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ACCOUNTING FOR INDIVIDUAL SHOOTING SKILLS IN COMBAT MODELS

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ABSTRACT

There is significant variation in shooting ability among U.S. Army soldiers, which is often overlooked in combat simulations. This study introduces a Monte-Carlo model to estimate the dispersion of a soldier's shot group based on their marksmanship score. This model is used to assess the impact of marksmanship on a squad's performance through two analyses. The first analysis employs a dueling model to examine various marksmanship skills between dueling teams, offering insights into overmatch requirements. The second analysis uses an agent-based combat simulation to investigate the influence of marksmanship on squad performance in a dueling scenario in addition to tactical rural and urban missions. The results reveal that marksmanship becomes increasingly crucial in enhancing lethality and survivability as the distance between combatants grows. Notably, superior marksmanship skills are particularly vital in offensive, rural operations. These findings emphasize the significance of marksmanship and its implications for military requirements and tactical decision-making.

1 INTRODUCTION

According to U.S. Army doctrine, soldiers must be able to shoot, move, and communicate. The first of these three functions, shooting, is a core competency that soldiers spend a tremendous amount of time training on. The quality and frequency of training results in a significant amount of variance in shooting ability across the U.S. Army. For example, new Reservist soldiers may only have trained with an actual M4 while at Basic Combat Training. Meanwhile, soldiers in the Ranger Battalions go to the rifle range multiple times per month. Despite this variance, combat models typically do not account for individual shooting performance, treating all soldiers as being at the same level of marksmanship.

This paper presents a method to correct standard combat models to reflect individual shooter expertise. In particular, it maps the size of the shot group for an individual soldier with an M4 Carbine to their Basic Rifle Marksmanship score. The paper then uses this mapping to perform two different analyses. The first analysis uses a stochastic dueling model to better understand overmatch requirements, a key aspect of military requirements development. The second analysis uses an agent-based model to capture the changes in lethality, survivability, and mission success of a squad of soldiers as a function of individual soldier marksmanship.

2 BACKGROUND

2.1 The M4 Carbine and Marksmanship

The M4 carbine is a lightweight, gas-operated, air-cooled, magazine-fed, selective fire weapon that is primarily used by the United States Armed Forces. It is designed to be highly versatile and is used by various military personnel, including infantry soldiers, special forces operatives, and vehicle crews. The

M4 is capable of firing both single shots and bursts of up to three rounds, with a maximum effective range of 500 meters.

To assess a soldier's individual shooting proficiency, they must annually complete the Basic Rifle Marksmanship (BRM) qualification with their M4 carbine. Although a new BRM test is currently being implemented across the U.S. Army, this analysis uses the long-standing BRM test that has been used for the last two decades (**?**). The qualification requires that soldiers shoot at pop-up targets at different ranges from different shooting positions. Soldiers initially shoot at 20 targets at ranges from 50 meters to 300 meters from a prone supported position, where the weapon is propped up on a sandbag. The soldier then shifts to a prone unsupported position where they remove the sandbags and engage 10 targets at 50 meters to 300 meters. They then switch to a kneeling position and engage 10 targets at 50 meters to 150 meters. The targets are human-sized and typically pop up for 3 to 7 seconds. While this test is no longer considered the primary evaluation for BRM, its simplicity makes it easily modeled. Additionally, due to its extensive use over several decades, a substantial amount of data has been accumulated over a number of studies, making it suitable for modeling purposes.

After completing the BRM course, the soldier will receive a score which is based on the number of targets hit. To qualify as an expert marksman, soldiers must achieve a score of at least 36 out of a possible 40 points on the qualification; soldiers who score between 30 and 35 points qualify as sharpshooters; and those who score between 23 and 29 points qualify as marksmen. Soldiers who score below 23 points are required to undergo additional training to improve their marksmanship skills.

2.2 Shooting Methodologies

Most combat simulations follow a series of three stateless models to determine the incapacitation of a target: Search and Target Acquisition, Delivery Accuracy, and Casualty Assessment (**?**). The Search and Target Acquisition model determines whether the soldier is able to detect and identify their target. Upon identifying their target, the soldier will shoot at the target, and the Delivery Accuracy model determines where the bullet strikes relative to the target. The Casualty Assessment model then determines whether that round will incapacitate the target.

Typically, the Search and Target Acquisition model is based on the Acquire Target Task Performance Metric (ACQUIRE-TTPM) algorithm, which is explained in detail in (**?**). This algorithm treats the eye as a sensor looking at an image with certain contrast and resolution to determine the probability, given infinite time, that the shooter can detect the target.

The Casualty Assessment model is based on where the round hits the target and is assigned certain probabilities (**?**). For example, a shot to the chest with a 5.56mm round may have a 40 percent probability of incapacitating an armored soldier. These models are rooted in biomedical research and often highly simplified for combat models.

The Delivery Accuracy model is a mathematical model used to simulate the performance of weapon systems in hitting their intended targets. This model considers a variety of factors that can affect the accuracy of the weapon system, including environmental conditions, the shooting position of the operator, and the precision of the weapon system itself. The output for the Delivery Accuracy model is the location that a bullet strikes relative to where it was aimed, which is typically assumed to be the center of the target. To determine where the bullet strikes, the Delivery Accuracy model determines the angle dispersion, in milliradians (mrad), of the shot, as shown in Figure 1. The Infantry Warrior Simulation (IWARS) and similar entity-level combat models break this angular dispersion into three components: variable bias, fixed bias, and random error (**?**) (**?**).

Fixed bias is a systematic error that affects the accuracy of the weapon system. This type of error is often caused by the weapon not being properly zeroed and is assumed to be constant across simulation runs. Fixed bias is modeled as a constant offset from the true value of the target. Most combat models assume that the weapon has been properly zeroed, such that the fixed bias can be disregarded.

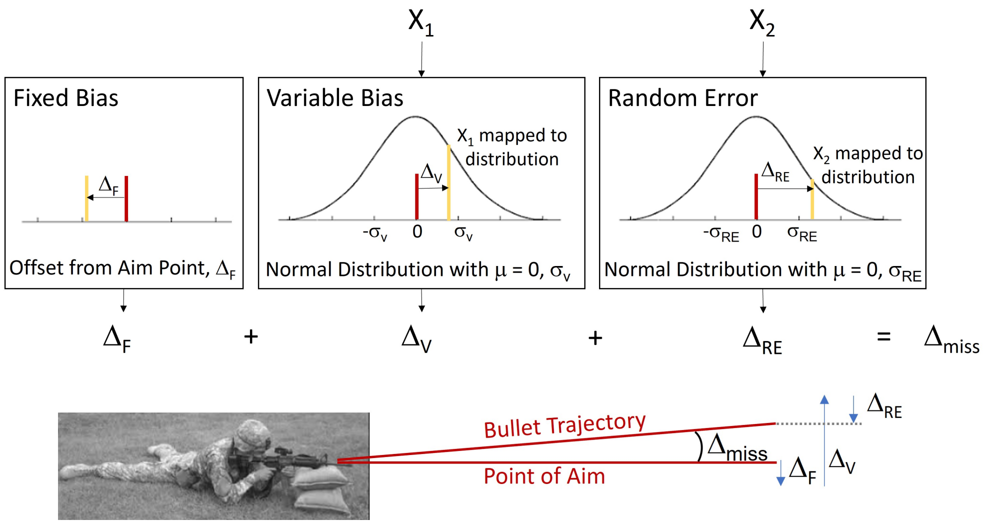

Figure 1: The miss angle (Δ_{miss}) is the sum of the fixed bias (Δ_F), variable bias (Δ_V), and random error (Δ_{RE}), which can be mathematically modeled from two random numbers fit into normal distributions.

Random error is the error that occurs due a variety of factors including environmental factors and ammunition tolerances. This type of error is modeled using a random number generator and introduces a degree of unpredictability into the model.

Variable bias is an error that can occur due to variations in the operator's ability to aim the weapon. The U.S. Army trains soldiers to minimize their variable bias through marksmanship training, including focusing on proper trigger squeeze, site picture, and breathing. This type of error is not consistent from one simulation run to another and can vary in magnitude and direction. Variable bias is often modeled using a statistical distribution, which allows the model to include a range of possible outcomes for each variable. Note that variable bias will change based on the position that the firer is shooting from. For example, a soldier in the prone supported position will have a lower variable bias than a soldier in a standing position.

By including all three types of errors in the delivery accuracy model, combat models can provide more realistic simulations of the performance of weapon systems in different scenarios. The use of statistical distributions and random number generators allows the model to generate a range of possible outcomes for each simulation run as shown in Figure 1 (**?**). For every shot that is fired, the horizontal and vertical angular misses are each calculated independently by drawing two random numbers uniformly distributed between 0 and 1. The angle is initially offset by the fixed bias (Δ_F). The variable bias is captured by a normal distribution with a mean of 0 and a standard deviation (σ_V) set to a given value. The first random number is mapped to this normal distribution, using an inverse transform (*invNorm* in the Equation 1). This provides the offset for that shot associated with the variable bias. The random error is similarly captured by a normal distribution with a mean of 0 and a standard deviation (σ_{RE}) set to a given value. The second random number is then mapped to this normal distribution to give the offset due to random error. The three offsets are then summed and multiplied by the distance to get the vertical distance that the bullet hit relative to the point of aim as shown in Equation 1. The typical miss angle is under 10 mrad, such that the small angle approximation can be used; otherwise, the equation would require the tangent of the angle. The process is repeated for the horizontal component with two separate random numbers.

$$Miss\,Distance = (\Delta_F + invNorm(X_1, 0, \sigma_V) + invNorm(X_2, 0, \sigma_{RE})) \times Distance\,To\,Target \qquad (1)$$

For simplicity, combat simulations typically assign a fixed bias of 0 mrad for most weapons, which assumes that the weapon has been properly zeroed. The variable bias and random error are captured in terms of the standard deviation of their relative distribution. Many combat models, including IWARS and One Semi-Automated Force (OneSAF), assign these standard deviations as characteristics of the weapon system, such that every agent in the simulation has the same shooting proficiency. Also for simplicity, these combat models may assign the same variable bias and random error for the horizontal and vertical miss distances.

3 CALCULATING VARIABLE BIAS FOR SHOOTERS

The U.S. Army quantifies shooting proficiency through a soldier's BRM score, which is captured by the soldier shooting from a prone supported, prone unsupported, and kneeling position. A simple shooting model can be used to capture the change in variable bias associated with different BRM scores.

Underlying this analysis is the need to capture the change in variable bias associated with different shooting positions. (**?**) performed a series of test that measured the probability of a target being hit at 150 m by soldiers shooting from a variety of different positions. These probabilities can be converted into a multiplication factor that increases the variable bias based on the shooting position; these values are given in Table 1. Note that the average shooter in the study by Hasselquist had a BRM score of 32.

Table 1: Values from (Hasselquist et al. 2013) on percent of targets hit at 150m from different firing positions.

Shooting Position	Likelihood to Hit Target	Variable Bias Multiplication Factor
Prone Supported	0.92	1
Prone Unsupported	0.90	1.088
Kneeling	0.74	1.664

Figure 2 displays an overview of the model used for determining the effect of BRM Score on the shooter variable bias. The variable bias for the weapon is set to values between 0 mrad and 2 mrad in 0.1 mrad increments. The fixed bias is set to be 0 mrad and the random error is set to be 0.5 mrad. The values for the horizontal biases are the same as the vertical biases. This model draws four random numbers for each shot fired. The first two random numbers determine the horizontal angular deviation based off the variable bias and random error. The second two random numbers then determine the vertical angular deviation. The angular deviations are multiplied by the distance to target to determine the miss distances, which can then be used to indicate whether or not the target was hit. The sequence is repeated for the 40 different targets that are part of the BRM course to determine the total number of targets hit.

Due to the stochastic nature of the model, it required multiple iterations to ensure an appropriate statistical distribution. This analysis used 1000 iterations, which allowed for confidence intervals less than 1 percent.

For each variable bias, the average BRM score from the 1000 iterations was determined. The output of the model provides the BRM score as a function of the variable bias. The function can then be inverted to approximate the variable bias as a function of the BRM score. The resulting plot is given in Figure 2.

Figure 2 displays the variable bias associated with a given BRM score. As expected the variable bias increases as the shooter has a lower BRM score. The center section that encapsulates most shooters (BRM = 23-35) is fairly linear. However, the curve becomes convex as the BRM score increases to 40, which requires a very low variable bias. Similarly, the curve becomes concave as the BRM scores drop below 20, in which case the variable bias increases substantially as the shooter is missing more of the closer targets.

It is important to note that there are aspects of marksmanship not captured in this analysis. In particular, given the limited time given to hit each target, the BRM tests also capture the ability the reaction time for a soldier to spot the target, line up their weapon, and pull the trigger. This analysis does not account for this impact, simply focusing on the increased weapon stability (i.e., decreased variable bias) associated with higher BRM scores.

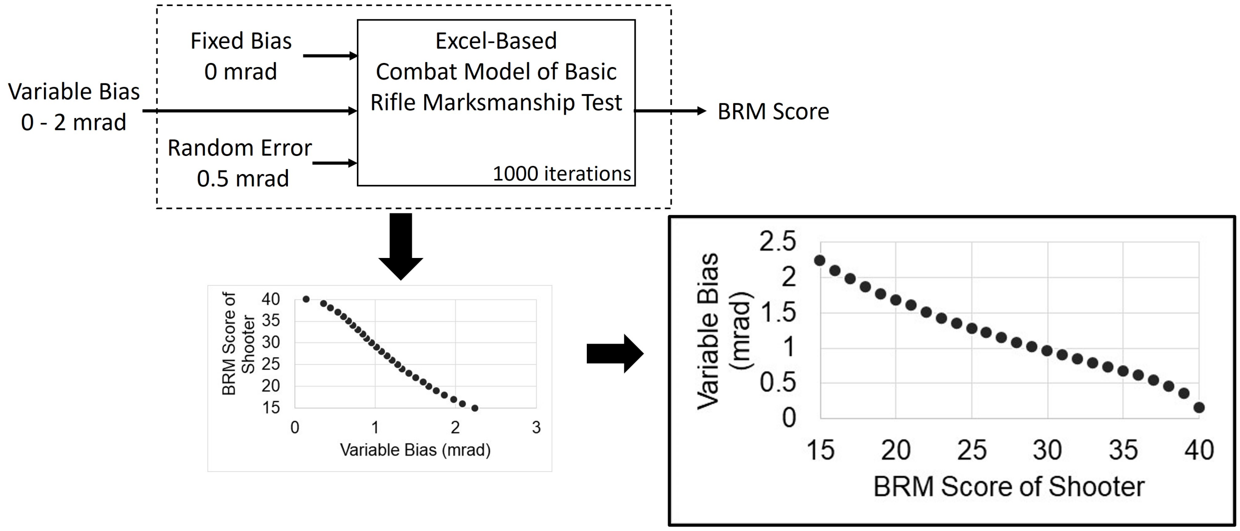

Figure 2: The methodology for determining the variable bias for a firer as a function of BRM score.

4 ANALYSIS 1: STOCHASTIC DUELS

Stochastic duels have been studied since the advent of combat simulation (**?**). Williams and Ancker explored fundamental ideas and foundational theories related to a one-on-one duel. The continued study of stochastic duels highlights the enduring nature of this research topic (**?**). Gupta et al. introduce complicated dueling scenarios and explore these scenarios with a deep learning model.

The brief excursion that follows explored a simple dueling scenario grounded in the context of the squad vs. squad scenario discussed in this paper. Two squads, both with nine members each, conduct a duel. A series of volleys ensues until one squad has been entirely eliminated. The firing order of each volley is random, and the target of each shot is random. The probability of a kill (P(K)) was established at three levels: bad (0.36), average (0.69), and good (0.99). The values for P(K) are based off the analysis in the previous section and are associated with BRM scores of 15, 25, and 40 respectively, for a target at 150 meters. The possibility of this scenario occurring in an open terrain environment with opposing forces, similar to 19th century infantry tactics, is clearly unlikely. However, dueling conflicts between autonomous or remote controlled entities, across any of our domains (land, sea, air, space, and cyber), is becoming an increasingly likely scenario.

Given a nine-person squad, each of which can have one of three levels of P(K), 55 possible combinations exist. Assume i, j, and k represent the number of individuals in each P(K) level. For each combination, $i+j+k=9$ and $(i,j,k) \leq 9$. Under these conditions, the total number of possible combinations is $\Sigma_{n=0}^{9}(n+1)=55$. We will refer to the two opposing squads as red squad and blue squad. For each squad composition pairing, 100 simulated duels have been conducted. This leads to a design of experiments (DOE) with $55^2 = 3025$ design points. Let $\vec{r}$ and $\vec{b}$ represent the red and blue squads, respectively. These vectors contain nine entities each, with each entity assigned the appropriate marksmanship proficiency. The algorithm used to simulate the duels follows: 1) store $\vec{r}$ and $\vec{b}$, each containing nine individuals with marksmanship probabilities in accordance with the DOE; 2) store $\vec{rb} = (\vec{r}, \vec{b})$ and randomly sort to choose the firing order; 3) if an entity is alive, the entity fires based on the sorted order—adjudication of the opposing side occurs based on random selection of a living target entity and the P(K) of the firing entity. This sequence repeats until either red or blue is eliminated.

Figure 3 summarizes the results of this simple dueling simulation. The horizontal axis measures the difference in the average marksmanship proficiency between blue and red entities. The vertical axis measures the proportion of blue victories from 100 simulated duels. Each black dot represents a simulation result, and the red line represents a logistic regression fit of the data.

This simple analysis invites the discussion of a concept commonly mentioned within military circles: overmatch. Discussions related to overmatch often focus on strategy and concepts, however much of the literature lacks ideas related to how we should measure overmatch (**?**). Tradeoffs related to overmatch vary depending on the domain and systems under use. Compare overmatch in the space domain with overmatch in the land domain. Negative consequences in the space domain center on the loss of technology, autonomous vehicles, and information. Negative consequences in the land domain center on human lives and land-based resources. Negative consequences in either domain could result in an existential crisis at some future point, however the dynamics surrounding the consequences clearly varies between domains. The model shown in Figure 3 and methodology presented in this brief excursion provides a general method to explore and discuss overmatch in any domain.

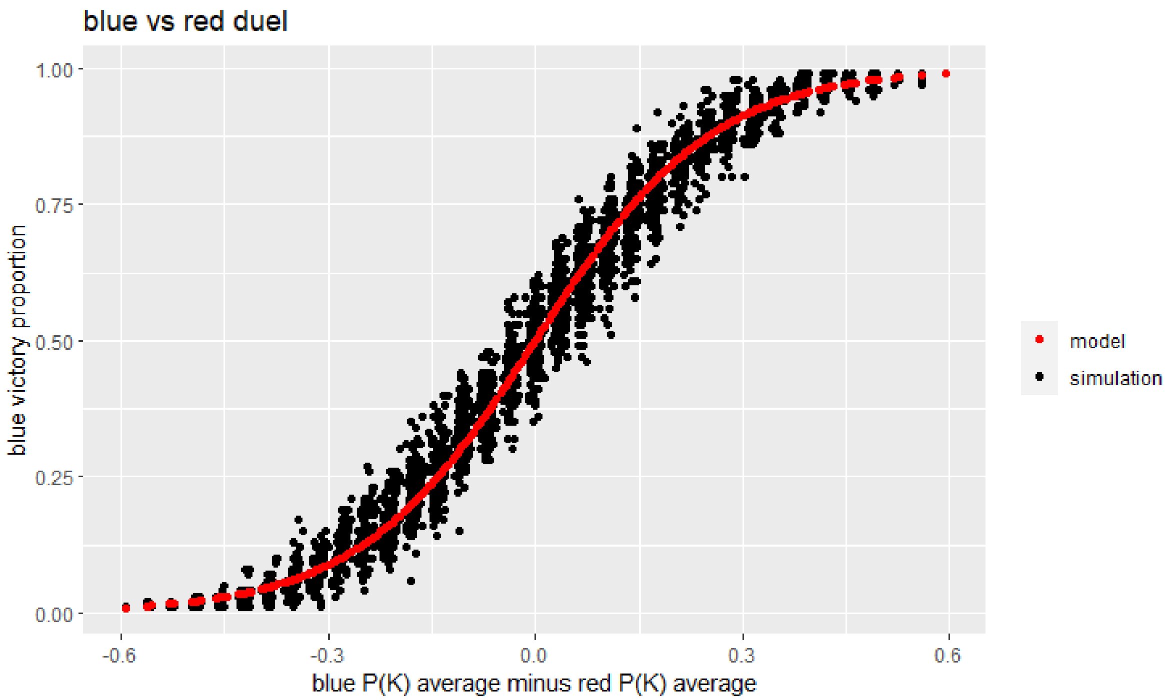

Figure 3: Results of simple stochastic duel where the marksmanship of each shooter was modified to look at changes in mission success.

5 ANALYSIS 2: AGENT BASED MODELING

The relationship between a shooter's variable bias and their BRM score can further be integrated into a more complex agent-based combat models. This analysis integrates this variation into IWARS, an agent-based simulation package that analyzes small unit operations for small-scale, ground-based military operations (**?**). An IWARS model is developed by placing friendly, enemy, and neutral agents onto a three-dimensional map. Each agent is assigned equipment, movement paths, and behaviors which then allow them to perform a set of tasks that constitute their mission.

This analysis includes three different models. The first is the basic dueling model analyzed in the previous section, involving a squad of blue and a squad of red soldiers. The second model analyzed an operation where a group of blue soldiers are attempting to seize a hill controlled by red soldiers. The third model involves a squad of blue soldiers holding a control point in an urban environment against a squad of red soldiers attempting to take control of that point.

5.1 Agent-Based Dueling Model

The first model is shown in Figure 4. In this model, a squad of blue forces is spread out, evenly spaced at 10 meter intervals. Opposing them is an evenly-spaced squad of red forces. The distance between the two lines of forces is initially set at 150 meters. All of the soldiers are assigned M4 weapons. The Red Forces are set such that all of the shooters have a variable bias associated with a BRM score of 25. Meanwhile, the individual BRM scores for the Blue forces are varied from 15 to 40 in increments in 5. At the start of the simulation, both sides will engage the enemy upon detecting them.

Since IWARS is stochastic, the simulation must be run a number of times to ensure an appropriate data sampling. For every case, the number of simulation runs (n) was 100 times, which allowed for a 95 percent confidence interval being within 0.14 KIA of the mean as seen in Equation 2. Equation 2 uses the maximum standard deviation across the results, which is 0.74 KIA for the Red forces when the Blue forces have a BRM score of 15. It also uses a t-value of 1.984, which is for n = 100 for a two-tailed distribution.

$$Desired\,Absolute\,Precision = t_{n,1-0.05/2} \times \frac{(standard\,deviation)}{\sqrt{n}} = 1.984 \times \frac{0.74}{\sqrt{100}} = 0.14\,KIA \qquad (2)$$

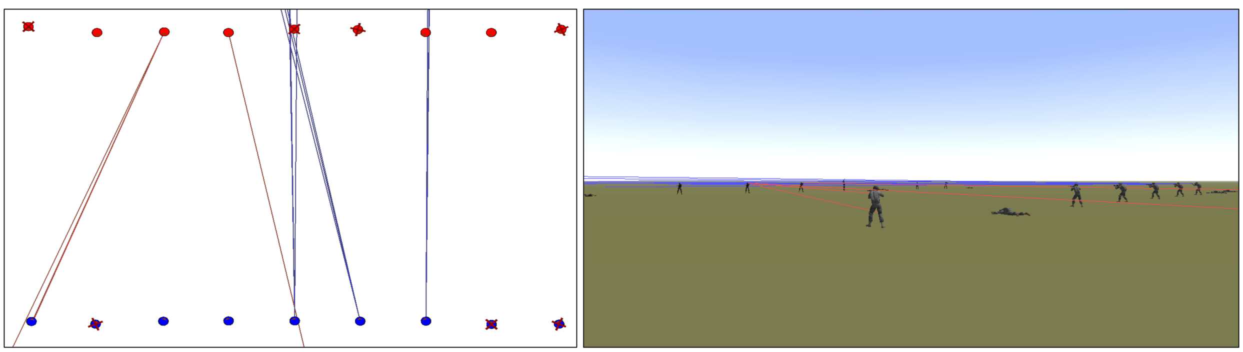

Figure 4: Top down view (left) and 3D view (right) of dueling model where nine blue forces engage nine red forces.

The results are shown in Figure 5 with the two squads being spaced out by 150 meters. As expected, as the Blue shooting proficiency increases, the average number of Red KIA increases. Since the Red forces are being killed faster and more effectively, this trend corresponds to less Blue KIA. Figure 5 also indicates that when the BRM score for the Blue forces is set to 25, such that it is the same as the Red forces, both sides have similar KIA. Note that with both sides equally matched, there is typically either 0 or 1 survivor.

Figure 5 also displays the impact of range on the shooting performance. The vertical axis of the plot shows the difference between Blue and Red KIA. When the number is positive, the Blue force had less KIA and win the match; similarly, when the number is negative, the Red force wins. The plot indicates that the impact of shooting proficiency is heavily dependent on the range between the forces. When the forces are further apart, the impact of an increased variable bias increases resulting in more missed shots. When the forces are closer together, the probability of hitting the target is greater even with a large variable bias. By the time that the shooters are within 50 meters of each other, the shooting proficiency of the Blue forces had no significant impact on Blue and Red KIA.

5.2 Tactical Mission Models

While the simulation analyzed in the previous section showed numerous interesting trends related to lethality and survivability of soldiers based on variable bias correlated to BRM score, the scenario is somewhat unrealistic. Soldiers do not engage each other from a stationary position at a set distance. Rather soldiers

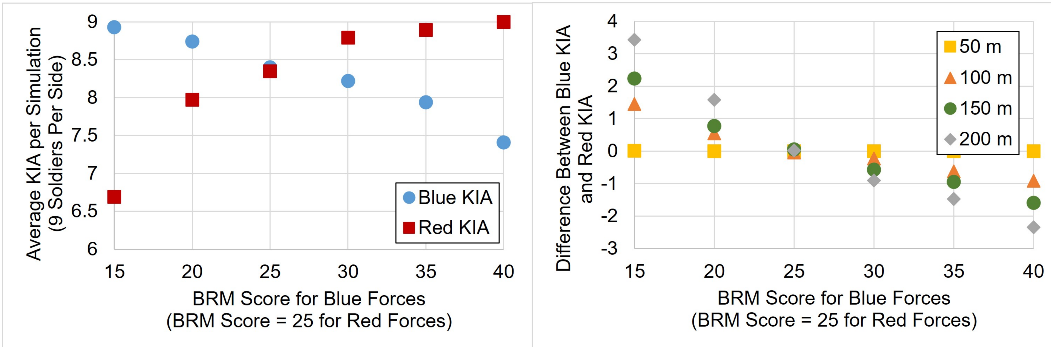

Figure 5: Average KIA for Blue and Red forces as a function of the Blue BRM score when the units are spaced 150 meters (left). Difference between the average Blue and Red KIA as a function of Blue BRM score when the units are spaced at different intervals (right).

are dynamically moving tactically across the battlefield, seeking cover, and coordinating fires to achieve success on the battlefield.

In order to explore the impact of marksmanship on a realistic mission set, two models were built in IWARS. Both are assault-type missions, where a force of soldiers are attacking another force of soldiers in a fixed position. The first scenario uses a rural environment, where the forces are engaging each other at a distance. The second scenario is urban, where the forces are in closer proximity.

5.2.1 Rural Mission

The first model, as shown in Figure 6, has the blue forces hold a defensive position at the top of a hill. Meanwhile, the red forces approach the base of the hill undetected. The red forces break into two fire teams, who take turns bounding up the hill. While one fire team is running up the hill, the other fire team is providing cover fire. The red force's goal is to move into the blue position and kill all blue members. Meanwhile, the blue force's goal is to hold their position and kill all red members. At the start of the scenario, the soldiers are separated by 250 meters. They begin engaging each other at around 220 meters. Most of the engagement is complete prior to the distance closing to 100 meters.

The models were run initially maintaining the defensive, blue forces with a BRM score of 25 and varying the offensive, red force's BRM score from 15 to 40. Table 2 shows the change in KIA and wins associated with these changes. Note that in a certain number of simulation runs, both sides were completely eliminated, resulting in a draw; hence, the percentage of blue and red wins do not add up to 100. The results indicate that when the offense has low BRM scores, they sustain heavy casualties and seldom are able to take the hill. However, as their BRM scores improve, there is an increased probability of the red forces winning. Meanwhile, they inflict more blue force casualties, while sustaining less of their own casualties.

The models were then run again, but this time varying the BRM score of the blue forces in defense, while maintaining the red forces BRM score at 25. The results are also included in Table 2. A similar trend can be seen. When the defensive forces have a low BRM score, the red forces have an increased probability of taking the hill. This probability decreases to almost 0 as the BRM scores increase past 25. Similarly, as the blue's BRM scores increase, they sustain fewer casualties and inflict more casualties on the opposing forces.

This model shows that the defense has a higher likelihood of winning than the offense, which is commonly the case when the two opposing sides are the same size. The models indicate a clear dependency on casualties and mission success based on the relative BRM scores of the offensive and defensive forces. This makes sense given that the soldiers are firing at each other from distances between 100 and 200 meters. However, the results also indicate that the impact of marksmanship is larger for soldiers in the offense. There is little impact for the soldiers in defense until the offensive force's BRM score drops to 25.

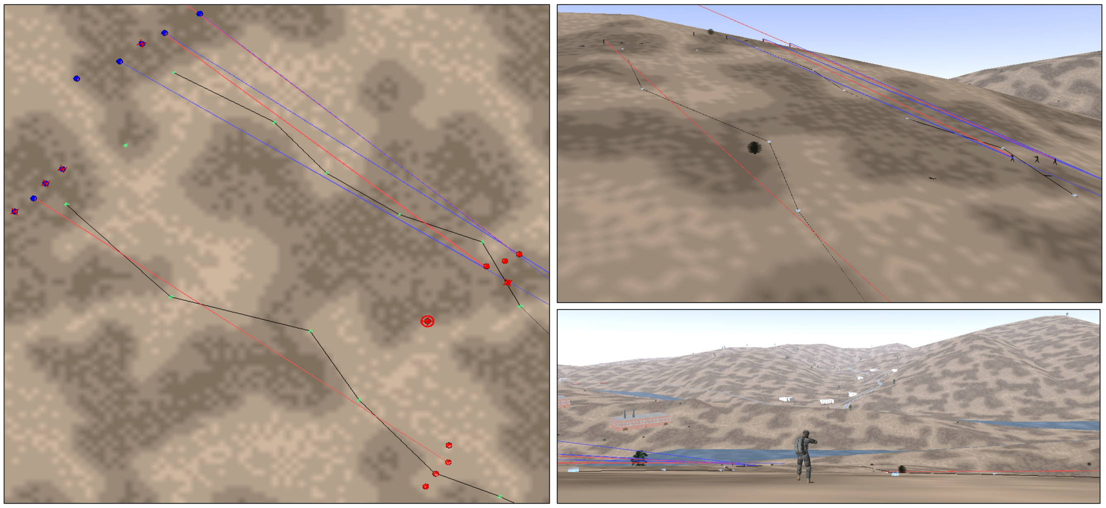

Figure 6: Top down 2D view (left) of nine red soldiers assaulting up a hill to take a blue position held by nine soldiers. 3D view from the top of the hill (right bottom) and side of the hill (right top).

5.2.2 Urban Mission

The second model takes place in an urban environment, as shown in Figure 7. In this scenario, the blue forces have established a traffic control point in the center of a city, blocking traffic from the east and west and inspecting all personnel that enter from the north or south. As such, there are entrances to the north and south of the control point. Four red force agents attack from the south; simultaneously, five red force agents attack from the northeast. Their attacks are initiated by a grenade into the control point, followed by the red forces charging in and taking firing positions to engage the blue forces. The engagement distances in this model vary between 20 meters to 150 meters. The goal of the blue force is to kill all red forces while maintaining control of their position. Meanwhile, the goal of the red force is to kill all the blue forces and take control of the position.

The scenario was run for 100 iterations at the same 12 design points used for the rural mission. The first six vary the BRM scores for the red forces in the offense from 15 to 40 in increments of 5, while the other six vary the BRM scores similarly for the blue forces in defense. The results of these simulations are given in Table 3.

The results indicate that there was not a substantial change in offensive or defensive performance based on the change in shooting accuracy. Further, the average number of KIA for either side does not change significantly for different offensive or defensive BRM levels. These results logically follow from both sides being in close proximity as they shoot. As mentioned in the simpler model, the influence of reduced variable bias, linked to improved marksmanship, diminishes as the range decreases. In this case, the range is compressed such that all the soldiers are in close proximity.

Although this analysis did not find statistical significance between the BRM scores and KIAs or mission success, the general trend of the results indicate that with many more runs, there is the potential for statistical significance. However, this would require a very large number of iterations that would exceed the capacity of IWARS. It is also important to note that this analysis only accounts for the relationship between variable bias and BRM score. However, there are other relationships that would be more significant in urban scenarios, in particular soldier reaction times. Future work will include these correlations, which are better captured in the newer BRM tests.

Table 2: Effects of BRM score on mission success and KIA for a rural assault modeled in IWARS.

Offensive BRM Score	Defensive BRM Score	% Offensive Wins	% Defensive Wins	Average Offensive KIA	Average Defensive KIA
15	25	0	100	9.0	4.0
20	25	4	91	8.9	5.3
25	25	7	85	8.8	6.6
30	25	19	66	8.6	7.2
35	25	38	45	8.2	7.9
40	25	60	18	7.5	8.7
25	15	55	35	7.5	8.2
25	20	20	69	8.6	7.2
25	25	7	85	8.8	6.6
25	30	0	96	9.0	5.6
25	35	0	97	9.0	5.3
25	40	0	100	9.0	4.6

Figure 7: Top down view (left) and 3D view (right) of tactical, urban model where a blue control point is attacked by nine red soldiers .

6 EXTENSIONS AND APPLICATIONS

The U.S. Army training community is moving towards having large scale training events that integrate live, virtual, and constructive simulations. The vision for this type of training exercise would be a Division-level training which includes three brigades under it. The first brigade would be completely simulated in a constructive combat simulation, such as the Warfighter Simulation (WARSIM). The second brigade would be virtually simulated where the soldiers execute missions in a virtual environment such as the Virtual Battlespace 3.0 (VBS3). The third brigade would be completed a training rotation at the National Training Center. As a live simulation, the performance of the third brigade would reflect individual soldier-to-soldier variation; however, the other two brigades would not necessarily have this variation.

The models developed in this paper showed that the soldier-to-soldier variation in BRM score can readily be integrated into a constructive simulation. While IWARS was the simulation package used in this paper, other simulations, including WARSIM, also can be modified to account for this variation. In doing so, the training exercises would better reflect the state of the unit. Similarly, these models can be expanded into virtual simulations.

More broadly, this paper analyzed individual soldier performance in marksmanship, quantified through their BRM score, and integrated into a combat simulation. Similar analyses can be performed for other

Table 3: Effects of BRM score on mission success and KIA for a urban assault modeled in IWARS.

Offensive BRM Score	Defensive BRM Score	% Offensive Wins	% Defensive Wins	Average Offensive KIA	Average Defensive KIA
15	25	19	49	7.9	8.7
20	25	24	49	7.7	8.6
25	25	17	53	7.7	8.7
30	25	27	51	7.8	8.5
35	25	25	52	7.7	8.6
40	25	23	58	7.6	8.6
25	15	20	50	7.8	8.6
25	20	19	53	7.6	8.7
25	25	20	53	7.9	8.6
25	30	24	56	7.6	8.4
25	35	21	58	7.5	8.6
25	40	23	56	7.7	8.6

common soldier metrics. For example, there is a correlation between a soldier's 2-mile run time and their maximum sustainable movement speeds under load (**?**).

7 CONCLUSIONS AND FUTURE WORK

There is significant variation across the U.S. Army in shooting proficiency. While some shooters barely meet the standard, other soldiers can reliably get perfect scores. However, combat simulations often do not account for this variation. Rather, they simply assign the variable bias to be a fixed value based on the properties of the weapon. This study presented a Monte-Carlo shooting model that correlates the variable bias of soldiers to their BRM score. The results were then implemented in two different analyses to understand the impact of soldier marksmanship on combat scenarios.

The first analysis used a simple dueling model to explore a range of marksmanship skills between dueling teams to provide insights related to overmatch requirements, a key aspect of military requirements development. This dueling model has potential applications in domains where conflict between manned and unmanned systems, with varying degrees of autonomy, is possible.

A second analysis used IWARS to examine the effect of shooting proficiency for a squad of soldiers on their lethality and survivability through a series of three models. The first model was a simple dueling model, which found that as soldiers move closer together, the impact of marksmanship decreased. This impact was better highlighted through two tactical models, one in a rural environment and one in an urban environment. The rural environment found that marksmanship had a strong relationship with soldier survivability, lethality, and mission success. However, the study found that soldier marksmanship did not significantly affect the squad's performance in urban combat missions due to the close proximity involved.

This study focused on the relationship between BRM score and the variable bias of the shot group. However, it is probable that additional relationships exist, particularly in combat scenarios such as urban combat. Factors such as reaction times and the ability to adjust fire are likely to have a significant impact on survivability, lethality, and mission success across a wide range of missions. Future research will focus on establishing these correlations by linking them to the newer BRM tests, which incorporate assessments supporting these relationships.

Overall, the study highlights the importance of assessing the impact of soldier marksmanship on squad performance and provides a valuable tool for modeling and simulating combat scenarios. These relationships can be extended into other analyses in addition to support the training simulation community.

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