Sensor-Fuzed Munition Modeling Framework

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ABSTRACT

Sensor-fuzed munitions are a class of fire-and-forget weapons having one or more sensors and a logic unit to transform sensor data into target engagement strategies. A modeling and simulation framework for sensor-fuzed munitions has been developed to assess whole system and sub-system performance with respect to various terrains, meteorological conditions, target types, and weapon-target engagement dynamics. The framework supports simulation of complex terrain, target geometries and thermal signatures, lethal search, target acquisition, engagement, and lethal effects. Most importantly, the framework enables a rapid prototyping environment by providing strategic simulation breakpoints for recycling data and hot-swapping sub-system models. This unique modeling framework was made possible by identifying and forging together existing methodologies and models from multiple different disciplines, programming languages, and levels of fidelity. This model claims it uniqueness due to its unmatched level of fidelity, modularity, and scalability. To date, the framework and data products to be presented continue to be critical for answering sensor-fuzed munition system performance questions across multiple US ARMY programs. Regular data products include kill-chain performance probabilities and target hitpoint maps. Additionally, the framework includes custom tools for conducting data analysis for tracking system performance against defined requirements, providing insight into performance sensitivities, and for making well-informed design choices and down-selections. Current efforts are focused on statistical based design of experimentation techniques, model fitting, and predictive analytics. This document starts by familiarizing the reader with relevant concepts and terminology and the importance of simulation framework design. Following through, the document presents the fundamentals of a simulation framework design that serves as a solution for complex system design requiring high levels of collaboration and interoperability.

ABOUT THE AUTHORS

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INTRODUCTION

The Department of Defense is continuously striving to optimize and streamline acquisition and sustainment processes and standards when designing and developing relevant and reliable systems to win the race of sustained battlefield superiority. Given the pace at which advancements in technology are made, evaluating new weapon systems in real-time through physical prototyping and testing alone is becoming increasingly impractical from a logistics standpoint. Out of necessity and in the absence of time and resources for physical prototyping and testing, modeling and simulation (M&S) is now an indispensable means for predicting system performance. Though M&S can reduce physical testing and allow for exploration into the "what-ifs" of a system, some physical testing is required to validate and improve modeling capabilities.

Modeling and simulation is a powerful tool but it is limited in efficiency and insightfulness without proper experimental design. As weapon systems increase in complexity, the necessary degrees of freedom needed for implementing a meaningful model also increases. Consequently, as the degrees of freedom increase, to adequately sample and characterize system performance, scientists and engineers can either sample system performance via a brute force full factorial design or save time and resources by employing efficient experimental designs, leveraged from the statistical method of Design of Experiments (DOE).

A prerequisite to effective M&S is the adequate modeling of systems. To implement adequate models, subject matter expertise needs to be gathered from multiple disciplines, e.g. aerodynamics, sensors, algorithms, and lethality. If expertise is lacking in a particular discipline, then statistical based or lower-fidelity models can be employed to stand-in and help bound system performance until higher modeling fidelity is possible. When models involved in a simulation are subject to change due to rapid R&D, having a framework with strict interface control is necessary for managing disparate models of varying fidelity.

Presented in this white paper is a Sensor-Fuzed Munition (SFM) Framework that establishes a modeling and simulation approach designed to keep up with a highly fluid and rapid prototyping environment. To date, this framework has been sought after and used across multiple government and contractor organizations to support optimal design and down-select decisions that fill capability gaps and provide the warfighter increased lethality and survivability. This paper will first focus on relevant concepts and terminology, then on simulation framework design for modularity and interoperability, followed by data products and analysis tools, and lastly how the framework may be adapted for use in other applications.

CONCEPTS / TERMS

Below are sections that are provided as convenience to the reader needing to establish a baseline understating of the topic domain.

Sensor-fuzed munitions

Smart Munitions (SM) have the self-contained capability to search for, detect, acquire, and engage targets. They can be delivered to target areas by guns, rockets, unmanned aerial systems (UAS) or missiles, with each carrier delivering from one to a few dozen SMs. With this self-contained capability and the means to rapidly deliver large quantities of munitions, smart munition weapon systems can perform new missions on the AirLand Battlefield. For example, large arrays of land-mobile targets can be effectively and efficiently engaged at longer ranges; thus, important segments of the enemy force can be engaged before they can effectively fire on our forces. With the advent of smart munitions weapons systems, the Army Materiel Command (AMC) was faced with complex management issues as shown in Figure 1. The development of smart munitions involves a large number of diverse organizations with overlapping areas of responsibility or authority. The many smart munition concepts proposed exceed budget resources. The timely maturation of the tech base and availability of testing resources is critical. And, the detailed criteria for transitioning of smart munitions from Tech Base to Proof of Principle (PoP) and from PoP to Development and/ or Prove out are unclear" (Smart Munitions Program Office, 1987, p. 1)

Smart munitions have transformed the battlefield for many reasons:

- Ability to perform target detection, and identification
- Increase the likelihood of target engagement and lethal effects
- Often times requiring less munitions to be deployed to neutralize a target(s) with precision, unlike unguided munitions
- Aim to minimize collateral damage and neutralize a target as efficiently as possible (Keller, 2021)
- The ability to adapt to moving targets, after deployment, at increasingly farther ranges, by coupling the munition's "smarts" with its guidance to navigate to where the target is as opposed to where it was at the time of deployment. (Dean, 2008)

Factors, Levels, and Responses

Factors are the input variables, categorical or numerical, that may drive a result. (Franc, 2020) Examples of factors for Sensor-Fuzed munitions (SFMs) that may drive its ability to hit a target would be the target type and speed, countermeasures, clutter, etc. as illustrated in Figure 1.

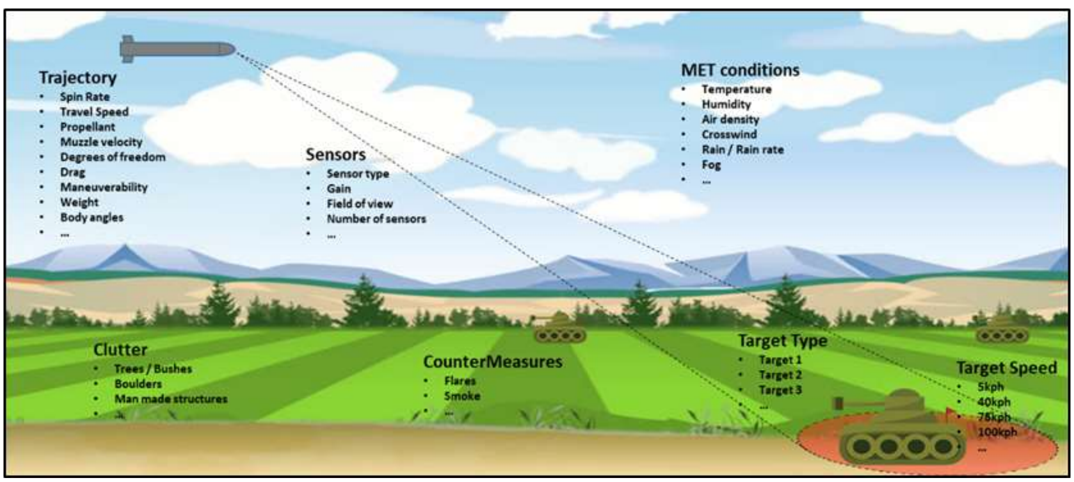

Figure 1. Illustration of a weapon-target-engagement scenario factors.

Possible values for a given factor are known as the levels of a factor. . (Franc, 2020) For example, target type is a categorical factor with three levels. The three levels are target 1, target 2, and target 3. An example of continuous levels of a factor, such as target speed, might be any target speed between 5 kph - 100 kph.

Responses are the dependent variables of interest looking to be understood through experimentation (Franc, 2020); an example of a response would be the munition impact location.

Design of Experiments

A DOE is a systematic approach that applies statistical techniques for data collection to ensure the generation of defensible engineering conclusions while potentially avoiding unnecessary tests that do not offer additional insight into the relationships between the factors and responses. DOEs aid in the development of controlled tests with the intention to evaluate factors that impact a given response. By aiding in the quantification of sensitivity between factors-levels and the responses of interest, DOEs reduce both physical and M&S test matrices and required resources. Additionally, DOEs are capable of identifying high-order interactions between responses and factors. Interactions between one or more factors and a response, found to have high correlation, can aid in smart cross-[Intergraded Product Team] IPT design efforts. Ultimately, DOEs aim to minimize conducting experiments via brute force full factorial designs. (*Design of Experiments (DOE) Tutorial*, 2018)

Figure 2 is an illustration, of how a DOE can aid in reducing the number of experiments. As a word of caution, DOEs are subject to losing information as the number of experiments and/or the dimensionality of factors/levels are reduced. On this note DOEs are typically iterative, with earlier iterations being more coarse to serve as factor screening opportunities; while successive iterations aim to optimize the experimental design for drawing out response sensitivities and insights.

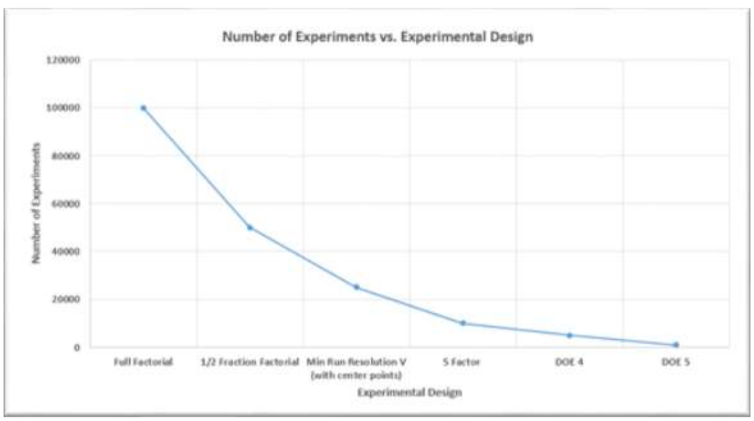

Figure 2. Example illustrating potential reduction in the number of experiments needed though different types of DOEs.

Cohesion and Coupling in Software Design

Cohesion refers to the measure in which a module has been developed to execute a specific task. The more focused the model, the higher the cohesion. If a module contains unrelated functions or elements within it, it would be said to have low cohesion. Modules with a well-defined purpose lend themselves to be highly reusable and are easier to maintain, update, and test. (Montiel, 2019) Figure 2 shows a class implemented with low and high cohesion.

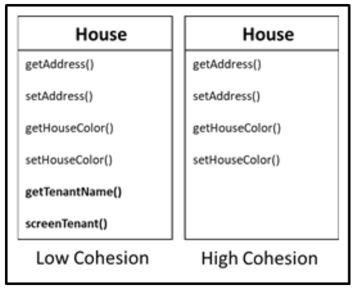

Figure 3. Example of a class with low and high cohesion.

Coupling is the measure in which modules are connected or depend on the inner working of another model to perform its intended function. The more a module relies on the inner workings of another model to execute its function, the higher the coupling. (Montiel, 2019) Figure 4 shows an example of loosely and highly coupled class dependencies.

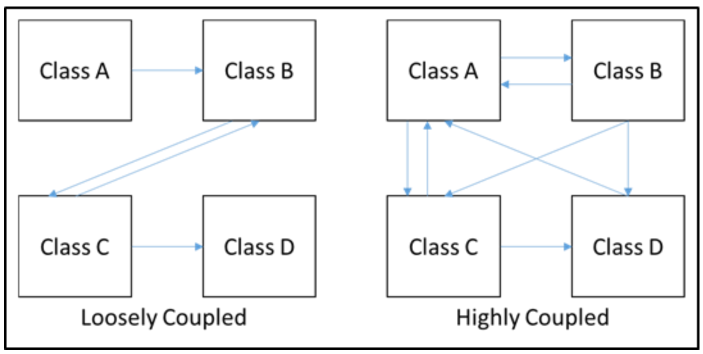

Figure 4. Example of a loosely and highly coupled model design.

Smart Munition Modeling Complexities

> Pentagon chief Ash Carter laid out the problem during a preview of the Defense Department's 2017 budget, which includes a request for $1.8 billion to buy 45,000 smart bombs and other guided munitions. But he also highlighted a shift away from a single-minded focus by the U.S. military on the conflicts of the moment and more on what he termed a "high-end enemy"—that is, a peer military power like Russia or China. (Dillow, 2021)

Smart munitions are a modern goal for the DoD to address increasing lethality, minimizing collateral damage, and cost of mission for current and future threats. These types of munitions are increasingly complex; being designed with onboard sensors, algorithms, guidance, and collaborative capabilities. Naturally, these design efforts require a multidisciplinary team of teams working towards a common goal. To ensure smart munition systems can be efficiently managed and produced, "The FY 2017 National Defense Authorization Act required DOD to address issues that were preventing its departments and offices from collaborating with each other… [The] DOD's strategy for collaboration identifies critical objectives that would benefit from cross-functional teams". (Office , U. S. G. A., 2020)

The DoD recognizes tomorrow's enemies are becoming more advanced, thus it has no choice but to maintain its technological advantage and consequently face increasing weapon design and deployment complexity. (Vergun, 2016) To overcome increasing complexity, M&S is an excellent choice for decreasing physical testing while increasing design explorations. Physical testing is decreased through M&S by the creation of a digital twin—a modeled representation of the physical system sufficient enough in detail such that a change in the digital model adequately represents a change in the physical model. Additionally, a digital twin enables an engineering team to sufficiently explore the design space without the need to physically build and test every concept configuration. The design of an

M&S framework must be built with the consideration to lend itself to not be a roadblock but foster a collaborative team effort where the CFT may not necessarily speak the same language.

Sensor-Fuzed Munition Modeling Framework

Framework Design

Figure 5 illustrates an SFM simulation framework designed and built to:

- Enable trade space performance analysis of whole systems and their sub-systems
- Ensure flow of models and data between the M&S framework and the working IPT
- Execute data analytics that can handle big data to provide system performance insights

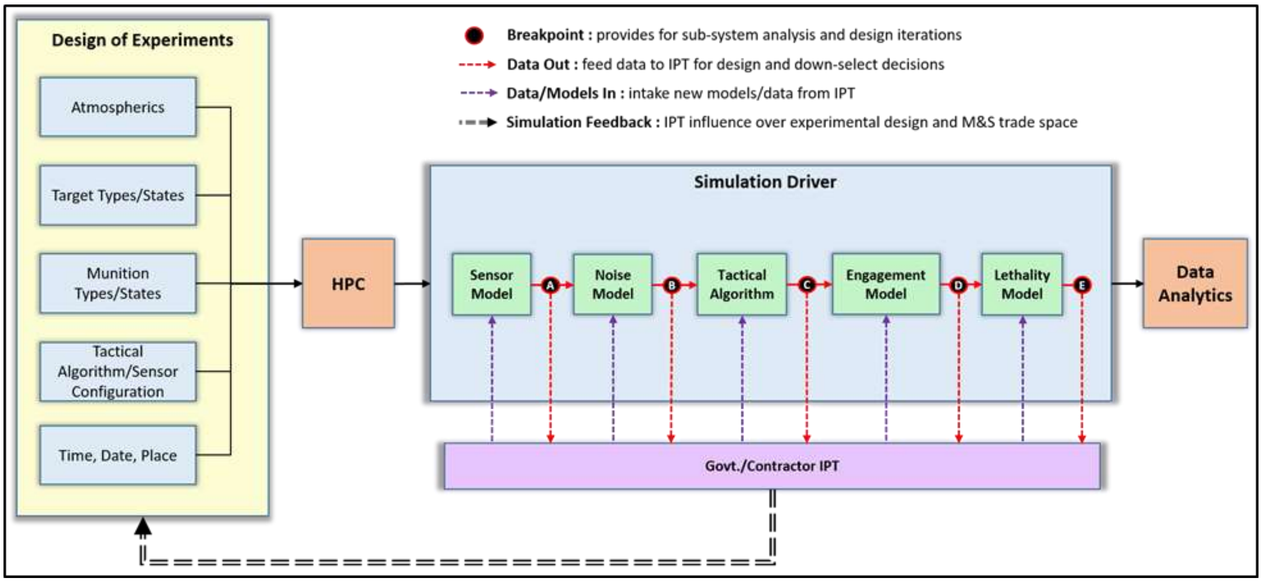

Figure 5. SFM Simulation Framework block diagram, illustrating workflow and feedback opportunities.

Experimental Design

The experimental design approach involves first understanding the stakeholder's objectives and requirements across the system's operating environments. Once these objectives and requirements are understood, functional decomposition of the system into its constituent parts is required so that the subsystems can be tested individually and as a whole. As illustrated in Figure 1, there are many factors to consider that are derived from many cross-functional IPT's, each possibly containing many levels that make implementing a full factorial design less effective. DOE's serve as the vehicle to assess many factors simultaneously through strategic experimentation across the design space of a system to minimize the time needed to assess both system and subsystem performance and sensitivities.

A DOE is only as good as the M&S framework you have to execute it. More specifically, a good DOE is wasted on an inefficient framework design. DOEs are intended to be used to save resources but when paired with a poor framework, return of benefits are diminished.

High-Performance Computing Clusters

In addition to or in the absence of Design of Experiment techniques, the design space for sensor-fuzed munitions can be incredibly large and often require complex and computationally expensive simulations. The use of High Performance Computing Clusters (HPCCs) can be used to decrease the time between program questions and deliver answers related to system performance and inter-subsystem sensitivities. This decreased turn-around time is critical for rapid prototyping and development efforts.

Simulation Driver

The simulation driver can be thought of as a low overhead glue code that enables the use of disparate models to stitch together a simulation in a loosely coupled yet highly cohesive manner. Fundamentally, the driver architecture supports parametric input sets and simulation breakpoints for data to be recycled against various sub-system designs. For instance, the simulation driver could take advantage of a breakpoint by allowing IPTs to isolate sub-system performance analyses, without the need to rerun the M&S chain from the beginning. Further, the strategic architecture of M&S breakpoints allows for tracking and documenting the evolution and pedigree of system performance over time.

Enabling unimpeded and efficient model development and updates across multidisciplinary IPTs requires strict interface control to ensure maximum efficiencies in integration. The simulation driver, only having knowledge of the expected input and outputs driving the execution of models, enforces the concept of Object Oriented Programming (OOP). With such an approach, identifying points of failure and modifying model interfacing for execution becomes highly compartmentalized, lending to greater control in managing impact across the rest of the simulation. The modeling of smart munitions does not only require extensive efforts in modeling all key sub-system components but also both controllable and uncontrollable environmental factors needed for meaningful simulations to test the digital twin of the system. Given the compartmentalization of all inputs, proper representation and assessment of the system is only achieved through driving the execution of a simulation through a regimented routine, in this case referred to as a simulation driver.

Sensor Model

The sensor model is designed to capture electromagnetic information at the sensor dome, i.e. the absolute truth before entering a sensing system’s electro-optical software and/or hardware. To do this, the sensor model allows a weapon’s state and the number, type, and orientation of its sensors to be simulated over time. The electromagnetic energy tracked at each time-step is a function of not only the weapon system, but also a specific time, date, location, target type, and time-varying target state. Figure 6 depicts a notional sensing system’s detector values over time. In comparison to Figure 7, shown later, the signal-to-noise ratio (SNR) is relatively high and more apt for easy target detections.

The output of the sensor model provides for the first simulation breakpoint opportunity. The sensor model output can be recycled against various sensor system characteristics, e.g. spectral responsivity, lens area, gain factors, integration time, low/high pass frequencies, and saturation rails. By design, the sensor model breakpoint allows the sensor system IPT to iterate the sub-system design to shape the kinds of signals that the tactical target detection and engagement algorithm will have to process across various different weapon-target engagement scenarios.

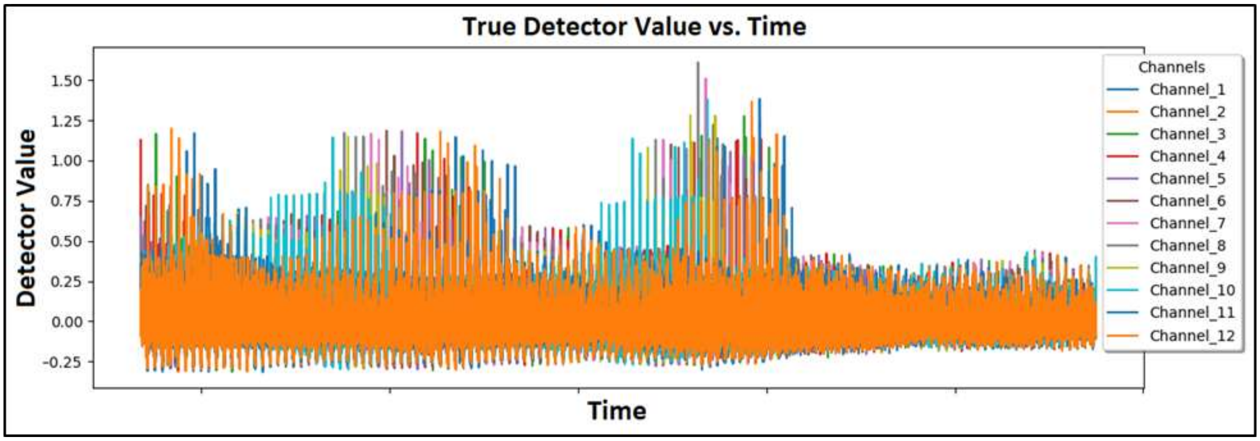

Figure 6. A notional system's detector values vs. time plot without accounting for various system noises.

Noise Model

As stated in the sensor model section above, the noise model serves to transform the true electromagnetic information at the sensor dome into signal values flowing into the tactical target detection and engagement algorithm, indicative of having passed through a specific sensor system having some input set of electro-optical performance characteristics. Essentially, the model directly effects the SNR and implicitly the probability of target detection and false alarm. Figure 6 illustrates a notional sensing system's detector values over time given the specific effects of its electro-optical performance characteristics, accounting for the various sub-system noise sources. In comparison to Figure 7, it can be seen that the envelope of the signal peaks rising above the noise floor is generally maintained while the SNR is negatively affected, leading to a relatively more difficult job for the tactical target detection and engagement algorithm.

The output of the noise model serves as the second breakpoint in the M&S chain. The noise model provides for recycling tactical algorithm input data against various different tactical algorithm implementations. In essence, this breakpoint provides the tactical algorithm and sensor IPTs to adjust the algorithm and/or sensing system design to preserve system strengths and overcome weaknesses. For example, through iterative sub-system analyses it was found for a particular sensing system, under specific weapon-target engagement geometries, that there existed a target detection null across an approximately 13% swath of the total search area due to a tactical algorithm implementation bug. The identified problem was shared with the IPT, fixed, and ultimately saved the program an invaluable amount of time, money, and costly battlefield underperformance.

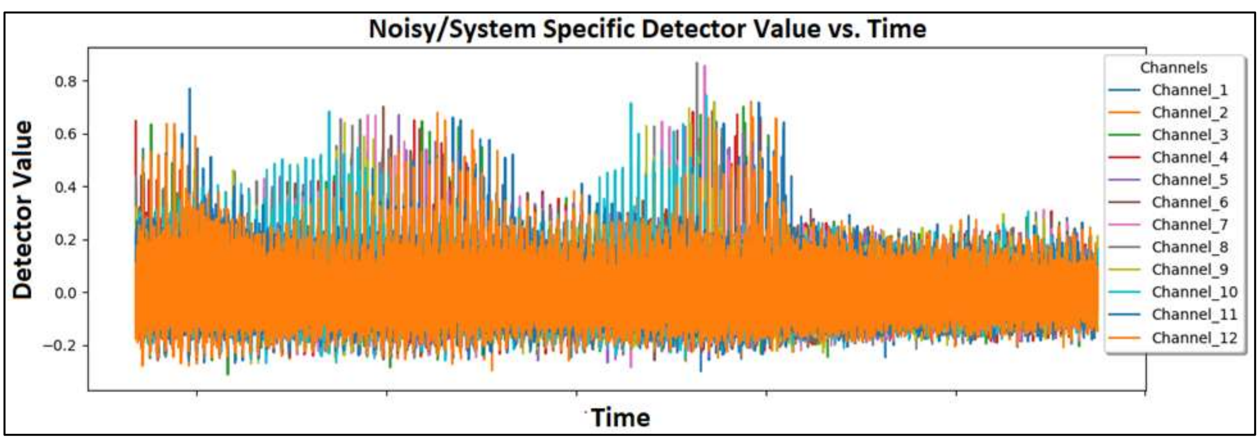

Figure 7. A notional system's detector values vs. time plot accounting for various system noises.

Tactical Algorithm

The tactical algorithm is the brain of smart munitions. A smart munition's tactical algorithm provides methodology for sensor fusion, target detection, target tracking, and decision logic for optimizing target engagement strategy to maximize lethal effects. The output of this algorithm serves as the third break point in the M&S chain. The engagement decision produced by the tactical algorithm can be recycled and used again following updates made to the engagement model to improve and/or test hit point generation accuracy. Decoupling the firing decision from the engagement model, allows for the engagement model representation to evolve over time. Like all sub-systems in a complex smart munition design effort, the engagement model is subject to change and may be initially limited to a lower fidelity in the absence of a concrete sub-system characterization.

Engagement Model

The engagement model is responsible for assessing the outcome of the engagement following a decision made by the tactical algorithm. The decision from the algorithm often comes in the form of a command to fire the lethal mechanism of the munition. The engagement model allows for flexibility to be had on the fidelity of the engagement from the time a fire signal was generated to the resulting impact location. It offers an opportunity to take into account real-word nuances that may impact the resulting lethal mechanisms impact location following an engagement. Opportunities to account for a munitions spin rate, hardware delays, software delays, delivery error, etc. are had with this model. Through testing, as behaviors become better characterized, modeled factors can be updated to improve the hit point predictive capability through establishing higher levels of alignment with the physical system and modeled behaviors.

Lethality Model

The lethality model provides one of many methods for parametrically evaluating the outcome(s) of target engagements against varying lethal mechanism design iterations. As shown here, lethal performance is assessed against target Vulnerability Map (VMAPs). The direct output of the lethality model is the metric probability of kill. Probability of kill is leveraged by the IPT to inform lethal mechanism design and down-select decisions. Target engagement data can be archived and recycled for future use as the lethal mechanism design and target lethality intelligence evolves.

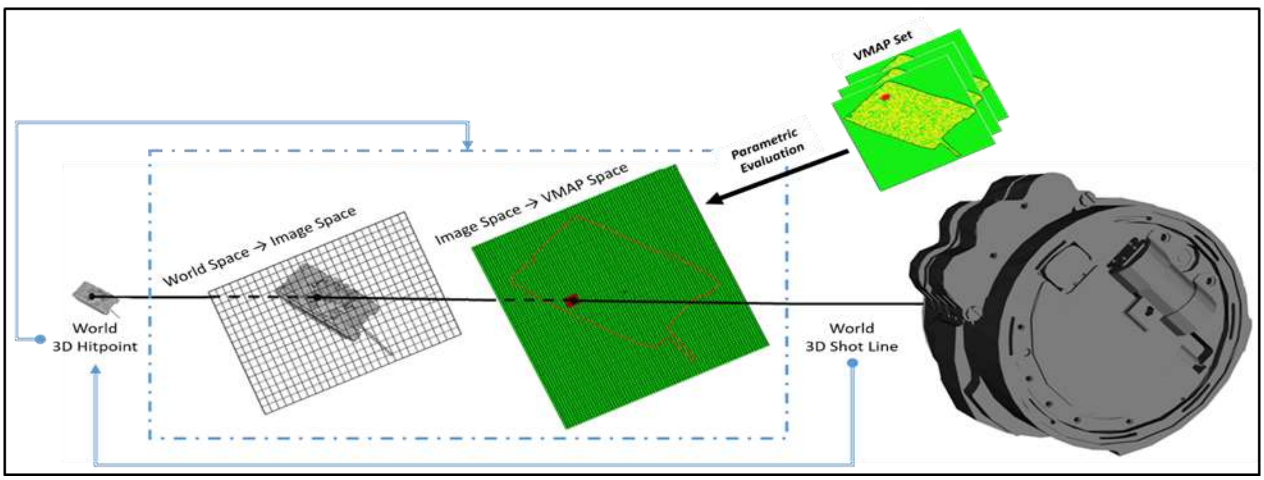

Figure 8. Illustrates a modeling procedure for evaluating target engagement lethal effects using parametric sets of VMAPs.

Data Analytics

Each framework breakpoint produces a plethora of output data for analytics. Ultimately, all sub-system IPTs are concerned with their respective levels of performance and any potential inter-subsystem performance sensitivities.

This framework provides tools built for and capable of digesting the data from each breakpoint, for quickly producing standardized data products that highlight system performance strengths, weaknesses, and sensitivities. The data analytics potential of each sub-system model and its breakpoint are outlined below with accompanying figures.

The output of the *Sensor Model* are detector values, with respect to time, without any account of the sensing systems noise. This data product is useful for determining the tactical algorithm's baseline performance with respect to probability of detection, engagement, and hit. Establishing a system baseline enables:

- Bounding performance expectations
- Guiding of initial design decisions
- Providing a reference for tracking performance sensitivities, shown in Figure 9
- A useful debug opportunity

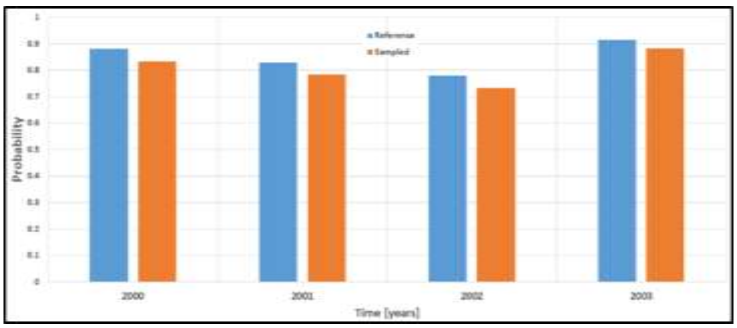

Figure 9. Notional illustration of tracking sub-system performance over time.

The output of the *Noise Model* are detector values, with respect to time, accounting for the sensing system's noise. This data product is useful for testing the tactical algorithm's performance, given current sensor system electro-optical performance characteristics, with respect to probability of detection, engagement, and hit. Understanding the signal levels propagating from the detector into the tactical algorithm allows:

- Tuning algorithm performance across different operational contexts
- A useful debug opportunity

The output of the *Tactical Algorithm Model* are the target engagement strategies, e.g. a detonation time or a coordinate for direct hit. This data product is useful for mapping what part(s) of the target body are being engaged by the lethal mechanism, a precursory set for determining lethal effects. Additionally, analyzing the target engagement strategies across sets of experiments allows for assessing probability of detection, engagement, and hit against system requirements.

The output of the *Engagement Model* are spatial coordinates of the area(s) of the target body being effected by the lethal mechanism. This data product is useful for mapping target engagements into probabilities of kill.

The output of the *Lethality Model* are probability of kill values for each target engagement attempt. This data product is useful for tracking lethal mechanism design performance against system requirements.

For convenience, a data analysis tool has been developed to consolidate the regular data products typical sought after by the customer. An example view of the tool display is shown in Figure 10. Given the nature of complex smart munition design efforts, the tool enables data exploration via the use of data filters. The filters lend themselves to be invaluable for isolating and evaluating system performance against program requirement in niche operational contexts, as well as, providing average performance across operational contexts.

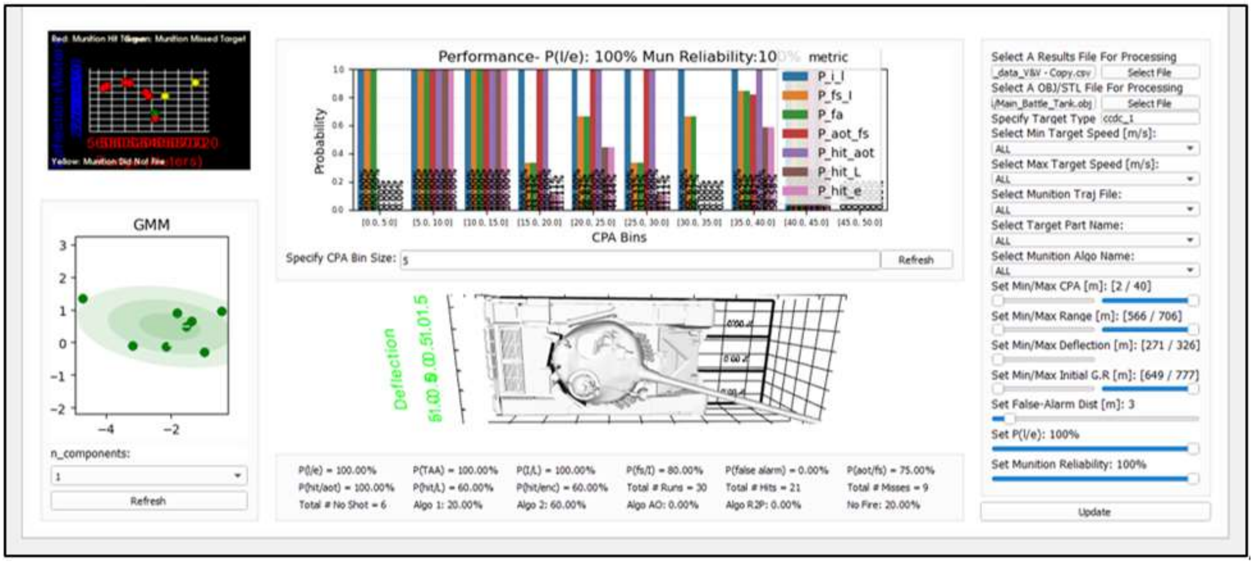

Figure 10. Notional data analytics tool display of trade space results, statistics, and data exploration filters.

Conclusion

Timely and successful design of complex system depends on smart experimental design and smart M&S. It is proposed that the nature of the framework presented can be an excellent solution for DOD efforts to remain competitive against adversaries in today's rapid R&D environment, all the while helping to save time, resources, and provide the warfighter with enhanced lethality and survivability. The framework presented in this document is a unique application of advanced object-oriented programming for the design of defense weapon systems. Though the framework has been applied to the domain of smart munitions, there is nothing to stop an interested party from adopting the presented methodologies for their own system design effort.

Fundamentally, if a system can be functionally decomposed into highly cohesive subsystems and an interface can be established to support low coupling between the subsystems, then any system design effort can benefit from iterative whole system or subsystem development cycles, in a modular and scalable fashion. Any cross-disciplinary team stands to suffer from inefficiencies that stem from their domain specific tools and terminology when collaborating to integrate up to a whole system. It is stressed that design teams can greatly benefit from the presented framework, due to the natural support for collaboration and interoperability. Plainly speaking, this approach allows the number of and fidelity of the subsystems to evolve over time—it is highly scalable.

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