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Civilians on the Battlefield: Creating a Realistic Training Aid for the United States Military

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CIVILANS ON THE BATTELFIELD: CREATING A REALISTIC TRAINING AID FOR THE UNITED STATES MILITARY

by

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ABSTRACT

CIVILANS ON THE BATTELFIELD: CREATING A REALISTIC TRAINING AID FOR THE UNITED STATES MILITARY

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The requirements for the military to adhere to international laws of war when interacting with civilians and the recognition that warfare is conducted across a broad spectrum of areas contributes to a steady requirement to train military forces to respond properly when confronted with civilians on the battlefield. Unfortunately, the only viable method to provide this training is to employ large numbers of role-players – either in a live training setting or controlling entities in a wargame. There are currently no viable autonomous simulation solutions. This results in military leaders choosing to forego this important training.

This study designs a multi-agent model based on sound cognitive principles and tests its validity as a viable, low-cost tool in time and resources to address military training and decision making with civilians in a battlefield setting.

The research showed that the Agent Zero cognitive multi-agent model is a viable and useful tool to develop effective military simulation architecture for use in training and course of action development.

This thesis is dedicated to my boys, Dustin and Logan, who have followed me all over the world and are the pride and joy of my life.

ACKNOWLEDGMENTS

There are many people who have contributed to my completion of this thesis. Dr. John Sokolowski not only helped me to develop the idea for this thesis but carried me across the finish line. My committee members provided some keen insight and feedback on how to improve my final product. Finally, my wife has been incredibly patient with me throughout the process, despite seeing way too much of me.

NOMENCLATURE

α	Salience of Unconditioned Stimulus
β	Salience of Conditioned Stimulus
δ	Type of Learner the Agent Is
D	Total Disposition Value of Agent
λ	Maximum Affective Value of Agent
p	Rational Value for the Agent, Probability Mean
τ	Threshold for Action
t	Timestep, Hours
v	Affective Value for the Agent
w	Weighted Social Value

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INTRODUCTION

1.1 Thesis Statement

Agent based models using the Agent Zero framework can effectively replicate civilian behavior on a battlefield, providing commanders with a training tool to show not only how civilians will behave in kinetic operations but also why they behave that way based on neurocognitive modeling.

1.2 Problem Statement

The United States and our allies and partners have adopted a humane approach to warfare based on established principle of the laws of war centered around the principles of Military Necessity, Humanity, Proportionality, Distinction, and Honor [1]. These principles dictate that US Military forces conduct warfare with a careful consideration of our impact on civilian populations with a special duty to protect and limit harm as much as possible given the accomplishment of a mission.

Likewise, the US Military has developed a sound counterinsurgency and unified action military model that recognizes that warfare is not fought simply with kinetic force, but rather is conducted across an array of areas, including the battle for “hearts and minds” of civilian populations to assist with military actions and legitimize lawful governments [2].

These two factors contribute to a steady requirement to train military forces to respond properly when confronted with civilians on the battlefield. Unfortunately, the only viable method to provide this training is to employ large numbers of role-players – either in a live training setting or controlling entities in a wargame. These role-players must either be hired [3] or be tasked from other military units. There are currently few viable autonomous solutions that are available to US Army trainers. The result is that commanders often choose to forego this training as too costly – which could have serious long-term ramifications for military forces confronting civilians in the real world.

Can agent-based modelling accurately represent civilians confronted with military operations to provide realistic training for military leaders and Soldiers?

1.3 Motivation

Training military units is costly [4]. Not training military units properly can be even more costly in strategic costs and civilian interactions is one area where small mis-steps can have a huge impact [5]. Military trainers and leaders require adaptive, low-cost training solutions to prepare for a wide spectrum of operations across the world.

1.3.1 Cost

In 2015, I was part of a team designing a large regional exercise in Eastern Europe called Immediate Response 2015 [6]. One of the countries participating, partially in response to the refugee crisis in the Balkans at that time, requested we include a robust civilian presence in the scenario. Problematically, we did not have an accurate civilian simulation model that did not require large numbers of role-players and simulation operators to replicate the civilians. The training audience participants were not willing to provide the people or the money to adequately present this part of the scenario, so we had to pull the civilians from the simulation design and use a series of scripted training injects instead.

This pattern was repeated multiple times as I planned simulation driven training events at the US Army's Joint Multinational Simulation Center in Grafenwoehr, Germany [7]. The training audience, a US or NATO unit, would request robust civilian interaction, but were unable to provide the human or financial resources necessary to do so. Military commanders allocate training resources months or even years in advance [8]. For a computer assisted exercise (CAX), these costs generally include the cost to transport, house, and feed the training audience and enemy (REDFOR) role-players, any costs associated with the computer networks and simulation distribution, and costs for technical staff that may be more than the servicing exercise center can provide. Despite their desire to train with civilians in a simulated combat setting, unit commanders do not routinely budget money to pay for the costs associated with simulated civilians on the battlefield – either the cost to transport, house, and feed additional military personnel to replicate those civilians or money to hire contracted civilian role-players for inclusion in the exercise [9].

Unfortunately, there is not an autonomous solution available. This paper will explore the feasibility of agent-based modeling, using the framework laid out in Joshua Epstein's work, "Agent_Zero: Toward Neurocognitive Foundation for Generative Social Science," [10] to develop responsive and realistic battlefield civilian agents as a realistic training enhancement for military war gaming exercises.

1.3.2 Achieving Strategic Goals Through Sound Counterinsurgency Operations

A military commander achieves broad strategic goals through operational and tactical means in a conflict including direct and indirect efforts to maintain security and counter insurgent methods across the full range of the strategic area and governmental and non-governmental actors [2]. Although other regimes may utilize violence and fear to maintain security [11], the US and its allies generally adhere to contemporary norms regarding the use of force and protection of civilian lives. The basic elements of this are military necessity; humanity which is broadly defined as preventing unnecessary suffering; discrimination, which is the requirement to distinguish between civilian and military actors when applying force; proportionality, or using the least amount of violence necessary to achieve reasonable military ends; and honor [2]. This requires a careful approach that must be practiced in a training environment before attempting it in an operational environment [8].

CHAPTER 2

LITERATURE REVIEW

2.1 Research on Civilians on the Battlefield

There are limited studies directly touching on civilian behavior on the battlefield. Most studies deal with patterns of civilian participation in insurgencies or refugee patterns, rather than on civilian behavior patterns when confronted with violent conflict [12]. That is not to say that studies are completely lacking. There are two distinct schools of thought that look at effects of military actions on civilians, one that considers building trust to be advantageous [13] and indiscriminate violence disadvantageous in that it pushes civilians to aid or join the enemy and a second line of thinking that considers using fear to suppress violence as a valid military tactic [14].

The first school of thought, which the United States military adheres to [2], is that violence in occupied areas is lessened through control and security in that area [13]. Where necessary, discriminate action is used against civilians when it can be shown that they are collaborating with or harboring enemy forces. Indiscriminate violence may produce a short-term reduction in violence, but long-term, will lead to a greater amount of violence as there is no perceived incentive by the population to cooperate with the occupying force that uses indiscriminate violence [13]. I find this theory to be more compelling and more in compliance with US military doctrine, so I will incorporate elements of this theory into the model on civilian behavior.

An interesting work on this theory further distinguishes between 5 distinct zones of control in an occupied area in which civilians behave in distinct ways. Zone 1 is an area of total insurgent control, zone 2 is an area predominantly controlled by insurgents. Zone 3 is contested. Zone 4 is primarily controlled by government forces, and zone 5 is an area completely controlled by government forces [13]. Although this work is primarily a study on predicting combatant violence in the different zones, it is also useful to understand the civilian behaviors that help to predict the violence in each of those zones and will help to form the model I will use to show civilian behavior in a conflict.

In stark contrast to the theory that security and discriminate violence is the key to positive civilian behavior, is the theory, which can be seen practiced in the current Syrian conflict [15], that indiscriminate violence against combatants and civilians has a positive effect on civilian behavior. [14] A 2009 study on Russian use of indiscriminate violence against civilians in Chechnya provides a case in point. The study, using data collected by the Russian military, shows that insurgent attacks dropped following indiscriminate artillery attacks on Chechnyan villages. The study suggests that both methods, building trust or using fear, are potentially effective at reducing civilian violence and insurgency. [11] I believe the studies on fear are potentially flawed in that they study near-term outcomes, but fail to address longer-term effects of indiscriminate violence on civilian attitudes and behavior.

The problem that I wish to study and model is not the behavior of combatants, but rather the behavior of civilians. And while Kalyvas' work on violence addresses civilian behavior [13], it is not the focus of his research. This is an area that has largely gone unstudied outside of predictors of migratory behavior in wartime [16]. Research suggests that low to moderate levels of violence discourage migration, but higher amounts of violence encourage migration. This will be useful in determining threshold behaviors in an agent zero model. In addition, some researchers view violence as an additional variable in every civilian's cost-benefit analysis of staying versus migrating [17], reinforcing the idea that migration is a binary decision once a certain threshold is reached in each civilian's cognitive decision-making process.

There is only one large scale study of civilian behavior when faced with wartime levels of violence outside of the migratory studies. In a 2006 study on the behaviors of civilians in London during the German air raids of WWII, the authors concluded that civilian behavior was predicated on two factors. The first, morale, enabled the civilians to productively and rationally respond to acts of violence. This factor was positively or negatively affected by political and societal actions. The second factor, panic, was linked to the intensity and type of violence encountered. The higher the civilian panic, the more likely that they would act irrationally and incur more serious casualties. [18] The conclusions reached that societal structure and morale can counter violence-induced panic provide a useful starting point for development of an agent zero model. Unfortunately, the study does not provide a framework to validate that model's results or qualitative inputs to the model itself other than shaping a notion of the two threshold dispositional variables to model in the agent zero model, fear/security as one and trust/distrust as a second.

The Agent_Zero framework, by contrast to these targeted studies provides a neurocognitive foundation for literally any human behavior but stops short of developing detailed analysis of specific groups or situations (8).

2.2 Previous Attempts to Model Civilian Behavior

Because of the importance of training soldiers and leaders to interact with civilians in a conflict, there have been many attempts to model civilians on the battlefield, generally in a tactical setting, and using simple crowd modeling behavior to replicate civilian actions [19] [20] [21]. There have been a few attempts at more complex agent behavior using existing human behavior models [22] [23] or game theory [24], but these are computationally complicated and are difficult to integrate into normal military training events. The attempts at multi-agent models with human behavior algorithms have been kept small in both the number of agents and the scope of the scenario, focusing on tactical vignettes [20] [19] [21]. I have not located any examples of these models being used in a military training event outside of the research institutions creating them. Civilian encounters are either scripted, as shown in figure 1 below, or played by role-players.

Figure 1. Scripted encounter inside the US Army's Virtual Battle Space 3 (VBS3).

2.2.1 Crowd Behavior Models

Crowd modeling is a well-established field in the modeling and simulation community. The models fall into two categories. The first are agent-based models that demonstrate emergent crowd behavior based on the individual agents' decisions. The second treats the crowd as a fluid governed by the discipline of fluid dynamics [25]. In agent-based crowd models, the agents have simple rules they operate with to limit the computational requirements of large crowd sizes [25]. More complicated agent behavior models are not as scalable due to computational limitations [26].

An early attempt to use a crowd behavior model to represent a tactical vignette was made by researchers at Old Dominion University in conjunction with the Defense Modeling and Simulation Office, the Air Force Research Laboratory, and the U. S. Joint Forces Command. The project was successful at federating a civilian crowd model, using a commercial application, AI.implant, into a tactical scenario. The scope was small and not applicable to typical larger exercises that focus on training military leadership [20]. The crowd model used reactive agents and does not provide the level of detail about civilian actions, motivations, and outcomes that is necessary to provide useful feedback to military leaders about their actions.

A contemporary attempt at modeling civilian behavior by the U.S. Army Training and Doctrine Command Analysis Center uses a multi-agent crowd behavior system to represent the interactions of civilian and military agents over time. The agents interact based on their role: ethnicity, gender, age, disposition, political affiliation, goals, and interactions with military forces to generate a detailed crowd model that can be analyzed to determine the impact of military operations on a civilian population and vice versa

[21]. This model was federated with the COMBATXXI military simulation platform. This model is promising but does not allow for change within the agents in the model. The agents behave based on pre-selected factors. This is a promising approach to providing realistic civilian agents in military simulations but does not allow for measuring changes in the civilian agents that would provide a deeper understanding of the costs and benefits of military actions.

2.2.2 Human Behavior Models

There have been some attempts to integrate civilian agents into military simulations using existing human behavior models. Researchers from the U.S. Army Training and Doctrine Command Analysis Center created a normative agent model that used Bayesian belief networks to predict the attitude and behavior of civilians in a counterinsurgency scenario [22]. The cultural geography model developed for the US military is loosely based on the work of the philosopher Fisher, who developed a cognitive theory based on narration [27]. His theory states that each human being has a unique story based on their experiences and culture that shape the way they interact with the world. This individual narrative translates directly into a model of how the individual will view the world, which in this case was the Bayesian belief network. The cultural geography model work is interesting but was a stand-alone model that did not integrate with other military simulations. It is intended as an analysis tool to see how a course of action will impact civilian behavior and attitudes [22]. This model was successful within its narrow scope but may not be broadly suitable to plug into general military training scenarios.

A more recent attempt to use agents to populate a military simulation attempted to use the belief, desire, intent (BDI) framework, covered below, to create realistic civilians inside the Virtual Battle Space 2 (VBS2), a tactical gaming application. The civilian agents were programmed using the CoJACK platform, a commercial BDI modeling tool. Based on the agents' percepts, they would choose from plans that each included decision trees that covered how the agents would react [19]. Although the scope was small, including a single suicide bomber in a marketplace, this was a good indication that agents can behave realistically using a cognitive model inside a military simulation. This model requires substantial set-up to build the agent plans that are pertinent to each scenario. This may negate the hoped-for cost savings of using an agent-based approach to military training and analysis scenarios.

2.2.3 Other Models

The attempts to model civilian agents in a conflict setting have been primarily either crowd model or cognitive model based, but there is a recent attempt to use a game theory agent decision model to replicate civilian behavior. In a 2013 study on the Ukrainian civil war immediately following WWII, the author used a game theory epidemic based model to study civilian responses to violence. The civilians would either *balance* against the more violent side, or conversely *bandwagon* with the more violent side. In both cases, this was done to attempt to limit losses and was generally predicated on communication or lack thereof to help inform the civilian responses. [24]

2.3 Agent Decision Making Models

There have been many efforts to create autonomous agents that mimic behaviors or react in a primitive fashion to stimuli [23]. The intent of this research is to create agents that behave like a human would behave in similar circumstances using the relatively novel Agent_Zero framework. The attempt to replicate human behavior in agent-based models, is not novel, however, and a brief discussion of the state of the art as it currently stands is warranted. This paper only seeks to review agent decision making models that look to mimic or replicate human behavior patterns. This paper will break current methods into four categories, summarized below. They are production rule systems, belief desire intent (BDI) and its derivatives, normative models, and cognitive models. [28]

2.3.1 Production Rule Systems

These systems vary in their complexity, but at their core, they are rules-based systems that can be viewed as a series of conditional statements. The most advanced of these systems came to be known as expert systems that took a series of facts and applied rules to reach an outcome [29]. These were the first agent cognitive models and require substantial coding for each scenario to prepare for simulation use.

2.3.2 BDI and its derivatives

The Belief Desire Intent (BDI) agent model has been very influential in the agent cognition field. This agent theory was initially developed by the philosopher Michael

Bratman and has been refined many times since its inception. This is a very influential agent modeling framework that is still widely used [28].

2.3.2.1 Belief Desire Intent

The BDI framework attempts to create agents that behave rationally, just as a human would behave rationally. It attempts to solve two problems with agents behaving rationally. First, the agents must be able to conduct means-end analysis while simultaneously weighing competing alternative courses of action. Second, this reasoning must be conducted in a resource bounded environment that limits the computational time devoted to each decision [30]. It accomplishes these competing goals using plans to reach decisions rather than creating novel solutions for each task.

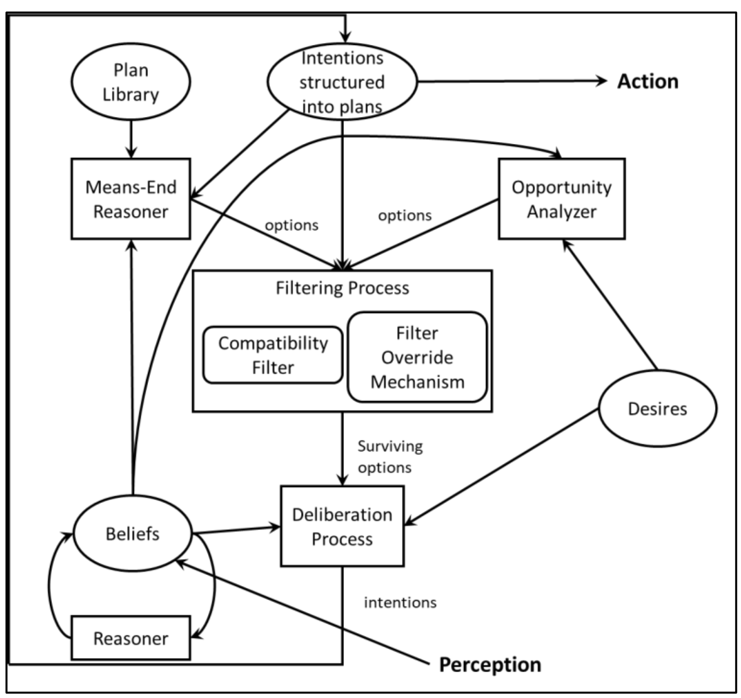

Figure 2. BDI Architecture.

The BDI architecture is a series of information stores, represented by the ovals in Figure 2 above, and filters, represented in the rectangular boxes above. Each decision draws on the information stores and is put through the filters which not only determine if a plan will meet desired ends, but as situations change, the agent will weigh whether reconsidering a decision is worth the computational effort to do so. The result is not necessarily a perfect decision, but it is an acceptable decision based on resource boundedness that can be adjusted by the agent programmer [30]. Distilled to its basics, the BDI agent uses a set of filters to first select an existing plan and then to select an action based on that plan after further filtering.

BDI only considers the rational decisions of each agent which has led to some criticism of its applicability as an accurate cognitive model. There have been several attempts to update this model with emotional and social elements as described below. The development of the plans for use in the model requires significant time and will change with each scenario, making this a difficult choice for a general civilian model.

2.3.2.2 Emotional Belief Desire Intent (eBDI)

The eBDI framework was an attempt by researchers to address the lack of an emotional element in the BDI agent model. Different teams took different approaches to modifying the BDI model. One group added an emotional consideration to the interpretation of perceptions that is another filter in the agent decision-making process as shown in Figure 3 below [28]. Other teams use emotions as an influencer on the BDI process throughout the various stages as shown in Figure 4 below [31]. Although there has been substantial effort placed into the theory of the eBDI model, practical applications have not emerged [28].

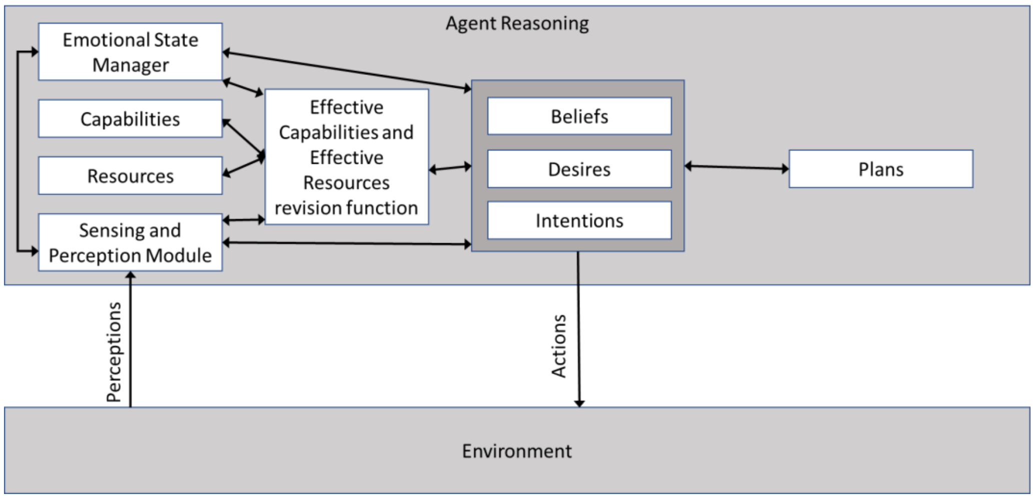

Figure 3. eBDI model 1.

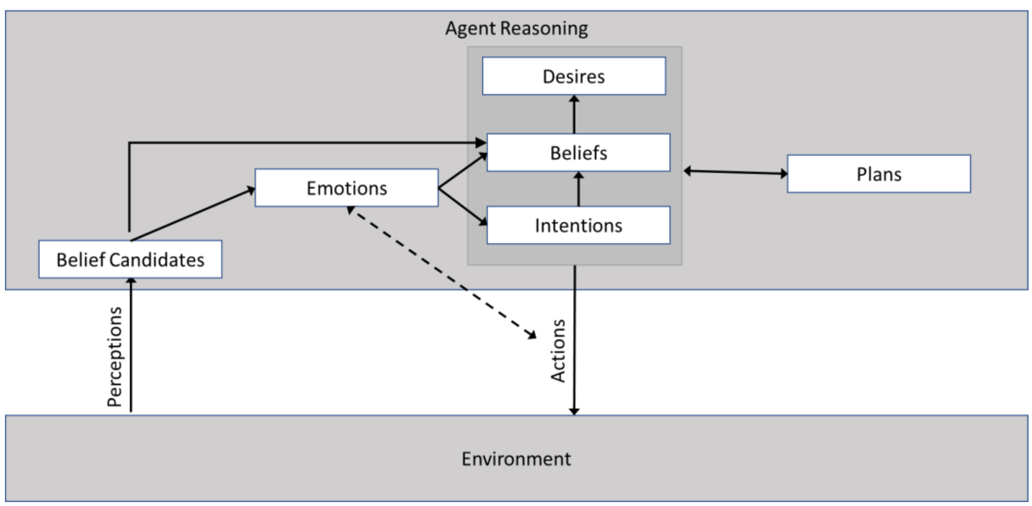

Figure 4. eBDI model 2.

2.3.2.3 BOID

The Beliefs-Obligations-Intentions-Desires(BOID) model is another attempt to add to the BDI model architecture. It adds a normative element to the BDI framework in the form of obligations. This agent model uses the concepts of BDI, but the interaction is different. In the BOID model, the decision-making process is completed through the conflict between the four considerations, beliefs, obligations, intentions, and desires. Different agent personalities cause a different weight being assigned to each of the four elements. A selfish agent, for example, would have desire weigh more heavily and obligations take a lesser role in agent deliberation. A social agent, by contrast, would weigh obligations more heavily than desires. The different agent types go through the decision-making process in different orders, a selfish agent would consider desires before obligations while a social agent would consider obligations before desires. Other agent types include realistic agents, who weigh beliefs heavily, and simple-minded agents, whose intentions overrule desires and obligations [32].

2.3.2.4 BRIDGE

The Belief-Response-Intent-Desire-Goal-Ego (BRIDGE) agent model is an attempt to add a more complex social element to the BDI architecture as well as a more complete internal decision-making process. It adds three new filters to the agent's decision-making process. Response describes the basic needs of each agent such as food, water, and shelter. Goals arise from desires and are realized by the selection of intentions or plans. Finally, ego refers to the agent's personality type and much like the BOID architecture, determines the priorities the agent will give to different filter types [28].

This architecture utilizes social norms to shape an agent's behavior but allows for each agent to override those norms through personality and necessity [33]. A key component to this architecture is the use of deontic logic to show the social relationships between agents through obligations and norms [34]. Both the BOID and BRIDGE models do not have a developed architecture to use in a simulation setting [28].

2.3.3 Normative Models

Whereas the rules-based and BDI based agents focused primarily on internal deliberations within the agents, there have been some efforts to more fully implement normative behavior models on agent systems [28].

2.3.3.1 Deliberate Normative Agents

This model predates the BOID architecture but is similar in its approach to agent modeling. Although not described as a BDI derivative, it takes a similar approach, but adds a layer of social norms as a filter that must be applied before selecting goals, plans, or actions [35]. The deliberative element of the model and architecture is that the agent must be able to adopt or violate the norm when it conflicts with other norms or personal goals.

2.3.3.2 EMIL-A

EMIL-A, or Emergence In the Loop Architecture is an attempt to model norm development by agents in a multiagent system. Essentially, this architecture discusses not only the internal deliberation of an agent that creates and deliberates about norms, but also the process of externally introduced norms and how the agent internalizes those. The developers describe it as a top-down and bottom-up process [36]. This model was specifically developed to mimic norm innovation in a social system as shown in Figure 5 below reproduced from Andrigehtto et al's work [37].

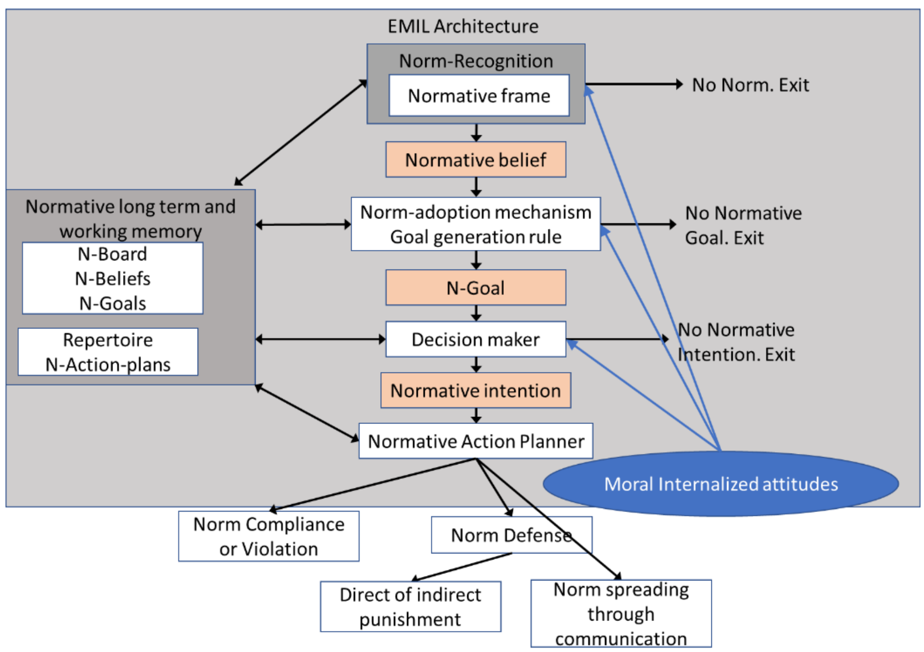

Figure 5. EMIL-A.

2.3.4 Cognitive Models

The remaining models can best be described as cognitive models that attempt to mimic the functions of the human brain. The models described up to this point require considerable tailoring to each scenario. Cognitive models, on the other hand, attempt to create agents that can generally be adapted to a wide variety of scenarios due to their attempts to mimic human cognition [28]. This is not a comprehensive list but should cover examples that represent current practice and theory.

2.3.4.1 PECS

The first cognitive model in the list is PECS which stands for: physical conditions, emotional states, cognitive capabilities, and social status. The creators of PECS explicitly call it a more detailed replacement model for BDI and its derivatives. PECS agents choose between three types of behavior, reactive, deliberative, and reflective, which are influenced by personality traits that are determined by set constants for each agent. The model is flexible, but at its core, it utilizes two functions. The first function handles the changes to internal state variables and the second reflects how the internal changes convert into agent behavior [38]. The model becomes complex as each agent can be further broken down into several components, each with a set of functions. For example, the cognition element of an agent includes a self-model, environment model, protocol memory, planning, and reflection. When you add to this the physical, emotional, and social elements, each agent becomes very complex. The model requires a communication center as well for each agent to communicate with the other agents in the model [39]. This model, along with most of the cognitive models, is complex and requires a substantial amount of computational resources for each agent. This model did not receive much practical use and was primarily a well-developed reference model [28].

2.3.4.2 CLARION

CLARION, or Connectionist Learning with Adaptive Rule Induction ON-line, is a model developed expressly to cover two dichotomies in cognitive models. The first is implicit cognition, or the “bottom up” learning and explicit cognition, or “top-down” learning of new skills by an agent [40]. The second dichotomy is the difference between action-centered and non-action centered representation [41]. The model is specifically designed to be broadly applicable to social systems due to its broad array of dual-process subsystems and ability for the agent to learn through trial and error, bottom-up, or through explicit means, top-down learning.

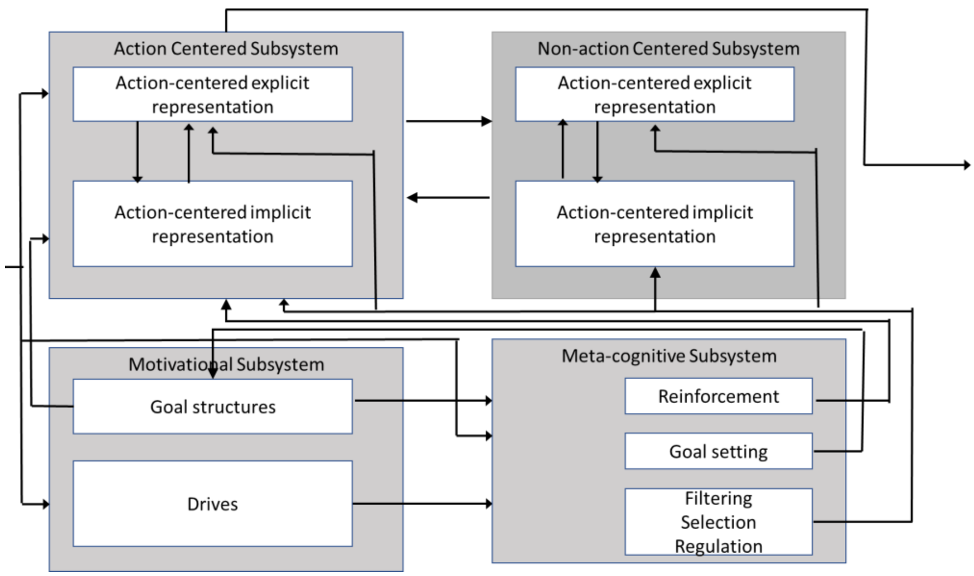

Figure 6. CLARION Architecture [41].

2.3.4.3 ACT-R/PM

ACT-R, Adaptive Control of Thought-Rational, is a high-level cognitive model for single agents that does not include a social element, although in theory multiple agents could exhibit emergent social behavior. It is very detailed in its internal deliberation as well as its interaction with the external world and has been applied primarily in artificial intelligence and robotics studies [42]. Because it has been mapped onto the human brain, researchers use it to predict human behavior [43]. The model uses two sets of memory, the declarative memory which stores facts and the procedural memory which stores rules to help it determine its actions based on its sensory input [28]. This model has been used in military applications in robotics [42], but is too resource intensive for use in a large multi-agent system.

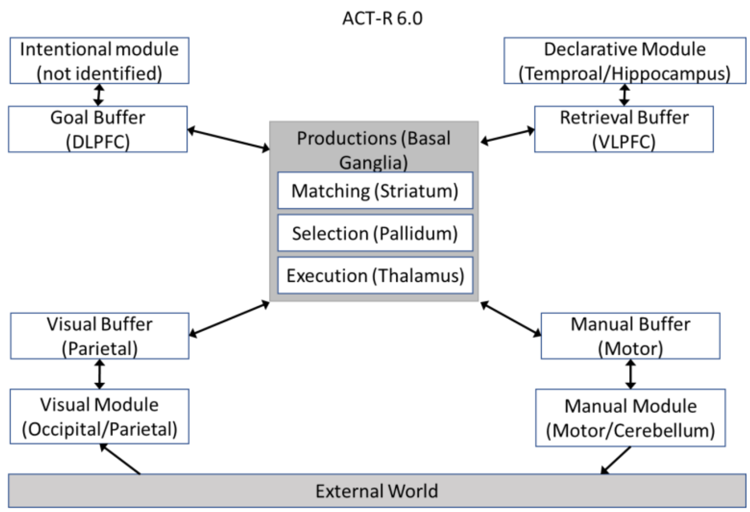

Figure 7. ACT-R 6.0 Architecture [43].

2.3.4.4 Soar

Soar is another influential attempt at developing a unifying cognitive framework to model agents on human behavior. It was developed by a series of researchers as a practical architecture for artificial intelligence [44]. Soar operates with a problem space computational model. It considers a problem from the context of its current state using its various memories and learning functions and then selects a new state based on its perception and application of its memory spaces [45]. An overview of the Soar version 9 architecture is provided below in Figure 8. Soar is a powerful model and architecture of human-like cognition. It is also complex and complicated and is not a good choice for a large multi-agent model like a military simulation.

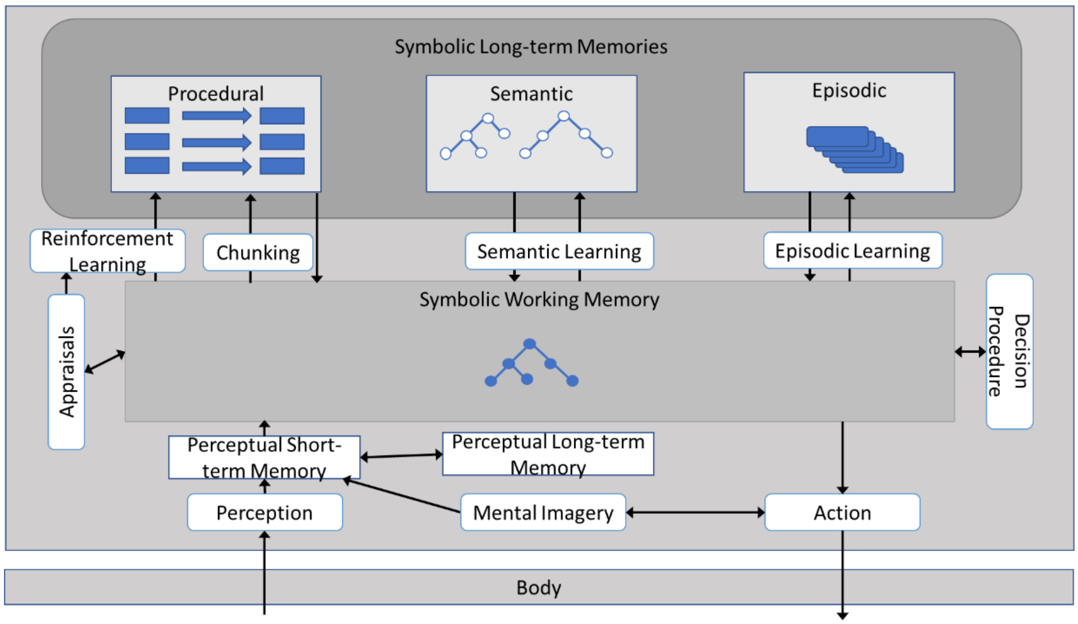

Figure 8. SOAR 9 Architecture [45].

2.4 Agent_Zero cognitive framework

The preceding agent neurocognitive models have limitations in either their scope of coverage of human cognition or in the complexity of their implantation and execution in a large multi-agent system. A recent neurocognitive model, the Agent Zero model, attempts to bridge the divide between a complete human neurocognitive model and a computationally manageable model in a multi-agent system [10].

2.4.1 Overview

For a successful civilian model to work, it must have the computational requirements of the simpler rules-based architectures, the internal emotional deliberations of the BDI derivative models, the social elements of the normative models, and a sufficiently realistic cognitive model. Earlier attempts to model civilians in a wartime setting have had different levels of success as shown above. Joshua Epstein proposed a new model, the Agent_Zero model, that addresses these requirements. It is computationally simple relative to other cognitive models. It gives each agent an internal rational and emotional process. It gives each agent a social element. Most importantly, the model uses sound neurocognitive science to develop adaptive agents that will work across a wide spectrum of scenarios with minimal time to develop new scripts and behaviors for each scenario.

The agent zero paradigm provides a launching point to develop a useful model that will not only show realistic emergent behavior of large groups of civilians represented by agents [46], but will also allow for analysis by the commander and his staff of what their military actions or inaction have wrought in the civilian population.:

Agent zero uses three connected modules to develop a decision threshold for each agent in a model. These are mathematically represented by the following:

$$D_i^{tot} = D_i^{solo}(t) + \sum_{j \neq i} w_{ji} D_j^{solo}(t)$$

As the solo disposition of each agent is determined by the affective and deliberative values over time or:

$$D_i^{solo}(t) = v_i(t) + p_i(t)$$

The equation can be rewritten as:

$$D_i^{tot} = v_i(t) + p_i(t) + \sum_{j \neq i} w_{ji}(v_j(t) + p_j(t))$$

where $D_i^{tot}$is the overall disposition value of each agent *(i)*, $D_i^{solo}(t)$is the sum of each agent's affective *v(t)* and rational *p(t)* values, $w_j$is the social weight of every other agent in the model other than *i* applied to the other agents' $D_j^{solo}(t)$value which is their affective and rational values. The functions *v(t)* and *p(t)* are each agent's internal affective and rational deliberations and memory respectively. The social element is simply the sum of all other agents' dispositions, with each agent being assigned a weight, *w*, based on their influence on the solo agent. The model will compare each agents' disposition against a threshold value τ, which once exceeded, will trigger agent actions, dependant on the scenario [10].

2.4.2 Affective Component

The affective or emotional component of the model is based on the Rescorla-Wagner theory of emotional conditioning. It mimics the plasticity of the human brain and relies on the idea of conditioning over time. The model replicates emotional learning and considers the effect of an unconditioned stimulus on the agents' response to associated stimuli. The example that Epstein uses is the attacks on 9/11 [10]. The flying of the planes into the world trade center and pentagon buildings were unconditioned stimuli. Many Westerners learned to associate these attacks with Muslims and developed a conditioned response to seeing perceived Muslim individuals. This learning to associate conditioned stimuli with unconditioned stimuli accumulates over time with exposure to the unconditioned stimuli, although the increase grows smaller with each exposure until it approaches a maximum value. [10] The equation used to determine each agent's affective state is:

$v_{t+1} - v_t = \alpha\beta(\lambda - v_t)$ where *t* represents trials, v_{t+1} is the new state, α is the salience of the conditioned stimulus, β is the salience of the unconditioned stimulus, and λ is the maximum value of *v* for that agent.

When written as a differential equation, the equation becomes $\frac{dv}{dt} = \alpha\beta v^{\delta}(\lambda - v)$ where δ is a value between 0 and 1 that represents the type of learner the agent is. The classical Rescorla-Wagner learning equation sets δ at 0 and can be solved as:

$$\frac{dv}{dt} = \alpha\beta(\lambda - v)\ where\ the\ solution\ is\ v(t) = \lambda\left(1 - e^{-\alpha\beta t}\right)$$

Represented graphically, the classic Rescorla-Wagner learning curve is represented in Figure 9 below. Note that the threshold, τ, is the point at which the agent will act based on the strength of the affective disposition.

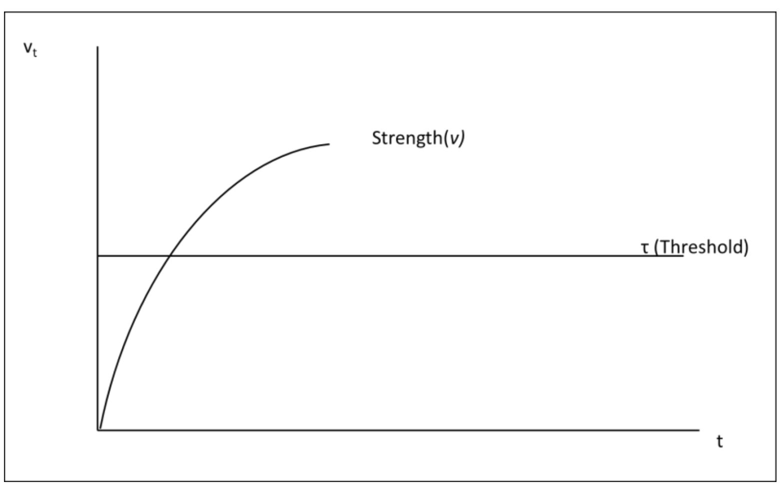

Figure 9. Rescorla-Wagner emotional learning curve.

The affective portion of the model also includes a decay element as well that considers the unlearning of conditioned stimuli and responses over time. The conditioned associations will decay over time in a process called extinction [10]. This process is expressed with the differential equation $\frac{dv}{dt} = \alpha\beta(0 - v)$ with $v(0)=v_{max}$ where , α is the salience of the conditioned stimulus, β is the salience of the unconditioned stimulus, and v_{max} is the maximum affective value reached prior to the extinction trigger. The equation's solution is: $v(t) = v_0 e^{-\alpha\beta t} = v_{max} e^{-\alpha\beta t}$. Figure 10 below shows the Rescorla-Wagner affective learning curve with the extinction element added at the point where the individual is no longer receiving the conditioning events.

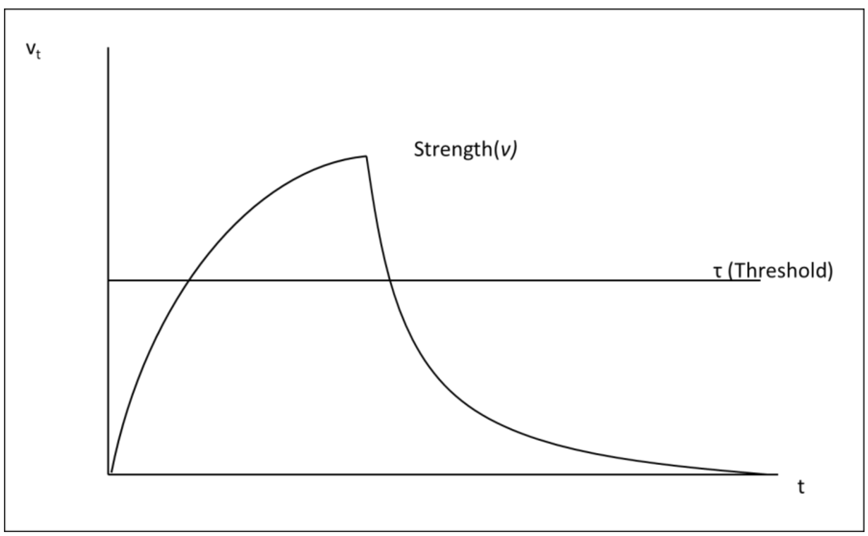

Figure 10. Rescorla-Wagner emotional learning curve with extinction.

2.4.2 Deliberative Component

The second module of the model is the rational or deliberative module. This portion of the model gives each agent the P value that will be added to the *v* value to determine the individual disposition of the agent without the inclusion of the third element of the model, the social. Each agent will use observation of their proximate areas to develop probabilities that certain events will happen. This local sampling will influence each agents' reasoning about the state of the entire world, with over and under sampling based on the local relative frequency of salient events. This value is added to the affective *v* value to give the individual agent's disposition without any social influence. [10] This sample area is illustrated in Figure 11, below.

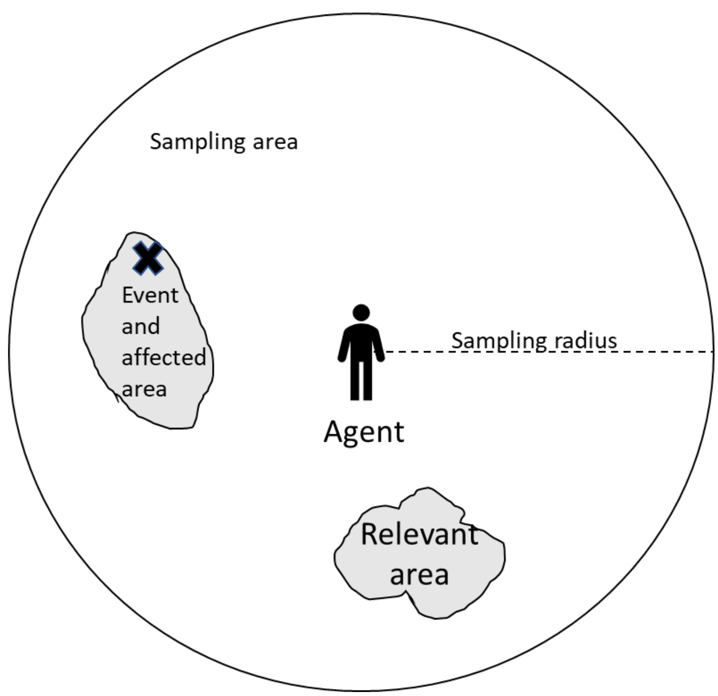

Figure 11. Agent probability value based on sampling area.

In Figure 11, there is an agent in the middle of the sampling area. The area is defined by a sampling radius. Inside the area, the agent will look for relevant affected areas determined by certain events. The affected areas inside the sampling area are then divided by the overall sampling area or ${total\ affected\ area}/_{total\ sample\ area}$ to arrive at the probability that a similar event affecting the agent's surroundings will occur in the immediate future. So for example, in a sampling area with and area of 30 and two relevant events that affect an area of size 6, the probability value would be 6/30 or 20%.

The Agent_Zero model adds a learning factor, or memory, to the rational element of the model as well by having each agent use an average of a given number of their observational probability estimates. This can be set at any value, but as an example, the agents' P value could be the average of the agents last five observations rather than only the last observation the agent made. So if the agent's last five probability values were 20%, 30%, 10%, 40%, and 0% the rational value for that agent would be 100%/5 or 20%. Even though the last probability calculation was 0%, the value used in the agent's disposition equation will be 20% based on its probability memory.

As a practical matter for the model to be developed, this rational P value will be updated with each time step in the simulation. The observation of the local neighborhood will be taken at each time step and the list of previous observational probability values will be updated as well.

2.4.3 Social Component

The last module of the agent zero paradigm is the social element. The Agent_Zero model uses the notion of emotional and rational contagion [10]. The concept is that even without direct observation, each agent will learn socially from the other agents in the simulation. In a modern context, this learning will be ubiquitous due to the inescapable communication technology pervasive in contemporary society. This value is derived by taking the sum of all the other agents weighted emotional and rational values. [10] The weight for the influence each agent will have on another agent can be set based on numerous factors such as family ties, ethnicity, proximity, or can be randomly assigned in more homogeneous populations. The modified dispositional determination for each agent will be:

$D_i^{tot} = v_i(t) + p(t)_i + \sum_{j \neq i} w_{ji}(v_j(t) + p_j(t))$ where $D_i^{tot}$is the overall disposition value of each agent *(i)*, $v(t)$is the affective value of each agent over time, *p(t)* is the rational value of each agent over time, and $w_j$is the social weight of every other agent in the model other than *i* applied to the other agents' $D_j^{solo}(t)$value which is the sum of their affective and rational values.

In the equation, each agent will be assigned a value, w, corresponding to the weight of their influence on the subject agent. The computation for each agent can be extensive in a large multi-agent simulation, so the scope of the simulation and the available computational power and time must be considered.

After adding each of the three values, these are compared to each agent's threshold value, τ, to determine whether the agent takes an action. [10] Each agent will have their own threshold value that will be compared to the net disposition at each time step in the simulation.

CHAPTER 3

RESEARCH PROJECT

3.1 Agent Zero Model Development

The model for this research begins with the basic Agent_Zero format developed by Epstein [10], but will utilize a more complex agent model that greatly increases the three agents that Epstein uses to explain his model. The model will use two disposition equations with separate thresholds, one which will track a spectrum of security and fear as laid out in the literature on civilian behavior and military tactics [14] and one which will track a spectrum of trust and anger levels per military doctrine and studies on counterinsurgencies and wartime actions in England [2, 18, 11]. Also, to address the unpredictable nature of human behavior in conflict and to cover past observed behaviors, the agents will not utilize a binary action threshold but stochastically choose between weighted actions upon reaching threshold values. The stochastic state changes are based on the research on fear and trust and will result in new behavior patterns for the agents based on the new state. In the case of both thresholds being reached in a single time step, a third group of stochastic decisions will be chosen.

3.1.1 Model Structure

The research model will be built using the NetLogo [47] programmable modeling environment in an enclosed 400 x 400 grid representing an urban area. Each trial will begin with 100 civilians, 20 enemy forces, and 10 friendly forces. For this research, we will assume that the civilians and forces are aggregated for simplicity to represent individuals. The model easily handled agent counts over 1000, but that many entities was distracting. The model resolution is kept low purposefully to reduce the computational and preparatory resources to implement in a simulation federation. The fidelity of the model, or accuracy of the model's representation of civilian behavior is intended to be high enough that the model's intended users will view the model as credible [48]. The purpose of the research is to show that a high level cognitive model can be used in a multi-agent system to realistically provide an autonomous civilian training model to military simulations.

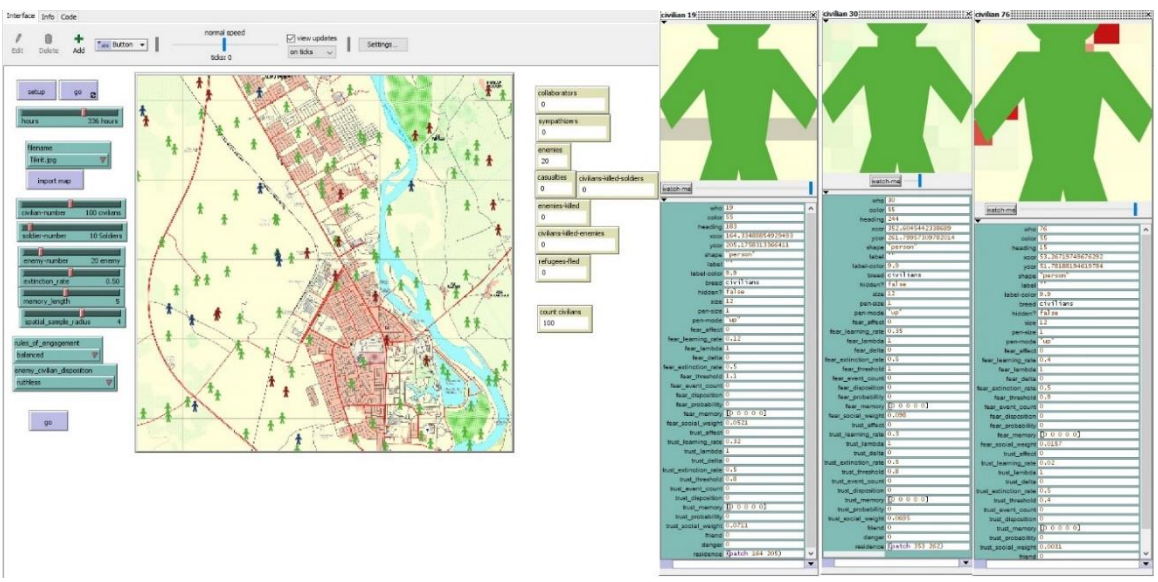

Figure 12. Simulation setup using Tikrit, Iraq and following 3 sample agents. Green figures are civilians, blue figures are friendly forces, red figures are enemy forces.

3.1.1.1 Disposition Calculations

The model will utilize the following two equations to measure each agent's disposition:

$$Dfear_i^{net} = vfear_i(t) + pfear_i(t) + w_i \sum_{j \neq i}(vfear_j(t) + pfear_j(t)) - \tau_{fear}^i$$

$$Dtrust_i^{net} = vtrust_i(t) + ptrust_i(t) + w_i \sum_{j \neq i}(vtrust_j(t) + ptrust_j(t)) \text{-}\ \tau_{trust}^i$$

D represents the disposition of each agent. The function *v(t)* is the value of each agent's emotional or affective state over time. The function *p(t)* is the rational probability calculation for each agent over a selected time period representing memory. The addition of *fear* and *trust* to each of the variables in the equations represents the two separate disposition calculations that each civilian agent will make. The value of *w* is a randomly assigned weighted social value that is applied to the sum of the other agents' dispositions. It should be noted that this is a slight departure from Epstein's social weighting mechanism. To simplify the computational load, each agent has a randomly assigned weight *w,* uniformly distributed between .001 and 0.1 that is applied to the sum of all the other agent's dispositions. This weight represents the different susceptibility of individuals to social pressure. This weight is applied to the sum of 99 other agents and should be somewhat equal to the affective and rational elements of the agent's disposition. Epstein weights each individual agent's disposition minus the social element before taking the sum and adding it to each agent's overall disposition. The threshold value τ is a randomly assigned value for each agent uniformly distributed between 0.2 and 1.1. The higher the value, the more resistant that agent is to act based on their disposition. In the basic Agent_Zero model created by Epstein, his agents have a threshold of 0.5 [10]. To replicate the different resistance to action each individual shows, the uniform distribution of thresholds is used.

The NetLogo code for the fear disposition is:

*set fear_disposition fear_affect + fear_probability + (fear_social_weight * ((sum [fear_affect] of other civilians) + (sum [fear_probability] of other civilians))) – fear_threshold*

This code matches the equation $Dfear_i^{net} = vfear_i(t) + pfear_i(t) + w_i \sum_{j \neq i}(vfear_j(t) + pfear_j(t)) - \tau_{fear}^{i}$ shown above and is executed with each time step. The trust disposition function is also executed in the same manner each time step.

Each civilian has a fear and a trust disposition and independent variables that interact with both. The enemy collaborators and friendly sympathizers each use only one disposition calculation, a trust calculation for the collaborators and a fear calculation for the sympathizers. All the disposition functions are structurally the same as the code shown above.

3.1.1.2 Affective Value Calculations

Recall from the discussion above that the equation to find the affective portion of each agent's disposition is represented by: $\frac{dv}{dt} = \alpha\beta v^{\delta}(\lambda - v)$. To represent this in NetLogo, the code becomes:

*set affect affect + (learning_rate * (affect ^ delta) * (lambda – affect)*

The learning rate for the research project replaces $\alpha\beta$ or the salience of the conditioned stimuli times the salience of the unconditioned stimuli. The rate is randomly assigned in the code as a uniformly distributed value between 0.01 and 0.5. The learning rate in the model shows the level of surprise to the stimuli exhibited. Some individuals will show more surprise than others. Epstein, in his three-agent base model, sets each agent's learning rate at 0.1 [10]. The affect is v from our equation. Delta can be any value between 0 and 1, but in the classic Rescorla-Wagner equation, delta is set at 0 [10] and for this research project, the classic value is used. Lastly, lambda is the maximum affective value possible for each agent. In this research project, that maximum value is set at 1, which approaches the maximum value for each agent's disposition threshold.

If the agent does not encounter the stimuli that change his affective value, a decay will occur in their affective value v, $\frac{dv}{dt} = \alpha\beta(0 - v)$. When implemented in the NetLogo language, this becomes:

*set affect affect + (learning_rate * (affect ^ delta) * extinction_rate * (0 - affect))*

This may look slightly different, but in the classic Rescorla-Wagner equations, delta is set at 0 [10], which reconciles the NetLogo code with the above equation.

3.1.1.3 Probability Value Calculations

The rational portion of each agent's disposition is a probability based on a sample area as shown in Figure 11 above. The agent looks for conditions in the area and divides this by the total area. The NetLogo code used for this for the civilian fear probability is:

let fear_current_probability (count patches in-radius-nowrap spatial_sample_radius with [pcolor = orange or pcolor = red or count casualties_by_soldier in-radius-nowrap 3 > 0 or count casualties_by_enemy in-radius-nowrap 5 > 0] / (count patches in-radius-nowrap spatial_sample_radius))

This example, shows the method each civilian agent uses to establish a single fear probability determination. Each will look for orange areas which are enemy controlled areas, red areas, which are areas where the two forces are in direct conflict, and will look for dead civilians, shown by an ‘x’ on the map. It will take the total number of red or orange tiles and dead civilians and divide this by the total sampling area to arrive at a probability value. This probability value represents the perceived likelihood that a fear-inducing event will happen to the agent in the immediate future, in this case a single timestep. In the research trials, the sampling radius for each agent was six tiles. The probability for the trust disposition was calculated similarly, but the agent looked for blue patches or enemy casualties to use in that probability sampling.

Each agent has a probability memory that uses the mean of the last five probability samplings to form their final $p(t)$ value used in their disposition calculation. At each time step, they will discard the probability sample from the sixth time step prior and use the new sample value to reach a new $p(t)$ value.

3.1.1.3 Model Progression

The disposition value will be updated each time step. The time steps used in the research model will represent hours and will be set for 336 steps, the number of hours in a typical 2-week military exercise. The model is computationally able to represent behavior in real-time, with appropriate adjustments to the movement speed and rate the agents develop disposition values.

The model will establish zones based on the behavior of the combatants that the civilian agents will determine their individual affective and rational values from. The presence of slain civilians will also affect the civilian dispositions as well. Areas of fear, which are enemy influenced will be represented using orange. Areas secured by friendly forces will be shown by blue, and areas where the opposing forces are in conflict will be shown in red. The dead bodies will be represented by 'x' symbols.

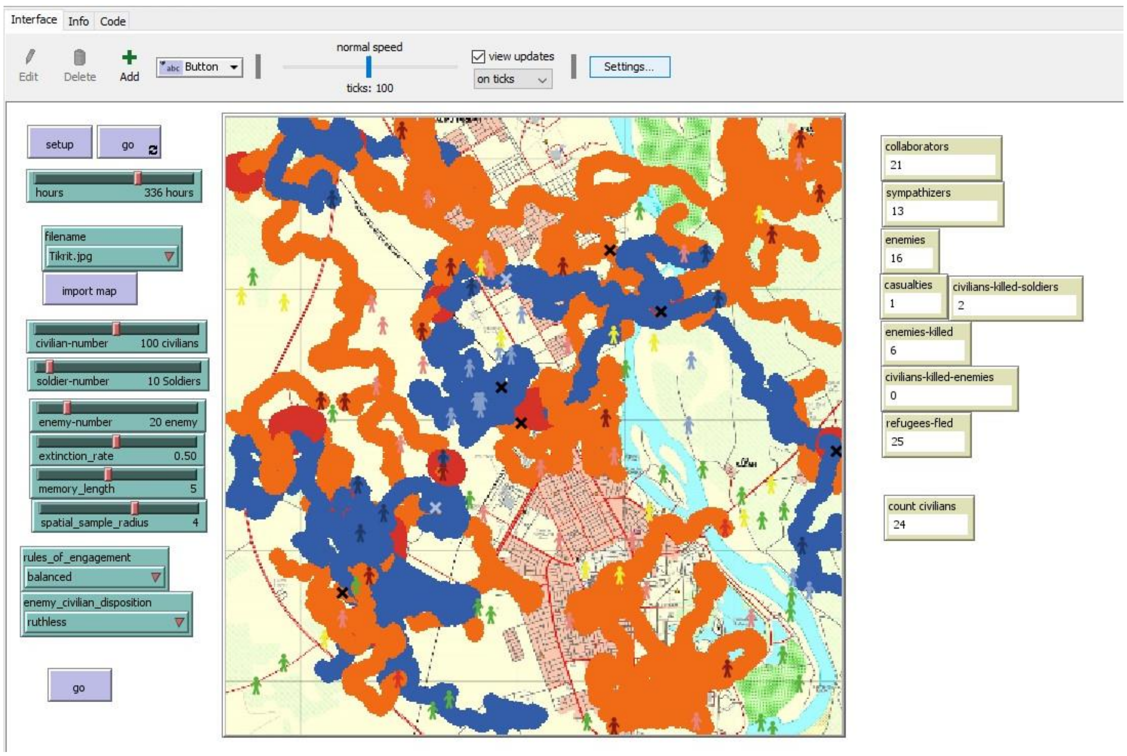

Figure 13. Simulation after 100 timesteps. Orange is an enemy patrolled area, blue is a friendly controlled area, red is a battle area, 'x's represent battle related deaths. Light blue figures are friendly sympathizers, pink figures are enemy collaborators, and yellow figures are civilians fleeing the area.

3.1.1.3 Agent State Change

This research project will use the two competing theories of civilian behavior on a battlefield to calculate stochastic state changes that will occur when one of the two thresholds are reached: the fear threshold that coincides with violence and enemy intimidation and the trust threshold that coincides with security and effective military behavior. As discussed above, some evidence points to violence leading to advantageous outcomes with regards to civilians – either their removal from the area with death or migration or their decision to aid the forces terrorizing them [14]. For this reason, when the fear threshold is exceeded, there will be a strong inclination to either collaborate with or join the enemy or to leave the area altogether. When friendly forces control and secure areas and deal with enemy forces effectively, the civilians will exhibit a state change in which they cooperate with the friendly military forces as established in both U.S. military doctrine [2] and also by academics looking at the motivations for exerting control through violent means [13]. For this reason, when the trust threshold is exceeded, the civilians will tend to sympathize with and assist the friendly forces in the model. When both thresholds are exceeded simultaneously, both options will be stochastically available to the civilian agent with the likelihood skewing towards cooperation with the enemy or flight.

The model will then measure the disposition values against the fear and trust thresholds for each agent to determine actions based on the following pseudo code:

$If\ Dfear_i^{net} \geq \tau_{fear}^i\ \&\ Dtrust_i^{net} \geq \tau_{trust}^i$ *then:*

35% Aid enemy

10% Aid friendly

15% Flee

40% No change – drop fear and trust disposition down by 0.5

$If\ Dfear_i^{net} \geq \tau_{fear}^i\ \&\ Dtrust_1^{net} < \tau_{trust}^i$ *then:*

30% Flee

30% Aid enemy

5% Aid friendly

5% Join enemy as a combatant

30% No change – drop fear disposition by 0.5

$If\ Dfear_i^{net} < \tau_{fear}^i\ \&\ Dtrust_i^{net} \geq \tau_{trust}^i$*then:*

30% Aid friendly

70% No change – drop trust disposition by 0.5

$Dfear_i^{net}$is the fear disposition of each agent. $\tau_{fear}^i$is the fear threshold value for each agent. $Dtrust_i^{net}$is the overall trust disposition for each agent and $\tau_{trust}^i$is the trust threshold value for each agent. At each time step in the simulation, the agent will first check whether both threshold's have been exceeded. Next, they will check to see if the fear threshold alone has been exceeded and last, each agent will check to see if the trust threshold has been exceeded.

As an example of how the NetLogo code works, the first stochastic state change shown above is:

```
ask civilians [
  if fear_disposition > 0 and trust_disposition > 0 [
   let x random 20
```

```
cf:when
cf:case [ x < 7 ] [
  hatch-collaborators 1 [
  **collaborator variable initiation code removed for brevity**
 die]
cf:case [ x < 9 ] [
  hatch-sympathizers 1 [
  **sympathizer variable initiation code removed for brevty**
 die]
cf:case [x < 12 ] [
  hatch-refugees 1 [
  die ]
cf:else [
  set fear_disposition fear_disposition - 0.5
 set trust_disposition trust_disposition - 0.5
]
]
```

The final if:else statement reduces the disposition values so that the civilians will need to build up to the threshold value again if they do not undergo a state change. It should be noted that the NetLogo code subtracts the threshold value from the disposition value to arrive at the final fear_threshold and trust_threshold values. This is then compared to zero (0) to determine if the state change threshold has been reached for the two values by each agent.

The model also uses an Agent_Zero calculation for the friendly sympathizer and enemy collaborators as well. The friendly sympathizers use a fear disposition formula that is checked against a randomly assigned threshold. When it is exceeded, they have a 50% chance to become normal civilians again with newly initialized fear and trust disposition values, a 5% chance to flee the conflict area, and a 45% chance to remain the same.

The enemy collaborators use a trust disposition formula that has the following results then the threshold is exceeded: 50% chance to return to a normal civilian, 5% chance to flee the area, 45% chance to remain an enemy collaborator. These values for the sympathizers and collaborators were chosen after calibrating the model to maintain an environment with different agent types interacting with the friendly and enemy forces.

It should be noted that normal civilians, when faced with dangerous conditions, will internally displace themselves away from danger until they find a secure area on the map. The externally displaced refugees will flee until reaching the edge of the map and then become a statistic for the training audience to track and address.

3.1.1.3 Agent Behavior

The remainder of the code used in the simulation deals with the behavior of the various agents as they navigate the battlefield. In the first tactical variation, Soldiers and enemies will search the battlefield for targets using a cone that extends out in the direction they are facing. Once they identify a target, they will then move towards that target and attempt to neutralize it. Their ability to effectively combat each other is influenced by cooperating civilians near the engagement. Civilians aiding the enemy forces will make the enemy more effective in combat by a factor of 2. This value was chosen after model calibration because civilian cooperation makes military operations by either side of a conflict much more efficacious. Likewise, civilians cooperating with friendly forces will make them more effective at neutralizing enemy forces by a factor of 2 as well. This corresponds to the human intelligence that noncombatants provide about location, composition, and disposition of combatants on the battlefield.

In order to show that the model varies based on the tactical decisions of the Soldiers, two other behavior models for the Soldiers will be used in 30 trial experiments for comparison. The second Soldier behavior tactic will be a protection function where the Soldiers will randomly select a civilian and an enemy across the battlefield and attempt to keep themselves between those two agents. The third tactic to be tested will be a much more local protection function in which the Soldier will find the nearest civilian and nearest enemy to themselves and again attempt to interpose themselves between those two agents.

Normal civilians will stay in their neighborhood, moving around their residence assigned at the creation of the trial. If the area becomes dangerous, they will attempt to keep a Soldier between themselves and the enemy and will move until they find a new secure area which they will make their residence and roam around. This replicates internal displacement patterns in an area and is different from the external displacement of civilians who have undergone a state change and are fleeing the area entirely.

Friendly sympathizers will attempt to place themselves between Soldiers and enemy forces and attempt to aid the Soldiers against the enemy through intel which makes the Soldiers more efficient at eliminating enemy forces. Likewise, enemy collaborators will do the opposite, attempting to assist enemy forces against the friendly Soldiers. Externally displaced civilians will move to the edge of the map in their current heading until they leave the area.

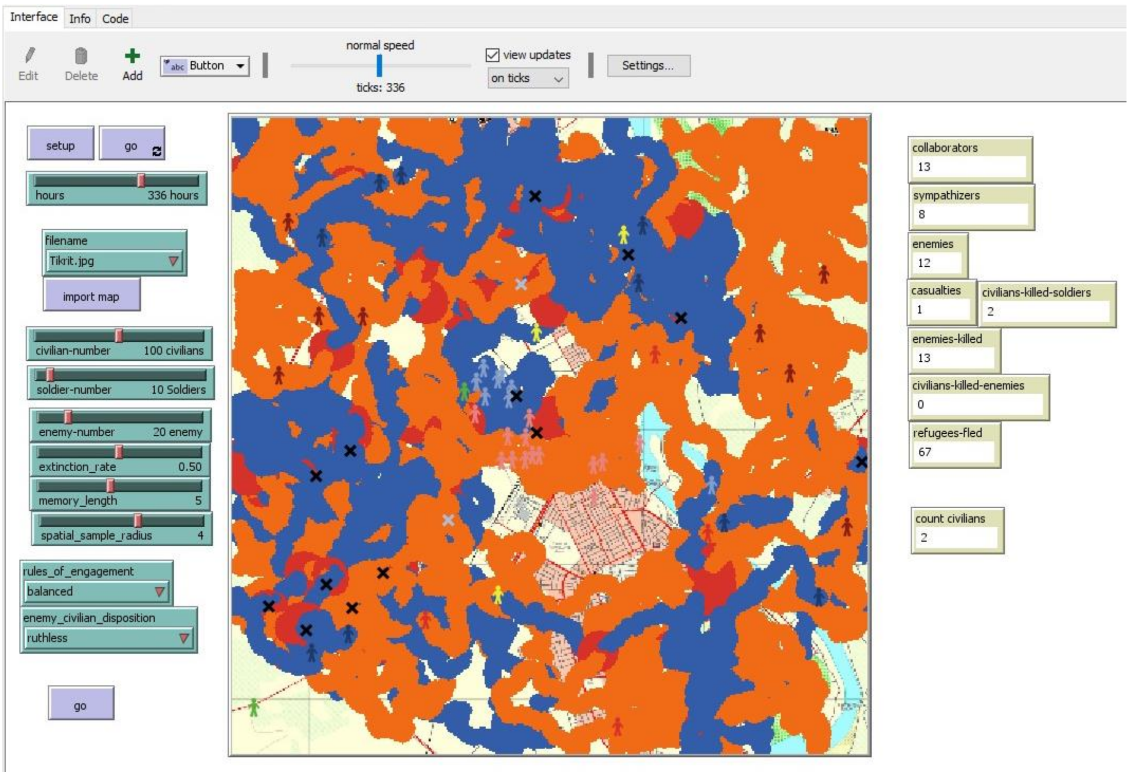

Figure 14. End state of a trial run.

3.1.2 NetLogo Code

Included in Appendix 1 is the code used for the NetLogo trials. It should be noted that the probabilities, social weights, sample areas, threshold values, learning rates, and behavior patterns can be quickly and easily modified to reflect different scenarios. All comments are preceded by a semicolon (;). The NetLogo version is 6.02 and uses an extension CF which allows for switch (choose from) statements in the coding.

3.2 Validation Methods

There were no quantitative values to conduct dynamic or formal testing methods to validate the model. Because of this, informal testing methods were employed to validate the model. [49]

The model results were sent to subject matter experts in the military for informal testing methods including checking the model methodology and reviewing the model results. The experts reviewing the model and material are located at the Joint Multinational Simulation Center in Grafenwoehr Germany, the NATO Center of Excellence in Simulation in Rome, and the US Military Academy at Westpoint to determine if the results are realistic and useable in a training environment. The experts were still reviewing the model and results at the time of publication of this thesis.

The author of this research, MAJ Aaron Beam, US Army, has served as a combat advisor in both Iraq and Afghanistan and was formally trained in counterinsurgency operations by the US Army prior to deploying to Iraq in 2007. The generation and calibration of the model was partially based on this experience and knowledge of the topic. MAJ Beam is a subject matter expert on civilian behavior in urban insurgency situations as used to test the model and conducted a thorough review of the results. He concluded that the model uses simplistic behavior algorithms, but the internal cognition of the agents is sound, and the behavior of the civilians is realistic and valuable to a training audience or decisionmaker.

The author will continue to seek model validation and feedback to increase the fidelity levels of the model moving forward. Further efforts in this area will lend more credibility to the model as a decision making and training tool suitable for military use.

CHAPTER 4

RESULTS AND ANALYSIS

4.1 Data Analysis

As part of the experiment, 90 trials were conducted using three behavior patterns with the Soldiers. The complete trial results can be studied in appendix 3. In the first 30 trials, the Soldiers search for enemies and attack them. In the second 30 trials, the Soldiers attempt to protect civilians using a selection pattern across the entire battlefield. In the third series of 30 trials, the Soldiers select the closest civilians to protect from the nearest enemy. In the following tables, the charts show a comparison of the results for the trials across a 95% confidence interval for data points that would be of interest to a commander. Specifically, the variables measured are the number of “normal” civilians that remain at the end of the battle, the number of externally displaced civilians who have fled the area, the number of civilians who are actively collaborating with the enemy, the number of civilians who are actively working with friendly forces, the final count of enemy forces, the number of enemy deaths, the number of friendly deaths, and the number of civilian deaths. The chart below takes each of these variables for the three types of trials and compares them using a 95% confidence interval to measure whether the model is statistically different when the Soldiers vary their tactics.

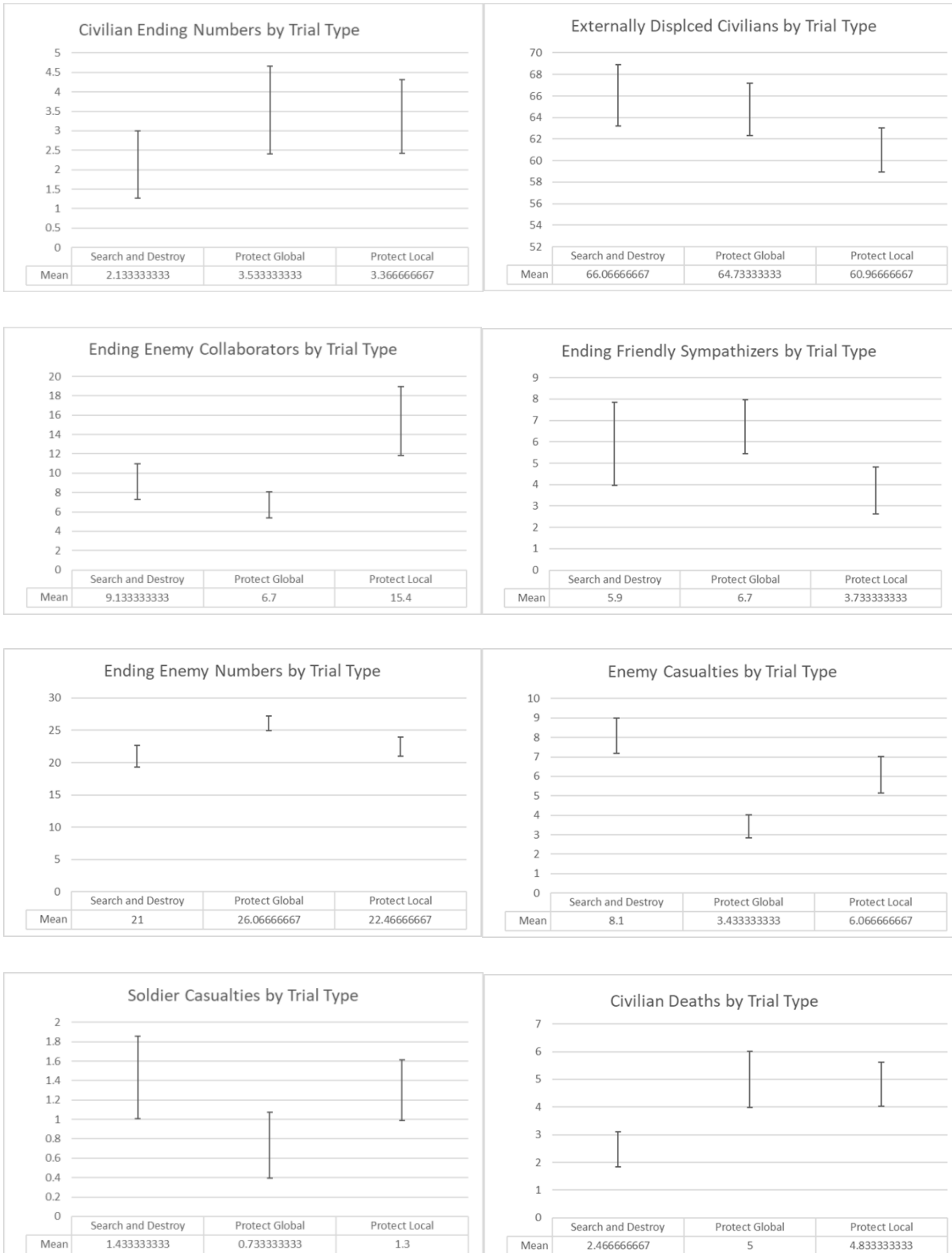

Figure 15. Statistical comparison of 3 Soldier tactics.

The trials produced some statistically distinct results and some that showed statistical overlap at the 95% confidence interval. The ending numbers of regular civilians were statistically the same despite Soldier tactics. This could be due to threshold values that are too low or social weights that are too high. Further calibration could be taken if more civilians are expected to remain on the battlefield. The search and destroy tactic produced a statistically significant higher number of collaborators than the local security tactic. The enemy casualties were predictably statistically higher when the Soldiers used the search and destroy tactic. This shows that different tactics cause the model to behave differently. The statistically similar results were interesting because the way the model arrived at them was very different. The trials also show surprising results for some metrics. For example, the two protection tactics used by the Soldiers result in more civilians remaining and fewer displaced civilians at the end, but also caused higher civilian casualties inflicted by the Soldiers. The proximity of the Soldiers to the civilians is the most likely cause and this would be an important factor for a commander to consider.

The results are promising. They are also easily adjusted to possible future gathered data on civilian behavior on a battlefield. NetLogo is not an efficient programming language from a computational standpoint, but the trials moved on a modestly built laptop at a pace that would easily keep up not only with a real-time training event, but also could be used in operational planning to evaluate civilian behaviors based on different courses of action. The use of the Agent_Zero neurocognitive model produced a robust response by autonomous civilian agents to a battlefield situation. It is also important that the civilians were reacting based on their scientifically supported internal deliberation, which the training audience can access and evaluate at any time. An example of this is shown in Figure 16 below. The agent’s internal memory is available and recordable for analysis on the impact of tactical and operational decisions. This will allow decisions to be modified towards desirable civilian outcomes in mission planning and training scenarios.

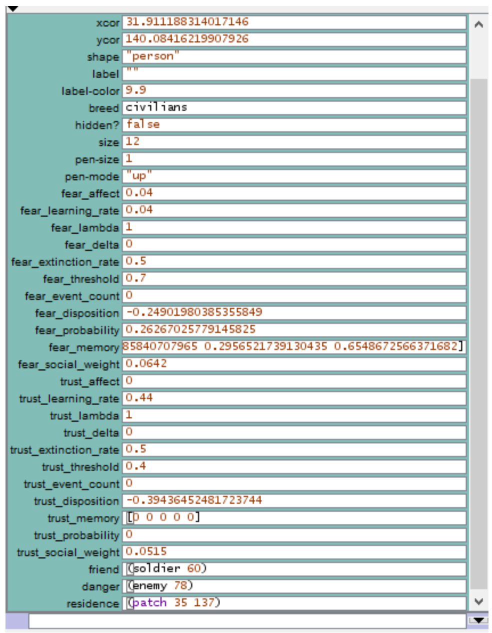

Figure 16. cognitive and behavior values for one civilian agent tracked by NetLogo.

This model was running a simple battlefield scenario with autonomous Soldiers and enemies inside the model itself. A useable model would not use internal combatants but would need to receive simulation data from a simulation federation. Only data about combatant positions, impact areas, and casualties would need to be passed through the federation infrastructure to the civilian model for it to make the requisite deliberation and behavioral computations. The civilian model would then need to pass the civilian positional data back to the federation for use by the other simulation programs to show how civilians are reacting to the battlefield. Using the High Level Architecture (HLA) data formats to pass the model information would be the ideal solution, using a standard HLA runtime infrastructure [48]. Development of a simple terrain capability within the model would be necessary to show civilian movement only in areas that make sense and to allow the model to work properly within a federated scenario [48]. Also, the ability of collaborators and sympathizers to pass human intelligence to combatants would need to be considered as well – either they would become low level sensors [48] in the federation or the intel could be passed via scripted injects.

The low computational requirements of this model provide flexibility in the use of hardware to implement it, conceivably running in the background of already existing exercise hardware. It is also not inconceivable that this could be used with military gaming applications such as the Virtual Battlespace 3 (VBS3) [50] to introduce more complex individual civilian behavior in those virtual scenarios.

4.2 Future Work

Moving forward, the author of this research would like to further calibrate the civilian state change algorithms and battlefield behavior patterns with more quantitative resources or the input of more subject matter experts. Following the refinement which will increase the fidelity and credibility of the model, work should done to federate the model into a military simulation to test civilian behavior when confronted with a more substantial and realistic military event than the simple military scenario produced in NetLogo for this experiment. This experiment was specifically designed to show that an Agent_Zero based model could be used to produce autonomous deliberative agents within a military simulation at a low cost, but the civilian behavior algorithms should be improved and made more complex, varied, and realistic to provide a more robust experience for the training audience. Interaction with the environment, rather than simply with the military events, would have to be included to some degree by the civilians, but was not considered in this experiment.

4.3 Conclusion

The military, particularly ground components, have a demonstrated need for training with civilians on the battlefield. Historically, this has proven to be a resource intensive training endeavor that causes leaders and training audiences to make difficult decisions about civilian interaction in training events. A neurocognitively sound, resource minimal, and implementable civilian training model is needed by the US Military. An Agent_Zero model has been shown by this experiment, with further refinement, to be a viable solution to this problem. It is a realistic, adaptive, resource minimal, and easily implemented solution to the need for civilian inclusion in battlefield and operational scenarios across a wide spectrum of military operations.

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APPENDICES

APPENDIX 1 MODEL VARIABLES

Variable Name	Value	Agent_Zero model equivalent	Description
fear_affect	Starts at 0	$v(t)$, where $\frac{dv}{dt} = \alpha\beta v^{\delta}(\lambda - v)$	triggered by a conditional that checks for fear inducing patches
fear_learning_rate	random .01 – 0.5	$\alpha\beta$ or the salience of the conditioned stimuli times the salience of the unconditioned stimuli	determines how susceptible the agent is to fear conditioning stimuli
fear_lambda	1	λ	maximum affective value possible
fear_delta	0	δ	type of learner the agent is. Classic Rescorla-Wagner models set this at 0
fear_extinction_rate	set at 0.5	$\frac{dv}{dt} = \alpha\beta(0 - v)$	the equation calculates the extinction rate of the affective value when stimuli are not present. In this model, $\alpha\beta$ is set at 0.5 by default
fear_threshold	random 0.2 – 1.1	τ	Point at which the agent will make an action. In this case, state changes based on the fear state
fear_event_count	starts at 0	not used	
fear_disposition	starts at 0	$Dfear_i^{net} = vfear_i(t) + pfear_i(t) +$	Equation used to determine the fear disposition of each civilian

		$w_i \sum_{j \neq i}(vfear_j(t) + pfear_j(t)) - \tau^i_{fear}$	by adding the affective, probability, and social values
fear_probability	starts at 0	*p(t)*, sample of events of a determined type within a set sample area divided by the overall area size	orange, red, or civilian dead patches over the area defined by the user determined sample radius with a default of radius 6
fear_memory	set by user, default 5	mean of a set number of current and prior probability samples	Takes the last current fear probability sample and averages it with the previous 4
fear_social_weight	random .0001 - .10	*w*, weight given to every other agents' affective and probability values	to conserve computing power, this value is applied to the sum of all other agents affective and probability values
trust_affect	starts at 0, 1.1 max	*v*, where $\frac{dv}{dt} = \alpha\beta v^{\delta}(\lambda - v)$	triggered by a conditional that checks for trust inducing patches
trust_learning_rate	random .01 – 0.5	$\alpha\beta$ or the salience of the conditioned stimuli times the salience of the unconditioned stimuli	determines how susceptible the agent is to trust conditioning stimuli
trust_lambda	1	λ	maximum affective value possible
trust_delta	0	δ	type of learner the agent is. Classic Rescorla-Wagner models set this at 0

trust_extinction_rate	set at 0.5	$\frac{dv}{dt} = \alpha\beta(0 - v)$	the equation calculates the extinction rate of the affective value when stimuli are not present. In this model, $\alpha\beta$ is set at 0.5 by default
trust_threshold	random 0.2 – 1.1	τ	Point at which the agent will make an action. In this case, state changes based on the trust state
trust_event_count	starts at 0	not used	
trust_disposition	starts at 0	$Dtrust_i^{net} = vtrust_i(t) + ptrust_i(t) + w_i \sum_{j \neq i}(vtrust_j(t) + ptrust_j(t))$- τ_{trust}^{i}	Equation used to determine the trust disposition of each civilian by adding the affective, probability, and social values
trust_memory	starts at 0	*p(t)*, sample of events of a determined type within a set sample area divided by the overall area size	blue or enemy dead patches over the area defined by the user determined sample radius with a default of radius 6
trust_probability	set by user, default 5	mean of a set number of current and prior probability samples	Takes the last current trust probability sample and averages it with the previous 4
trust_social_weight	random .0001 - .10	*w*, weight given to every other agents' affective and probability values	to conserve computing power, this value is applied to the sum of all other agents affective

			and probability values
friend	civilian randomly selected Soldier	n/a	if the civilian finds itself in a dangerous neighborhood, they will attempt to place a Soldier (friend)between themselves and an enemy (danger)
danger	civilian randomly selected enemy	n/a	see friend above
residence	anchor point set at civilian initiation and changed when current residence becomes unsafe	n/a	civilians will not move more than 20 patches from this point. Set at the civilian initiation point, will move if the civilian is in danger (internal displacement)
target	enemy selected by Soldier to engage	n/a	Soldier will pursue this agent until it is eliminated
invader	Soldier selected by enemy to engage	n/a	enemy will pursue this agent until it is eliminated
foreign_invader	collaborator randomly selected Soldier	n/a	collaborator agent will attempt to keep themselves between this Soldier (foreign_invader) and an enemy agent (defender)
defender	collaborator randomly	n/a	see foreign_invader

	selected enemy		
c_trust_affect	starts at 0, 1.1 max	v, where $\frac{dv}{dt} = \alpha\beta v^{\delta}(\lambda - v)$	triggered by a conditional that checks for trust inducing patches
c_trust_learning_rate	random .01 – 0.5	$\alpha\beta$ or the salience of the conditioned stimuli times the salience of the unconditioned stimuli	determines how susceptible the collaborator agent is to trust conditioning stimuli
c_trust_lambda	1	λ	maximum affective value possible
c_trust_delta	0	δ	type of learner the collaborator agent is. Classic Rescorla-Wagner models set this at 0
c_trust_extinction_rate	set at 0.5	$\frac{dv}{dt} = \alpha\beta(0 - v)$	the equation calculates the extinction rate of the affective value when stimuli are not present. In this model, $\alpha\beta$ is set at 0.5 by default
c_trust_threshold	random 0.2 – 1.1	τ	Point at which the agent will make an action. In this case, state changes based on the trust state
c_trust_event_count	starts at 0	not used	
c_trust_disposition	starts at 0	$Dc\_trust_1^{net} = v_1(t) + P_1 + w_1((v_2(t) + P_2) + (v_3(t) + P_3) + \cdots (v_n(t) + P_n)) - \tau_{c\_trust}$	Equation used to determine the trust disposition of each collaborator by adding the affective,

			probability, and social values
c_trust_memory	starts at 0	*p*, sample of events of a determined type within a set sample area divided by the overall area size	blue or enemy dead patches over the area defined by the user determined sample radius with a default of radius 6
c_trust_probability	set by user, default 5	mean of a set number of current and prior probability samples	Takes the last current trust probability sample and averages it with the previous 4
c_trust_social_weight	random .0001 - .10	*w*, weight given to every other agents' affective and probability values	to conserve computing power, this value is applied to the sum of all other agents affective and probability values
terrorist	sympathizer randomly selected enemy	n/a	the sympathizer will attempt to place itself between this enemy (terrorist) and a Soldier (liberator)
liberator	sympathizer randomly selected Soldier	n/a	see terrorist
s_fear_affect	starts at 0, 1.1 max	v, where $\frac{dv}{dt} = \alpha\beta v^{\delta}(\lambda - v)$	triggered by a conditional that checks for fear inducing patches
s_fear_learning_rate	random .01 – 0.5	$\alpha\beta$ or the salience of the conditioned stimuli times the salience of the unconditioned stimuli	determines how susceptible the sympathizer agent is to fear conditioning stimuli

s_fear_lambda	1	λ	maximum affective value possible
s_fear_delta	0	δ	type of learner the sympathizer is. Classic Rescorla-Wagner models set this at 0
s_fear_extinction_rate	set at 0.5	$\frac{dv}{dt} = \alpha\beta(0 - v)$	the equation calculates the extinction rate of the affective value when stimuli are not present. In this model, $\alpha\beta$ is set at 0.5 by default
s_fear_threshold	random 0.2 – 1.1	τ	Point at which the sympathizer will make an action. In this case, state changes based on the fear state
s_fear_event_count	starts at 0	not used	
s_fear_disposition	starts at 0	$Ds\_fear_1^{net} = v_1(t) + P_1 + w_1((v_2(t) + P_2) + (v_3(t) + P_3) + \cdots (v_n(t) + P_n)) - \tau_{s\_fear}$	Equation used to determine the fear disposition of each sympathizer by adding the affective, probability, and social values
s_fear_probability	starts at 0	*p*, sample of events of a determined type within a set sample area divided by the overall area size	orange, red, or civilian dead patches over the area defined by the user determined sample radius with a default of radius 6

s_fear_memory	set by user, default 5	mean of a set number of current and prior probability samples	Takes the last current fear probability sample and averages it with the previous 4
s_fear_social_weight	random .0001 - .10	*w*, weight given to every other agents' affective and probability values	to conserve computing power, this value is applied to the sum of all other sympathizer affective and probability values
engagement-area?	Boolean value true if Soldier and enemy present in 10 tile radius	n/a	used to set patch properties used in the affective and probability calculations. Sets patch color to red
atrocity-area?	not used	n/a	
secure-area?	Boolean value true if only Soldiers present in 10 tile radius	n/a	used to set patch properties used in the affective and probability calculations. Sets patch color to blue
fear-area?	Boolean value true if only enemy present in 10 tile radius	n/a	used to set patch properties used in the affective and probability calculations. Sets patch color to orange
dead-body?	not used	n/a	
civilian-number	set by user, default is 100	n/a	Starting number of Soldiers set by user. Default is 100
soldier-number	set by user, default is 10	n/a	starting number of Soldiers set by user. Default is 10

enemy-number	set by user, default is 20	n/a	starting number of enemies set by user. Default is 20
extinction_rate	set by user, default is 0.5	$\frac{dv}{dt} = \alpha\beta(0 - v)$	value chosen by the user to set the extinction rates used in the affective calculations
memory_length	set by user, default is 5	mean for *n* probability samples *p*	allows the agent to use their current probability sample as well as *n* recent samples to derive the probability value *p*
spatial_sample_radius	set by user, default is 6 tiles	used to derive probability of events in a proscribed area	In this model, samples for area types and casualties
rules_of_engagement	set by user. Can be “restrictive”, “balanced”, or “liberal”	n/a	changes the probability values in the model that civilians will be harmed by Soldiers
enemy_civilian_disposition	set by user. Can be “cautious”, “aggressive”, or “ruthless”	n/a	changes the probability values in the model that civilians will be harmed by enemies

APPENDIX 2 NETLOGO CODE

```
extensions [CF]

;civilian types
breed [civilians civilian]
breed [soldiers soldier]
breed [enemies enemy]
breed [collaborators collaborator]
breed [sympathizers sympathizer]
breed [refugees refugee]

;civilians killed
breed [casualties_by_soldier casualty_by_soldier]
breed [casualties_by_enemy casualty_by_enemy]

;enemies killed
breed [dead_enemies dead_enemy]

;counters
globals [refugees-fled enemies-killed casualties civilians-killed-enemies civilians-
killed-soldiers]

civilians-own [
  ;fear threshold variables
  fear_affect
  fear_learning_rate
  fear_lambda
  fear_delta
  fear_extinction_rate
  fear_threshold
  fear_event_count
  fear_disposition
  fear_probability
  fear_memory
  fear_social_weight

  ;trust threshold variables
  trust_affect
  trust_learning_rate
  trust_lambda
  trust_delta
  trust_extinction_rate
  trust_threshold
  trust_event_count
```

```
  trust_disposition
  trust_memory
  trust_probability
  trust_social_weight

  ;designators for movement behavior
  friend
  danger
  residence
]

soldiers-own [target]

enemies-own [invader]

collaborators-own [
  ;designators for movement behavior
  foreign_invader
  defender

  ;trust threshold variables for enemy collaborators. Initiated with civilian state
change
  c_trust_affect
  c_trust_learning_rate
  c_trust_lambda
  c_trust_delta
  c_trust_extinction_rate
  c_trust_threshold
  c_trust_event_count
  c_trust_disposition
  c_trust_memory
  c_trust_probability
  c_trust_social_weight
]

sympathizers-own [
  ;designators for movement bevhavior
  terrorist
  liberator

  ;fear threshold for friendly sympathizers. Initiated with civilian state change
  s_fear_affect
  s_fear_learning_rate
  s_fear_lambda
  s_fear_delta
```

```
  s_fear_extinction_rate
  s_fear_threshold
  s_fear_event_count
  s_fear_disposition
  s_fear_probability
  s_fear_memory
  s_fear_social_weight
]

patches-own [
  ;area checks. If true, then the patch will exhibit a color change that will affect the civilians in the vicinity
  engagement-area?
  atrocity-area?
  secure-area?
  fear-area?
  dead-body?
]

to setup
  clear-all
  setup-civilians
  setup-soldiers
  setup-enemies
  reset-ticks
end

to go
  ;slider interface determines length of the simulation. Default is 336 hours (2 weeks)
  if ticks >= hours [stop]

  ;movement of the dfferent agents
  move-civilians
  move-collaborators
  move-sympathizers
  move-enemies
  move-soldiers
  move-refugees

  ;stochastic death determination based on Soldier proximity
  kill-enemies
  if count enemies = 0 [
    stop
  ]
```

```
;stochastic death determination based on enemy proximity
kill-soldiers
if count soldiers = 0 [
  stop
]

;stochastic death determination based on enemy or Soldier proximity, checks civilians, collaborators, and sympathizers
kill-civilians
if count civilians = 0 [
  stop
]

;searches the area around the patch to determine whether certain Boolean variables are true or false
check-patches

;based on the Boolean values, changes patch properties
change-patches

;checks the area around the civilian and updates the fear and trust variables
update-affect

;samples the area around each civilian and determines the probability of fear or trust events occurring
update-probability

;uses the affect, probability, and social formula to determine a disposition value
update-disposition

;if the disposition value is greater than zero, a stochastic state change determinatino is performed
change-states

tick
end

to setup-civilians
;civilians randomly placed on the map. default is 100, but number can be adjusted with a slider
create-civilians civilian-number [setxy random-xcor random-ycor]

;civilian initialization. This is for neutral, default civilians. Other types will be initialized following a state change
ask civilians [
```

```
          ;regular civilians are a green person
          set shape "person"
          set color green
          set size 12
          ;;setxy of residence of self, the agent will remain in proximity to their residence
unless their residence resides in a fear or conflict area in which case they will seek a safer
residence (internally displaced)
          set residence patch-here          ;;this stores the location of the agent in residence

          ;all of the agent_zero variables are initialized here
          set fear_delta 0
          set fear_lambda 1
          set fear_learning_rate  (random 50 + 1) / 100 ;learning rate set to a value
between .01 and .5
          set fear_extinction_rate extinction_rate
          set fear_threshold  (random 10 + 2) / 10 ;threshold value is between .2 and 1.1
          set fear_event_count 0
          set fear_disposition 0
          set fear_affect 0
          set fear_probability 0
          set fear_memory []
            repeat memory_length
          [set fear_memory lput random-float 0 fear_memory]
            set fear_delta 0
          set fear_social_weight random (100 + 1) / 1000 ;assigns a social weight to the
sum of all other civilians emotional and rational values between .0001 and .10

          ;;the trust disposition is initialized and calculated independently of the fear
disposition. The random variable assignments are assigned the same as the fear
          set trust_lambda 1
          set trust_learning_rate  (random 50 + 1) / 100
          set trust_extinction_rate extinction_rate
          set trust_threshold  (random 10 + 2) / 10
          set trust_event_count 0
          set trust_disposition 0
          set trust_probability 0
          set trust_affect 0
          set trust_memory []
            repeat memory_length
          [set trust_memory lput random-float 0 trust_memory]
          set trust_delta 0
          set trust_social_weight random (1000 + 1) / 10000
         ]
        end
```

```
to setup-soldiers
    ;soldiers are dark blue and assigned random locations on the map. Number is
determined by slider, but the default is 10.
  create-soldiers soldier-number [setxy random-xcor random-ycor]
  ask soldiers [
    set shape "person"
    set color blue - 2
    set size 12
  ]
end

to setup-enemies
  ;enemies are dark red and assigned random locations on the map. Number is
determined by slider, but the default is 20.
  create-enemies enemy-number [setxy random-xcor random-ycor]
  ask enemies [
    set shape "person"
    set color red - 2
    set size 12
  ]
end

to move-civilians
  ask civilians [
    set friend one-of soldiers
    set danger one-of enemies
    ;;set conditionals: first, check for map edge.
    if xcor < 1 or xcor > 399 or ycor < 1 or ycor > 399 [
      right 180
      fd 3
    ]
    ;Second, check for danger. Will attempt to keep a Soldier between themselves and
enemy.
    if pcolor = red or pcolor = orange [
    facexy [xcor] of friend + ([xcor] of friend - [xcor] of danger) / 2
          [ycor] of friend + ([ycor] of friend - [ycor] of danger) / 2
      fd 3
    ]
    ;Third, check for security and make new residence
    if pcolor = blue [
      set residence patch-here
    ]
    ;last, check distance from residence and turn around if a threshold is reached
    ifelse distance residence > 20 [
      face residence
```

```
    fd 3
   ]
   ;civilian will move randomly in own neighborhood
   [right random 360
    fd 3
   ]
  ]
end

to move-collaborators
  ask collaborators [
   set defender one-of enemies
   set foreign_invader one-of soldiers
   ;collaborators will attempt to keep themselves in between a Soldier and an Enemy
   facexy ([xcor] of defender + [xcor] of foreign_invader) / 2
   ([ycor] of defender + [ycor] of foreign_invader) / 2
   ifelse random 10 > 4 [fd 3][back 1]
  ]
end

to move-sympathizers
  ask sympathizers [
   set liberator one-of soldiers
   set terrorist one-of enemies
   ;sympathizers will attempt to keep themselves in between a Soldier and an Enemy
   facexy ([xcor] of liberator + [xcor] of terrorist) / 2
   ([ycor] of liberator + [ycor] of terrorist) / 2
   ifelse random 10 > 4 [fd 3][back 1]
  ]
end

to move-enemies
  ask enemies [
   ; searches in a cone for Soldiers. If it finds one, it will move towards that Soldier
until itself or the Soldier are dead

   ifelse invader = true
   [face invader
    right random 90
    left random 90
    forward 3]
   [
   if xcor < 5 or xcor > 395 or ycor < 5 or ycor > 395 [
    right 180]
   if any? soldiers in-cone 60 100 [
```

```
    set invader one-of soldiers in-cone 60 100
    face invader
    ifelse random 10 > 3 [right random 90 back 3][right random 45 fd 5]]
   right random 90
   left random 90
    fd 4]
  ]
end

;first function is the "seek and destroy" mission for Soldiers
;;to move-soldiers
;  ;searches in a cone for enemies. If the Soldier finds one, it will move towards that enemy until itself or the enemy are dead
;
;  ask soldiers [
;   ifelse target = true
;    [face target
;      right random 60
;      left random 60
;      forward 4]
;    [
;    if xcor < 5 or xcor > 395 or ycor < 5 or ycor > 395 [
;      right 180]
;    if any? enemies in-cone 100 135 [
;      ifelse random 10 < 2 [rt random 360]
;      [set target one-of enemies in-cone 100 135
;        face target]]
;   right random 75
;   left random 75
;      forward 5]
;    ;ifelse random 10 < 2 [rt random 360]
;    ;[set target one-of enemies
;    ;  face target]
;    ;forward 5
;  ]
;end

;second function of same name is the broad, global protect and secure civilians mission for Soldiers
;to move-soldiers
;  ask soldiers [
;    set target one-of enemies
;    set friendly one-of civilians
;    ;Soldiers will attempt to keep themselves in between a Civilian and an Enemy
;    facexy ([xcor] of target + [xcor] of friendly) / 2
```

```
; ([ycor] of target + [ycor] of friendly) / 2
; ifelse random 10 > 4 [fd 5][back 1]
; ]
;end

;third function of same name is a local protection tactic
to move-soldiers
  ask soldiers [
    set target min-one-of enemies [distance myself]
    set friendly min-one-of civilians [distance myself]
    facexy ([xcor] of target + [xcor] of friendly) / 2
    ([ycor] of target + [ycor] of friendly) / 2
    ifelse random 10 > 4 [fd 5][back 1]
  ]
end
to move-refugees

;if the refugee state change occurs, the civilian will move towards the edge of the
map and leave the area (will "die" and update a counter)
  ask refugees [
    if xcor < 5 or xcor > 395 or ycor < 5 or ycor > 395 [
      set refugees-fled refugees-fled + 1
      show refugees-fled
      die]
    fd 5
  ]
end

to check-patches
     ;; patches check for agent types around them and assign a boolean true/false to
their boolean variables
     ask patches
    [
    set engagement-area? ( count soldiers in-radius-nowrap 5 > 0 and count enemies
in-radius-nowrap 5 > 0 )
    ;set atrocity-area? ( count enemies-on neighbors > 0 and count civilians-on
neighbors 3 > 0 )
    set secure-area? (count soldiers in-radius-nowrap 3 > 0 and count enemies in-
radius-nowrap 3 = 0 )
    set fear-area? ( count enemies in-radius-nowrap 3 > 0 and count soldiers in-
radius-nowrap 3 = 0 )
    ]
end

to change-patches
```

```
        ;; changes the color of the patches based on their 4 boolean values. The color is
used by the civilian agens to change their social factors.
        ask patches
        [
       if secure-area? [
        set pcolor blue
          ask patches in-radius-nowrap 3 [set pcolor blue]
       ]
       if fear-area? [
        set pcolor orange
          ask patches in-radius-nowrap 3 [set pcolor orange]
       ]
       ;if atrocity-area? [
        ;set pcolor black
       ;]
       if engagement-area? [
        set pcolor red
          ask patches in-radius-nowrap 10 [set pcolor red]
         ]
        ]
      end


      to kill-enemies
       ;; 5% chance per hour for insurgents in proximity of Soldiers to die, unless
sympathizers are present, then 10% chance
       ask enemies [
        ifelse count sympathizers in-radius-nowrap 10 > 0 [
          if count soldiers in-radius-nowrap 10 > 0 [
          if random 10 < 1 [
            set enemies-killed enemies-killed + 1 ;; global variable used to count
            hatch-dead_enemies 1 [
              set shape "x"
              set color black
              set size 10]
              die]
          ]
        ]
        [if count soldiers in-radius-nowrap 10 > 0 [
          if random 20 < 1 [
            set enemies-killed enemies-killed + 1 ;; global variable used to count
            hatch-dead_enemies 1 [
              set shape "x"
              set color black
              set size 10]
```

```
          die]
      ]
    ]
  ]
end

to kill-soldiers
  ;; 0.5% chance per hour for soldiers in proximity of insurgents to die, unless collaborators are present, then 1% chance
  ask soldiers [
    ifelse count collaborators in-radius-nowrap 10 > 0 [
          if count enemies in-radius-nowrap 10 > 0 [
      if random 50 < 1 [
        set casualties casualties + 1 ;; global variable used to count
        die
      ]
    ]
    ]
    [if count enemies in-radius-nowrap 10 > 0 [
      if random 100 < 1 [
        set casualties casualties + 1 ;; global variable used to count
        die
      ] ]
    ]
  ]
end

to kill-civilians
  ;civilian death rates are determined by presence of Soldiers and enemies and the Soldier and enemy rules of engagement which are chosen in the user interface from 3 levels.

  ask civilians [
    if count soldiers in-radius-nowrap 10 > 0 [
      if rules_of_engagement = "restictive" [
        if random 200 < 1 [
          set civilians-killed-soldiers civilians-killed-soldiers + 1
          hatch-casualties_by_soldier 1 [
            set shape "x"
            set color blue + 3
            set size 10]
          die]]
      if rules_of_engagement = "balanced" [
          if random 100 < 1 [
          set civilians-killed-soldiers civilians-killed-soldiers + 1
          hatch-casualties_by_soldier 1 [
```

```
          set shape "x"
          set color blue + 3
          set size 10]
        die]]
    if rules_of_engagement = "liberal" [
        if random 50 < 1 [
        set civilians-killed-soldiers civilians-killed-soldiers + 1
        hatch-casualties_by_soldier 1 [
          set shape "x"
          set color blue + 3
          set size 10]
        die]]
  ]
      if count enemies in-radius-nowrap 25 > 0 [
    if enemy_civilian_disposition = "cautious" [
      if random 40 < 1 [
        set civilians-killed-enemies civilians-killed-enemies + 1
        hatch-casualties_by_enemy 1 [
          set shape "x"
          set color red + 3
          set size 10]
        die]]
    if rules_of_engagement = "aggresive" [
        if random 20 < 1 [
        set civilians-killed-enemies civilians-killed-enemies + 1
        hatch-casualties_by_enemy 1 [
          set shape "x"
          set color red + 3
          set size 10]
        die]]
    if rules_of_engagement = "ruthless" [
        if random 5 < 1 [
        set civilians-killed-enemies civilians-killed-enemies + 1
        hatch-casualties_by_enemy 1 [
          set shape "x"
          set color red + 3
          set size 10]
        die]]
  ]
]
ask collaborators [

  ;collaborator death rates are higher when Soldiers are in the vicinity than neutral civilians and lower with enemies in the area
  if count soldiers in-radius-nowrap 10 > 0 [
```

```
  if rules_of_engagement = "restictive" [
    if random 100 < 1 [
      set civilians-killed-soldiers civilians-killed-soldiers + 1
      hatch-casualties_by_soldier 1 [
        set shape "x"
        set color blue + 3
        set size 10]
      die]]
  if rules_of_engagement = "balanced" [
      if random 50 < 1 [
      set civilians-killed-soldiers civilians-killed-soldiers + 1
      hatch-casualties_by_soldier 1 [
        set shape "x"
        set color blue + 3
        set size 10]
      die]]
  if rules_of_engagement = "liberal" [
      if random 25 < 1 [
      set civilians-killed-soldiers civilians-killed-soldiers + 1
      hatch-casualties_by_soldier 1 [
        set shape "x"
        set color blue + 3
        set size 10]
      die]]
]
    if count enemies in-radius-nowrap 25 > 0 [
  if enemy_civilian_disposition = "cautious" [
    if random 80 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
      hatch-casualties_by_enemy 1 [
        set shape "x"
        set color red + 3
        set size 10]
      die]]
  if rules_of_engagement = "aggresive" [
      if random 40 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
      hatch-casualties_by_enemy 1 [
        set shape "x"
        set color red + 3
        set size 10]
      die]]
  if rules_of_engagement = "ruthless" [
      if random 10 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
```

```
          hatch-casualties_by_enemy 1 [
            set shape "x"
            set color red + 3
            set size 10]
          die]]
      ]
    ]
    ask sympathizers [

      ;sympathizer death rates are lower with Soldiers in the vicinity and higher when
enemies are in the vicinity
      if count soldiers in-radius-nowrap 10 > 0 [
        if rules_of_engagement = "restictive" [
          if random 400 < 1 [
          set civilians-killed-soldiers civilians-killed-soldiers + 1
          hatch-casualties_by_soldier 1 [
            set shape "x"
            set color blue + 3
            set size 10]
          die]]
        if rules_of_engagement = "balanced" [
          if random 200 < 1 [
          set civilians-killed-soldiers civilians-killed-soldiers + 1
          hatch-casualties_by_soldier 1 [
            set shape "x"
            set color blue + 3
            set size 10]
          die]]
        if rules_of_engagement = "liberal" [
          if random 100 < 1 [
          set civilians-killed-soldiers civilians-killed-soldiers + 1
          hatch-casualties_by_soldier 1 [
            set shape "x"
            set color blue + 3
            set size 10]
          die]]
      ]
          if count enemies in-radius-nowrap 25 > 0 [
        if enemy_civilian_disposition = "cautious" [
          if random 20 < 1 [
          set civilians-killed-enemies civilians-killed-enemies + 1
          hatch-casualties_by_enemy 1 [
            set shape "x"
            set color red + 3
            set size 10]
```

```
      die]]
    if rules_of_engagement = "aggresive" [
      if random 10 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
      hatch-casualties_by_enemy 1 [
        set shape "x"
        set color red + 3
        set size 10]
      die]]
    if rules_of_engagement = "ruthless" [
      if random 5 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
      hatch-casualties_by_enemy 1 [
        set shape "x"
        set color red + 3
        set size 10]
      die]]
  ]
 ]

ask refugees [
  if count soldiers in-radius-nowrap 10 > 0 [
    if rules_of_engagement = "restictive" [
     if random 200 < 1 [
      set civilians-killed-soldiers civilians-killed-soldiers + 1
      hatch-casualties_by_soldier 1 [
        set shape "x"
        set color blue + 3
        set size 10]
      die]]
    if rules_of_engagement = "balanced" [
      if random 100 < 1 [
      set civilians-killed-soldiers civilians-killed-soldiers + 1
      hatch-casualties_by_soldier 1 [
        set shape "x"
        set color blue + 3
        set size 10]
      die]]
    if rules_of_engagement = "liberal" [
      if random 50 < 1 [
      set civilians-killed-soldiers civilians-killed-soldiers + 1
      hatch-casualties_by_soldier 1 [
        set shape "x"
        set color blue + 3
        set size 10]
```

```
      die]]
   ]
     if count enemies in-radius-nowrap 25 > 0 [
    if enemy_civilian_disposition = "cautious" [
     if random 40 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
      hatch-casualties_by_enemy 1 [
       set shape "x"
       set color red + 3
       set size 10]
      die]]
    if rules_of_engagement = "aggresive" [
      if random 20 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
      hatch-casualties_by_enemy 1 [
       set shape "x"
       set color red + 3
       set size 10]
      die]]
    if rules_of_engagement = "ruthless" [
      if random 5 < 1 [
      set civilians-killed-enemies civilians-killed-enemies + 1
      hatch-casualties_by_enemy 1 [
       set shape "x"
       set color red + 3
       set size 10]
      die]]
   ]
  ]
end

to update-affect
ask civilians [
   ;if an orange fear area or a red conflict area or an area where civilians have been killed, the fear affect value is increased
   if pcolor = orange or pcolor = red or count casualties_by_soldier in-radius-nowrap 3 > 0 or count casualties_by_enemy in-radius-nowrap 5 > 0
   [set fear_affect fear_affect + (fear_learning_rate * (fear_affect ^ fear_delta) * (fear_lambda - fear_affect))]

   ;if a blue secure area or an area where Soldiers have defeated enemy forces, the trust affect value is increased
   if pcolor = blue or count dead_enemies in-radius-nowrap 3 > 0
   [set trust_affect trust_affect + (trust_learning_rate * (trust_affect ^ trust_delta) * (trust_lambda - trust_affect))]
```

```
    ;fear extinction procedure
    if pcolor != orange and pcolor != red and count casualties_by_soldier in-radius-
nowrap 5 = 0 and count casualties_by_enemy in-radius-nowrap 5 = 0
    [set fear_affect fear_affect + (fear_learning_rate * (fear_affect ^ fear_delta) *
fear_extinction_rate * (0 - fear_affect))]

    ;trust extinction procedure
    if pcolor != blue and count dead_enemies in-radius-nowrap 5 = 0
    [set trust_affect trust_affect + (trust_learning_rate * (trust_affect ^ trust_delta) *
trust_extinction_rate * (0 - trust_affect))]
  ]
  ask collaborators [
    ;only used trust for enemy collaborators as a means to bring them potentially
back to a neutral state
    if pcolor = blue [
     set c_trust_affect c_trust_affect + (c_trust_learning_rate * (c_trust_affect ^
c_trust_delta) * (c_trust_lambda - c_trust_affect))]
    if pcolor != blue [
     set c_trust_affect c_trust_affect + (c_trust_learning_rate * (c_trust_affect ^
c_trust_delta) * c_trust_extinction_rate * (0 - c_trust_affect))]
  ]
  ask sympathizers [
    ;used fear for friendly sympathizers as a means to potentially bring them back to a
neutral state if conditions warrant
    if pcolor = orange or pcolor = red or count casualties_by_soldier in-radius-
nowrap 5 > 0 [
    set s_fear_affect s_fear_affect + (s_fear_learning_rate * (s_fear_affect ^
s_fear_delta) * (s_fear_lambda - s_fear_affect))]
      if pcolor != orange and pcolor != red and count casualties_by_soldier in-
radius-nowrap 5 = 0 and count casualties_by_enemy in-radius-nowrap 5 = 0
    [set s_fear_affect s_fear_affect + (s_fear_learning_rate * (s_fear_affect ^
s_fear_delta) * s_fear_extinction_rate * (0 - s_fear_affect))]
  ]
end

to update-probability
  ask civilians [
    ;samples a local area to determine the probability of a fear inducing condition
    let fear_current_probability
    (count patches in-radius-nowrap spatial_sample_radius with
     [pcolor = orange or pcolor = red or count casualties_by_soldier in-radius-
nowrap 3 > 0 or count casualties_by_enemy in-radius-nowrap 5 > 0] / (count patches in-
radius-nowrap spatial_sample_radius))
    set fear_memory but-first fear_memory
```

```
set fear_memory lput fear_current_probability fear_memory
set fear_probability mean fear_memory

;samples a local area to determine the probability of a fear inducing condition
let trust_current_probability
(count patches in-radius-nowrap spatial_sample_radius with
  [pcolor = blue or count dead_enemies in-radius-nowrap 3 > 0] / (count patches
in-radius-nowrap spatial_sample_radius))
set trust_memory but-first trust_memory
set trust_memory lput trust_current_probability trust_memory
set trust_probability mean trust_memory
]
ask collaborators [
;samples local area around collaborators to determine probability of a trust (with
relation to friendly Soldiers) raising event
let c_trust_current_probability
(count patches in-radius-nowrap spatial_sample_radius with
  [pcolor = blue or count casualties_by_enemy in-radius-nowrap 5 > 0] / (count
patches in-radius-nowrap spatial_sample_radius))
    set c_trust_memory but-first c_trust_memory
set c_trust_memory lput c_trust_current_probability c_trust_memory

set c_trust_probability mean c_trust_memory
]
ask sympathizers [
;samples a local area around sympathizers to determine probability of a fear
inducing situation
let s_fear_current_probability
(count patches in-radius-nowrap spatial_sample_radius with
  [pcolor = orange or pcolor = red or count casualties_by_soldier in-radius-
nowrap 3 > 0] / (count patches in-radius-nowrap spatial_sample_radius))
    set s_fear_memory but-first s_fear_memory
set s_fear_memory lput s_fear_current_probability s_fear_memory

set s_fear_probability mean s_fear_memory
]
end

to update-disposition
 ask civilians [
;each civilian adds their fear affect value, their fear probability value, and a
randomly weighted sum of all of the other civilians affective and rational values. Once
summer, they subtract their random fear threshold to determine their disposition
```

```
        set fear_disposition fear_affect + fear_probability + (fear_social_weight * (( sum
[fear_affect] of other civilians) + ( sum [fear_probability] of other civilians))) -
fear_threshold
        ;same process as the fear disposition only with the trust variables
        set trust_disposition trust_affect + trust_probability + (trust_social_weight * ((
sum [trust_affect] of other civilians) + ( sum [trust_probability] of other civilians))) -
trust_threshold
      ]
       ask collaborators [
        ;same process as the neutral civilians with a higher social weight due to the much
smaller numbers and likely closer ties
        set c_trust_disposition c_trust_affect + c_trust_probability + (3 *
c_trust_social_weight * (( sum [c_trust_affect] of other collaborators) + ( sum
[c_trust_probability] of other collaborators))) - c_trust_threshold
       ]
       ask sympathizers [
        ;same process as the neutral civilians with a higher social weight
        set s_fear_disposition s_fear_affect + s_fear_probability + (3 *
s_fear_social_weight * (( sum [s_fear_affect] of other sympathizers) + ( sum
[s_fear_probability] of other sympathizers))) - s_fear_threshold
       ]
      end

      to change-states
       ask civilians [
       ;first checks if both the fear and trust thresholds have been exceeded in the same
time step
        if fear_disposition > 0 and trust_disposition > 0 [
        ;uses the netlogo equivalent of a switch procedure to choose from a list of
stochastic choices
         let x random 20
         cf:when
         cf:case [ x < 7 ] [
          ;changes state from neutral to a collaborator, initializing the collaborator. The
civilian "dies" and a collaborator is "hatched"
          hatch-collaborators 1 [
           set shape "person"
           set color red + 2
           set size 12
           set c_trust_lambda 1
           set c_trust_learning_rate  (random 50 + 1) / 100
           set c_trust_extinction_rate extinction_rate
           set c_trust_threshold  (random 10 + 2) / 10
           set c_trust_event_count 0
           set c_trust_disposition 0
```

```
    set c_trust_probability 0
    set c_trust_affect 0
    set c_trust_memory []
      repeat memory_length
      [set c_trust_memory lput random-float 0 c_trust_memory]
    ;set c_trust_memory [0 0 0 0 0]
    set c_trust_delta 0
    set c_trust_social_weight random 1000 / 10000
  ]
  die]
cf:case [ x < 9 ] [
 ;sympathizer state change and variable initialization
  hatch-sympathizers 1 [
    set shape "person"
    set color blue + 2
    set size 12
    set s_fear_delta 0
    set s_fear_lambda 1
    set s_fear_learning_rate  (random 50 + 1) / 100
    set s_fear_extinction_rate extinction_rate
    set s_fear_threshold  (random 10 + 2) / 10
    set s_fear_event_count 0
    set s_fear_disposition 0
    set s_fear_affect 0
    set s_fear_probability 0
    set s_fear_memory []
     repeat memory_length
     [set s_fear_memory lput random-float 0 s_fear_memory]
    ;set s_fear_memory [0 0 0 0 0]
    set s_fear_delta 0
    set s_fear_social_weight random 1000 / 10000
  ]
  die]
cf:case [x < 12 ] [
 ;regugee change state
  hatch-refugees 1 [
    set shape "person"
    set color yellow
    set size 12]
  die ]
cf:else [
 ;if the random number does not meet any of the CF (choose from) conditions,
then the dispositions are dropped below the threshold and the civilian remains in a neutral
state for the time being
  set fear_disposition fear_disposition - 0.5
```

```
     set trust_disposition trust_disposition - 0.5
    ]
]
  ;CF (switch) procedure for the fear disposition only exceeding 0
  if fear_disposition > 0 and trust_disposition < 0 [
    let x random 20
    cf:when
    cf:case [ x < 6 ] [
      hatch-refugees 1 [
        set shape "person"
        set color yellow
        set size 12]
      die]
    cf:case [ x < 12 ] [
      hatch-collaborators 1 [
        set shape "person"
        set color red + 2
        set size 12
        set shape "person"
        set color red + 2
        set size 12
        set c_trust_lambda 1
        set c_trust_learning_rate  (random 50 + 1) / 100
        set c_trust_extinction_rate extinction_rate
        set c_trust_threshold  (random 10 + 2) / 10
        set c_trust_event_count 0
        set c_trust_disposition 0
        set c_trust_probability 0
        set c_trust_affect 0
        ;set c_trust_memory []
          ;repeat memory_length
        ;[set c_trust_memory lput random-float 0 c_trust_memory]
        set c_trust_memory [0 0 0 0 0]
        set c_trust_delta 0
        set c_trust_social_weight random 1000 / 10000
      ]
      die]
    cf:case [ x < 13 ] [
      hatch-sympathizers 1 [
        set shape "person"
        set color blue + 2
        set size 12
        set s_fear_delta 0
        set s_fear_lambda 1
        set s_fear_learning_rate  (random 50 + 1) / 100
```

```
      set s_fear_extinction_rate extinction_rate
      set s_fear_threshold  (random 10 + 2) / 10
      set s_fear_event_count 0
      set s_fear_disposition 0
      set s_fear_affect 0
      set s_fear_probability 0
      ;set s_fear_memory []
       ;repeat memory_length
       ;[set s_fear_memory lput random-float 0 s_fear_memory]
      set s_fear_memory [0 0 0 0 0]
      set s_fear_delta 0
      set s_fear_social_weight random 1000 / 10000
    ]
    die]
  cf:case [ x < 14 ] [
   hatch-enemies 1 [
      set shape "person"
      set color red
      set size 12]
    die]
 cf:else [
   set fear_disposition fear_disposition - 0.5
  ]
]
 ;CF (switch) procedure when only the trust disposition is greated than 0
 if fear_disposition < 0 and trust_disposition > 0 [
  let x random 20
  cf:when
  cf:case [ x < 6 ] [
   hatch-sympathizers 1 [
      set shape "person"
      set color blue + 2
      set size 12
      set s_fear_delta 0
      set s_fear_lambda 1
      set s_fear_learning_rate  (random 50 + 1) / 100
      set s_fear_extinction_rate extinction_rate
      set s_fear_threshold  (random 10 + 2) / 10
      set s_fear_event_count 0
      set s_fear_disposition 0
      set s_fear_affect 0
      set s_fear_probability 0
      ;set s_fear_memory []
       ;repeat memory_length
       ;[set s_fear_memory lput random-float 0 s_fear_memory]
```

```
          set s_fear_memory [0 0 0 0 0]
          set s_fear_delta 0
          set s_fear_social_weight random 1000 / 10000
         ]
         die]
       cf:else [
        set trust_disposition trust_disposition - 0.5
       ]
      ]
     ]
     ;collaborator decisions when threshold trust value is exceeded
     ask collaborators [
      if c_trust_disposition > 0 [
       let x random 20
       cf:when
       cf:case [ x < 10 ] [
        hatch-civilians 1 [
          set shape "person"
          set color green
          set size 12
          set residence patch-here          ;;this stores the location of the agent in
residence
          set fear_delta 0
          set fear_lambda 1
          set fear_learning_rate  (random 50 + 1) / 100
          set fear_extinction_rate extinction_rate
          set fear_threshold  (random 10 + 2) / 10
          set fear_event_count 0
          set fear_disposition 0
          set fear_affect 0
          set fear_probability 0
          set fear_memory []
          repeat memory_length
          [set fear_memory lput random-float 0 fear_memory]
          set fear_delta 0
          set fear_social_weight random 1000 / 10000
          set trust_lambda 1
          set trust_learning_rate  (random 50 + 1) / 100
          set trust_extinction_rate extinction_rate
          set trust_threshold  (random 10 + 2) / 10
          set trust_event_count 0
          set trust_disposition 0
          set trust_probability 0
          set trust_affect 0
          set trust_memory []
```

```
        repeat memory_length
        [set trust_memory lput random-float 0 trust_memory]
        set trust_delta 0
        set trust_social_weight random 1000 / 10000]
       die]
       cf:case [ x < 11 ] [
        hatch-refugees 1 [
        set shape "person"
        set color yellow
          set size 12]
       die]
       cf:else [
        set c_trust_disposition c_trust_disposition - 0.5
       ]
      ]
    ]
    ;sympathizer decisions when fear threhold is exceeded
    ask sympathizers [
      if s_fear_disposition > 0 [
   let x random 20
      cf:when
      cf:case [ x < 10 ] [
       hatch-civilians 1 [
        set shape "person"
        set color green
        set size 12
        set residence patch-here           ;;this stores the location of the agent in
residence
        set fear_delta 0
        set fear_lambda 1
        set fear_learning_rate  (random 50 + 1) / 100
        set fear_extinction_rate extinction_rate
        set fear_threshold  (random 10 + 2) / 10
        set fear_event_count 0
        set fear_disposition 0
        set fear_affect 0
        set fear_probability 0
        set fear_memory []
        repeat memory_length
        [set fear_memory lput random-float 0 fear_memory]
        set fear_delta 0
        set fear_social_weight random 1000 / 10000
        set trust_lambda 1
        set trust_learning_rate  (random 50 + 1) / 100
        set trust_extinction_rate extinction_rate
```

```
    set trust_threshold  (random 10 + 2) / 10
    set trust_event_count 0
    set trust_disposition 0
    set trust_probability 0
    set trust_affect 0
    set trust_memory []
    repeat memory_length
    [set trust_memory lput random-float 0 trust_memory]
    set trust_delta 0
    set trust_social_weight random 1000 / 10000]
   die]
   cf:case [ x < 11 ] [
    hatch-refugees 1 [
    set shape "person"
    set color yellow
     set size 12]
   die]
  cf:else [
   set s_fear_disposition s_fear_disposition - 0.5
    ]
   ]
  ]
end
```

APPENDIX 3: TRIAL RESULTS

Trial Type 1: "Search and Destroy" Soldier Behavior

Trial #	Turns	Ending Civilians	Refugees	Ending Collaborators	Ending Sympathizers	Ending Enemies	Enemies Killed	Casualties	Civilians Killed by Soldiers
1	336	2	74	4	7	20	11	0	0
2	336	6	53	7	20	18	7	3	1
3	263	0	55	20	9	24	7	1	0
4	332	0	74	10	8	14	10	1	0
5	313	0	68	9	3	24	8	1	6
6	336	2	68	5	5	22	11	1	2
7	336	1	80	0	10	18	8	1	2
8	325	0	69	11	4	21	9	2	1
9	336	2	74	7	5	20	8	0	1
10	336	4	67	10	2	22	3	5	5
11	336	3	72	5	1	23	7	2	3
12	336	4	72	10	1	16	13	1	4
13	336	9	75	3	3	19	7	1	1
14	253	0	53	7	21	16	9	1	1
15	336	1	73	9	0	28	4	1	1
16	336	3	66	13	2	21	8	2	5
17	336	2	59	15	1	29	10	3	1
18	336	4	70	8	6	19	6	2	1
19	336	3	65	12	4	18	9	1	4
20	254	0	64	10	5	24	7	3	4
21	336	2	68	12	3	21	6	2	3
22	199	0	45	19	6	27	5	0	3
23	336	2	63	7	1	31	7	3	4
24	246	0	58	21	4	21	8	0	5
25	336	6	64	8	9	10	14	1	3
26	336	2	65	4	11	22	10	0	1
27	302	0	71	6	5	20	6	1	3
28	287	0	63	9	12	20	6	1	4
29	336	6	66	3	9	17	10	2	3
30	315	0	68	10	0	25	9	1	2
MEAN	**315.7667**	**2.13333**	**66.06667**	**9.133333333**	**5.9**	**21**	**8.1**	**1.4333333**	**2.466666667**
VAR	1317.013	5.42989	58.54713	24.32643678	26.78275862	19.7931	5.88621	1.2885057	2.87816092
Sigma	43.90042	0.181	1.951571	0.810881226	0.892758621	0.65977	0.19621	0.0429502	0.095938697
t	2.04523	2.04523	2.04523	2.045229642	2.045229642	2.04523	2.04523	2.0452296	2.045229642
CI-	**302.2155**	**1.26322**	**63.20951**	**7.291625644**	**3.967546267**	**19.3387**	**7.19406**	**1.0094712**	**1.8331778**
CI+	**329.3178**	**3.00345**	**68.92382**	**10.97504102**	**7.832453733**	**22.6613**	**9.00594**	**1.8571955**	**3.100155534**

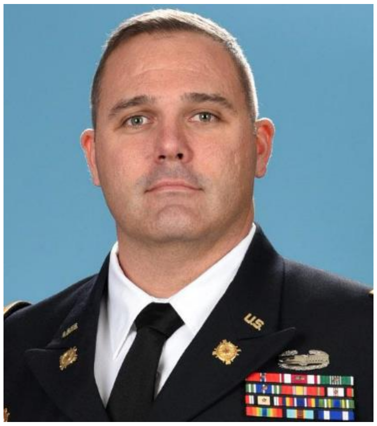
Trial Type 2: Broad Search Protection Soldier behavior

Trial #	Turns	Ending Civilians	Refugees	Ending Collaborators	Ending Sympathizers	Ending Enemies	Enemies Killed	Casualties	Civilians Killed by Soldiers
1	336	4	74	6	4	22	6	3	3
2	336	4	65	5	6	25	5	1	7
3	336	3	57	11	5	31	3	1	7
4	336	2	77	3	7	23	4	0	4
5	336	1	70	2	2	28	6	2	8
6	336	3	68	2	12	26	3	1	4
7	318	0	63	11	7	25	3	2	4
8	335	0	76	6	6	25	2	0	3
9	336	2	60	10	3	28	5	1	6
10	336	10	57	12	7	26	3	0	2
11	336	3	75	7	3	25	1	1	4
12	336	3	62	8	11	25	6	1	1
13	336	7	63	5	9	27	4	2	3
14	336	2	77	3	2	25	2	0	5
15	336	2	62	12	5	27	4	0	5
16	336	2	66	8	8	22	5	1	7
17	336	6	64	3	5	25	4	1	8
18	336	2	60	4	13	29	1	0	3
19	336	3	55	12	7	21	5	0	14
20	336	13	52	7	6	28	2	1	9
21	336	5	64	3	9	23	5	0	5
22	275	0	66	7	12	30	0	0	2
23	336	5	63	1	16	23	2	0	5
24	336	5	63	5	7	28	3	0	4
25	336	2	67	11	4	28	2	0	1
26	336	2	63	11	3	22	5	0	8
27	332	0	64	8	4	35	2	0	4
28	336	1	68	2	7	29	3	0	7
29	336	7	55	12	6	25	3	1	4
30	336	7	66	4	5	26	4	3	3
MEAN		3.533333	64.73333	6.7	6.7	26.06667	3.433333	0.73333333	5
VAR		9.085057	42.27126	13.11379	11.52759	9.305747	2.529885	0.82298851	7.517241
Sigma		0.302835	1.409042	0.437126	0.384253	0.310192	0.08433	0.02743295	0.250575
t		2.04523	2.04523	2.04523	2.04523	2.04523	2.04523	2.04522964	2.04523
CI-		2.407834	62.30558	5.347785	5.4322	24.92758	2.839408	0.39458409	3.97621
CI+		4.658833	67.16108	8.052215	7.9678	27.20575	4.027259	1.07208258	6.02379

Trial Type 3: Local Search Protection Soldier behavior

Trial #	Turns	Ending Civilians	Refugees	Ending Collaborators	Ending Sympathizers	Ending Enemies	Enemies Killed	Casualties	Civilians Killed by Soldiers
1	336	6	69	1	10	16	8	2	8
2	336	3	53	25	1	24	7	1	4
3	336	3	69	2	4	22	8	0	7
4	336	3	67	3	10	24	5	2	5
5	336	10	57	16	1	21	6	2	7
6	336	5	57	25	2	17	9	1	5
7	336	10	56	18	2	18	8	1	4
8	336	4	63	10	4	24	6	3	5
9	336	5	64	6	3	26	4	1	6
10	244	0	50	29	2	24	6	0	5
11	323	0	61	18	1	26	4	2	4
12	324	0	65	9	5	20	9	2	4
13	336	4	61	20	1	20	2	1	11
14	336	3	64	7	5	26	7	2	5
15	336	4	54	31	1	25	1	2	3
16	336	4	65	14	2	17	10	1	4
17	320	0	68	8	2	24	5	1	5
18	336	4	65	7	8	22	5	1	8
19	336	5	54	24	5	21	8	0	0
20	336	4	62	5	6	29	5	2	3
21	336	3	64	3	5	24	9	0	7
22	291	0	65	18	3	27	1	1	6
23	336	2	68	3	11	25	4	1	6
24	336	1	60	24	1	23	5	0	3
25	336	3	54	27	6	18	7	3	2
26	336	4	66	14	2	15	12	2	5
27	280	0	53	26	0	31	5	1	3
28	336	4	56	27	2	22	6	1	3
29	336	2	60	27	3	18	5	2	4
30	336	5	59	15	4	25	5	1	3
MEAN		3.366667	60.96667	15.4	3.733333	22.46667	6.066667	1.3	4.833333
VAR		6.447126	29.8954	90.8	8.547126	15.22299	6.34023	0.7	4.557471
Sigma		0.214904	0.996513	3.026667	0.284904	0.507433	0.211341	0.023333	0.151916
t		2.04523	2.04523	2.04523	2.04523	2.04523	2.04523	2.04523	2.04523
CI-		2.418544	58.92501	11.84185	2.641663	21.00976	5.126437	0.987586	4.036177
CI+		4.314789	63.00833	18.95815	4.825004	23.92357	7.006896	1.612414	5.63049

VITA



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Major Aaron Beam was selected while an active duty Army officer for the U.S. Army's prestigious Advanced Civil Schooling program. His academic and professional focus is on effective use of simulation to train and assist military leaders and forces through blended live, virtual, and constructive training models.

Major Beam came to Old Dominion University from the Joint Multinational Simulation Center (JMSC) in Grafenwoehr, Germany where he planned and executed training events for U.S. and NATO units across Europe. Upon completion of his degree program, he will begin working in July 2018 at the Joint Staff J7 in Suffolk, Virginia as an exercise planner for the Joint U.S. Commands around the world.

Major Beam lives in Virginia Beach with his Wife, Victoria and two sons, Dustin, age 13 and Logan, age 11. He enjoys spending time outdoors, whether that is at the ocean, in the mountains, or somewhere in between. He has enjoyed the time he has been able to spend with his family while attending Old Dominion University as well.

Education

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