MATHEMATICAL ALGORITHMS FOR TRAINING EFFECTS DETERMINATION IN CGF

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Abstract

Advanced distributed simulations (ADS) along with computer generated forces (CGFs) are used to provide troops with tactical combat training and to perform research. Current CGFs behave as perfectly trained troops, their ability to perform missions to do not vary. This is an inaccurate portrayal of human performance. If the military cannot model human factors, such as training and physiological stressors in ADS, they cannot perform trade-off analyses. For the military to be able to use ADS and CGFs to answer resource allocation and system design questions, the CGFs have to be affected by a human performance model. Micro Analysis & Design, Inc. (MA&D) was awarded a Phase II SBIR entitled “Improving Soldier Factors in Prediction Models” by the Army Research Institute (ARI). The goal of this SBIR was to develop a model that uses training and other performance shaping factors (PSFs) to affect the abilities of CGFs. This performance effects model incorporates the benefits of different types of training, the effects of skill decay, physiological stressors and aptitude. The final model will allow users to affect a wide range of tasks. It is generalizable to both military and non-military applications. The military will be able to use it to affect the performance of CGFs in ADS. Once the model is implemented, the military will be able to conduct trade-off analyses. They will also be able to better prepare troops for combat by having them train against opponents of different skill levels.

Biographical Sketch:

Alia Oster received her Bachelor of Science in Applied Mathematics from the University of Colorado at Boulder in 1999. For the past two years she has been employed at Micro Analysis and Design where she has been developing human performance models and providing software support for various projects. Ms. Oster developed naturalistic decision-making models for work with Klein and Associates. She also created a human performance model library for the Plant-Human Review and Effectiveness Decision (PHRED) tool.

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INTRODUCTION

Advanced distributed simulations (ADS) with computer generated forces (CGFs) and man-in-the-loop simulators provide a cost-effective and safe environment for tactical combat training. These simulations are not only proving to be a cost-effective way to train forces, but they are proving to be powerful analysis tools. Militaries are starting to use ADS and CGF to aid decisions in areas such as resource allocation and system design. Simulation is an excellent environment for officials to test how different command systems and weapons might influence combat outcome. Because command systems and weapons are key determinants of battlefield success, it is crucial that the military understand the exact implications of new purchases and designs. ADS and CGFs makes this possible, by allowing the military to test out new technology and see how it might help in a battle.

Unfortunately, ADS and CGF only complete part of the question that the military must answer when it comes to acquiring and designing new systems. Troop readiness and troop ability to use new technology are also determinants of battlefield success. If troops are unprepared for battle, new command systems and weapons will not provide them with an advantage over the enemy. Trade-offs between technology and maintaining force readiness are central issues when it comes to resource allocation and system design. In both situations, figuring out how much training troops need to perform well in combat is a major part of the problem. To perform accurate simulation-research for resource allocation and system design, military officials need to be able to incorporate the training aspect of their problems. Current ADS do not allow users to vary the ability of CGFs. There is no way for the military to determine the correct balance of training and technology (Biddle, Hinkle & Fischerkeller, 1999).

Current CGFs perform complex military tasks based on algorithms that closely mimic standard tactics and doctrine. Entity performance does not vary in the same manner as real human performance would (Gillis & Hursh, 1999). The slight variations in performance that do occur are usually the result of equipment models or simplistic models of human performance. Consequently, the value of ADS for performing trade-off analysis is degraded by the absence of these types of models.

If training models are not developed, our military is at risk of making serious miscalculations about the amount of training needed to prepare forces for today's battlefield (Biddle et al., 1999). They are also at risk of designing and purchasing systems that require more training then we can provide troops. The military needs models that link training and performance shaping factors (PSFs) to combat performance and combat support operations.

By allowing researchers to effect the performance of CGFs with training and PSFs models, they will be able to perform accurate trade-off studies that involve training and system design. These models will also provide the military with the ability to train troops against opponents of varying skill levels. This enhanced realism will better prepare troops for the uncertainties of combat.

TRAINING EFFECTS AND COMPUTER GENERATED FORCES

Micro Analysis & Design, Inc. (MA&D) was awarded a Phase II SBIR entitled "Improving Soldier Factors in Prediction Models" by the Army Research Institute (ARI). The goal of the Phase II SBIR, in the effort described here, was to develop a usable training and PSFs model for CGF. This model should allow users to test how different combinations of types and amounts of training affect performance. It is essential to capture the varying benefits of training, because numerous studies have found that training benefits are determined by the amount and type of training an individual receives. By allowing users to experiment with different training schedules, it will be easy for them to perform analyses where training cost versus training effectiveness is an issue.

Additional elements of training that must be included in the model are aptitude and experience. Skill acquisition theory and research shows that people learn at different rates and this difference is directly related to an individual's aptitude. A person with higher aptitude reaps more benefits from training than a person with less aptitude. Including aptitude as a variable in the performance effects model, will allow users to determine how much training different troops will need based on aptitude.

When calculating an individual's ability to perform a task based on the amount of training he has had, it is also important to take into consideration how much time has passed since the training occurred. This means that skill decay must be included in the model for it to be an accurate representation of human performance.

The final model will not only reflect the direct results of training, but it will also reflect some of the indirect influences training has on combat performance. How well an individual is trained not only determines how he will perform under ideal conditions, but it will also determine how well he will perform under stress. Current theory and research indicates that physiological stressors have less effect on individuals that are highly trained and more experienced. This means that in addition to the training parameters already discussed, the model must include the effects of physiological stressors such as heat, fatigue and noise.

Including these PSFs and various elements of training into the model will make it robust enough to provide users with the flexibility they need to perform complex military and non-military analyses.

This robust performance effects model will influence CGF performance by effecting

- Task times
- Task accuracy
- Decisions/Course of actions

As mentioned earlier, current CGFs behave according to doctrine and equipment models. They behave as if they are perfectly trained. With the performance effects model in place, the CGF will have the potential to make errors. Whether a CGF's performance is degraded or improved will depend on the results of the model. For instance, if an entity is poorly trained, it will take the entity longer to load his gun and to track a target. On the other hand, a highly trained entity will be more likely to identify another entity correctly, as friend or foe. The changes mean that CGF performance will more closely mimic how a real human would perform in combat. This increased realism will enhance the value of ADS for both performing analyses and for troop simulator training.

DEVELOPING A TRAINING MODEL

The training portion of the human performance model has three main features. These features contribute to the overall performance effects model's ability to model human performance. They are implemented in way that makes them generalizable to numerous military and non-military scenarios.

The first feature of the training model is that the differences between different types of training are captured. This was done by creating mathematical models of learning – learning curves. These learning curves are based on current skill acquisition theory. They can be used to reflect the training benefits for any number of training types that a user might want to model.

The second feature of the training portion is the incorporation of skill decay. In particular, the fact that different skills decay at different rates was characterized by using a mathematical model found in the literature. This model was used to reflect the effects for a particular set of skills, but it is general enough that it can easily be apply to any set of skills a user might want to use.

The last feature of the training portion of the model is that both the learning and decay curves were developed for skills opposed to being developed for a specific set of tasks. By creating the curves for skills instead of tasks, the curves can be used to calculate the effects of training and decay for large number of tasks. This provides users the flexibility of being able to apply the training portion of the model to a large number of simulations and models where training is an issue.

Skill Acquisition Theory

Before deciding on the mathematical models to use for modeling training effects, an extensive study of current skill acquisition theory was conducted. It was found that there are four basic learning curves, which are commonly accepted within the skill acquisition community (Lane, 1986; Lowry, Rappold & Copenhaver, 1992; Newell & Rosenbloom, 1981; Rickard, 1994). In a review of nearly 3,000 research titles and abstracts, Lowry, Rappold and Copenhaver (1992) identified these curves as the power law, the exponential curve, the hyperbolic curve, and the logistic curve.

The hyperbolic curve is a special case of the power law and it tends to fit empirical data almost as well as the power law does (Lane, 1986). The logistic curve produces S-shaped or sigmoid curves. This shape is usually found when the empirical data are performance ratings provided by instructors (Lane, 1986). Since the hyperbolic curve is a special case of the power law and the logistic curve does not fit most empirical data, we decided against using them in the performance effects model. This leaves us with the most commonly used curves, which are the power curve (see Figure 1) and the exponential curve (see Figure 2).

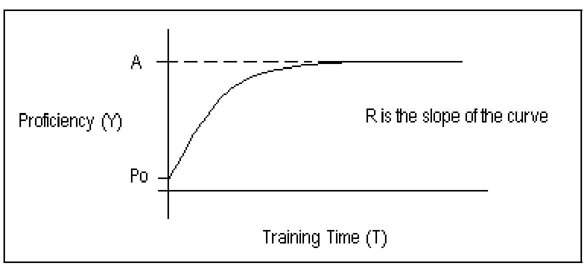

Figure 1. Power law curve

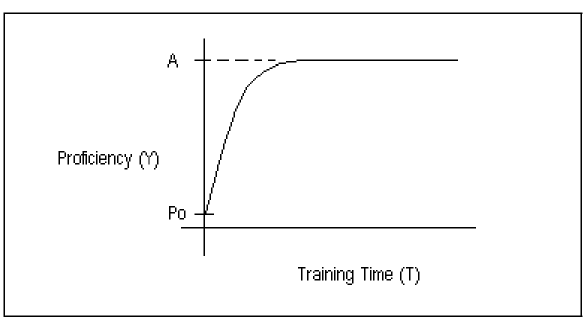

Figure 2. Exponential curve

The power curve was initially associated with only perceptual-motor skills, but it is now found to apply to a wide range of skills, such as cognitive and motor skills (Newell & Rosenbloom, 1981; Lowery et al., 1992). This curve is an increasing function with negative acceleration, which takes the form:

$$Y = A - (A - P_o)(T + E)^{-R} \qquad (1)$$

Where the major parameters are

T	=	time spent training
Y	=	proficiency level after training
R	=	rate of learning
A	=	asymptotic proficiency
P_o	=	innate proficiency
E	=	prior experience

Some of these parameters are self-explanatory, such as time spent training (T) and proficiency level after training (Y). These are input and output of the function, respectively. The rest of the parameters define how quickly a person can learn from the training and the maximum amount of benefit a person can attain from his training.

Learning rate (R) defines the slope of the power curve, which directly reflects how quickly an individual's ability improves during training. The maximum benefit of training is determined by innate proficiency (P_o) and asymptotic proficiency (A). Innate proficiency is the level at which an individual can perform when he first attempts to use a skill or do a task; this is often referred to as his worst-case performance. The opposite of innate proficiency is the asymptotic proficiency. This proficiency is the highest level of proficiency that an individual can reach with a particular type of training. The last of the parameters in the power function is prior experience (E). This parameter indicates how much time an individual has spent performing or learning a skill before training occurred. This parameter is often set to zero.

The exponential curve is similar to the power curve, except that it does not have as many parameters and it has a constant acceleration. This constant acceleration results in a much steeper curve than what the power curve produces (Lowery et al., 1992). The exponential curve takes the form:

$$Y = A - (A - P_o)\, e^{-RT} \qquad (2)$$

The definitions for the parameters of this equation are the same as the definitions for the power function's parameters.

When data are fitted with both power and exponential curves, it is often difficult to distinguish which curve is the "better" fit by conducting a simple examination of the curves (Lane, 1986). Generally, an extensive statistical analysis is required to determine which function more accurately models the data. Because both of these curves were found to be adequate representations of learning, it was decided that training algorithms would be developed for each curve.

Skill Decay Theory

Another important factor in determining the effects of training on performance is the amount of time that has passed since the training was received. Decay, or the rate at which skills are forgotten or lost, is often characterized as a negatively accelerating function based on time since training. Unlike the literature on skill acquisition (learning), no general curves on decay (retention) are widely accepted. Decay data reported in the literature vary widely in terms of the time span over which they occur; measured in terms of seconds, minutes, hours, days, weeks, months, and years.

Some researchers agree that decay can be represented as a power function similar to the ones used to estimate the rate of learning, and they have attempted to quantify this function (Rose, Czarnolewski, Gragg, Austin, Ford, Doyle, & Hagman, 1984). For this reason, we decided to model decay mathematically by using a decreasing power function with negative acceleration (see Figure 3).

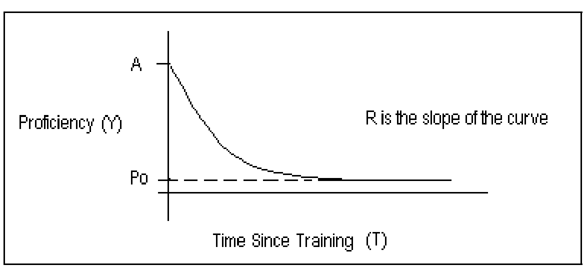

Figure 3. Decay curve

The decay curve has a very similar form to the power curve used for learning

$$Y = P_o - (P_o - A)(T + E)^{-R} \quad (3)$$

The parameters for this function are similar in nature to the learning curve parameters

- T = time since training
- Y = proficiency level after decay
- R = rate of decay
- A = maximum starting proficiency
- P_o = innate proficiency
- E = prior decay

The main difference is how innate proficiency is used. Earlier, innate proficiency was defined as worst-case performance. It would be illogical for an individual to decay past this point. This is why innate proficiency is used as the lowest point to which an individual can decay.

Skill Sets vs. Tasks

If these learning and decay curves were developed for a specific set of tasks the resulting training model would only be useful to a limited audience. As mentioned earlier we decided against limiting the potential of our model by developing task-level models. The final set of skills used in the training portion of the model was decided upon based on subject matter expert (SME) recommendation. This taxonomy was primarily developed with the military in mind, but most of the taxons are general enough that they can be applied to non-military tasks. The taxons in the training model's taxonomy are

- Planning
- Communication
- Command and control
- Technical proficiency with equipment
- Tactics and doctrine

Algorithms Used in the Training Model

Once the general forms of the learning and decay curves were decided upon, the algorithms for the training model had to be finalized. This finalization was performed in three steps. The first step was to determine exact situations of learning and decay that needed to be modeled to give the model flexibility. After this, modifications were made to each curve so they met the training models exact needs. Lastly, exact algorithms were laid out for calculating taxon proficiencies.

Learning Curve Algorithm

It was decided that to properly model training, a learning curve must be created for every combination of taxon and training type in our model. This was decided upon, because research indicates that not all training types provide the same degree of benefit and that different skills have different learning rates. The training model that was developed has three training types: classroom, simulator and field training. With these three training types and the five taxons mentioned earlier, there are fifteen learning curves in the training model.

These learning curves can be either power or exponential curves. The type of curves picked for the final training model were dependent on how well each type of curve fit the data that were used to calculate the curve parameters. Before either curve could be fitted to the data, a few modifications had to be made to the curves. The first of these modifications was made just to the power curve.

In the power curve there is a parameter referred to as "prior experience" (E). This value represents the amount of time an individual has spent training on the task or skill before official training was started. In a majority of the research reviewed, this parameter is set to zero, indicating that the individuals in the study had no prior experience on the task studied. When this parameter is set to zero the power curve has the form

$$Y = A - (A - P_o)\, T^{-R} \qquad (4)$$

This function is undefined at time zero (T = 0), which causes a problem in the training effects algorithm. If a user entered in zero hours of training for any one of the training types the entire algorithm would no longer work. This problem resulted in a search for a value of E (prior experience) that would make sense from a theoretical stance and that would cause the function to be defined at time zero. It was determined that at time zero, a person's proficiency is his innate proficiency. If the output of the power function should be innate proficiency at time zero then it turns out that prior experience (E) should be equal to one. Once this modification is made to the general power curve (Eqn. 1), it has the form

$$Y = A - (A - P_o)(T + 1)^{-R} \qquad (5)$$

One more modification was made that applied to both the power curve and the exponential curve. This modification was made to deal with situation when a user wants to create a training schedule for an individual that is already at a certain level of proficiency that is higher than his innate proficiency. The higher proficiency level is an indication that he has had prior training, but the user might not know the exact amount of previous training the individual he is modeling has had. To deal with this problem a new parameter was introduced. The new parameter is called starting proficiency, P_b. It is defined as the proficiency that an individual is at when he starts a particular training session. It is used to help calculate the amount of prior experience an individual has had. The newly modified power curve is

$$Y = A - (A - P_o)\left(T + \left(\frac{P_b - A}{P_o - A}\right)^{-1/R}\right)^{-R} \qquad (6)$$

When an individual's starting proficiency is his innate proficiency then the function simplifies to Eqn. 5. The modified exponential curve is

$$Y = A - (A - P_b)\, e^{-RT} \qquad (7)$$

The final algorithm used in the performance effects model can use either of these modified curves to calculate a taxon proficiency. One of the user inputs used by this algorithm is a taxon training schedule, which provides the number hours spent in each training type and the order in which the training occurred. Another input provided by the user is a starting proficiency (P_b). The algorithm for calculating taxon proficiency is

1. Calculate proficiency Y_1, using P_b and T_1 (time for first training type).
2. Calculate proficiency Y_2, using Y_1 as starting proficiency and T_2 (time for second training type).
3. Calculate final proficiency Y_3, using Y_2 as starting proficiency and T_3 (time for third training type).

This simple algorithm can also be used to calculate a taxon proficiency using a training schedule that has more than three training types, as long as there are learning curves defined for each training type.

Decay Curve Algorithm

It is has also been found that different skills decline at different rates. Some skills fall sharply during the time immediately following acquisition and decline more slowly as additional time passes, other skills do not begin to show decay until several months after acquisition. For example, perceptual-motor skills (e.g., driving, flight control, and sports skills), decay slowly. In contrast, procedural skills, which require a sequence of steps, such as how to use a text processor or how to run through a checklist for turning on a piece of equipment, tend to be quickly forgotten (Rose, 1989). This research lead us to developing decay curves for each taxon, instead of having one curve to calculate decay for all the taxons.

Once it was decided that a decay curve had to be developed for each training taxon, it was time to alter the basic decay curve (Eqn. 3) in a similar fashion to the learning curves. The primary difference is that the roles of asymptotic proficiency and innate proficiency have switched. The basic decay model assumes that an individual starts out at his asymptotic proficiency and then decays. In most cases, this will not be true. Normally an individual will be at another proficiency level, lower on the curve, P_b.

The decay curve was modified, so that an individual would not have to be at asymptotic proficiency before a user could decay his ability. This modification was done by interpreting the parameter in the basic decay curve (Eqn. 3) as "prior decay". Then innate proficiency, asymptotic proficiency, and starting proficiency were all used to calculate the amount of time that was spent "decaying" before time T. The new decay curve has the form

$$Y = P_o - (P_o - A)\left(T + \left(\frac{P_b - P_o}{A - P_o}\right)^{-1/R}\right)^{-R} \quad (8)$$

There are two input parameters for this function. The user provides one of these parameters, time since training (T). The other parameter, P_b, is the output from the learning algorithm. This means that an individual's taxon proficiencies are initially calculated using the training schedules. Once these calculations are complete these taxon proficiencies are lowered using the taxon decay curves, if the user has indicated that time has passed since training occurred. This algorithm is simple and easy to generalize, since there is only one decay curve per taxon and decay only occurs if no training has occurred.

Calculating Curve Parameters

The final step in developing the training portion of the performance effects model was calculating parameters for the learning and decay curves based on data. Initially, it was intended that SME data and empirical data would be used to determine these parameters. Unfortunately, there is limited empirical training data available. An even smaller percentage of the available empirical data sets have the inputs and outputs necessary for calculating taxon curve parameters.

Since there was a lack of empirical data, the learning and decay curves were only fitted to SME data. Data were collected from armor tank platoon leaders and platoon sergeants on the training they had received on 38 top level tasks from the ARTEP 17-237-10 Mission Training Plans (MTP) for Tank Platoons. We were able to use these data to come up with taxon learning and decay data, which could be used to calculate the needed curve parameters. Both exponential and power learning curve parameters were calculated. The power learning curve parameters turned out to be more reasonable than the exponential learning curve parameters. These values will be used in the performance effects model until more accurate empirical data is found or if the user has his own training parameters that he would like to use.

DEVELOPING EXPERIENCE, APTITUDE AND STRESSOR MODELS

In addition to the learning and decay models, there are several PSFs that are included in the performance effects model. These different PSFs are

- Aptitude
- Experience and
- Physiological stressors

Each of these factors has a direct influence on human performance. Aptitude and stressors have direct interactions with training and an individual's proficiency level. Experience is included because of its relationship with stressors. These different relationships have been documented in various psychological and military studies.

Aptitude

During the literature review conducted for the development of the performance effects model, evidence was found that correlates general aptitude to the rate at which skills are learned. For example, a 1969 study done for the US Army found that individuals in the bottom 20% of the ability distribution required up to five times as much instruction and practice to attain minimal proficiency in basic military tasks such as rifle assembly (Gottfredson, 1997; Sticht, Armstrong, Hickey, & Caylor, 1987). This indicates that people with higher aptitudes reach high levels of skill proficiency with the same amount of training than people with less aptitude.

One of the studies that was reviewed was the Army Selection and Classification Project (Project A), which was conducted in the 1980s to improve the recruitment and training process. Project A found that general mental abilities were highly correlated with technical proficiency and soldiering proficiency (Mchenry, Hough, Toquam, Hanson, & Ashworth, 1990). Since Project A is one of the few studies that has extensive training data relating to aptitude, it was decided that the performance effects model would use algorithms based on these data to calculate the effects of aptitude.

Stressors and Experience

Performance on a task or mission under ideal conditions may differ drastically from performance on the same task or mission under stressful conditions. The environment in which military operations (tasks and missions) are conducted can be very stressful. This is why physical stressors were included in the performance effects model. Incorporating stressors into the model allows users to estimate mission performance under "worst case" conditions.

A review of the relevant literature has produced performance degradation factors for the following stressors: heat, cold, noise, fatigue, circadian rhythm, Mission Oriented Protective Posture (MOPP gear), and altitude (Bradley & Robertson, 1998; Micro Analysis and Design Incorporated [MAAD] & Dynamics Research Corporation, 1999; Walters & French, 2000). Some of these degradation factors have been correlated to affect a specific set of taxons (e.g., visual, numerical, and cognitive skills). These taxons can be applied to wide variety of tasks. It is these algorithms and taxons that are used in the performance effects model to incorporate physical stressors.

Empirical and theoretical research has also been examined on the combined effects of multiple stressors and how to model them. Although an abundant amount of empirical data has been collected on the separate effects of stressors on performance, there has only been a small amount of work done on the combined effects of some stressors. Therefore, difficulties occur when equations are developed that try to generalize the interactive effects of multiple stressors. Two different human performance modeling tools were identified that contain equations that address the combined effects of stressors: the Integrated Performance Modeling Environment (MAAD, 1999) and the Improved Performance Research Integration Tool. Both of these equations are reasonable for modeling many interactions amongst stressors.

It was decided that the following equation would be used (Harris, 1985) to combine the effects of multiple stressors in the performance effects model:

$$DF_T = \Pi\ i = 1, n\ \sqrt[i]{DF_i} \qquad (9)$$

Where:

DF_T = Total degradation factor
DF_i = The i^{th} ordered degradation factor
n = Number of degradation factors

Using this equation, when two or more stressors are combined, the overall degradation is less than the sum of the individual degradations. The most severe stressor will have a full effect on performance. As additional stressors are added, they will have less and less impact on performance.

Lastly, many researchers have investigated the relationship between experience on a task and environmental stressors over time. Some of the findings are summarized in Hancock (1986). Mackworth (1950) found that less experienced workers suffered more disruption by increasing heat stress, and this was manifested earlier than for experienced workers. Similar results were found for several different types of tasks: Morse code message transmission, Naval lookout duty, and physical exercise. Blockley and Lyman (1951) found the same pattern of results for flight performance under heat stress. These findings, along with others that were reviewed, resulted in experience being added as the final PSF in the performance effects model.

FINAL PERFORMACE EFFECTS MODEL

Once aptitude, physiological stressors and experience are integrated with the training model the performance effects model is complete. It is this completed model that can be used to effect CGF behavior. The model has four high-level four steps that must be performed to calculate a new task time or accuracy. These steps are

1. Apply aptitude
2. Apply the training model (i.e. the learning and decay algorithms)
3. Apply stressors
4. Apply experience (i.e. decrease the effects of stressors if modeling a highly experienced person, increase the effects of stressors if modeling a less experienced person)

The output of the model will be used to effect CGF entity behavior. Simulation entities will behave as it they have received training and as if they are effected by physiological stressors.

CONCLUSION

The immediate benefit of the performance effects model will be the ability to create more realistic CGF behaviors in ADS. This increased realism will be beneficial for simulator-based training and research.

When it comes to simulator training, troops will be able to train against CGF entities of varying ability. Troops will no longer be able to predict the behaviors of their computer generated opponents. Currently, soldiers can distinguish which entities are manned simulators and which ones are computer generated. Because soldiers can make this distinction and they know how the computer generated entities will react, they alter their reactions to fit with the CGF actions.

At some point the performance effects model will effect enough of the CGF entity behaviors that soldiers will no longer be able to determine which entities are real people and which are computer driven. If soldiers cannot make this distinction, they will not be able to predicate the entities' actions. This is a more realistic portrayal of what troops will encounter in combat.

When the performance effects model becomes available for simulation-research the military will be able to conduct trade-off analyses between technology and training. As mentioned earlier, this is important for areas such as resource allocation and system design. Decisions that are concerned with balancing technology and training will be better informed. Overall, the increased realism and flexibility will result in the increased probability of combat success.

The benefits of the performance effects model will not only be felt by the military community, but non-military users will find it useful as well. The model is general enough that non-military users can use it to conduct modeling and simulation research that needs training effects. In particular, users will be able to conduct a wide variety of analyses that involve training, stressors, aptitude and experience.

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