Operational Synthesis Applied to Mutual NZ/US Questions. Part I:

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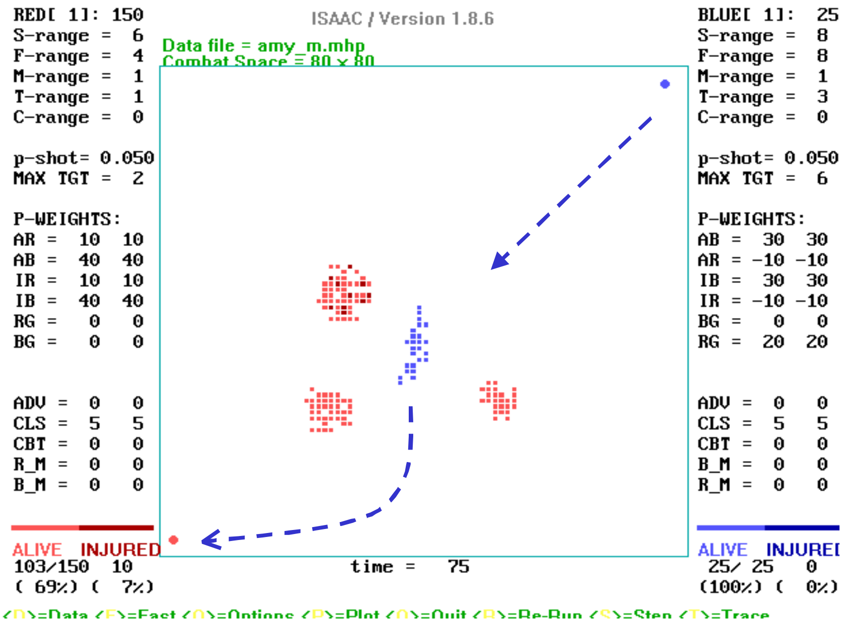
Abstract

The United States Marine Corps Combat Development Command and the New Zealand Defence Operational Support Establishment have begun collaborative work in the area of Operational Synthesis. In this paper we describe the research program initiated in the US called *Project Albert* which uses the process of Operational Synthesis. We then provide details on some specific research in this area initiated at the NZ Defence Operational Technical Support Establishment.

1 Project Albert

The United States Marine Corps has embarked on an effort to provide quantitative answers, where possible, to the important questions facing military decision-makers. The methodology used is called Operational Synthesis, which is being implemented through what we call *Project Albert*. In order to help answer important questions, we must be able to quantify three phenomena: non-linearity, the so-called intangibles, and co-evolving landscapes. By *non-linear* we mean that, under the right circumstances small changes *can* have large impacts on outcomes. To illustrate we condense a well-known saying: *For want of a nail…the battle was lost*. The reader can certainly supply many examples of non-linear effects, which are often ignored by traditional techniques. Similarly, current techniques tend to ignore important factors in war, namely the intangibles of morale, training, ethos, leadership, etc. Equally important is the need to determine the impact of co-evolving landscapes; the phenomenon where one's decisions are made in anticipation of the opponent's who in turn anticipate and so on. It is unlikely that any important military decision was made without co-evolving considerations. Given our poor ability to address these phenomena, depending on the question, each of the three effects above can dominate the answer. The choice for the operations researcher is either to give up trying to provide quantitative advice or to try to develop new methods to address these old questions.

Operational synthesis is the science developed to find ways to discover the quantitative components of the effects mentioned above. Because it tends to investigate the richness of structure, it acts as a complement to traditional analysis, which more and more has become fascinated with detail. While there is no universal approach to answering a question, our attack often starts with a *distillation*, which is a model that abstracts the essence of a situation. Often this distillation is constructed in the context of an agent-based simulation. One distillation we have used to create data to develop hypotheses in our initial research is the agent-based model ISAAC (Irreducible Semi-Autonomous Adaptive Combat), developed at the Center for Naval Analyses by Dr. Andy Ilachinski. ISAAC works by assigning parameters to a set of personality traits for each entity. Entities are then given simple goals to satisfy. The entities, called ISAAC agents display emergent (not scripted) group behavior as well as non-intuitive effectiveness when certain personality vectors are used. They also display clear and dramatic sensitivity to small perturbations in vector setting or locations. ISAAC is depicted below. In the run displayed, the red force (dots) groups into three separate cells while the blue force maneuvers to avoid red.



These distillations are run on the computer many, many times so as to observe non-linear effects and emergent behavior. It is often the case that only through this large number of runs that these effects can be identified and characterized. We use the tremendous capabilities of the Maui High Performance Computer Center (MHPCC) for many of these trials. MHPCC has also been invaluable in helping us develop visualization techniques for interpreting the data. We iterate by applying a technique, *Data Farming*, developed at the US Marine Corps Combat Development Command and described in detail in the US Marine Corps publication *Maneuver Warfare Science1998*. Data farming enables feedback between data mining and data creation.

Some general areas of research within *Project Albert* include:

TECHNIQUE DEVELOPMENT: A large part of our effort has been to develop ways of testing hypotheses and interpreting results. We now have database of several hundred million computer runs, serving as a test bed for honing these techniques. Our data visualization efforts fall under this area.

TACTICS DEVELOPMENT: We have made modest progress in supplying a quantitative basis for tactics as a function of combat parameters.

EXPERIMENTAL HISTORY: These efforts involve the distillation of the essence of various aspects of historical battles so as to quantify the value of alternative tactics.

GENERATIVE ANALYSIS: This effort involves investigating how to generate families of scenarios so as to stress various force structures.

COURSE OF ACTION ANALYSIS: Near real time COA analysis in a coevolving environment is obviously of great interest to us. Our ultimate goal here is to create a model useful to field commanders.

GILGAMESH: Gilgamesh is our effort to network our NT computers so that we can work on our questions requiring computer power greater than that of a desktop, but less than that provided by a supercomputer.

REAL TIME DECISION SUPPORT: We are in the process of implementing *Red Orm*, a project which may result in real time support to decision makers using a distillation engine in development called GAUSS.

2 Summary

Project Albert is a questioned-based scientific stream of inquiry. The general methodology is Operational Synthesis and initially the approach has been to utilize agent-based models and implement the Data Farming meta-technique. The key to the entire process, however, is the richness of ideas that emerges through multi-disciplinary, multi-service, and multi-national collaboration. Thus, the remainder of this paper is devoted to describing some of the details of a collaborative effort led by New Zealand that is considered to have the utmost potential to achieve the goals of *Project Albert*.

Part II: Characterising complexity on the battlefield using fractal statistics

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Abstract

The ISAAC automaton combat model is capable of providing a rich variety of behaviour. The difficulty we face in using this model is characterising that richness. In this part of our paper, we describe how changes in the statistics of ISAAC data brought about by differing levels of complexity can be characterised by the use of fractal methods.

1 The non-linear battlefield

Advances in electronics and computer technology have brought many enhanced capabilities to the modern battlefield. Extremely long-range firepower (e.g. accurate long-range missiles, air strikes and modern artillery) combined with a high-level of situational awareness, thanks to GPS and satellite technology, and enhanced sensors, has allowed war to be fought and won without relying on overwhelming numerical superiority. Emphasis must instead be placed on analysing how manoeuvre affects warfare.

In this increasingly complicated environment, defence forces have been using combat simulations for both analysis and training for a number of years. Thanks to advances in computer technology, such combat situations may be relatively easily modelled in pain-staking detail on a PC computer. This detail usually has a strong emphasis on the specifics of weapons systems. Thus assessments are often made on the basis of who has the best weapon system. Unfortunately, this ignores the wealth of intangibles which have been recognised to play vital roles in warfare. To quote Napoleon: “Morale is to the physical as three as to one”.

At the same time, the tendency to emphasise manoeuvre in modern warfare has led to a recognition that combat is “non-linear”. Here, we use the term non-linear with a double meaning. Firstly, in terms of military formations. Linear warfare is based on the use of formations such as lines and columns to conduct battles. Modern weapons have forced a more dispersed approach to army deployments, while armoured transportation provides a means by which armies may manoeuvre rapidly.

In the second sense, we mean mathematical non-linearity. i.e. the whole is more (or less) than the sum of its components. For example, there are countless examples in military history of a “superior” (either numerically or technically) force being defeated by an inferior force. In such a case, we say that the superior force would win if kill potential was the only determiner (i.e. if both sides merely lined up and slogged it out to the last man). Often in these cases, the supposed inferior force had some less-tangible attribute which allowed it to prevail. Certain military commanders, notably Alexander the Great and Napoleon Boneparte) have been particularly adept at exploiting the non-linear nature of warfare to defeat apparently far superior opponents, arguably without relying on superior technology.

Initial studies suggest that such dynamism on the battlefield is likely to lead to "clumpiness" in attrition, that is, brief bursts of engagement resulting in casualties which punctuate longer periods of few or no casualties. By contrast, purely attrition based models may describe combat in terms of a differential equation, assuming a continuous attrition rate, so that casualties occur constantly throughout the engagement. It is known from fields such as geophysics and finance that the existence of clumpiness in data leads to statistical behaviour which can be characterised conveniently with fractal models. Data which obeys fractal statistics tends to have greater extremities, and hence significant implications for assessing risk. That is to say, if modern "non-linear" methods of warfare do indeed produce clumpiness in the casualty rates, this affects the statistics, and hence risk.

Perhaps a good illustration of this is the Battle of Midway. Although this was a naval battle, it is perhaps indicative of how future land wars may be fought, with the outcome resting on a few high-value elements. Because the battle was largely determined by who was able to use their situational awareness to catch the other's carriers out, such an outcome to the battle could not be explained simply by kill potential (that is, could not be modelled by assuming each side continuously attrits the other until one runs out of forces). And because the battle was so non-linear, it may be expected that if the battle were re-run many times over, there would be a wide variance of results.

2 Properties of non-linear combat statistics

Recently, DOTSE has been investigating the effect non-linearity has on risk on the battlefield using the ISAAC model. Principally, this has been done by trying to characterise ISAAC data in terms of fractal statistics. This kind of statistics has been successfully used to characterise risk in other non-linear systems, such as the weather and the sharemarket, although it is fair to say that this field is still in its infancy.

Due to space limitations, it is only feasible to provide some of the flavour of these methods in this paper. There are three characteristics we look for to determine if fractal statistics are appropriate. These are: the smoothness of the data and the existence of a fractal dimension; clustering and intermittency in the data; and fat-tailed probability distributions.

2.1 Smoothness of data and fractal dimension

Figure 1 shows snapshots from three different ISAAC model runs with three different sets of parameters. Since the dynamics of ISAAC are driven by local rules, as for all cellular automaton models, any manoeuvring depends directly on the circumstances of each run.

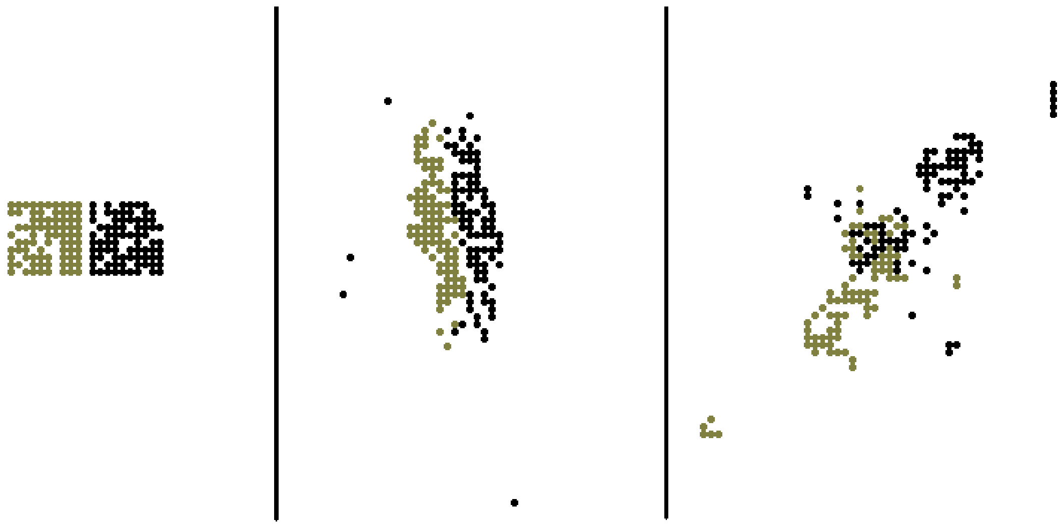

Figure 1. Three snapshots of the ISAAC model with different sets of parameters.

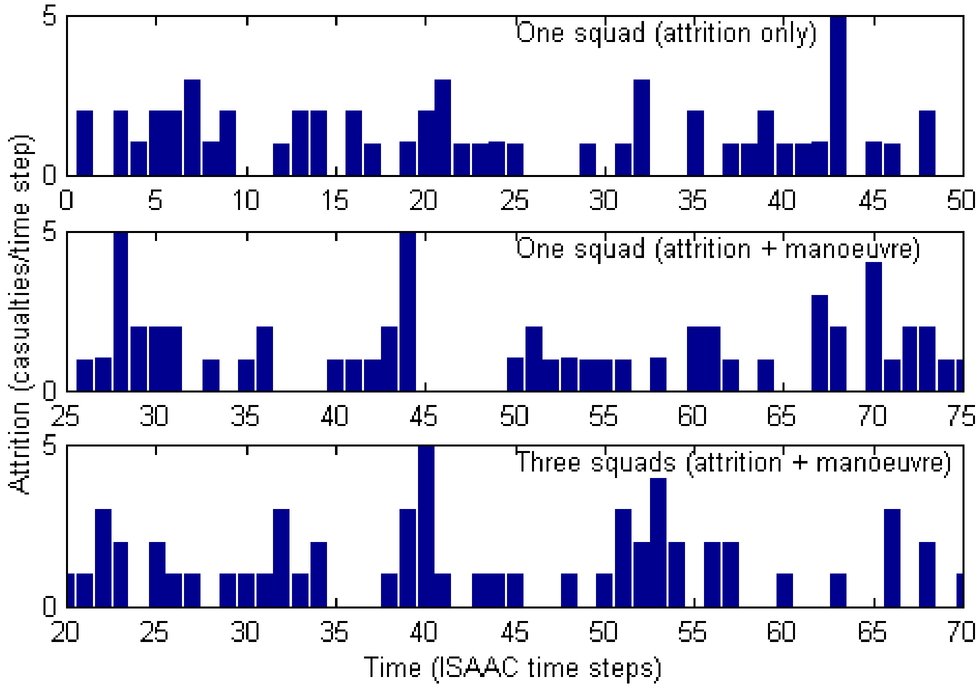

Figure 2. Attrition as a function of time for each of the cases shown in figure 1.

This is in contrast with traditional analytical combat models, which tend to run the same (or at least close to the same way) with each run.

The first case shows no manoeuvre at all, with each side forming a square. The second case shows manoeuvre with one type of automaton. Here the automata fight the battle by forming themselves into a line. The rules which govern their behaviour for this particular case cause them to fight in this way. The final case shows a run using three different types of automata. Here, the different nature of each type of automaton has caused the battle to take on a much more striated appearance. This makes the battlefield much more complex than the middle case.

Figure 2 shows attrition as a function of time for the model for one run of each of the different cases shown in figure 1, up to the point in time where the casualties level reaches 50 per cent. Clearly, the attrition function is not well behaved, being neither smooth, nor non-zero.

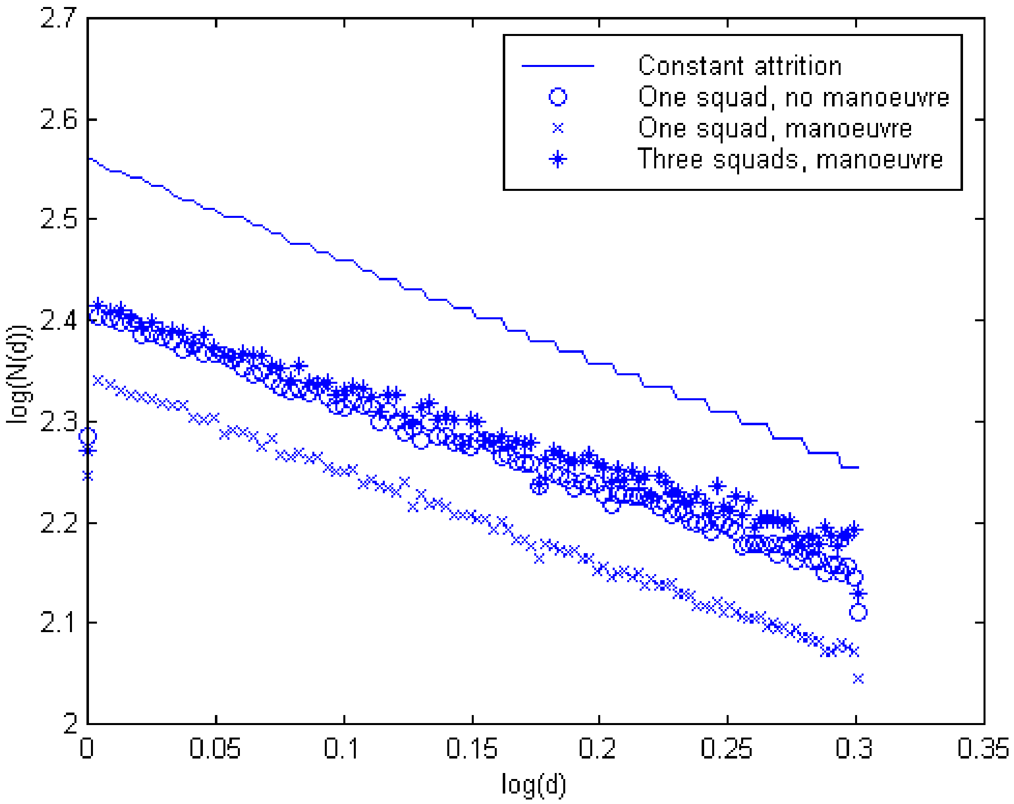

Figure 3. The plot shows how each of the functions in figure 2 "scale", that is, how many boxes of side length *d* are required to cover each attrition function in figure 1 (*N* is the number of boxes).

Thus it is not easily modelled by a differential equation (the traditional differential equations used to model attrition in military operations research were suggested by Lanchester at the start of the century). From the figure, the data in the bottom case at least appears to be more intermittent, with attrition somewhat irregular, and with periods of high attrition clustered at particular times.

Admittedly, such a qualitative observation is somewhat subjective. However, the use of fractal analysis can quantitatively determine the difference between each set of data. The first method is to find the fractal dimension of the attrition function for each case. This can be done using a so-called box-counting technique [2]. That is, imagine a box one attrition unit high and one time step wide, and count how many are required to cover each of the functions shown in figure 2. Then, increase the height and width of the box say, 10 per cent, and count how many are required again, and so on. If a fractal dimension exists, then the plot of the number of boxes required versus box size should produce a straight line on a log-log plot, the slope of the line related to the fractal dimension.

Figure 3 shows such a plot. The slopes for each case (from top to bottom, using a linear regression) were -0.87, -0.92, and -0.78 respectively. The difference in these values is interpreted as describing the differing degrees to which each function in figure 2 displays scaling structure (that is, structure on many scales). The results obtained suggest the last case possesses more scaling structure than the first two. Note that for a continuous attrition rate (and thus a perfectly smooth function), the slope is -1.0, as represented by the solid line in figure 3. Equally, uncorrelated random data also has a slope of –1.0, since it has no structure. Note that this parameter (and those following) were determined from ensembles of data from six different runs of each parameter set, so that in fact 200-300 data points were used.

2.2 Measuring intermittency and $K(q)$

Perhaps a more interesting fractal parameter is the so-called "intermittency" parameter which derives from multifractal analysis. This parameter is found by analysing the scaling of the statistical moments of the data (a.k.a. multiscaling analysis), and a good description of this method can be found in reference [1].

Data which obeys multifractal statistics is characterised by intermittency, and its statistical moments obey a law:

$$\langle a_i{}^q \rangle \propto \left(\frac{t}{T}\right)^{K(q)}$$

where a is the attrition rate at the ith time step, the angled brackets represent an ensemble average, t is the temporal resolution at which the distribution is being examined, T is the "outer" scale of the scaling range, and $K(q)$ is a non-linear function of the order of the statistical moments, q.

This equation implies that the statistical moments of the data scale. Figure 4 demonstrates the scaling of the second-order moment (variance) for the data in figure 2.

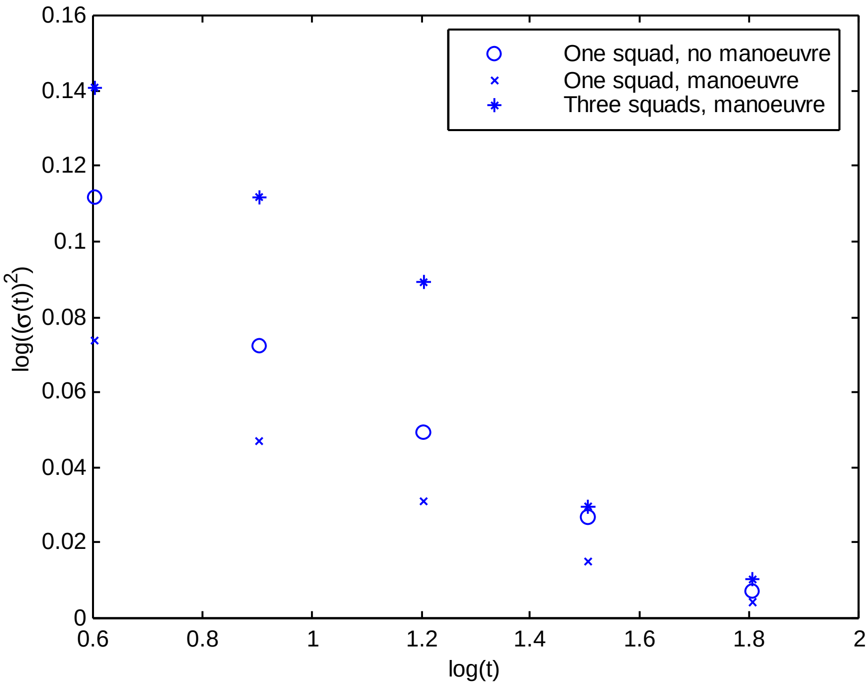

Figure 4. Scaling of the second-order moments for the data from figure 2.

Fitting straight lines to the points in figure 4 provides the value of $K(2)$ for each case. The slope tends to be steeper the more intermittent the data. Thus a popular measure of intermittency is the parameter C_1, defined as the derivative of $K(q)$ at $q = 1$. Figure 5 plots the $K(q)$ function for each case.

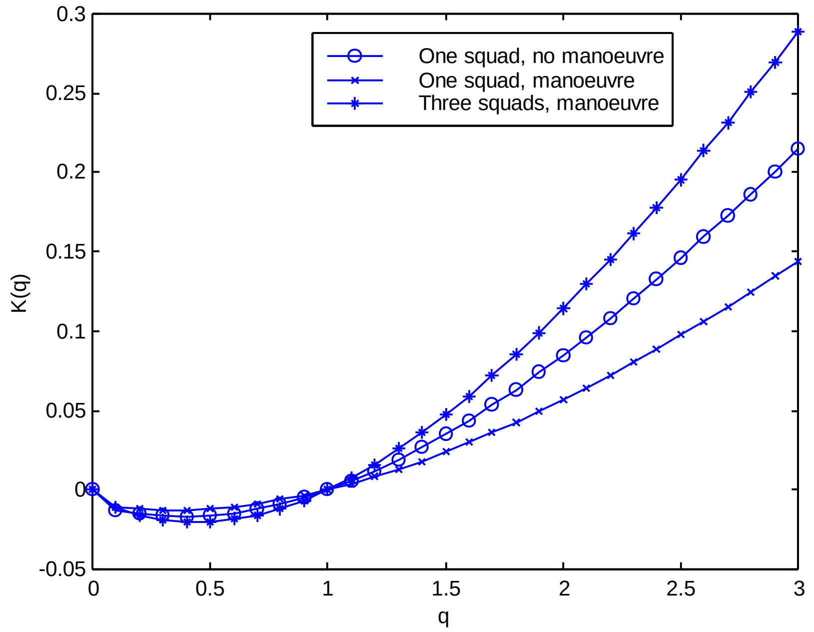

Figure 5. The $K(q)$ functions for the data in figure 2.

The intermittency parameters for each case (once again, from top to bottom in figure 2) are 0.053, 0.037, and 0.070.

2.3 Probability distributions

Figure 6 shows the probability distributions for the data in figure 2. It can be seen that while all the distributions have a "tail", the fattest tail belongs to the bottom case.

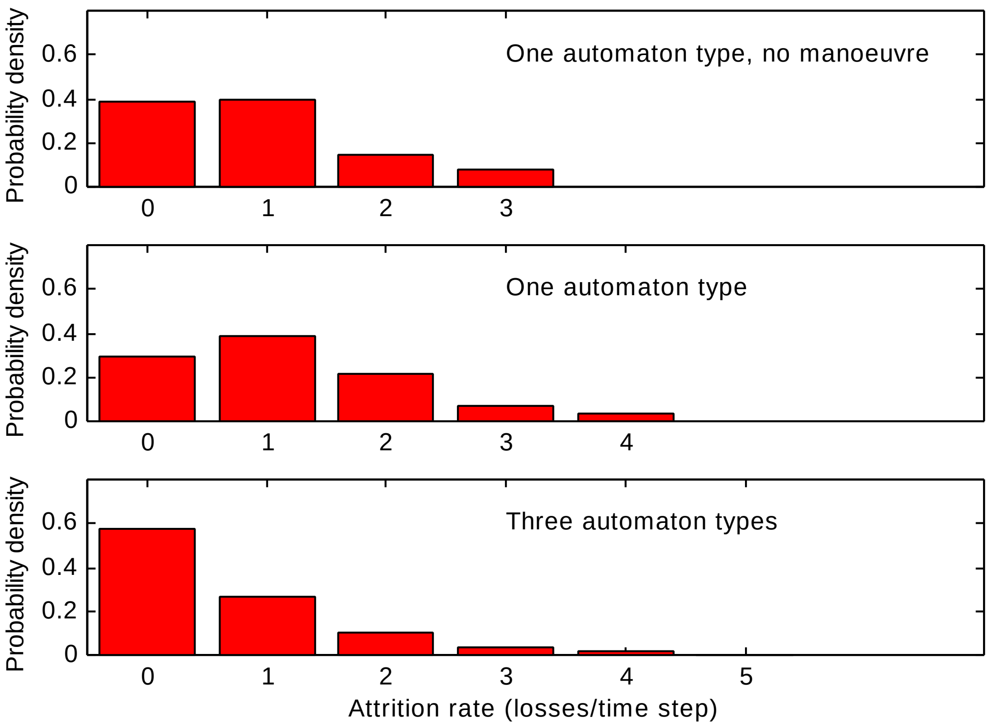

Figure 6. Probability distributions.

Given the results of the preceeding section, this is not surprising, because this case was also the most intermittent. Since this is the case, most of data represented periods of little attrition, with a greater number of extreme data points required to produce the same mean attrition rate.

Conclusions

Fractal statistics were used to examine model runs using three sets of ISAAC parameters. Each of the runs represented different levels of complexity. The fractal analysis showed that for the most complex case, that which used three different kinds of automaton for each side, the attrition data possessed a greater degree of scaling structure, greater intermittency and a fat-tailed probability distribution. This suggests that increasingly complex battlefield dynamics lead to increasingly fractal-like statistics.

On the other hand, the middle case in figures 1 and 2, which used one automaton type and allowed manoeuvring, did not appear to display any more structure or intermittency than the case with no manoeuvre (in fact, it was less intermittent). As can be seen from figure 1, this particular set of ISAAC parameters produced runs where the the automata fought in a “line”, literally “linear” warfare. Such a situation is not representative of how modern war planning suggests wars will be fought in future.

Of principal concern for future studies is determining when complexity arises on the battlefield, and determining the risks associated with complex warfighting.

In a broader context, the types of methods discussed here may be applied to a wide variety of complex systems. For example, the same methods might be applied to model attrition of equipment (rather than personnel) during military operations, or attrition of staff in a large corporation.

As noted, the time series in figure 2 clearly have different statistical characters depending on the degree of complexity. Assessing risk for complex situations which produce such time series must consequently take this into account. It should be particularly noted that the properties of scaling structure and intermittency in the data mean that a large loss in a given unit time step is likely to be surrounded by other time steps with large losses (i.e. when it rains, it pours).

Fractal statistics appear to be a good method for characterising such time series, as indeed Mandelbrot [3] has recognised for the sharemarket. This should sound a warning that for complex systems assumptions of risk based on normal statistics are likely to be erroneous.

References

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[3] B. B. Mandelbrot, *Fractals and Scaling in Finance*. Springer-Verlag, New York (1997).