An Analysis of Engagement Algorithms for Real-Time Weapons Effects

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ABSTRACT

When selecting algorithms for real-time weapons effects, performance and fidelity requirements are the main drivers in model selection. In many cases, look-up tables are the method of choice for real-time applications. Look-up tables have had wide-spread use in trade studies, planning tools, training simulations and other applications over a long period and have proven to be both extremely valuable for real-time casualty assessment and at times misunderstood in what capabilities they provide. Look-up tables facilitate fast retrieval of vulnerability data, with measurable tradeoffs between memory requirements, computation requirements and fidelity. As processing power has increased, higher fidelity algorithms of casualty assessment have gained wider use, suggesting that look-up tables may eventually become obsolete. This paper describes the casualty assessment modeling spectrum from low fidelity to high fidelity, including look-up tables, curve fits, physics-based models and finite element codes. Each type of model is examined, along with the advantages and disadvantages of each. Guidelines for how to determine what model type to select and what factors should be considered when selecting a model are discussed. Principles outlined in this paper are being used to support model selection for the OneTESS program, the Army's next generation tactical engagement simulation system.

ABOUT THE AUTHORS

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INTRODUCTION

In today's cost and schedule driven programs there is a desire for reuse from legacy simulations. The challenge in reuse is to effectively leverage solutions that were developed with different objectives in mind. Two recent programs that are attempting to leverage legacy capabilities are the One Tactical Engagement Simulation System (OneTESS) and Combat Training Centers Objective Instrumentation System (CTC-OIS). OneTESS is being developed for the U.S. Army as a tactical engagement system for both the training and operational test communities. These programs share a common requirement to improve realistic weapons effects for live training events.

OneTESS must be capable of handling multi-resolution engagement algorithms to support varying fidelity requirements. Player units used in OneTESS must be flexible enough to support the selection of the appropriate algorithm for the training or operational test communities. The player units must also support both classified and unclassified munitions data and the ability to receive updates to existing algorithms and data for new and modified weapon systems (OneTESS ORD, 2003).

There are some existing "low-hanging fruit" solutions for weapons effects that are attractive for reuse because they are easy to implement and currently exist, but as our results here suggest they may not be an appropriate solution for live training. There are two reasons for looking at other solutions. First, there are necessary modifications to existing algorithms to minimize the possibility of negative training (Gordon, Casey, Burns and Cohn, 2001). Second, advances in processor speed, memory capacity and our understanding of the problem has made new approaches to algorithm development more feasible.

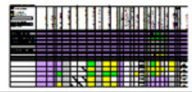
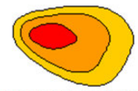
This paper examines some of the issues associated with weapons effects simulations in training and operational testing. We present the various methodologies for simulating weapon-target engagements and the potential results cast in the context of the trainee's experience.

BACKGROUND

Engagement algorithms have long been used to support military applications including targeting, trade studies, operational testing and training simulations. Targeting applications use the algorithms in deliberate and tactical/crisis scenarios to determine which munition to fire on the target – the munition with the highest probability of being most effective. Algorithms used in trade studies, often called analysis of alternatives or AoAs, provide simulations of weapons effects to support evaluations of weapon systems. The studies sometimes drive acquisition planning. Operational testing of weapon systems requires a thorough evaluation of vulnerability and weapon lethality to determine the weapon systems suitability for use in the field (Sondheimer and Fagan-Blanch, 2001). Training in the realms of live, virtual and constructive requires engagement models of varying fidelity depending on the training objectives and fidelity of the simulation.

OVERVIEW OF ENGAGEMENT ALGORITHMS

Algorithms used for damage assessment can be described in four general categories, ranging from low to high fidelity (Figure 1). These categories are not intended to rigidly classify models. Rather, they define general groupings of models along the continuum of complexity. Many algorithms exist that blend characteristics from more than one of the categories described here (Gordon, Casey, Burns, Cohn, 2001). The next sections describe these categories in more detail.

Methodology	Description	Example	Trends
Pre-calculated (PC)	Look-up tables		
Engineering model (EM)	Empirical equations, algorithms, curve fits	$t = .42e^{-5}W_f^{0.396}v_s^{1.103}(\cos(\phi))^{1.42}$ fragment penetration equation for steel	
Physics-based model (PBM)	Low degree of freedom approximation, time may be considered	 Time-dependent chemical plume	
First principles physics (FPP)	Hydrocodes, finite element codes	 SPH simulation of ball and plate	

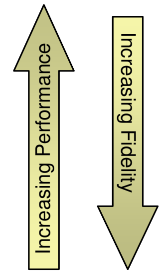


Figure 1 Engagement model spectrum

Pre-calculated (PC)

Pre-calculated damage assessment algorithms are commonly referred to as look-up tables. Another term that the Army Materiel Systems Analysis Activity (AMSAA) uses is item level analysis. This term refers to the whole platform versus individual components. These algorithms make extensive use of table data representing discrete damage values. Table values are derived from live weapon tests or from higher fidelity models. Pre-calculated damage assessment algorithms require little processing power because the bulk of the analysis was done during the creation of the tables. Minimal remaining effort, usually interpolation, is required to arrive at a solution. These characteristics make pre-calculated models ideal for situations where processing speed is of paramount importance, processing power is limited, and high fidelity is not required - an example might be direct fire engagements with short range weapons.

Engineering Model (EM)

An engineering model is an equation or curve fit based on empirical data or data from numerical simulations. In some cases, the model may be derived from a first-principles physics calculation. It is then simplified and the parameters are adjusted to fit available experimental data (parameter/system identification). In other cases, a simple fitting function may be applied to data. The function is then used to approximate the data gathered during live weapon tests.

Depending on the complexity of the model calculations, the tradeoff may be higher fidelity at the cost of computational performance. An engineering model likely can calculate results for a wider range of munition and target inputs than a pre-calculated algorithm since it is not limited to discrete table values but instead varies in a continuous manner. It also handles a larger number of parameters and more complex interactions between parameters, generally providing a more accurate solution.

Physics-based Model (PBM)

Physics-based models (PBMs) use algorithms that depend on physical properties and usually satisfy basic scaling and conservation principles. PBMs can be "chained together" to solve complex problems such as the interaction of a weapon with a fixed target structure. These types of models can generate damage results that appear highly realistic (Mann, York and Shankle, 2004).

PBM equations are usually simplified to a linear or mildly non-linear form that can be evaluated with standard numerical methods. The use of parameter identification to fit to experimental data is minimized. As a result, experimental test data requirements are generally lower for physical models, making the model development task easier, although some test data is usually required for validation and verification of the model implementation.

Physics based models can require detailed information about the environment in which they execute.

Frequently, comprehensive material property data, meteorological data and geometric data are required as input to the model. In environments where this information is not practically obtainable, there may be no alternative but to revert to a simpler model.

First Principles Physics (FPP)

First principles models are highly rigorous mathematical solutions. The appropriate governing mathematical equations such as conservation of mass, momentum, and energy are solved given any special assumptions and/or boundary conditions. Examples of first-principles models are hydrocodes, computational fluid dynamics (CFD) codes, finite element techniques, and meshless methods. Each method has its advantages and is typically used for certain classes of problems. Solution schemes (e.g., time integration routine or equation solver) are often dependent on the class of problem (e.g., static or dynamic).

The number of degrees of freedom can range into the millions for large problems run on parallel machines. Many types of data can be monitored throughout the domain of the solution to provide detailed insight into the problem. Lower fidelity, faster running algorithms have often been derived from higher fidelity methods such as hydrocodes (Lorey and Swenson).

Figure 2 illustrates the relationship between model types, fidelity, and execution time.

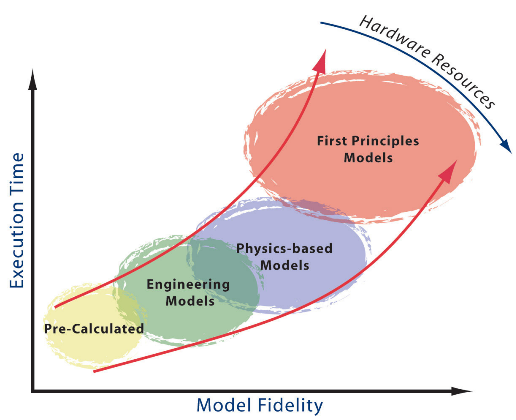


Figure 2 As the fidelity of the engagement model increases, the execution time goes up. One way to reduce execution time for high fidelity models is to increase the processor speed and memory capacity.

PROS AND CONS OF EACH MODEL TYPE

Table and curve fit models tend to run very fast but at low fidelity. Increases in fidelity are achieved by increasing the number of input parameters and the number of discrete values at which the input parameters are known. The disadvantage of this approach is that the resources required to store the data increase exponentially - each additional parameter adds another dimension to the table.

Models based on look-up tables or engineering models that use curve fits are limited to the scope of available tabulated data. Results cannot be obtained for cases other than what has been tabulated which can be a serious limitation in some cases. Curve fits may be ill-defined outside the boundary for which the curve was established, and results in those regimes are invalid.

Many legacy models are based on specific munition types and may have, for example, lethality data tabulated. When a variant of this munition or a new munition is contemplated, new or updated lethality data must be created. The model for the original munition cannot be reused for a new or modified munition.

Physics-based models (PBMs) can help mitigate this problem by weakening or eliminating the dependency on weapon system specific data. For example, instead of munition identifier, a PBM may use explosive weight and case mass as key input data to model the resulting fragment field. This fragment field is then used to compute lethality against the target. In this case, the PBM uses a two-stage approach to reach the final result in contrast to the tabulated approach which obtained the result in only one step. However, the two-stage approach methodology can be re-used for other weapon systems where the table cannot.

Models based on first-principles physics (FPP) potentially give the most realistic, accurate, and highest fidelity results. The amount of realism, accuracy and fidelity depends upon the amount and quality of the physics incorporated into the model. Although very effective, there are some draw backs to using FPPs. Physics models that seek to model the interaction of numerous entities and effects are computer resource intensive, especially when uncertainties in input parameters must be accounted for. They can require large volumes of detailed input data, much of which may not be known with satisfactory precision. These algorithms may be particularly difficult to develop. It may be difficult to guarantee convergence and stability of the mathematical algorithms used for the entire range of possible inputs.

Variations on how the models are implemented can yield a hybrid model approach. Hybrid models are an attempt to optimize efficiency and fidelity. Where the fidelity and physics are important, physics models are applied and where fidelity is not important (or the input data required to drive a physical model are not available), table or curve fit models may be employed. The hybrid model is optimized to meet the fidelity requirements as defined by the users and the computational resource requirements. For example, a hybrid model may use a physics based fly-out model to determine the impact point, but use a table-based model for the damage if the target is hit.

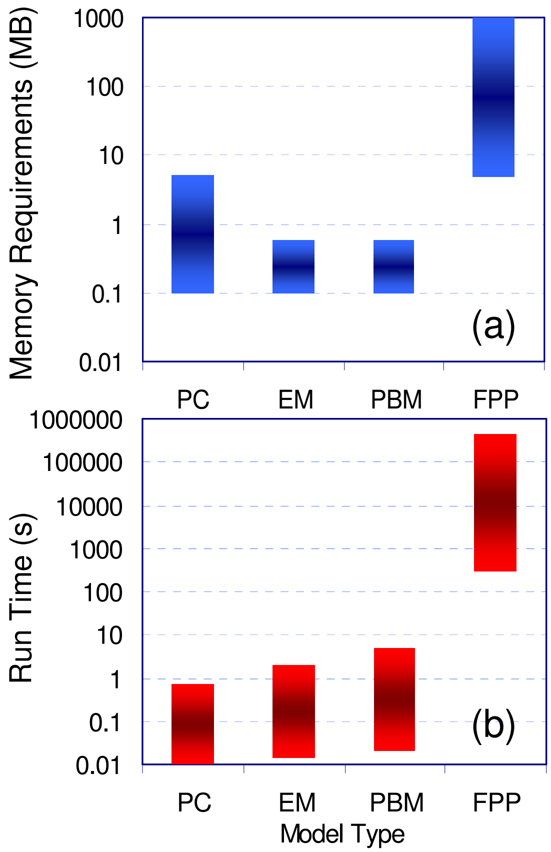


Figure 3 (a) Model comparisons by memory use, and (b) by run time. PC = Pre-calculated, EM = Engineering Model, PBM = Physics-based Model, FPP = First Principles Physics. The red and blue bars represent ranges of typical values (e.g. PC ranges from .01 – 1 second of run time depending on the complexity of the calculation).

Figure 3 shows an order of magnitude comparison of the various models. Of course there are special cases that may exceed our plot ranges, but these are the trends with which we are familiar in the area of weapons effects modeling.

ENGAGEMENT MODELS IN TRAINING SIMULATIONS

Negative Training Considerations

Low fidelity models in general do not accurately represent the true engagement from initialization, replication, to the final results. They tend to have many simplifying assumptions and/or statistically average over a large continuum of parameters and/or have coarse bins of resolution for the input parameters. The nonlinear nature of engagements implies that small changes in the inputs can have dramatic changes in the outcome of the engagement (e.g., hit or miss). Because of this averaging and coarse resolution of the input data, small changes in the input parameters will not be represented in the table models. Therefore the outcome of engagements that differ dramatically in high fidelity models may not differ at all in the lower fidelity models.

There are many issues with model fidelity, data availability, data resolution, and model correctness that may result in poor quality training or negative training. Depending upon the specific engagement and situation, the model's realism and fidelity play a major role in the quality of the training and in the elimination of any negative training (LaPorte, 2001).

The next few sections describe examples where models can be improved to provide better training.

Aiming

Many of the models used in today's training simulations make assumptions in the model inputs that could lead to incorrect conclusions. For example, most pre-calculated models assume that the aimpoint of a weapon is the center point of the target. In a live instrumentation system, using a hard coded aimpoint may lead a trainee to believe he can score a hit without accurate aiming.

If the shooter's firing ability is not taken into account, a below average shooter could think that he is better than he really is. On the flipside, a skilled shooter may lose trust in the instrumentation system.

Impact Point Calculation

Most pre-calculated algorithms do not calculate the real impact point, rather they count a shot as either a hit or miss. In some cases, this level of granularity is sufficient, but sometimes this is not enough and the results of a calculation based on an inaccurate impact point will return unrealistic damage results.

Damage Assessment

The standard PC look-up tables (e.g., OneSAF Testbed, OneSAF Objective System, etc.) for personnel and vehicle damage tend to be coarse, making it difficult to attribute detailed damage to a target. For example, wound location or type for personnel is not reflected. The result from a look-up calculation is normally the time to incapacitation. Including more information in the casualty assessment would provide training value for medical personnel, allowing for 'field treatment' of minor injuries (OneTESS ORD, 2003).

Wound type and incapacitation must be considered in the context of the mission – minor injuries may not significantly incapacitate infantry in a defensive posture. For example, if a soldier is wounded in the leg, he may still be able to fire. Minor wounds may slow a soldier affecting his ability to perform at 100%. This could be modeled by increasing shooting errors. Treatment of his wounds may allow him to continue fighting.

PC look-up tables for ground-mobile target vulnerability generally have four damage states – mobility kill, firepower kill, mobility and firepower kill and catastrophic kill. Sensor and communication kills are additional damage states that would be useful to be able to calculate (OneTESS ORD, 2003). If the weapon system firing at a target has sufficient accuracy, training could be improved by considering component level vulnerability in the real-time damage assessment. This would expand the damage states and allow for repairs and gradual degradation of capability.

Some munition effects are not sufficiently accounted for. Some algorithms that calculate fragmentation flyout, for example, don't consider concealment/obstructions. In some cases the fragmentation effects are completely ignored or lumped into an overall change of lethality/incapacitation. Fragments that miss the target can cause damage, but are usually ignored. These fragments have potential to cause damage to individual components like an antenna or machine gun.

Higher fidelity models can reduce the need for improvised changes to compensate for inaccuracies and missing components in low fidelity models. There is generally less human interaction and intervention for adjudication (e.g. from exercise observer/controllers) to compensate for the low fidelity of the model. These are particularly large problems with indirect fire engagements (LaPorte, 2001).

MODEL EVALUATION EXAMPLES

The following examples demonstrate issues in using pre-calculated models for delivery accuracy and damage assessment. We also compare low and high fidelity models as described in the previous section.

One of the objectives of these evaluations is to determine the suitability of models for representing weapon engagements in the live, virtual and constructive environments. Evaluation factors include performance assessment, data validity and accuracy.

M1 Firing a Sabot at a T62

Subject matter experts familiar with NTC training have voiced to us that aiming accuracy is not adequately reflected during training. Thus, we have examined how engagement methodologies might affect this situation, hopefully improving the training realism. We studied this question in a scenario with an M1 tank firing on a T-62 tank as shown in Figure 4. We used the pre-calculated (PC) lookup methodology developed by AMSAA and data from OneSAF Objective System (OOS) (AMSAA, 2004).

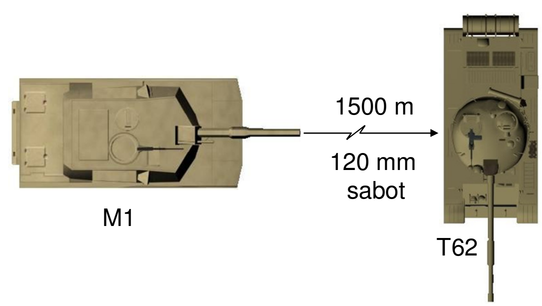


Figure 4 The M1 vs. T62 scenario uses a 120mm kinetic energy round at a fully exposed side view of a T62 tank from 1500 meters with both tanks stationary.

The AMSAA/OOS models used in this scenario assume that every hit on the tank is from a perfectly centered aimpoint at the center of visible mass (Figure 5). The models use bias and random error distributions along with Monte Carlo methods to determine the shot-to-shot variations assuming the center of visual mass aimpoint.

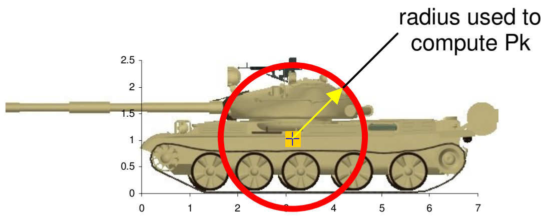


Figure 5 The OOS vulnerability algorithms assume the aimpoint to always be at the center of visible mass (yellow box), and vulnerability is calculated based on a radius that can vary from shot-to-shot.

If the objective is to improve training feedback for aiming accuracy under this scenario, we can consider two changes to the current algorithm:

1. Use a realistic aimpoint and subsequent hitpoint
2. Calculate probability of kill based on a hitpoint not always at the center of mass

If a training instrumentation and software system could predict a realistic aimpoint, it could be used in the vulnerability and probability of hit calculations. The probability of hit could be better predicted using the actual munition azimuth and target orientation (Figure 6). In addition, realism would be added by providing more realistic damage feedback to the trainee and avoiding potential negative training.

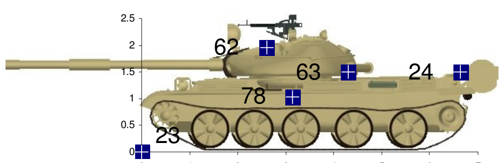


Figure 6 We calculated probability of hit (Ph) for five aimpoints using consistent delivery accuracy data and 10,000 iterations. The results follow intuition as the center of mass value is the highest at 78% and Ph reduces toward the edges of the target.

We know from experience that damage to a tank varies as the munition impacts different locations on the tank. We used the Modular UNIX™-based Vulnerability Estimation Suite (MUVES) to compute Pkm (probability of mobility kill) as we varied the aimpoint along the side of the tank such as that shown in Figure 7.

We overlaid the MUVES graphic with two dispersion circles. The dispersion circle centered on the assumed aimpoint is the one used by OOS algorithms. The dispersion circle around what might be an actual aimpoint demonstrates the difference in Pk values when one mentally integrates the amount of color within the two circles. In Figure 8 we have plotted the result from MUVES for comparison with the PC approach to demonstrate the variation in Pk that occurs with a higher fidelity model.

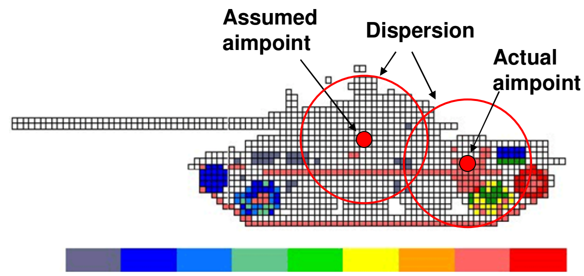


Figure 7 The cell plot from MUVES shows how vulnerability for mobility kill varies. Two notional aimpoints and dispersion radii are also shown to emphasize the different Pk values within the two circles.

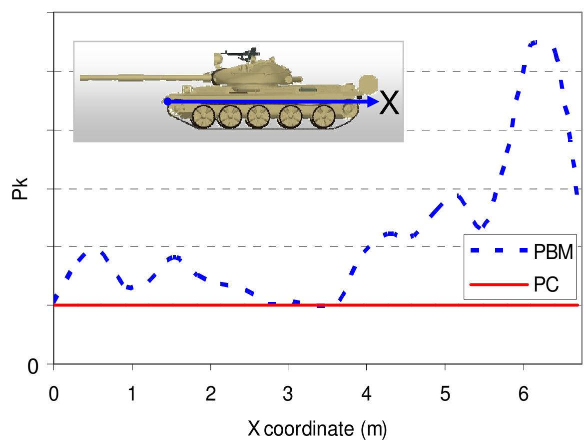


Figure 8 The PC methodology in OOS does not produce the realism of higher fidelity methods for vulnerability assessment.

With the assumption that MUVES provides reasonable results, it is clear that the higher fidelity model replicates reality better than the PC model. The accuracy of table based models could be increased by expanding the table values. However, similar results could be achieved with more efficiency by using a response surface.

A response surface is an Engineering Model that uses curve fit to data to determine the damage state. Depending upon the dimensionality of the curve and the number of parameters, the response surface technique can be more accurate with only a slight increase in computational resources.

Other Considerations

Another important point from this analysis and example of the coarse parameter bins is that the look-up table only contains values for a fully exposed tank or a tank in hull defilade (i.e. only the turret is exposed to fire). In reality, there can be many intermediate values of exposure. Such a calculation can be done using a line-of-sight algorithm to calculate the hit point and restricting the damage calculation to only the exposed parts of the tank.

Urban Operations Assault

Another example where aiming accuracy is critical for training is an urban assault scenario. The scenario is focused on a hardened command and control building disguised as a conventional structure in an urban setting. Blue forces are using an M203 grenade launcher to fire a grenade though a window on the second floor as shown in Figure 9.

Figure 9 The shooter is 50 m from a 1 x 1.5 m window on the second floor. The M203 is very accurate at 50 m, but small changes in the aimpoint have a significant effect on the hit percentage when firing at small targets.

The objective of the shooter is to propel the grenade through the window. Figure 10 shows the window hit percentage next to its corresponding aimpoint for an M203 grenade using the OneSAF direct fire accuracy algorithm. If the aimpoint is assumed to be the center of visual mass, there is a 99% probability the grenade will enter the building. However, notice how small deviations in aiming can considerably change the probability of success. The change in the shooter's aiming angle of less than ½ degree is the difference in getting nearly all the grenades through the window and getting only half through the window. There is a slight positive fixed vertical bias causing 100% PHit to be below the center of visual mass.

In a miss, the M203 likely will not penetrate the wall of the hard building. Thus, the grenade will detonate in direct line-of-sight to the shooter which may pose a hazard. Without aiming accuracy and the instrumentation to support it, there is high potential for negative training in that the shooter might always believe he shoots the grenade successfully through the window.

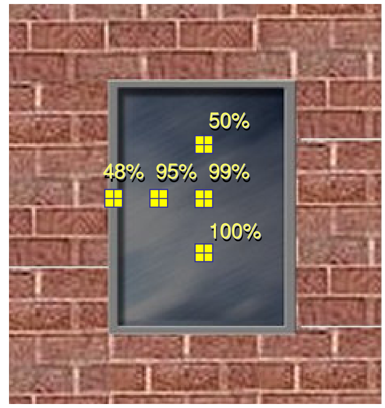


Figure 10 Aimpoints with their associated hit/penetrate percentage are shown. The percentage of window hit/penetrate varies dramatically if the aimpoint is slightly off center.

Vulnerability from a Grenade in a Building

No current training or simulation systems have the ability to simulate the urban assault scenario and include the effect of the grenade on the structure and occupants. The WARSIM environment damage assessment model (WEDAM) uses a combination of PC and EM models, but cannot resolve damage from a single small charge such as the grenade (Clark, 1999). WEDAM does not address damage to entities that might be inside the structure. OOS uses the ultra-high resolution building (UHRB) model for structures, but it is not currently coupled with engagement models that can compute structure damage or damage to internal entities.

We used an existing software tool that implements a hybrid engagement methodology to demonstrate that highly effective training could be achieved in this scenario. Figure 11 shows the problem set-up. We performed the analysis using the IMEA physics-based weaponeering tool (Harman & York, 2003). Figure 12 shows initial results.

The PBMs in IMEA calculate damage and casualty levels for equipment and personnel inside the building as a function of the environment created by the weapon. Of particular note is the fact that some fragments penetrate the interior walls and go into neighboring rooms. By avoiding PC lookup tables, this methodology extends to virtually any type of weapon by only defining a few munition parameters.

This analysis also demonstrates that using a rich synthetic environment can help make training more realistic. Figure 13 shows a comparison between the buildings with a wood floor versus a concrete floor. Fragments penetrate the wood floor (right) causing damage to the room below the detonation and generating a hazardous environment.

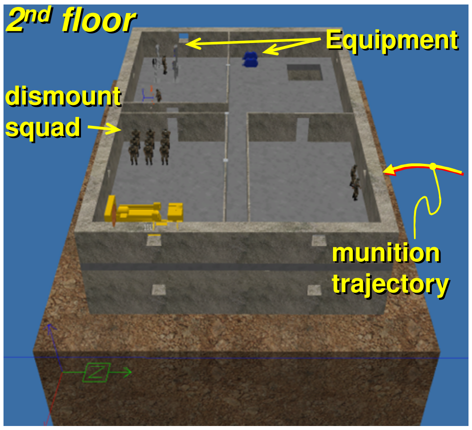


Figure 11 The top of the building has been removed to show a cut-away on the second floor. In this particular scenario the synthetic environment contains equipment and dismounts inside the building.

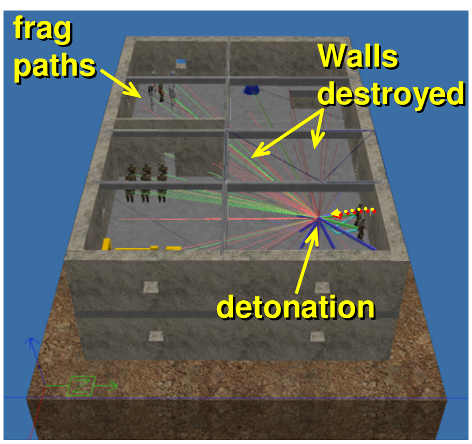


Figure 12 Key fragment paths are shown in various colors. The blast has destroyed the two walls of the room that contained the detonation. Note also that fragments penetrate interior walls and go throughout the second floor.

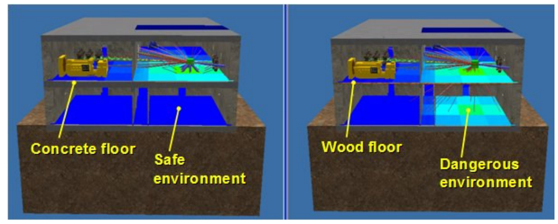


Figure 13 Physics-based models can exploit a rich synthetic environment to improve the fidelity of simulations. The model to the right has a wood floor that grenade fragments can penetrate causing potential casualties in the first-floor room below.

We are using tools such as IMEA to help us better understand the effects of various munitions with the objective of extrapolating lower fidelity models from higher fidelity models either by generating data for look-up tables or by simplifying the algorithms to trade off fidelity for performance (Davis, 1995).

FIDELITY VS. PERFORMANCE TRADEOFFS

There are several techniques that may be used to get the required performance, remain within the available computation resources, and retain the desired fidelity. One that has been previously discussed is the use of a hybrid model, retaining the fidelity where it is required and using faster, lower fidelity models where high fidelity is not required.

Depending upon the parameter and physics regime of the engagement, some terms in the equations for the physics models may or may not be important. Analysis and numerical experiments may be used to determine in what regimes certain terms do not make a significant contribution. Once these regimes have been determined, logic may be incorporated into the physics model to drop these terms, or use alternate potentially quicker methods to solve the equations, thereby reducing the calculation time.

Another technique similar to the above is to determine when simpler terms or equations and/or approximations may be used that would speed up the calculation time in the model without reducing the fidelity or reducing the fidelity beyond the lower limits. Again there are generally parameter regimes where these simplifications or approximations are valid and logic must be incorporated into the model's software for the models to know when to use the quicker techniques. For example, air drag may be neglected in certain regimes such as short distance between the target and the weapon. This analysis includes linearizing nonlinear models and determining in which regimes the linear model is valid.

UNCERTAINTIES

Weapons effects are inherently probabilistic in nature. Random and systematic uncertainties exist in every phase of a weapon-target engagement - examples are:

- Fire control: launch angle, azimuth, muzzle velocity,
- Impact conditions: impact angle, velocity, location, angle-of-attack,
- Weapon material properties: case thickness, case strength, explosive weight,
- Target components: thickness, strength.

When we develop models or simulations we sometimes create or have to deal with systematic uncertainties. These can originate from biases in measurements or biases in solution methods. Examples of systematic uncertainties include:

- Instrumentation system error when measuring gun tube elevation angle,
- GPS error in target location,
- Measurement error in depth of penetration data,
- Prediction error because a physical phenomena is not accounted for in the model equations.

Engagement algorithms must take uncertainties into account to achieve valid and realistic simulations and training. We will never know initial conditions and other variables to a sufficient extent such that we can rely on a deterministic solution. Inaccuracies and fidelity tradeoffs in the solution methodology also prevents us from using a purely deterministic solution.

The higher fidelity methods such as EMs, PBMs, and FPPs can treat uncertainties in a more robust and flexible manner than PC lookup tables. Lookup tables can grow very large if the number of uncertain variables or their resolution is increased. Thus, these methods are somewhat constrained in accounting for parameter variabilities. In our M1 tank example, the AMSAA lookup tables include shooter and target velocity as variables. However, there are only two bins for each variable: 0 m/s velocity and 5 m/s velocity.

One way higher fidelity methods achieve better uncertainty representation is by incorporating distributions of important parameters into the solution. For example, if a distribution defines the Circular Error Probable (CEP), the impact location and dispersion can be simulated each time a weapon is fired. Figure 14 illustrates the dispersion for 10,000 simulations of a munition with a 1 m CEP.

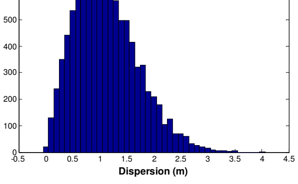


Figure 14 Dispersion distribution.

GUIDELINES FOR SELECTING MODELS

Model selection is driven by many considerations. Fidelity and computation requirements are a primary concern. High fidelity results necessary for weapons testing will require first principles physics calculations. In contrast, training simulations are generally driven more by the limitations of the computation platform than by the model fidelity. Tradeoffs must be made between these requirements to arrive at a reasonable compromise. The minimum fidelity requirements must be determined by the users, analysis and peer review. Computation requirements will be driven by the available hardware, costs and desired response time.

Another factor dictating the choice of models is the availability of data to drive the model. High fidelity physics models frequently require a large amount of high quality input data (e.g. geologic data required for detailed weapon penetration codes). If the data is not available, simpler models might have to be used.

If there are no existing models that can be integrated, the cost of developing a new model may be a consideration. Acquiring and analyzing sufficient experimental data or first-principles code output to cover the necessary range of parameters for a pre-calculated model may be cost prohibitive. In these situations, it may be possible to use a more detailed physics based model with a smaller data set for validation purposes.

CONCLUSION

The analyses discussed in this paper are just a starting point for the in depth research that is necessary to support the refinement of current engagement algorithms to meet the test and training needs of today's military. The Army transformation depends on enhanced training for our troops. Engagement algorithms that have been used again and again in simulations with little change over the years can no longer be expected to provide the fidelity necessary to effectively train our military. These methods were originally intended solely to provide a set of data and methods for weapon effectiveness studies and can have significant drawbacks for training (Driels 2004).

Our hope is that the information in this paper will spark a renewed interest in an area of critical importance.

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