning development procedure

A standard procedure is used to deploy machine learning algorithms on the data considered in this study.

1. Perform data cleaning if necessary
2. Split the data into training and validation datasets with an 80%-20% split ratio
3. Train a machine learning model on the training dataset using algorithms mentioned above based on the type of output response
4. Tune the solver and hyperparameters of the model using the validation dataset
5. Test the model's prediction accuracy using RMSE metric
6. Perform feature engineering and feature selection if necessary
7. Iterate over these steps until the desired model prediction accuracy is obtained.

Commercially off the shelf (COTS) solvers LS-OPT® for predicting scalar responses and ODYSSEE-CAE® are used for predicting transient field data including generating animations.

5. RESULTS & DISCUSSIONS

Once the input variables are established for both KE and CE scenarios, using space filling algorithm a set of training and verification points are generated.

5.1. APS-KE endgame

The main objective of APS hard kill of a KE type of threat is to impart a momentum transfer such that the fast-moving threat is deflected away from its intended target. The deflection of the threat away from its target as shown in Figure 6 is the main output response used to train the surrogate model.

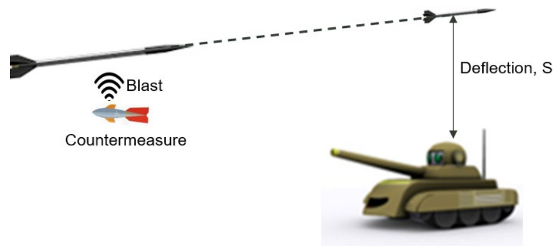


Figure 6 Deflection of a KE threat using APS hard-kill, also sometimes referred to as swerve.

Once all the training data has been collected, a sensitivity study was conducted to understand the variable contribution to the response. Figure 7 shows the Sobol indices demonstrating the influence of input variables on the deflection or swerve response. From the figure it is apparent that only four of the 10 variables considered in this study had more than 90% of influence on the response.

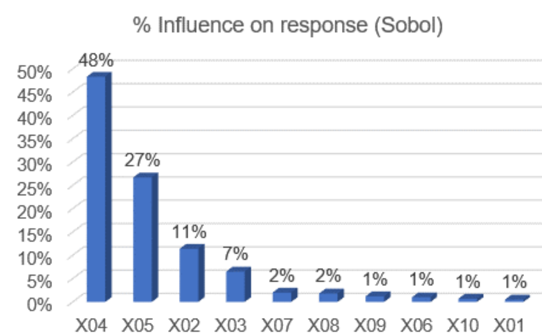


Figure 7 Only four variables have over 90% influence on the response.

Altogether five different scalar surrogate modeling techniques were investigated to find out the best suitable algorithm for this application which offered highest predictive accuracy using a commercially off the shelf software LS-OPT®. A scalar type of surrogate modeling technique is quite useful when there is a single objective function, where a response is rather smooth, based on a certain criteria. These scalar type of surrogate modeling techniques at the core differ only in the regression methods employed in the construction of those models. The simulation results from those 35 verification points are compared against those predicted from each of these surrogate models and a comparison is depicted in Figure 8. All five models predicted with a reasonable accuracy with RMS errors less than 10%. Neural network-based techniques performed slightly better with less than 5% RMS error.

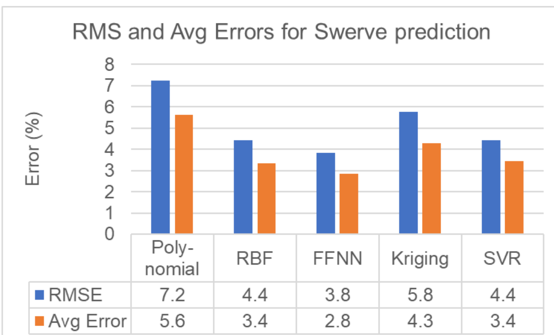


Figure 8 Predictive accuracy of various surrogate model types for APS-KE endgame.

Primary focus of defeating a threat in this study included only deflecting the threat away from its intended target, without any consideration of terminal ballistics. An aspect of this application is well suited for supervised learning such as classification. The outcome can be considered as binary, e.g., a hit or a miss based on an arbitrary target for deflection or swerve. Therefore, the training data collected can be suitably converted to labeled data and using a very popular technique such as support vector machine (SVM), a decision boundary of the design space can be constructed showing regions of interest. A binary classification chart can be constructed showing the subregions separating regions of hit or miss for APS-KE endgame as shown in Figure 9.

Thus created surrogate model with any given inputs within the domain runs very fast and predicts the response almost instantaneously making it ideal for incorporating in real time battle space gaming applications. A simple tool [11] was created based on the Neural Network based surrogate models within Excel for rapid exploration of trade space for engineers.

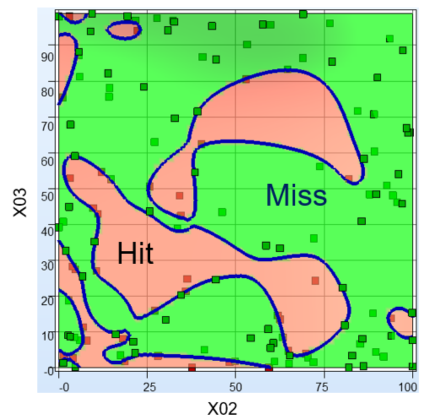


Figure 9 Explicit design space decomposition through classification technique showing regions of potential hits to the vehicle and misses (based on a given target swerve) plotted against two input variables.

5.2. APS-CE endgame

Because of inclusion of shaped charge within a CE threat, hard-kill engagement outcomes with an APS is quite varied and complex [12] [13]. In this paper our focus was primarily on the non-jet producing outcomes such as deflection of the threat away from its intended target (resulting in a dud) like the KE threat discussed before and the break-up of the threat assuming that the effect of sub-threats is negligible without forming any jet. From the physical test data, it has been observed that the predominant failure mode of a CE threat encountering a blast only type APS results in the breaking up of the threat just behind the ogive. Based on observed data the deformation angle between the two halves (ogive and the body) is monitored to determine the break-up criteria along with the swerve due to momentum transfer from the APS.

From the training data similar to the previous case a sensitivity study was performed, and the resulting Sobol indices chart is presented in Figure 10.

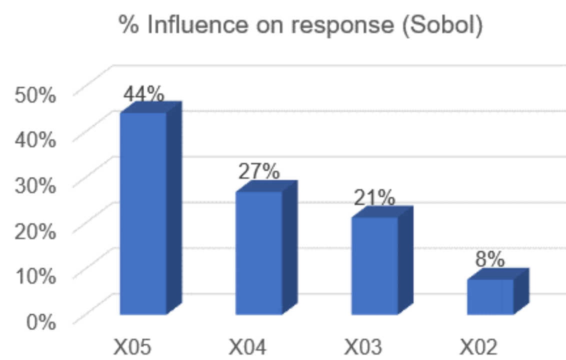


Figure 10 Influence of input variables on the response

Similar to APS-KE endgame case, five different scalar surrogate modeling techniques were investigated to find out the best suitable algorithm for this application which offered highest predictive accuracy. In addition to the scalar surrogate models, three full field surrogate model types were also investigated using commercially off the shelf software, Odyssee-CAE®. A full field surrogate model takes in field data from the high-fidelity simulation and performs a decomposition of the field allowing for the spatial and temporal domains to be handled in a decoupled manner and enabling the spatial-temporal response to be reconstructed via a multiplication of two uncoupled fields. Not only one can predict the scalar output response but also time histories.

The simulation results from those 6 verification points are compared against those predicted from each of these surrogate models and a comparison is depicted in Figure 11. RMS errors ranged from 15-25%. Full field models performed slightly better with less than 10% RMS error for the inverse distance type (Figure 12).

	RBF	FF	Poly-nomial	Kriging	SVR
RMSE	16.1	24.2	16.4	16.8	17.6
Avg. Error	14.5	19	15.1	14.5	14.9

Figure 11 Predictive accuracy of various scalar surrogate model types for APS-CE endgame.

	Inv D	RBF	Kriging
RMSE	9.3	20.8	25.9
Avg Error	6.7	17.2	20.6

Figure 12 Predictive accuracy of various full-field surrogate model types for APS-CE endgame.

Since the focus of this investigation was narrowed to only non-jet producing outcomes such as deflecting the threat away from its intended target or breaking up of the threat neglecting any risks of sub threats, the outcomes could be considered as binary, such as a hit or a miss. A binary classification similar to the previous case was performed. From the labeled training data collected, a decision boundary of the design space is constructed showing regions of interest. A chart is constructed showing the subregions separating regions of hit or miss for APS-CE endgame as shown in Figure 13.

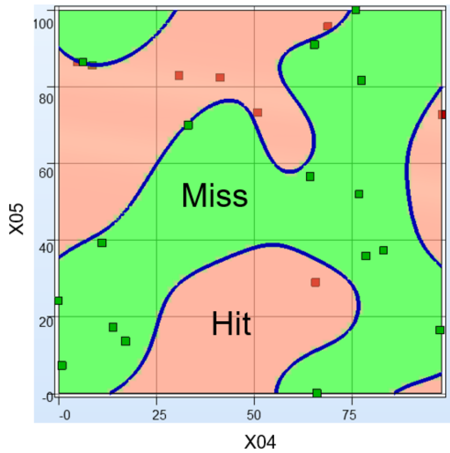


Figure 13 Explicit design space decomposition through classification technique showing regions of potential hits to the vehicle (APS failing to deflect or break up the threats) and misses (APS deflected and dismembered threats) plotted against two input variables.

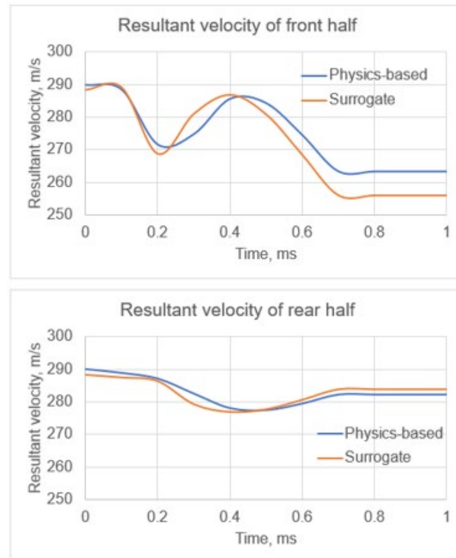


Figure 14 Velocity time history comparison from the threat break-up into two pieces

Time history responses obtained from full field surrogate models are compared against high-fidelity physics-based simulation results and the comparison is presented in Figure 14 for a case when APS succeeded in breaking up the threat into two pieces. A comparison snapshot from animations is also shown as Figure 15. It can be noted that the full field surrogate model runs much faster compared to the physics-based simulation without any need for a high-performance computer.

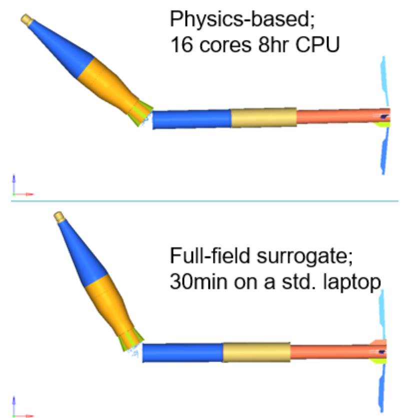


Figure 15 A snapshot of animations showing the comparison between physics-based simulation vs. from the surrogate model.

6. CONCLUSIONS

Physics-based direct numerical simulation of APS countermeasure engagement with oncoming threats is quite complex due to many factors involved. Prediction of such an engagement outcome depends on the accuracy of capturing the momentum transfer from the countermeasure to deflect/defeat the oncoming threat. This complexity requires very detailed modeling and sophisticated computational methods to avoid misrepresenting the underlying physics with numerical artifacts. This leads not only to significant effort in gathering geometry data and discretizing it, suitable for simulation but also exceedingly high computational costs.

With the proliferation of technologies in both lethality and survivability, there are various potential threat-countermeasure technology combinations with virtually unlimited possible engagement scenarios to be considered for vulnerability analysis.

Both these factors make it cost prohibitive to perform an analytical assessment through physics-based direct numerical simulation in a timely manner to support Army's needs of assessing competing technologies for vehicle survivability.

In this paper it is demonstrated that surrogate modeling of APS-threat engagement for simple outcomes is feasible, although it needs to be proven for other complex engagement outcomes. With the proliferation of technologies in both lethality and survivability, there are various potential threat-countermeasure technology combinations with virtually unlimited possible engagement scenarios to be considered for vulnerability analysis.

With emerging technologies both in APS and high energy threats, a high-fidelity physics-based M&S framework is beneficial to assess outcomes from any given high energy threat-countermeasure hard-kill engagement scenarios in a consistent manner to generate training data for generating fast-running surrogate models.

Many choice of surrogate modeling techniques exist offering varied degrees of predictive accuracy; about 5-25% error in predictions.

With a reasonably accurate surrogate model, many variabilities associated with hard-kill engagement scenarios can be quickly analyzed using Monte Carlo simulations on the physics-based surrogate model rather than heuristics-based engineering tools.

Kriging method offered the best predictive accuracy when there was a larger (140) training dataset, while Inverse Distance method offered the best accuracy when the training dataset is smaller (24).

Significant time save can be realized while analyzing new and what-if scenarios using surrogate models.

Scalar surrogate models can run in real-time which can enhance virtual battle space environment with more physics-based outcomes in gaming scenarios.

Full -field surrogate models although can not be run in real time but offers significant advantages for design exploration and analyzing what-if scenarios in an expeditious manner.

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