Modeling and Evaluating Irregular Warfare in the Age of Complexity

by

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Abstract

In this paper the use of agent-based models (ABMs) as modeling tools for irregular warfare (IW) is discussed. Furthermore, options for evaluating ABM-generated outcomes for simulated IW scenarios are presented. ABMs can be used to enhance traditional wargaming capabilities or as stand-alone simulations. Both possibilities are discussed, including criteria delineating when they are likely to produce beneficial results. An example of the complementary use of ABMs with an interactive wargame (crowd confrontation) is presented. Afterwards, the use of a stand-alone ABM to explore the complexity of combat is discussed. The flexibility and strengths of ABMs in capturing combat complexity lead to a need for suitable measures of effectiveness (MOEs) for capturing the complexity of IW quantitatively. These measures are (mostly) independent of attrition, and are able to capture manoeuvres including dispersion and re-aggregation of forces, as well as the interactions between spatial and temporal dynamics. The measures discussed can be used to evaluate traditional force-on-force attrition combat as well as less traditional operations in the presence of non-combatants, and to provide insights into the complex nature of warfare not easily gained through other quantities, including the possible critical nature of some types of conflicts. Lastly, implications of the complexity-based MOEs for real conflicts are briefly outlined.

I. Introduction

I.1. Background

The current security environment presents new challenges to the combat modeling community. In the past, the typical modeled conflict scenario would involve two forces trying to eliminate one another in all-out combat. The model focus was largely physics-based and the primary measures of effectiveness (MOEs) were typically attrition-related. However, the current security environment demands the adoption of a wider range of combat modeling capabilities than is currently employed to address complex situations, often with many competing parties involved, whose complex individual and group behaviours must be taken into account. Furthermore, the attrition of the opponents is not always desirable (e.g., crowd control, counterinsurgency) and hence typical MOEs might not yield appropriate data for analysis. The lesser reliance on attrition presents an additional complication in the assessment of the simulation outcomes, as well as in the assessment of real conflicts.

I.2. Measuring Effectiveness

Harnessing complexity in combat models requires a means of quantifying it in a relevant, robust and efficient way. In Section II a variety of measures and their applicability to combat evaluation are discussed. These measures enable the analyst to gain deeper insights into the emergent properties of analyzed systems, and furthermore record the changes in disorder in these systems from various vantage points. They capture the system characteristics without the need to deconstruct the system and separate it into subsystems, hence avoiding the potential loss of emergent properties that by definition constitute a property of the system as a whole.

I.3. Agent-Based Models

A promising approach to combat modeling is the use of non-interactive agent-based models (ABMs). ABMs have been used successfully as a supplement to or a replacement for traditional interactive wargames. Defence R&D Canada – Centre for Operational Research and Analysis (DRDC CORA) implemented the ABM developed by New Zealand Defence Technology Agency called Map-Aware Non-Uniform Automata (MANA) [1] to support its wargaming program. MANA has been successfully utilized for several projects, primarily in the area of hostile crowd management or confrontation [2].

Agent-based models represent a class of models with a philosophy entirely different from traditional wargames. Rather than focussing on the detailed representation of reality, their focus is primarily on the representation of the emergent behaviour. The entities are represented as autonomous agents that make their decisions on the basis of their interactions with other agents and the environment. In this manner, the complexity of the many-on-many interactions can be captured, and the complexity of the system is not lost due to the attempts to deconstruct it for the purpose of isolating fundamental effects. The discussion of agent-based models as a viable alternative to interactive wargames in several generic situations is presented in Sections III.1-III.4.

I.4. Use of Genetic Algorithms in Combat Modeling

Genetic algorithms (GAs) have been successfully used in a variety of fields as an efficient means of optimizing system behaviour. There has been some work done on the application of genetic algorithms to combat modeling as well [3]. A possible use of GAs in defence applications is the optimization of manoeuvres and activities. A variety of criteria can be used in the optimization. In Sections III.5 – III.6 particular focus is given to the use of complexity as a decision-making vehicle leveraged in the application of GAs to combat related optimization problems in irregular warfare.

II. Evaluating the Complexity of Combat

II.1. Limitations of Attrition-Based MOEs

In traditional combat models and wargames the primary measure of effectiveness is often attrition–whether measured directly (number of killed, loss-exchange ratio, etc.) or indirectly (attrition-based definition of mission success). However, in some cases the focus on attrition actually ignores the complexity of combat. This is especially evident if the focus is on the end-state only—then the entire complexity of the system dynamics is missed [4,5]. Furthermore, given the quality of the force protection of modern militaries and the often asymmetric nature of warfare, standard attrition-based measures might be misleading and/or inappropriate for describing combat dynamics, with potentially detrimental effects on the mission outcome (a good example of such a case is hostile crowd management).

In this section several potential complexity-based measures of effectiveness (CMOEs) are briefly described. It is only meant as an overview; details of these measures and their calculation have been extensively described elsewhere [5,6]. The authors' experience suggests that these measures are appropriate for dynamical analysis of a wide range of combat systems when viewed as complex adaptive systems. It should be noted that the applicability of a given measure is situation-specific and that none of them are universally relevant. A key determinant seems to be how disorder and the relevant reference patterns unfold in the system. The list of measures compiled herein is by no means complete, and serves only to highlight some of the possibilities with which the authors have some experience. More work in this area is planned.

II.2. Entropy and its Derivatives

Entropy in general is a measure of disorganization in a system, or alternatively a measure of the lack of information known about the system. There are several possible definitions of entropy (probably the best known being Boltzmann's definition in statistical physics). Shannon [7] devised a new definition for use in information theory; therefore it is often referred to as 'information' entropy. This definition is based on the probabilistic character of the information that is obtained about the analyzed system (e.g., the entities have a certain likelihood of being in a particular place). Shannon entropy of a system is defined using a probability of i^{th} option p_{i} as

$$S = \sum_i p_i \ln \frac{1}{p_i}$$

In the above expression, the summation is over all of the options considered in the model. Three entropy derivatives are examined below.

CR Entropy

Carvalho-Rodrigues (CR) proposed an attrition-based definition of combat entropy applicable to each force individually (e.g., RED or BLUE) or as a whole through reporting the difference in force entropies [8]. It is a form of Shannon entropy with the probability of an entity being killed expressed as a ratio between the number of entities already killed and the remaining entities [7]. The functional dependence of CR entropy is not monotonic; it peaks when the ratio reaches a value of about 0.37. This separates the CR entropy values into two regions. Prior to attaining a maximum value, higher CR entropy for a force translates into a more disordered combative state. Thus prior to the engaged forces reaching maximum CR entropy, the force having the lower CR entropy is considered to have the advantage. Once the CR entropy of a force breaches the maximum value, it enters into a *disintegration phase*, wherein combat capabilities are assumed to have declined substantially [4].

CR entropy was used to predict outcomes of battles and to estimate logistics requirements during exercises [8,9].

Spatial Entropy

Ilachinski [4] suggested a specific form of Shannon entropy based on the spatial distribution of soldiers relative to a regular grid covering the battlefield area. The resulting ‘spatial entropy’ is closely related to the fractal dimension (discussed below) when the latter is computed via the ‘box counting’ method. Rather compact, non-dispersed patterns display low spatial entropy whereas disorganized, spread-out patterns display high spatial entropy.

Spatial entropy was employed by Ilachinski [4] to characterize the spatial distribution of soldiers on the battlefield, force concentration, and the degree of disorder. It has been also proposed as a possible measure to characterize crowd cohesion in crowd confrontation operations [5].

Symmetropy

A new measure was proposed [5] on the basis of Shannon entropy that measures the symmetry and entropy of a given spatial pattern or shape. This measure is called symmetropy and has been applied to investigations of critical behaviour [10]. The spatial distribution of units is projected onto a pattern basis to determine the relative contribution of reference symmetries to the observed pattern. The pattern symmetries belong to four main classes: vertical, horizontal, centro, and double symmetry. The rise and fall of the various spatial symmetries can be tracked during a simulation. When the pattern is random, the symmetropy value is high (close to one), and when dominating symmetries are present in the system the symmetropy value is low (close to zero).

The concept of symmetropy is a new quantity of consideration for combat dynamics. It has been used in the previous study by Sprague and Dobias [6] to distinguish between force components on the basis of the symmetries they feature. Symmetropy seems to hold promise for spatial pattern recognition under a degree of disorder, possibly extending to the identification or classification of forces or force organizational states based on limited situational awareness. Examples from the geological sciences involving earthquakes and/or acoustic transitions leverage symmetropy values and corresponding symmetry projections to describe various dynamical aspects of the complex system in question.

II.3. Fractal Dimension

The fractal dimension can also be used as a measure of the spatial distribution of combat units (e.g., crowd, BLUE force) [4,5]. It is a statistical quantity that quantifies the self-similarity of the distribution of units on the battlefield from the large distance scales of the system to finer and finer scales. In particular, it describes the clustering properties of force units (which has been related to firepower concentration [11]) and can act as a rough criterion for the transition from linear to nonlinear combat dynamics [12].

The fractal dimension and corresponding power-laws have been used to describe the statistical distribution of the intensities of wars [13], warfare statistics [14] and attack casualties [15,16,17]. When applied to spatial patterns of force confrontations on a turbulent battlefield, the fractal dimension expresses how the forces engage each other by forming clusters, and to what extent a large cluster of combatants might itself be viewed as a collection of smaller clusters (self-similarity) and so on [15].

II.4. Persistence, Self-similarity and the Hurst Coefficient

Temporal and spatial correlations in agent velocity (speed and direction) are other characteristics that could possibly provide additional insights into complex system dynamics. Such correlations can be calculated independently for each velocity component of moving entities. Correlations can be described in terms of the Hurst coefficient H [18] and/or the self-similarity parameter (SSP) [19]. In many cases, H and the SSP display the same basic pattern. For both, velocity correlations are characterized by a scaling between the number of steps and the root mean square distance traveled. When H or SSP values are at 0.5, the motion is random; between 0.5 and 1 the motion is correlated; between 0 and 0.5 the motion is anti-correlated; and if 0, the motion is centered about a point. There are notable differences between the two, however, that are most evident in computational aspects and the interpretation of SSP for values larger than one.

The Hurst coefficient has been utilized to describe motion in hostile crowd management and, in particular, signal a phase transition between a group confrontational mindset and the inclination to disperse [5]. The SSP potentially could have been used in an analogous manner.

II.5. Intermittency and Fractal Processes

A sequence of events is called *intermittent* if its dynamics sometimes deviate from the usual behaviour [20]. For instance, sudden, positive deviations increase the mean of a sequence to values much higher than the most probable value. An example of such dynamics can include sudden spikes in human activity or sudden spikes in casualty numbers. The intermittency can be measured using the correlation co-dimension, which connects the variance of the data series with 'box size' (i.e., a partitioning of the series into disjoint boxes of a given size). The variance is calculated via a power law [20]. An alternative measure of intermittency is the Fano factor, which connects via a power law the ratio of the variance to the mean, with the box size over which the two are calculated.

For a class of processes called fractal point processes (FPP), there is a relationship between the co-dimension C_2 and the Fano factor α: $\alpha = 1 - C_2$. These processes are often characterized by medium to high intermittency, and are characteristic for anti-correlated systems. For processes in which the timing between events obeys a fractal distribution (fractal rate point processes) this relationship between the co-dimension and the Fano factor does not hold. Such processes typically feature lower intermittency as a consequence of being correlated over time. In the latter case the Fano factor is related to the Hurst coefficient H as $H = (1+\alpha)/2 > 0.5$.

III. Agent-Based Models

III.1. Interactive Wargaming and its Limitations

Wargaming has been a significant part of the evaluation and assessment of combat effectiveness for a long time. It can be argued that the attempts to understand the impact of changes in courses of action (COA) on the outcome of a battle are almost as old as the history of warfare. With the recent advances in computational technologies, computer-assisted wargames have become an integral part of option analysis, requirement identification, and operational analysis in general.

Traditional interactive wargames require human interactors who make decisions on behalf of the entities that are represented on a computer. The computer then calculates outcomes of possible engagements, as well as managing detections and interactions between entities and the environment.

This human-in-the-loop approach has many benefits when interactors with relevant, real-world experience are employed, chief among them being the ability to react in real time to the changes in the battlefield dynamics and to adapt to opponents' tactics, and the valuable insights gained by interviewing them after a wargaming session. Other important benefits include the ability to incorporate tactical decisions and the ability to react to enemy actions "on the fly". A possible alternative is semi-automated models, in which one or more of the sides are computer driven, and the most important side(s) is (are) controlled by human operators. An example of this approach is crowd federates for interactive wargames simulating behaviour of non-combatants within a conflict.

A step further on are constructive simulations in which entity decision-making is completely pre-programmed, and the entities follow their COAs based on their interactions with other entities, the environment, and predefined decision points.

All of the above approaches have in common a major limitation – they tend to reduce the complexity of combat by separating the system into subsystems operated by the interactors or predefined decision-making algorithms and by making significant assumptions about human behaviour and decision-making. These approaches can work well in the context of a traditional force-on-one force conflict or conflicts involving only a few parties, but their applicability is limited in the context of many-on-many encounters (number of factions, allegiances, and subgroups with their own agendas). In some cases these factions can be incorporated at the cost of adding more interactors and computational resources, which significantly increases the cost and effort associated with running such simulations. Therefore, most frequently the complexity of the problem is reduced to accommodate realistic time/cost budgets.

III.2. Agent-Based Models as an Alternative to Wargames

As mentioned in Section III.1, the interactive models face significant limitations when used to model conflicts with a high degree of complexity. This problem is akin to attempts to describe a physical system with many mutually interacting parts by trying to separate it into a variety of scales and subsystems that can be described using analytical methods (e.g., differential equations). However, at some point the real dynamics of the system can be lost, especially if it is driven by interactions that act across scales, and across subsystems.

Wolfram [21] proposed an alternative approach to modeling some complex systems by substituting the equations of motion with a field of locally interacting cells. This class of models is called cellular automata. The interactions of actual entities (e.g., particles) are substituted by the interaction of the cells in which these entities reside. An example application of this nature is Conway's "Game of Life" [22].

Agent-based models typically employ the same philosophy, while adding an extra layer of complexity by allowing the cells to move and to interact with the environment in addition to their mutual interactions (thus they become independent agents whose dynamics are driven by their interactions with one another and the environment). The interactions can have many forms (detecting, communicating, shooting, refuelling, etc.), and thus the possible range of complexities that can be captured is rather large.

As mentioned above (Section I.3) DRDC CORA implemented MANA as a non-interactive supplement to interactive wargaming. It provides quick repetition capability and comprehensive data farming, in addition to sufficient flexibility to support the capability to efficiently scope or 'course-grain' many problem domains of interest.

Furthermore, MANA provides a versatile platform for exploring the complexity of combat and mutual interactions of various aspects of tactical combat.

III.3. An Example of ABM Applications to Combat Modeling

An example of MANA as a supplement to interactive models is described briefly below. It represents a concrete example illustrating how ABMs can be used to approach problems requiring decision-making (autonomy) that are not conducive to interactive wargaming. It involves crowd confrontation modeling [23] using non-lethal models. This example is meant to show some of MANA's capabilities; the details of actual results are not discussed, since they are beyond the scope of this paper.

Crowd confrontation was modeled in LFORT in the context of evaluating the effectiveness of particular non-lethal weapons. Originally, an interactive wargame was intended as the sole methodology. However, it was identified that the proposed wargaming tool would only be able to model scenarios up to platoon level and it was desirable to perform modeling up to company level. Also, the wargame was too time-consuming to explore a wide range of crowd configurations or additional weapon mixes. Therefore it was decided to use MANA as a supplement to the interactive wargame to provide the capability to extend the scope of the study. MANA behavioural and weapon parameters were set so that the outcomes for the basic platoon-level scenario agreed with the wargame results. The same setup was then used to model additional options such as company-level engagement or additional weapon mixes.

In general, crowds are difficult to model using traditional interactive wargame applications. One complication is that in a typical crowd consisting of a large number of individuals, the global crowd behaviour is an emergent property arising from complex interactions between crowd members and the security force at a local level. This is challenging to model with a single interactor or a few interactors gaming a large number of individuals. The approach necessitates global rules of engagement for the crowd (e.g., if there is a certain ratio of BLUE (the security force) to RED (crowd members), or a certain number of casualties, the crowd will respond by acting in a prescribed way).

ABMs with their bottom-up approach (local interactions driving global behaviour) can be exploited to mirror the above crowd dynamic. The individual crowd members can have their properties influenced by both their personal interaction with BLUE, and the properties of their group members.

The scenario involved a large crowd (300 people) confronted by a company of light infantry using non-lethal weapons. The objective was to disperse the crowd while limiting casualties on either side, and to prevent further hostilities. Various non-lethal weapon mixes and tactical options were compared to one another to gauge their relative effectiveness in dispersing the crowd while minimizing negative outcomes. An outline of the scenario is shown in Figure 1. The crowd had two access routes (A and B) leading to their objective—a government building. Other possible routes were not accessible. Two platoons were deployed, referred to as ‘1 Platoon (1Pl)’ and ‘2 Platoon (2Pl)’. 1 Platoon was deployed near Barricades 7 & 8, and 2 Platoon at the main access route (Route A) close to Barricade 5.

MANA was successfully used to model the crowd dynamics [2], and significantly enhanced the scope of the study by providing an efficient way of modeling a company level scenario, and exploring a wide range of additional non-lethal mixes, as mentioned above. The study provided an efficient means of comparing MANA’s capabilities to those of the interactive wargame. The main advantages of the interactive wargame were the ability to provide valuable expert judgments and insights by the interactors and the high fidelity of representing technical details such as weapon characteristics. The main limitations of the interactive wargame were mainly crowd representation (too artificial given the need for global prescription for the crowd dynamics), and scope limitations due to heavy resource requirements.

On the other hand, the main advantages of MANA were the efficiency of modeling, enabling significant scope increases including scaling up to company level, the exploration of a variety of excursions in terms of weapons and crowd behaviour, much better crowd representation (local interaction driving emergent crowd dynamics), consistency in the crowd behaviour (movement, level of aggression) across weapon mixes, and the ability to introduce a state-based definition of dispersal (individual level) rather than a purely attrition-based definition. The weaknesses of MANA were mainly the high level of weapon abstraction (which required external inputs to be defined realistically, based on the dynamics from the interactive game), lack of immediate subject expert insights, and the fact that the results of individual runs were less reliable than for the interactive wargame (the results were only reliable in a statistical sense, averaged over large numbers of repetitions).

Overall, MANA demonstrated that it provides valuable capabilities and can significantly enhance DRDC CORA modeling capabilities especially in complex scenarios involving large groups of non-combatants (such as crowds). It also provides quick run capabilities to explore potential

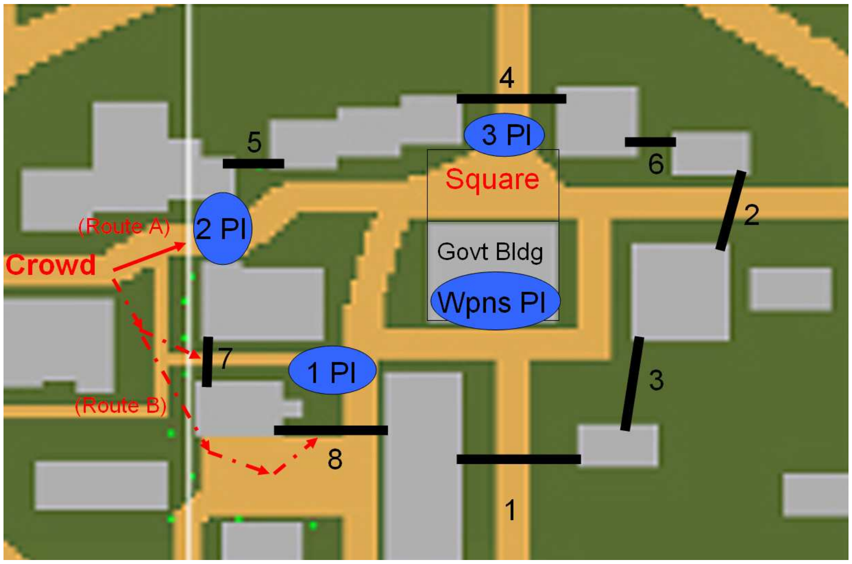

Figure 1. *Scenario overview for the CCO simulation.*

scenarios at a conceptual level and overall demonstrates the significant value that ABMs can bring to the modeling community.

III.4. Characterizing the Complexity of Combat in ABMs

As is mentioned above, ABMs employ a bottom-up approach to the modeling of combat dynamics. The basic constituents of an ABM are individual, autonomous agents, each representing a single entity or amalgamated group of entities capable of reacting to the environment and the activities of other agents. Since each agent can theoretically interact with all other agents and act accordingly, ABMs are capable of capturing nonlinearity and the complexity of the battlefield in line with actual human perceptions.

In many realistic cases, the global dynamics of a conflict have been argued to be the result of an emergent property of the system driven by the local rules and the local dynamics of individual agents, rather than something that is prescribed globally [1,23]. This enables characterization of the multi-scale nature of certain conflict parameters, and provides a venue for understanding the complexity inherent in the conflict.

However, to really gain insights into the complex dynamics of combat, the models have to be supplemented by efficient means of quantifying the dynamics of the system (not just the end state, but rather the entire duration of the encounter). Furthermore, the measures used to evaluate the encounter must be capable of capturing the relevant forms of complexity and enable understanding of the relationships between different aspects of the encounter (spatial and temporal force distribution, casualties, detections, communications, etc.). Examples of these were discussed in Section II.

III.5. Harnessing Complexity in Simulated Decision-Making

It is desirable to develop schemes capable of harnessing the complexity and self-organization of warfare in order to selectively “drive” a conflict towards more favourable outcomes [6]. The two key factors to be considered to achieve this goal are 1) awareness of and response of modeled entities to complexity within the system and 2) the optimization of combatant behaviour in response to this awareness. The complexity of the analyzed systems can be quantified using a set of complex systems measures of effectiveness (CMOEs). The example in Section III.6 will show the interplay between behaviour and the CMOEs in a combat simulation [6].

Given fixed forces, weaponry and equipment, the success probabilities of a particular side in a conflict modeled using an ABM can be varied by changing the behavioural settings of interacting agents. The collective pattern of behaviour that emerges for a group under fixed settings relates to their combat prowess on the battlefield. In the context of ABMs, this amounts to manoeuvre tactics. It includes varied reactions to stimuli in terms of attraction or repulsion towards friends, enemies, particular threats, or towards terrain features. Unless otherwise stated, hereafter the term 'behaviour' refers to these kinds of reactions to stimuli.

ABMs such as MANA provide a convenient environment for exploring such lines of interest. They provide a means to represent a battle scenario, including the emergent behaviour driven by the lower-scale interactions. They also provide controls to vary the behaviour of combatants through built-in agent parameters covering personality, weaponry and sensor capabilities.

In MANA, the behaviour of friendly and opposition forces can be arranged to automatically adapt, within user-specified ranges, according to an embedded genetic algorithm (GA). This allows one to explore a large parameter space of behavioural possibilities in the search for an optimal solution, and thus optimize the agent's performance within a given scenario. It is important to note that ABMs are inherently stochastic, and therefore an outcome of a single run can be a product of lucky coincidences. Therefore it is prudent to optimize the system by considering an average performance across several replications of the same configuration.

A final point concerns the robustness of a GA solution. A highly optimized solution to a problem may hinge on minor features (or even errors) within the simulation environment, rather than the main drivers. Such a solution runs the risk of performing poorly when the simulation conditions are altered even slightly. Thus one has to be careful not to 'over-adapt' the population.

III.6. Example of Complexity-Driven Optimization Using GA in MANA

This example illustrates how knowledge of combat complexity can be characterized in real-time and how it may lead to tactical advantage within a conceptually simple combat situation exhibiting fractal properties. More details can be found in reference [6].

The presented scenario (Figure 2) was designed to present a significant challenge for BLUE. Two 6-member BLUE patrols (A1 and A2) are 'searching' for waypoint B (e.g., hostage holding place) occupied by 10 RED defenders (SITE). There are also a significant number of RED distributed over the battlefield (coloured pink) (PATROL). The average path of the BLUE patrols is actually predefined (marked by grey lines in Figure 2), but the capability of the agents to recognize the waypoints relies on the proper interpretation of a CMOE. To get to the waypoint, the BLUE squads expect multiple encounters with PATROL. PATROL members are to be identified and eliminated by the indirect fire (IF) support. However, IF is not to be used when near the final waypoint (e.g., to protect against accidental targeting of civilians in a hostage situation). The IF is connected to the squad situational awareness (SA). It has to quickly classify an encounter as a PATROL or a SITE based on the available CMOE data. The determination is based on the pre-defined encounter-type signature recognition.

Symmetropy (Section II.2) was used as the CMOE of choice [6]. Comparing mean symmetropies of the two RED force constituents (both fully and also partially based on detections) turned out to be ineffective. The mean values were very close together, and the spread (standard deviation) was high enough to blur any distinction. If the mean values had been significantly different, they could have been used to determine the encounter type (SITE or PATROL) and hence fix the decision whether or not to use the IF support, but under current situation this was not feasible.

There was, however, another option worth exploring. The detection data can be separated into distinct symmetropy modes. Symmetropy modes are defined here as dominant combinations of the basic symmetries that appear in the symmetropy data as recurring numbers. These modes are a reflection of commonly encountered patterns in the symmetropy matrix. They can be simply labelled consecutively as Mode 1, Mode 2, etc., rather than refer to the specific, unwieldy

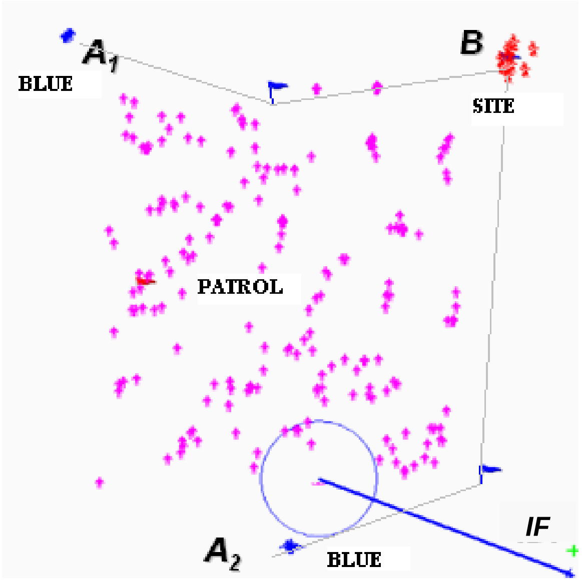

Figure 2. *Scenario overview for the complexity-driven GA example.*

numeric mode values. In Figure 3 the frequency of symmetropy modes is shown for the two RED encounter types SITE and PATROL (out of 30 sets of 5 detections). There was a significant difference between the two encounter types. Mode 6 accounts for 40% of all SITE detections, and only 13% of PATROL detections. Plus, the distribution of the PATROL symmetropy modes is far more uniform than that of the SITE modes. Thus the spikes for Modes 6 and 8 are the sought-after signature to distinguish between the SITE and the PATROL.

Due to the sparseness of detection data in this scenario, and for the simplicity reasons, a conservative approach was taken – the IF support was used until Mode 6 appeared in the detection data. Using a combination of Modes 6 and 8 would decrease the chance of false positives, but would increase the likelihood that the SITE would be detected too late. All other detections were ignored. Then the IF was temporarily turned off while the BLUE assault team dealt with the perceived SITE threat. The overall mission was deemed ‘completed’ if BLUE had reached the waypoint B, and mission success was based on a count of the number of SITE defenders left untouched by the IF before detection (an indirect way of measuring how often the IF fired on the no-fire zone). The mission success MOE ranges in value from 0 to 10 (maximum of 10 SITE defenders remaining).

The results of the simulations are displayed in Table 1. On average 35% (47 of 133) of the BLUE force’s opportunities to detect and classify the RED site defenders were successful. Statistically, the result is in line with expectations based on the histogram of symmetropy modes (Figure 3). False positives occurred in 3.3% of cases (16 of 485), somewhat less than the expected 13% as judged from the histogram. The mission was completed in all runs. For comparison, if there was no difference in treating both types of RED (no CMOEs), the mission was still completed in 100% of the runs, but the site defenders were destroyed by IF almost always. On the other hand, if the decision to use or not use the IF was random, the mission was completed in only 40% of runs, and the MOE still performed much poorer than with CMOEs contribution.

Overall, a CMOE was successful in improving mission success for a real-time combat scenario; this in spite of the fact that the forces were sparse and hence the available data were quite limited. In the case considered, a CMOE was used in a precursory-like fashion, hinting at the nature of an imminent near-future change in the system dynamics. The precursors took the form of specific patterns of spatial disorder with respect to a set of predefined symmetries (Walsh functions [24])

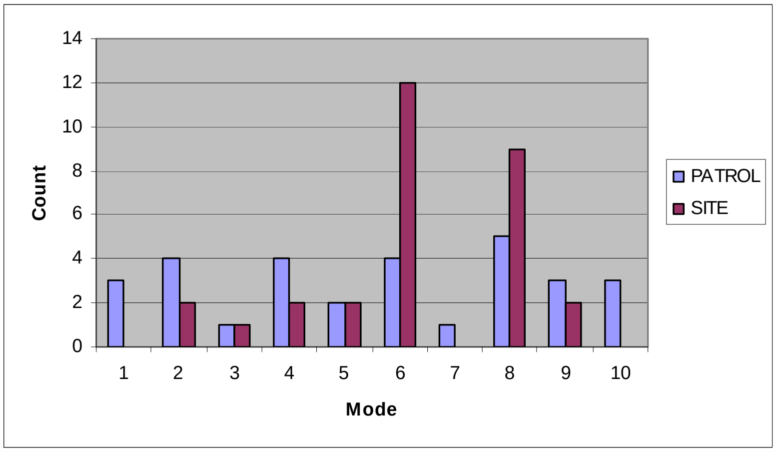

Figure 3. *Symmetropy modes is shown for the RED SITE and PATROL.*

residing within the spatial distribution of the enemy force. In other scenarios, the suitable CMOEs might be different, and might be used in a conjunction with traditional measures.

Although the situation presented in this example is artificial, the methodology seems to show promise. Thus, tracking and responding to CMOEs in combat simulations seems to have potential for enhancing awareness about the underlying complex system dynamics at work in a conflict. Such an awareness can also translate into an advantage, both in real-time and through statistical analysis of repeated simulations.

Table 1. *Classification and mission success results.*

Simulation Number	Correct SITE Ids	False Positive SITE Ids	MOE (out of 10)	Mission Completed
1	2 of 2	0 of 88	5	YES
2	4 of 16	0 of 0	7	YES
3	2 of 5	2 of 22	3	YES
4	3 of 6	0 of 67	5	YES
5	11 of 26	0 of 113	7	YES
6	0 of 4	11 of 26	1	YES
7	19 of 49	0 of 4	9	YES
8	1 of 4	2 of 68	4	YES
9	1 of 9	1 of 94	5	YES
10	4 of 12	0 of 3	5	YES
Averages	***35%***	***3.3%***	***5.1***	***100%***
No CMOEs	***N/A***	***N/A***	***0.4***	***100%***
Random decision	***N/A***	***N/A***	***1.6***	***40%***

IV. Intermittency and Self-Organized Criticality

Until now the focus was on the applicability of the CMOEs to combat modeling. However, they can be applied to real conflicts as well. To demonstrate this fact, the analysis of intermittency and its application towards distinguishing between the nature of conflicts in Afghanistan and Iraq is presented. The difference is closely related with the concept of self-organized criticality (SOC).

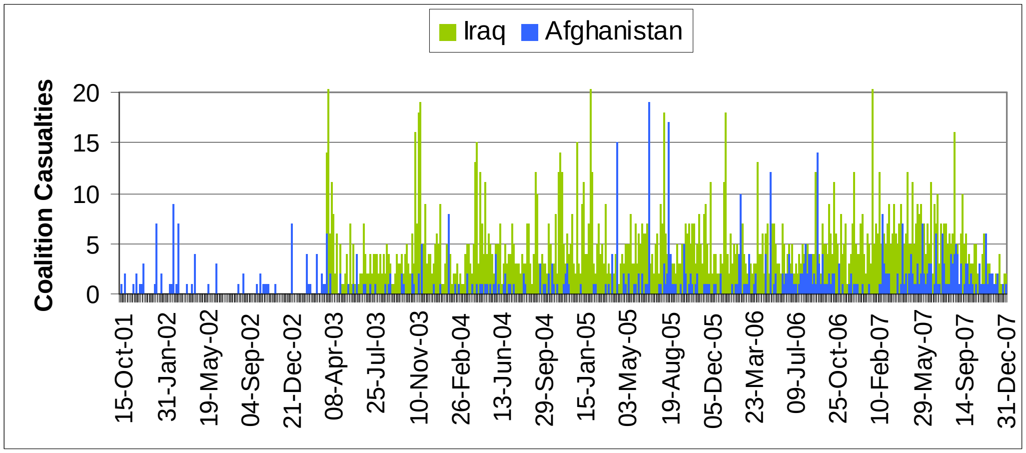

Figure 4. *Fatalities numbers for the conflicts in Afghanistan and Iraq.*

It has been argued in several works that conflicts exhibit characteristics of self-organized criticality [25]. Richardson [14] identified a power-law relationship between conflict size and frequency of occurrence. Cederman [26] suggested SOC as a mechanism for the scaling in the conflict size. Lauren [15] identified the presence of power-law scaling in fatalities during World War II. All of the above studies focus on symmetric, international conflicts, and their analysis is based mainly on the power-law scaling. For critical systems, dynamics of the system have an avalanche character. The number of fatalities is neither causally related, nor proportional to the intensity of events that led to fatalities (e.g. there can be a large violent battle with almost no fatalities, and then a minor accident can lead to a large number of fatalities).

Dobias [16] analyzed frequency/size scaling and long-term correlations in fatalities for conflicts in Afghanistan and Iraq, and the results suggest that both conflicts are self-organized systems with Iraq exhibiting all of the characteristics of the critical state. On the other hand, daily coalition fatalities in Afghanistan were anti-correlated, characteristic of sub-critical discharge event systems [27].

To expand on this work, the intermittency in fatality numbers for the two conflicts was analyzed. At first, the coalition fatality numbers in Afghanistan were analyzed. The fatality occurrences for Afghanistan are much sparser than for Iraq (Figure 4), and thus it can be expected that there is an actual difference in the nature of the two conflicts.

To obtain either co-dimension or the Fano factor, a counting process, consisting of a series N_k, summing the events Z_i for varying numbers of time steps k up to the entire duration of n time steps covering the entire analyzed period, is calculated as

$$N_k = \sum_{i=1}^{k} Z_i, \quad k = 1,2,\ldots,n\,.$$

Afterwards, to obtain the co-dimension, the dependence between the variance $S_k = \langle N_2(k)\rangle$ and the time $T = kT_0$ is obtained for all $k = 1,2, \ldots, k_{max} \le n$. Finally, the value of $2 - C_2$ is estimated from the regression of the slope of log S_k vs. log k. The Fano factor can be estimated in a similar fashion as the co-dimension. The log-log relationship between $F_k = (\langle N^2(k)\rangle - \langle N(k)\rangle^2)/\langle N(k)\rangle$ and k is used in this instance, yielding the Fano factor α. The Fano factor can then be used to either verify that the process is a fractal point process (FPP) ($\alpha = 1 - C_2$), or in the other case, estimate the Hurst coefficient H, given that it is a fractal-rate point process (FRPP).

For the conflicts in Afghanistan, the scaling factor obtained from the log S_k vs. log k dependence was $2 - C_2 = 1.64$. This in turn implies that the co-dimension is $C_2 = 0.36$. In other words the

Afghan conflict yields medium intermittency of fatalities, suggesting that the spikes are not correlated, and that the overall system is likely anti-persistent (increase at a given time means decrease for the future). On the other hand, for the fatalities in Iraq the scaling factor is $2 - C_2 = 1.90$, yielding rather low intermittency ($C_2 = 0.10$). In both cases, the log-log dependence of S_k on k was linear across the entire range of k, and the goodness of fit was estimated to be $R^2 = 1.00$.

The Fano factor was also estimated for both conflicts. The calculated value was $\alpha = 0.61$. This value is reasonably close to the expected theoretical value of $\alpha = 1 - C_2 = 0.64$, as is to be expected for an FPP. The goodness of fit was R2 = 0.99. For Iraq, the value of $\alpha = 0.38$, far from the theoretically expected value $\alpha = 1 - C_2 = 0.90$ for an FPP (0.90). This, combined with the low intermittency, suggests that the conflict in Iraq exhibits the properties of an FRPP.

Thus for Iraq, the Fano factor can be used to estimate the Hurst coefficient. In this case the value is $H = (1 + \alpha)/2 = 0.69$. This is in a good qualitative agreement with the earlier findings that analyzed the correlation in the coalition fatality data in Iraq and came to the conclusion that indeed the data exhibits long-term correlations [16] (although the value that was estimated there was slightly higher (up to $H = 0.8$). The difference is caused by a lower accuracy of the present estimate given smaller set of different box sizes used to estimate the Fano factor.

To summarize, there is a significant qualitative difference between the coalition fatality numbers in Afghanistan and Iraq. Fatalities in Afghanistan are intermittent, exhibiting properties of an FPP, while fatalities in Iraq exhibit very low intermittency, and correspond to the characteristics of an FRPP. The intermittency properties identified in this paper are consistent with the earlier observations. The intermittent fatalities observed for the Afghanistan conflict correspond well to an anti-correlated system (an occurrence of a significant event in terms of fatalities is rare). This, combined with the relationship between the Fano factor and the co-dimension, is consistent with the conflict being an FPP. For the fatality numbers in Iraq, the long-term correlations are well reflected in the low intermittency of the series as is well corroborated by the value of the Hurst coefficient obtained from the Fano factor. In summary, both analyzed representatives of IW exhibit characteristics of fractal processes. This reinforces the suggestion that the IW can be described as a self-organized critical or sub-critical system [16].

V. Summary and Conclusions

The use of agent-based models (ABMs) as a viable alternative to interactive wargames for irregular warfare, and alternative options for evaluating simulation outcomes were discussed. An example of the use of ABMs in the context of traditional combat modeling (crowd confrontation) was presented. Then the use of ABMs to explore the complexity of combat was discussed in addition to harnessing this complexity in an attempt to optimize the entities' response to the battlefield situations. It can be concluded that ABMs can be used to enhance traditional wargaming capabilities or on their own as stand-alone simulations.

The application of an ABM to the exploration of battlefield complexity highlights the inadequacy of traditional end state-focused, attrition-based assessment. A new set of measures of effectiveness (MOE), suitable to capture the complexity of irregular warfare, was discussed. These measures are not strictly dependent on attrition (the determination is situation-specific), and are able to capture the dynamics of the battlefield including dispersion and re-aggregation of forces. These MOEs also provide a possible means of classifying some combat systems and investigating the complexity and criticality of combat in general. An example application of a complexity-based assessment for a real-time, simulated conflict was presented.

To summarize, the combination of ABMs and the complexity-based assessment of the modeled (or observed) conflict dynamics provides a promising toolset for gaining deeper insights into the complex nature of combat. In the longer term, this can benefit combat modeling and provide better and more realistic models for capability assessment.

VI. References

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