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CAPTURING SOLDIER FITNESS LEVELS IN COMBAT SIMULATIONS

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ABSTRACT

Combat simulations typically depict individual soldiers as identical entities, neglecting differences in their ability to execute warfighting tasks. An essential aspect of a soldier's effectiveness is their physical fitness, which impacts their performance on the battlefield, including their mobility, survivability, and lethality. This paper develops two models to correlate soldier physical fitness to movement speeds and shooting accuracy. The first model, derived from literature, links soldier movement speeds and durations to their physical fitness levels, characterized by their $VO_{2,\max}$, which is correlated with their two-mile run time. The second model used data collected from soldiers (n=60) to correlate shooting accuracy, fitness, and marksmanship scores when firing from a standing position. These models are integrated into an agent-based combat simulation to assess the impact of physical fitness on soldier survivability and lethality in urban operations. The results show that increased soldier physical fitness significantly improves soldier survivability.

1 INTRODUCTION

Military personnel dedicate a significant portion of their training regimen to enhancing and sustaining their physical fitness. Indeed, physical readiness stands as a cornerstone in assessing the operational prowess of warfighters, especially in ever-changing combat settings. Further, it holds a critical position in multiple facets of military preparedness, impacting the proficiency of soldiers in both shooting and maneuvering. As shown in Figure 1, increased levels of physical fitness result in soldiers having increased anaerobic strength, endurance, explosive power, core stability, arm strength,and body strength. In turn, this allows soldiers to carry more equipment, move faster on the battlefield, and shoot more accurately.

Across any military, there will naturally be a range of physical fitness levels, since military training programs are designed to develop a soldier's overall strength and endurance. New recruits are still developing the muscle strength unique to the military. Meanwhile, older soldiers may have suffered injuries over their careers that limit their physical performance. Despite the range in physical capabilities, combat simulations typically tend to treat all soldiers as identical when it comes to their physical fitness, resulting in all soldiers in a model having comparable movement speeds and shooting accuracies. It is important for combat simulations to accurately reflect individual soldier performance, as these simulations are used for military analysis and and support important force design decisions.

This paper aims to develop models that capture the relationship between an individual soldier's physical fitness level and their proficiency in shooting and maneuvering within a military framework. Initially, it reviews the standard models used by combat simulations for movement and shooting. Subsequently, it introduces an enhanced movement model that incorporates a soldier's physical fitness, determined by their $VO_{2,\max}$ derived from their two-mile run time. Additionally, it presents a shooting model based on empirical data, correlating changes in shot group size with a soldier's physical fitness score. These models are then integrated into an agent-based combat simulation to examine the impact of physical fitness on small-unit urban operations.

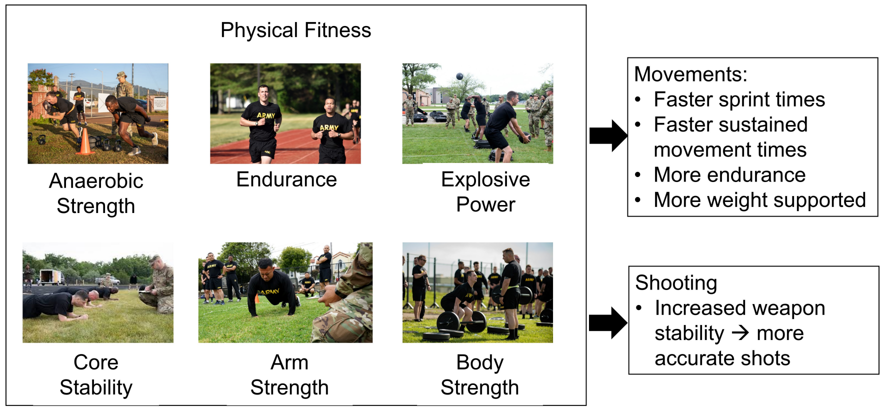

Figure 1: Different aspects of physical fitness and the impact on soldier movement and shooting.

2 BACKGROUND

2.1 Soldier Fitness

Physical fitness is paramount for soldiers as it directly influences their operational effectiveness and overall well-being. Soldiers must maintain peak physical condition to meet the demanding physical requirements of their duties, including carrying heavy loads over long distances, maneuvering in challenging terrain, and maintaining weapon stability while aiming at targets (Orr et al. 2010). A high level of fitness enhances all of the dimensions indicated in Figure 1, which are crucial for withstanding the rigors of combat and recovering quickly from exertion or injury. Moreover, optimal physical fitness contributes to mental resilience, enabling soldiers to stay focused, alert, and adaptable in stressful and high-pressure situations. Overall, prioritizing physical fitness is essential for soldiers to perform their roles effectively, safeguard their health, and enhance their operational readiness in the field.

While different military services have various methods for assessing the physical fitness of their soldiers, the United States Army currently uses the Army Combat Fitness Test (ACFT). The ACFT and its requirements are discussed in detail in Army Training Publication (ATP) 7-22.01, *Holistic Health and Fitness Testing*, (U.S. Army 2022). The ACFT consists of six events, each targeting different aspects of physical fitness crucial for military performance.

- The Deadlift: Soldiers lift a weighted hexagonal barbell from the ground to hip level and back down, assessing lower body and core strength, as well as grip strength.
- The Standing Power Throw: This event measures explosive power as soldiers throw a 10-pound medicine ball backward over their heads for distance, simulating the action of throwing equipment or evading obstacles.
- The Hand-Release Push-Up: Soldiers perform push-ups but lift their hands off the ground at the bottom of each rep before pushing back up, emphasizing upper body and core strength, as well as endurance.
- The Sprint-Drag-Carry: This event combines sprinting, dragging a sled, lateral shuffling, and carrying kettlebells over a course to assess speed, agility, anaerobic capacity, and strength endurance.
- The Plank: Soldiers assume a plank position similar to the start of the push-up event, but with their forearms on the ground. The soldier must maintain this position as a test of core strength.
- The Two-Mile Run: This classic endurance event evaluates aerobic capacity and cardiovascular fitness as soldiers run two miles for time.

Each event is scored on a scale between 0 and 100 based on performance standards tailored to the soldier's age and gender with a score of 60 in an event considered passing. The ACFT measures a soldier's ability to meet the demands of modern warfare, emphasizing functional fitness, agility, and strength across various domains. Training for and performing well on the ACFT is essential for maintaining military readiness and operational effectiveness. Since the ACFT is the standard method used by the U.S. Army for measuring physical readiness, the ACFT test score will be used in the subsequent sections as a method of quantifying an individual's physical capability.

2.2 Conventional Combat Models for Movement

Most entity-level combat simulations rely on a movement model developed by Kent Pandolf, a researcher at the US Army Institute of Environmental Medicine (Pandolf et al. 1977). Pandolf developed the following equation, commonly referred to as Pandolf's equation, to determine the metabolic expenditure of a soldier that is road marching:

$$M = a \cdot W + b \cdot (W+L) \cdot \left(\frac{L}{W}\right)^2 + \eta(W+L)(c \cdot V^2 + d \cdot VG) \tag{1}$$

$$a = 1.5\,\frac{\text{Watts}}{\text{kg}} \qquad b = 2\,\frac{\text{Watts}}{\text{kg}} \qquad c = 1.5\frac{1}{\text{s}} \qquad d = 0.35\frac{\text{m}}{\text{s}^2} \tag{2}$$

where M is the metabolic rate in Watts, W is the weight of a Soldier in kg, L is the load carried in kg, V is the speed in m/s, G is terrain grade in percent, and η is the terrain factor given below:

- Blacktop: η = 1
- Hard Surfaced Road: η = 1.2
- Ploughed Field: η = 1.5
- Snow: η = 1.6
- Sand Dunes: η = 1.8

While energy expenditure is useful, combat simulations typically use Pandolf's equation to set the movement speeds for a soldier as a function of the load that they are carrying. Equation 1 can be solved for the soldier's velocity using the quadratic equation. However, to actually get a movement speed, it is necessary to set a value for the metabolic rate. ATP 3-21-18, *Foot Marches*, gives the maximum duration that a soldier can perform a task involving a certain calorie expenditure before reaching exhaustion (U.S. Army 2017). For a value of M = 350 W, a soldier can perform a task for an indefinite amount of time. Therefore, combat simulations commonly use a value of 350 W as a conservative estimate for M when determining the speed of the soldier.

Take for example, that a simulation has a 90 kg soldier carrying 40 kg of equipment, walking on a hard-surfaced road, at a 1 percent incline. That soldier can maintain a pace of 0.59 m/s, which equates to 1.32 mph, for an indefinite amount of time. This speed might seem slow, but keep in mind that the soldier is carrying a large amount of equipment. If the load was removed and the surface was switched to blacktop at a 0 percent incline, the movement speed would increase to 1.1 m/s, approximately 2.5 mph.

Although Pandolf's equation is commonly used throughout combat simulation, it has come under a significant amount of scrutiny. For example, Pandolf's equation has been criticized for under-predicting the metabolic rate of soldiers carrying modern combat loads, as compared to the combat loads carried in the 1970s (Drain et al. 2017). Moreover, Pandolf's equation is inaccurate for characterizing soldier loading when they are wearing a significant amount of equipment, such as a explosive ordnance disposal suit (Bach et al. 2017). Furthermore, when soldiers are running at high speeds while carrying significant loads, other equations are more applicable (Epstein et al. 1987).

2.3 Combat Models for Shooting

While older combat simulations simply used the probability of hitting the target as a function of distance, and the probability of killing the target given a hit, most modern combat simulations use a more advanced algorithm for modeling the shooting process. The most common algorithm uses the following three stateless models: Search and Target Acquisition, Delivery Accuracy, and Casualty Assessment (Tolk 2012). The Search and Target Acquisition model determines if the soldier detects a target. When the target is detected, the soldier shoots at it, and the Delivery Accuracy model determines where the bullet hits relative to the target. The Casualty Assessment model then determines the impact of the shot on the target. This study will focus on the Delivery Accuracy model, since the stability of the weapon when firing will be dependent on a soldier's core and arm strength, which are assessed in the ACFT (Anderson and Plecas 2000).

The Delivery Accuracy model determines 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 2. Most combat models break this angular dispersion into three components: variable bias, fixed bias, and random error (Comstock 2014).

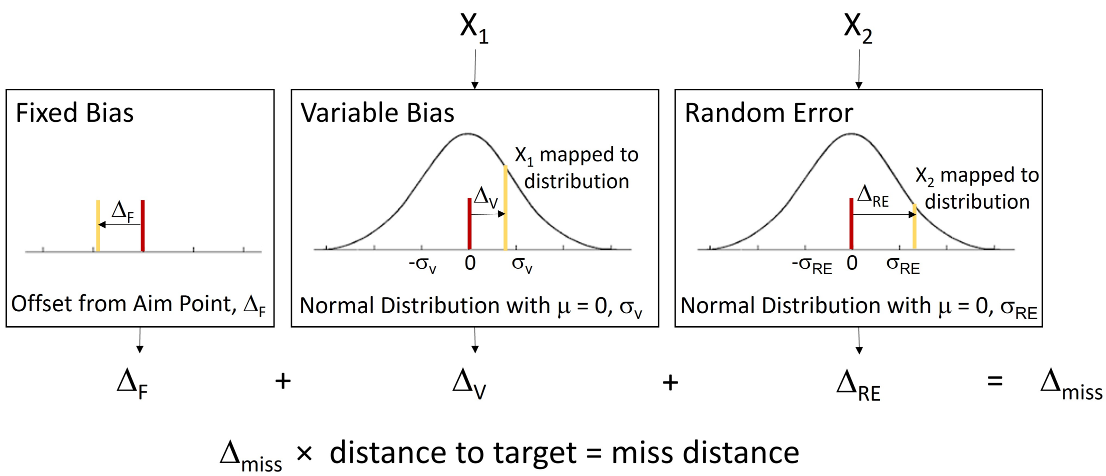

Figure 2: The miss angle (Δ_{miss}) is the sum of the fixed bias (Δ_F), variable bias (Δ_V), and random error (Δ_{RE}), which can be mathematically modeled from two random numbers fit into normal distributions.

Fixed bias is a constant error in the weapon system's accuracy, often because the weapon is not properly zeroed. This offset is the same across simulation runs. Random error, on the other hand, occurs because of different factors like weather and variations in ammunition quality. Variable bias is linked to how well the shooter aims the weapon and changes from one simulation run to another. Soldiers are trained to minimize this bias through techniques like proper trigger squeeze and breathing. While the fixed bias is captured as a fixed angular offset, the random error and variable bias are captured as normal distributions associated with a given standard deviation and a mean of 0.

For each shot fired, the horizontal and vertical components of the angular misses are calculated independently by drawing four random numbers uniformly distributed between 0 and 1. First, the horizontal angular miss is offset by the fixed bias (Δ_F). The horizontal angular miss from the variable bias is then calculated by mapping the first random number to a normal distribution with a mean of 0 and a standard deviation (σ_V), using an inverse transform (*invNorm* in the Equation 3).

$$Miss\,Distance = (\Delta_F + invNorm(X_1, 0, \sigma_V) + invNorm(X_2, 0, \sigma_{RE})) \times Distance\,To\,Target \tag{3}$$

The horizontal random error is similarly captured by mapping the second random number to a normal distribution with a mean of 0 and a standard deviation (σ_{RE}). The three offsets are then summed and multiplied by the distance to get the horizontal distance that the bullet hit relative to the point of aim as shown in Equation 3. When the miss angle is under 100 mrad, the small angle approximation can be used; typically, the miss angles are on the order of 10 mrad. This process is then repeated for the vertical component with the other two random numbers.

3 FITNESS LEVELS TO MOVEMENT TIMES

3.1 Model Development

Pandolf's equation only uses the weight of a soldier to differentiate between the metabolic loading on a soldier and does not adequately account for fitness levels. This study presents a technique for calculating the maximum sustainable metabolic load in Pandolf's equation as a function of the physical fitness of the soldier as shown in Figure 3. The technique relies on the maximum volume of oxygen consumed during exercise, or $VO_{2,\max}$, which is a commmon indicator of a person's level of endurance. Since every soldier completes the ACFT, this approach approximates the $VO_{2,\max}$ as a function of the 2-mile run time.

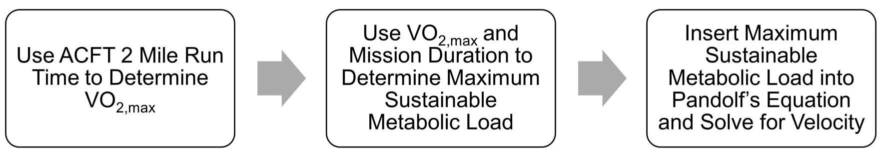

Figure 3: Process for determining the maximum sustainable velocity of a soldier as a function of their physical fitness, captured by their two mile run time.

The US Army Research Institute conducted a study with male and female subjects of varying age and fitness levels to estimate the relationship between fitness level, two-mile run times (t_{2MR} in minutes) and soldier weight (W in kg) (Mello et al. 1984). The relationship was highly significant with equations for determining male and female $VO_{2,\max}$ in liters per minute:

Males:

$$VO_{2,\max} = (110.9 - 2.79t_{2MR} - 0.25W)W/1000 \tag{4}$$

Females:

$$VO_{2,\max} = (72.9 - 1.77t_{2MR})W/1000 \tag{5}$$

For example, a male soldier weighing 70 kg who completed the 2-mile run in 13 minutes, 15 seconds would have a predicted $VO_{2,\max}$ of 3.96 L/min.

With the maximum oxygen intake now known as a function of a soldier's two mile run time, the maximum metabolic load of the soldier can be determined. FM 21-18 gives data on sustainable metabolic output for a given time duration, based on data for the average Soldier. A study by Wu and Wang also gives data on sustainable relative VO_2 rates for given durations, as a percentage of $VO_{2,\max}$ (Wu and Wang 2002). Matching the two sets of data provides the maximum work duration as a function of the relative work intensity, quantified by the percent of the $VO_{2,\max}$, as shown in Table 1.

The correlation equation between the $VO_{2,\max}$ in L/min for the Soldier and the maximum sustainable metabolic output rate (M) in W is given by Equation 6.

$$M = 308 \cdot VO_{2,\max} \cdot \%VO_{2,\max} \tag{6}$$

where $\%VO_{2,\max}$ is taken from Table 1.

The value for the maximum sustainable metabolic output rate is then entered into Pandolf's Equation. Since terrain type, grade, Soldier weight, and Soldier load are all inputs into the model, these values are known. Therefore, the equation can be solved for the maximum sustainable velocity.

Table 1: Maximum work duration estimated based on relative task intensity.

Duration	% $VO_{2,\max}$
10 seconds	213.8
1 minute	150
5 minutes	100
30 minutes	75
1 hour	63
3 hour	41
6 hour	31
indefinite	25

Take the aforementioned 70 kg soldier that has a 2-mile run time of 13.25 minutes and a $VO_{2,\max}$ of 3.96 L/min. Their maximum sustainable metabolic load would be 305 W for activities that last for an indefinite amount of time. However, for an activity that only lasts an hour, that soldier would be able to maintain a metabolic load of 770 W. Going back to Pandolf's equation and solving for velocity, this equates to a maximum sustained velocity of 4.24 mph while carrying a 40 kg load on a flat road for an hour. Meanwhile, a similarly sized soldier with a 2 mile run time of 20 minutes would have a $VO_{2,\max}$ of 2.63 L/min. Their movement speed for 1 hour on a flat road carrying a 40 kg load would be 3 mph.

3.2 Model Limitations

The model presented in the previous section has a number of limitations. Indeed, the model integrates into Pandolf's Equation, which itself has come under scrutiny for having a limited number of test subjects and a lack of diversity across the test subjects (Pearson et al. 2013). Further, the equipment worn by the test subjects was lighter than the full combat load carried by many on the current battlefield (Drain et al. 2017). Regardless, Pandolf's Equation is still relevant across a range of weights and speeds used in modern combat (Potter et al. 2013).

Additionally, while the model accounts for different soldier body weights in Pandolf's equation and through physical fitness through $VO_{2,\max}$, it does not account for other variation in soldiers including gender or body mass index.

Further, for military operations, movement speeds are often set by operational conditions. In particular, soldiers will often be required to maintain a certain speed to ensure appropriate cover and concealment. They could also be moving at night, where their movement speeds are more limited by visibility than by their physical fitness.

4 FITNESS LEVELS TO SHOOTING ACCURACY

4.1 Model Development

The act of shooting involves skill and practice to master the basics of marksmanship. This is particularly the case for shooting from a position where the shooter is in a prone supported position, such that the weight of the weapon is fully supported by the ground. However, in combat, especially urban operations, the bulk of shooting occurs from a standing position, where the soldier must support and stabilize the weapon. As such, shooting from a standing position requires a combination of arm strength, core stability, and endurance (Evans et al. 2003). Further, the physical fitness of the soldier, in addition to their shooting skill, will effect the overall variable bias associated with shooting from a standing position. This relationship is well documented in the military, police, and competitive shooting communities.

Despite a number of studies indicating the relationship between physical fitness and shooting, those studies did not produce results that readily translated for use in combat models. Many of these studies used smaller quantified marksmanship by hits on a target and did not provide the necessary information to convert that information into a variable bias term. Further, the weapon platforms used in many of the studies were lighter and more compact than the M4 carried by U.S. Army soldiers. As such, this study developed an initial series of experiments to develop a model where a soldier's variable bias is a function of their physical fitness and marksmanship. Their physical fitness is quantified through their ACFT score. Meanwhile, the soldier's shooting skill is measured by the score that soldiers receive on the basic rifle marksmanship (BRM) test; this score is between 0 and 40 and involves a soldier shooting at targets between 50 m and 300 m from prone and kneeling positions.

The experiments were conducted on the Engagement Skills Trainer 2000, a simulated rifle range, where pneumatic systems allow the weapons to properly replicate the weapon recoil. Each soldier was assigned a range and zeroed an M4 carbine. They then assumed a standing position, where they shot 20 rounds at a target 175m away. After each iteration of 20 rounds,the soldiers recorded the shot group size. They repeated this three times. They then used the shot group size and converted it to the standard deviation for the variable bias. The soldiers also reported their most recent ACFT score and BRM score.

The test was performed with sixty soldiers. The results found a large amount of variability in the variable bias of soldiers shooting from a standing position. An image from these experiments and a summary of the results are given in Figure 4.

Number of subjects:		60
Variable Bias		
	min:	1.15 mrad
	average:	2.19 mrad
	max:	3.48 mrad
ACFT Score		
	min:	460
	average:	542
	max:	598
BRM score		
	min:	23
	average:	29
	max:	40

Figure 4: (Left) Image of soldier firing M4 on an Engagement Skills Trainer 2000. (Right) Summary of test results.

The study found a strong correlation (p-value < 0.001) for both marksmanship score and ACFT score with the variable bias. The associated equation is given in Equation 7 where the ACFT score is between 0 to 600, BRM score is between 0 and 40, and the variable bias is measured in mrad.

$$\sigma_V = 9.48 - 0.076 \cdot BRM - 0.0089 \cdot ACFT \tag{7}$$

Figure 5 compares the experimentally collected variable bias to the variable bias calculated from Equation 7, showing a generally good fit.

4.2 Model Limitations

This model uses the ACFT and BRM scores of soldiers to predict their variable bias when shooting an M4 from a standing position. Since this study requires a soldier to have taken an ACFT and conducted a BRM test, the study would only be applicable to soldiers in the U.S. Army. Furthermore, it is only applicable to those soldiers firing an M4. Though this is the most common weapon carried by American soldiers, the results for a soldier carrying a M249 or an M4 with an M320 attachment would be different (Byers et al. 2018).

Moreover, this study only accounted for an individual soldier's BRM score and ACFT score, and did not account for other individual soldier features. The model did not account for individual soldier body

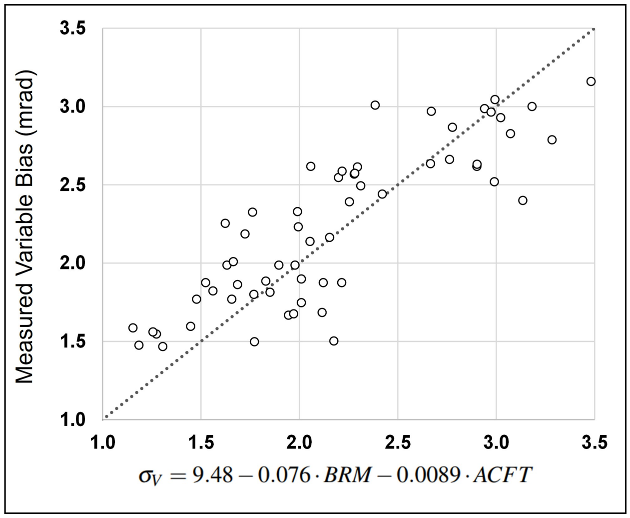

Figure 5: Comparison of variable bias collected experimentally and the approximated variable bias based on a soldier's ACFT and BRM scores.

type. Generally, soldiers with more mass are better able to absorb the weapon recoil (Selva et al. 2015). Other features, such as arm length and body height potentially also play a significant role in shooting accuracy (Noor 2023).

Furthermore, this model does not capture the temporal nature of physical exhaustion. Indeed, as soldiers engage in physical activity, their marksmanship skills temporarily degrade until they recover, with recovery times potentially taking upwards to 15 minutes (Nibbeling et al. 2014). A more complete model would account for this degradation as a function of the soldier's physical fitness level.

Despite these limitations, the model presented in the previous section better captures soldier-to-soldier variation when compared to simply using a constant value across all soldiers. This is indeed important, especially as unmanned ground vehicles emerge into the battlefield. The soldier-to-soldier variation is a key aspect that would differentiate soldiers from simply the unmanned ground vehicles and needs to be captured in combat simulation (Blais and McGregor 2016).

5 EXAMPLE

This section sets out to provide an example of an analysis that captures the importance of physical fitness to the survivability and lethality of soldiers in a combat scenario. To perform this analysis, the models presented in the previous section are integrated into an agent-based combat simulation. Note that the impact of physical fitness on survivability and lethality will be very dependent on the combat scenario, so the results from this example will not represent the full breadth of military operations.

5.1 Infantry Warrior Simulation

This analysis uses the Infantry Warrior Simulation (IWARS), an agent-based simulation package that focuses on small unit operations for small-scale, ground-based military operations (Samaloty et al. 2007). An IWARS model consists of friendly, enemy, and neutral agents placed on a three-dimensional map. Each agent is assigned equipment, movement paths, and behaviors which then allow them to replicate a series of combat tasks.

The IWARS methodology is stochastic, using random numbers to capture the uncertainty in different events (e.g., where the bullet strikes relative to center mass). As such, the simulation must be run in batches to properly capture key output parameters, including measures of survivability and lethality.

Underlying IWARS is a database that includes the relevant data for movement speeds and shooting accuracy. This database can be readily modified to capture changes related to physical fitness. In particular, the sustained and short-duration movement times for the soldier can be modified based on their 2-mile run time. Further, the variable bias when shooting from a standing position can be modified to reflect different ACFT and BRM scores.

5.2 Base Model

The scenario considered for this analysis is a set of Blue forces entering and clearing out a town of Red forces. As shown in Figure 6, a group of ten Red agents have taken positions to defend the town from an assault from the north. It should be noted that three of the Red agents are located on the second floor of buildings. The Blue forces, consisting of 18 soldiers, approach from the north. The first Blue fire team takes control of the eastern building and sets up a base of fires to support a second Blue fire team which then secures the western most building. The other two Blue fire teams then move into the town and clears the buildings of Red agents.

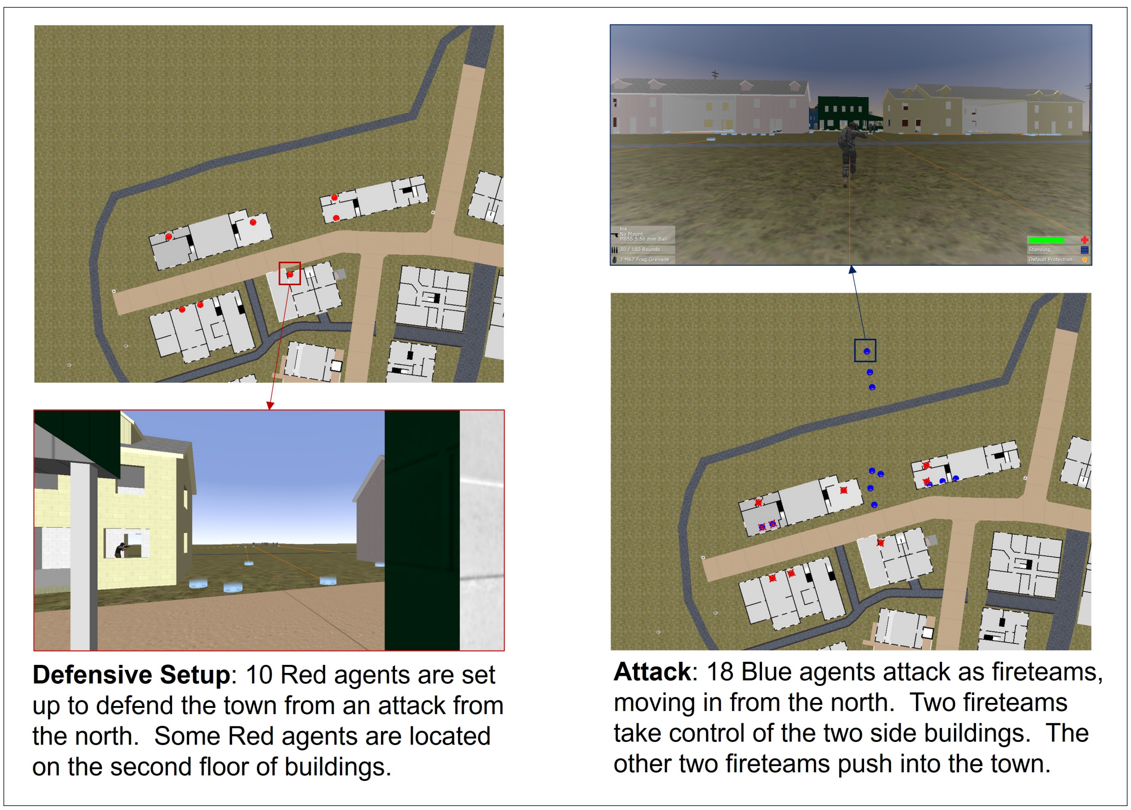

Figure 6: Graphical visualization of the IWARS scenario. Left: Red forces have a defensive position in the town to protect from a Blue attack from the north. Right: Blue forces attacks the town from the north.

The example considers the impact of physical fitness of Blue soldiers on their survivability and lethality for this simulation. All of the Blue soldiers are set to 80 kg carrying a load of 30 kg. The Blue soldiers are set to have a 420 ACFT score, including an 18 minute 2-mile time. This equates to having an approach speed of 0.92 m/s and a short burst speed of 1.6 m/s using Equation 6. From a shooting perspective, this ACFT score, combined with an average BRM score of 28, approximates the variable bias of the soldiers to be 3.6 mrad based on Equation 7.

The simulation was run 100 times to look at the number of Blue and Red casualties for this base case. The results are given in Figure 7 with 95 percent confidence intervals. The Blue forces, given that they outnumber the Red forces, are typically able to concentrate their fires and kill most of the Red forces. On average, the Blue forces sustained 8.2 casualties while the Red forces sustained 9.1 casualties. The Red forces that typically remain at the end of the scenario are those that are on the second floor of a building, and the Blue soldier tasked with clearing the building had been incapacitated. Most of the Blue casualties are sustained on the initial approach into the town. Once they secure the two side buildings and establish their base of fire, they typically take minimal casualties.

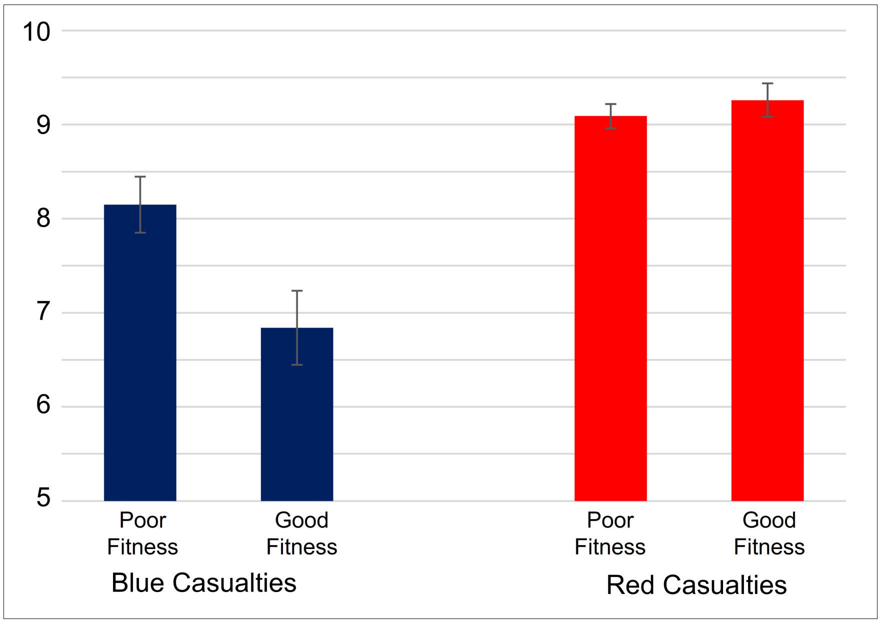

Figure 7: Blue and Red casualties from IWARS simulations (100 iterations) varying the fitness level of the Blue forces.

5.3 Impact of Fitness

The simulation was modified to reflect the Blue force being composed entirely of fit soldiers, who achieved a 13 minute 2-mile time and a 600 ACFT. In turn, this changed the approach speed to being 1.2 m/s and the short duration burst speed to 2.9 m/s. Meanwhile, it decreased the variable bias to 2 mrad, given an average BRM level of 28.

The simulation was run for 100 iterations to look at the impact the change in physical fitness had on survivability and lethality. Figure 7 includes the results from these runs, with 95 percent confidence intervals. The results indicate that there was no significant change in red casualties for this specific scenario. However, there was a significant change in the number of blue casualties, with the average number of blue casualties decreasing to 6.8.

Further analysis of the results indicated that the increase in survivability is due to two primary factors. First, the increased shooting accuracy of the Blue forces during the approach march limited the ability for the Red forces to kill the Blue forces when they were most vulnerable. Second, the faster movement speed of the Blue forces reduced the time that they were exposed in the initial assault.

These results are unique to this scenario. The impact of fitness would vary based on the scenario. For example, in a mission where the soldiers are primarily stationary, such as a defensive position, a fit soldier would only benefit from the increase in shooting accuracy and not from the faster movement times. As such, the impact would be different. Meanwhile, more complicated scenarios that involve long-distance approach marches coupled with agile movements across the battlefield, while engaging enemies at substantial ranges would expect to see a larger impact on survivability and lethality.

6 CONCLUSIONS

Most constructive combat simulations treat individual soldiers effectively as robots, where they perform a mission mechanically with little soldier-to-soldier variation. This paper set out to fill that gap by presenting two models to capture the change in soldier performance tied to their individual physical fitness. The first model combined several studies to correlate a soldier's 2-mile run time to their $VO_{2,\max}$, which can then be used to determine their maximum metabolic loading as a function of duration. This value can then be inserted into Pandolf's equation, the standard equation used for military movement models, to determine the soldier's movement speed. The second model used experimental data to correlate ACFT scores and marksmanship level to the variable bias of the shot group. The data indicated that the variable bias of the shot group decreases as soldiers are more fit, likely tied to increase stability.

These two models were then used in IWARS to analyze how physical fitness impacted the ability of a group of soldiers to assault a well-defended town. The results indicated that more fit soldiers were exposed for less time and incapacitated their adversaries faster, resulting in a significant increase in survivability.

The models developed in this paper showed that the individual fitness level of a soldier can be readily integrated into a constructive simulation, such as IWARS. However, a similar approach can be used to integrate these models into larger constructive military simulations, such as WARSIM. In doing so, the performance of a unit in the simulation space could better replicate the unit's current level of physical fitness. Future work will focus on better developing these physical fitness models and more holistically integrating them into combat simulations.

Moreover, while physical fitness is important for success on the battlefield, there are numerous other aspects that relate to the outcome on the battlefield. Factors such as tactics, training, and equipment all play key roles as well. While combat simulations, such as IWARS, can capture some of these effects, they are not able to capture the interactions between physical fitness and these different factors. Future work will also look at attempting to model these interactions for integration into combat simulation packages.

Paraphrasing one of the author's drill sergeants, physical fitness is important in combat because the more fit a soldier is, the harder they are to kill. Indeed, physical fitness is a key component of military training. As such, it is imperative that combat simulations be able to better reflect the change in soldier performance based on their physical fitness level.

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