AGENT-BASED MODELLING IN THE NEW ZEALAND DEFENCE FORCE

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ABSTRACT

MANA (Map Aware Non-uniform Automata) is an agent-based distillation modelling environment developed by the Operations Analysis group at the Defence Technology Agency in New Zealand. MANA purposefully leaves out detailed physical attributes of the entities concerned if they are expected to have little bearing on the study at hand. This allows scenarios to be run relatively quickly, over many excursions (i.e. Monte Carlo simulation), in order to uncover capabilities or tactics where Blue can achieve dominance over Red. Another key feature of agent-based models is that, although the one-to-one interaction between various agents and their environment may be quite simple, the combined effect of many agent interactions can lead to complicated group dynamics and emergent behaviour. This paper provides the reader with an understanding of the philosophy behind the design of MANA, an overview of its features and some examples of its use.

Keywords: agent-based modelling, operations analysis, tactics, intangibles, defence, combat, capability, experimentation, technology.

1. INTRODUCTION

The Defence Technology Agency (DTA) provides applied research, exploratory development and policy studies on science and technology with application to military technology, force development and operational needs. Primary customers include the New Zealand Defence Force (NZDF) and the New Zealand Ministry of Defence (MOD). DTA also often partners with other government agencies and industry.

DTA employs approximately 70 scientists and engineers from a variety of disciplines. Research areas at DTA include operations analysis, sensor systems, electronic warfare, network systems, structures and materials, chemical and biological defence, undersea warfare, environmental science, human factors and autonomous systems.

1.1. DTA Strategic Position

DTA has a number of science and technology goals which are outlined as follows:

- Support current operations and capabilities
- Develop knowledge on emerging technologies
- Explore innovative and cost effective ways of employing technology
- Enhance force performance
- Support force development and capability acquisition
- Provide robust justification for future capability requirements
- Reduce the costs of acquisition and ownership of platforms and equipment
- Extend the life of platforms, weapons and systems
- Improve force sustainability
- Solve problems caused by New Zealand's unique strategic environment

1.2. Operations Analysis at DTA

The Operations Analysis group at DTA consists of 6 science researchers and acts as a conduit to other DTA science and technology expertise and to the international defence community. Key roles for this group include:

- Future concept exploration
- Capability methodology development
- Trade-off/balance of investment studies
- Experimentation methods and their execution
- Market surveys & technology assessments
- Supporting the development of operational tactics, techniques and procedures

The OA group intentionally therefore maintains a broad operational and strategic view to ensure the best overall NZDF and NZ Government outcomes by employing a range of tools and approaches. These include field experimentation, subject matter expert knowledge elicitation, modelling, simulation and wargaming.

1.3. NZDF Modelling Requirements

Models designed to represent complex adaptive systems produce results that are significantly different from conventional force-on-force combat models. The development of the Map-Aware Non-uniform Automata (MANA) modelling environment first began in 1999, after realising that such models better met the requirements of the NZDF (i.e. small unit operations).

2. MANA BACKGROUND

The history of physics has been characterised by the search for systems simple enough to be able to be accurately described by mathematical equations. Isaac Newton's laws of motion are an example. Although extremely accurate at predicting, for example, the path and distance travelled by a heavy projectile, they cannot in general be relied on if the projectile is light, has an irregular shape and is subjected to a turbulent atmosphere. This simple example illustrates a powerful point: that the world is often far more complicated than Newton's equations. To this day, there exists no set of equations that can with absolute certainty predict the evolution of the vast majority of phenomena we see in everyday life for any significant period into the future.

2.1. History

Our motivation for developing MANA began with a frustration with the highly physics-based combat models that were available to us at the time (e.g. CAEn and Janus).

Warfare is inherently chaotic, and although these models purport to be detailed, highly physics-based and rigorous, it became clear when one started to try to analyse the value of things such as human behaviour and knowledge-based warfare, they become quite limited. They also do not reflect the capabilities of the NZDF or the types of operations that the NZDF is principally involved in (e.g. peace keeping and humanitarian operations).

Moving to an agent-based modelling environment was driven by the key idea that the behaviour of entities (both friend and foe) was a critical component of the analysis of the possible outcomes. Distillation models also require less data and effort than high fidelity models, which better suited a small operational analysis group (Lauren 1999).

2.1.1. Agent-Based Models

MANA is in a general class of models called Agent-Based Models. These have the characteristic of containing entities that are controlled by decision-making algorithms. Hence an agent-based combat model contains entities representing military units that make their own decisions based on their situation, as opposed to the modeller explicitly determining their behaviour in advance.

3. THE MANA MODELLING ENVIRONMENT

MANA purposefully leaves out detailed physical attributes of the military entities concerned if they are expected to have little bearing on the study at hand. This allows scenarios to be run relatively quickly, over many excursions. Although it contains fairly simple input parameters, these can still result a surprisingly wide set of behaviours (Anderson et al 2004).

MANA is often used in conjunction with a technique known as Data Farming. This is an iterative process which uses the repeated execution of stochastic simulation models (such as MANA) to map out a problem landscape. The idea is that this can provide insights that may otherwise be overlooked by analysts.

3.1. Model Features

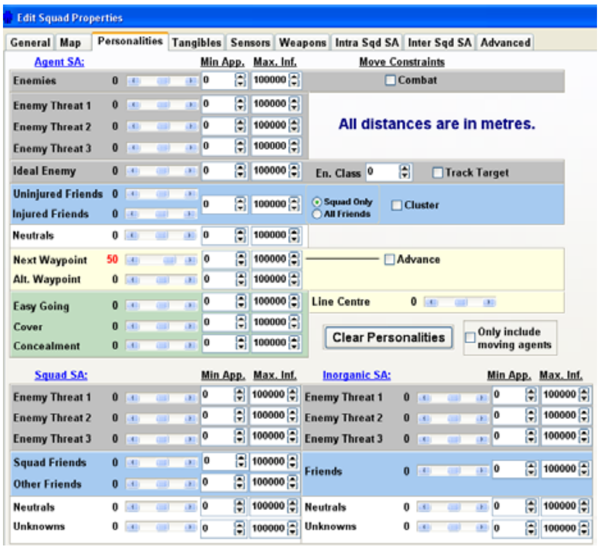

Figure 1: A screenshot of the MANA 'personalities' squad properties tab.

The *Personalities* squad properties tab determines an agent's propensity to move towards friendly, neutral or enemy units, waypoints and terrain features. Agents can either use information that is obtained individually (i.e. from the sensors they possess) or from other sources. Different personality states can also be triggered by battlefield events (such as being shot at). These can either affect an individual or a whole squad at once and will then last for a set timeframe.

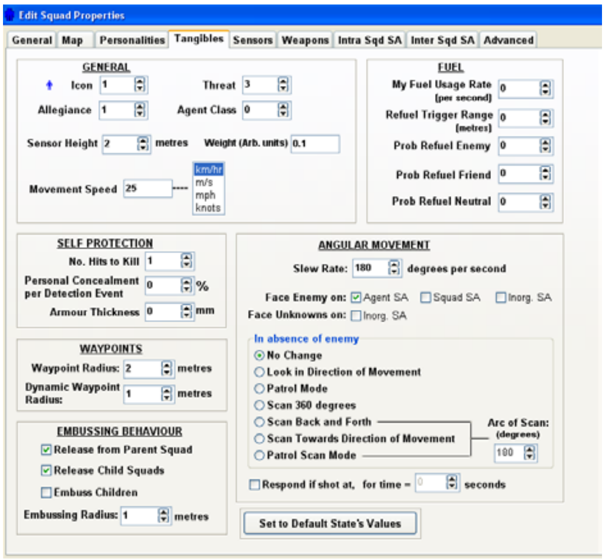

Figure 2: A screenshot of the MANA 'Tangibles' squad properties tab.

The *Tangibles* squad properties tab defines agent capabilities such as their allegiance (friendly, enemy or neutral), movement speed, inertia, endurance, concealment and protection (armour). It also contains parameters that can control the ability agents have to influence one other.

Users can choose from a built-in selection of icons to represent different agents or they can load in their own custom icons instead.

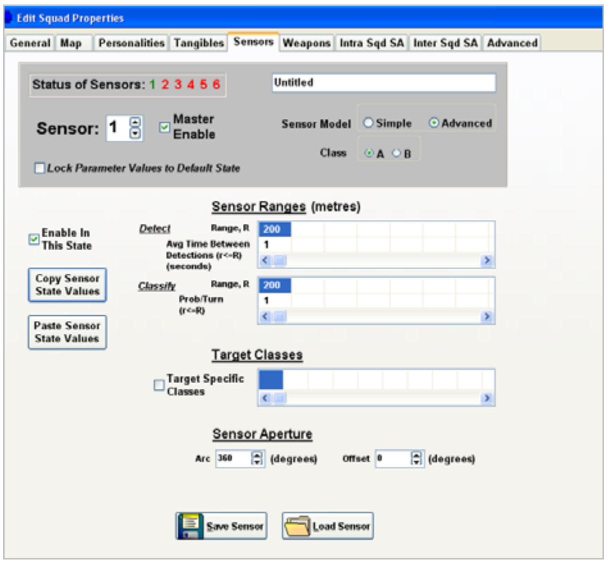

Figure 3: A screenshot of the MANA ‘Sensors’ squad properties tab.

The *Sensors* squad properties tab is used to define the sensing characteristics of agents. These can be represented with simple ‘cookie-cutter’ ranges for detection (unknown entity) and classification (allegiance is determined). Alternatively, advanced sensor options can also be used to introduce sensors that have a finite aperture (angle), range dependent probabilities of detection and integration times.

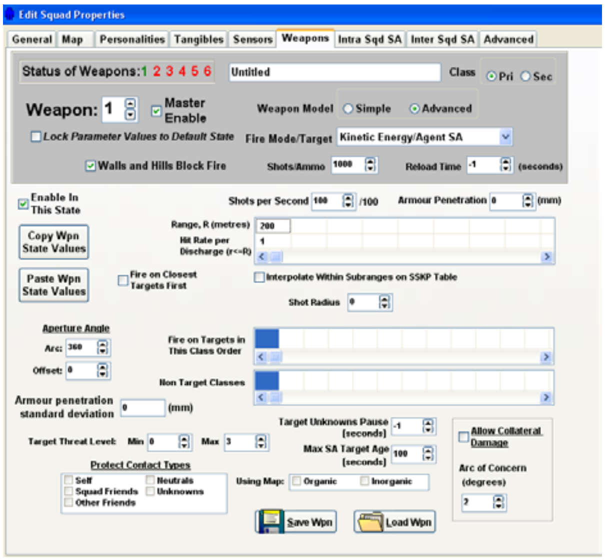

Figure 4: A screenshot of the MANA ‘Weapons’ squad properties tab.

The *Weapons* squad properties tab is used to define agent weapon capabilities. Weapons can either be direct (kinetic) or indirect (high explosive) in nature. Weapon parameters include ammunition levels, armour penetration characteristics and firing rates. Weapon employment rules can also be introduced, whereby targets can be prioritised by their distance and/or threat level. Options are also available to prevent agents from firing when there may be a risk of fratricide or collateral damage.

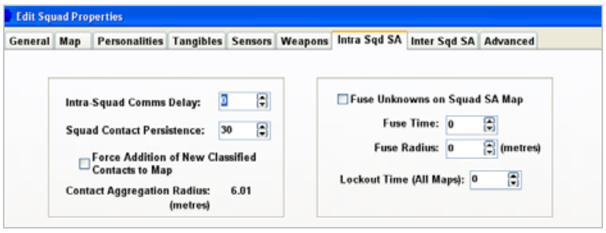

Figure 5: A screenshot of the MANA ‘Intra squad situational awareness’ squad properties tab.

Situational Awareness Maps are used by squads to maintain a group memory of detected contacts, along with whether they have been previously classified as friendly, neutral or enemy units. Users must select how often to update contact reports and maintain tracks for. Information can be shared between agents in the same squad (intra) or between agents in other squads (inter).

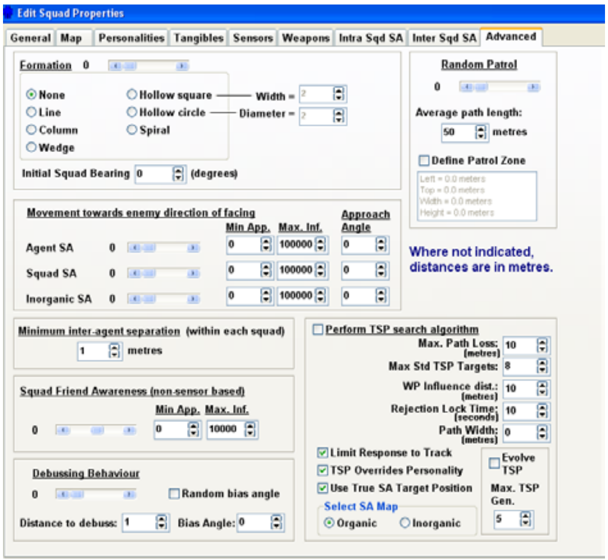

Figure 6: A screenshot of the MANA ‘advanced’ squad properties tab.

The *Advanced* squad properties tab is used to tweak the MANA agent movement algorithm. It enables users to force agents to maintain custom formations, separation distances and directionality. It also controls the degree of random movement (jitter) as agents move. A travelling salesman algorithm is also included, which gives agents a more sensible order in which to visit multiple contacts.

In addition to these tabs, MANA also incorporates tick boxes which can be used to disable certain attributes, such as line of sight calculations for sensors and communication links between agents. If these features are not required, then disabling them has been found to significantly speed up the run time of the model by reducing computational overheads.

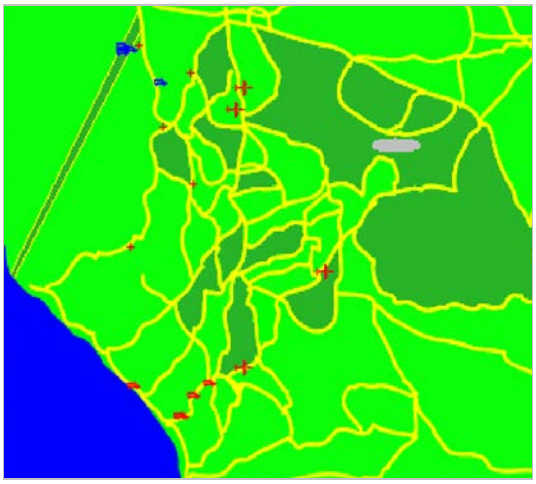

Figure 7: A screenshot of a MANA 'terrain map'.

The *Terrain Map* is used to contain terrain features (e.g. roads, undergrowth, buildings) that agents can use to improve their mobility, concealment or protection. MANA includes a simple terrain map editor for adding such features into scenarios.

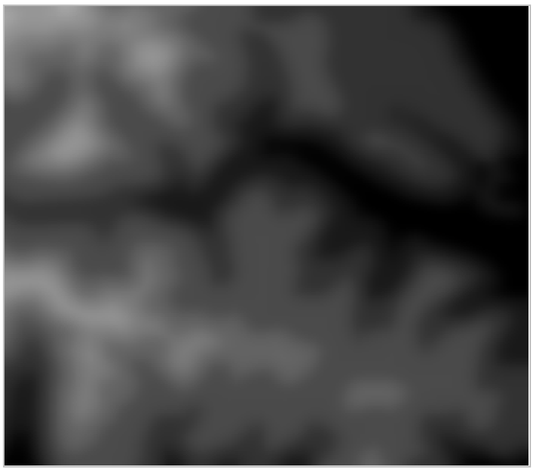

Figure 8: A screenshot of a MANA 'elevation map'.

The *Elevation Map* is a grey-scale map which is used to define the height of terrain features. This will then influence agent line-of-sight calculations. A sensor height parameter can also be used to give agents the ability to see over obstacles and not be affected by terrain, for example, if they represent aircraft.

In addition to the terrain and elevation maps, a custom background image (e.g. a satellite image) can be used to give the scenario a more realistic appearance.

3.2. Recent Developments

- Genetic Algorithm tool: This gives MANA the ability to automatically mutate agent personality weightings over multiple generations to produce desirable outcomes. This could include maximising Red casualties, minimising Blue causalities or capturing designated battlefield spaces.
- Intelligent Path Finding: This feature uses wavelet principles to guide agents through complex terrain.
- Vector-based Movement: Version 5 of MANA implements vector-based movement. This resolved a number of issues attributed to the previous cell-based movement algorithms (such as diagonal movement and the scaling of maps).
- Operating System Enhancement: A version of MANA has recently been released for 64-bit operating systems.

4. NZDF APPLICATIONS OF MANA

Within the NZDF, MANA has been used to assist with identifying capability gaps, developing user requirements, evaluating tactics, techniques and procedures (TTPs) and in support of operations. Study topics have included:

- Maritime surveillance and patrols
- Land sensor mixes
- Cordon tactics
- Humanitarian assistance
- Maritime force protection
- Weapon effectiveness studies

Several specific examples are provided below.

4.1. Food Distribution Study (McIntosh 2004)

This study gives an example of how MANA can produce emergent behaviour, even with only a simple set of agent parameters being used.

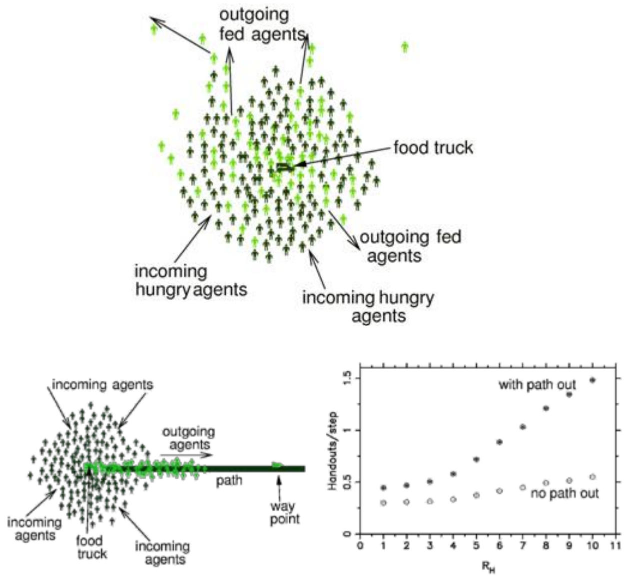

Figure 9: MANA food distribution study.

This study involved exploring strategies for food distribution in a humanitarian aid scenario. Only two personality weightings were given to the agents (get food when hungry and depart when fed) but one of the surprising observations was that agents tended to self-organise into temporary chains in order to get past one another (a phenomena that occurs in real crowds).

The results of this study showed that the food distribution rate depended most on controlling the outgoing flow of people rather than the incoming flow.

4.2. Land Sensor Mix (Anderson 2008)

This study gives an example of how the 'distillation' of a complex scenario can be used to enable different Red and Blue course of actions to be evaluated in a fairly short time period.

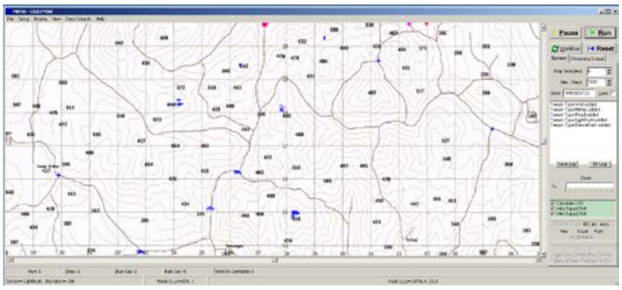

Figure 10: MANA sensor mix study

In this scenario, a motorised NZ platoon was given a screening mission near a rural village in undulating terrain (19 km wide by 7 km deep). Intelligence reports indicated insurgents with small arms were expected to try and infiltrate from the north on foot, giving Blue sufficient notice to deploy sensors and set up observation posts. Assets available to Blue included three light armoured vehicles, three remote ground sensors, five observation posts, a ground surveillance radar and a small tactical unmanned aerial vehicle (UAV).

An initial sensor deployment strategy was decided by the NZ Army during a tabletop exercise however during a subsequent wargame (using a virtual battlefield simulation) enemy units managed to slip through its sensor screen undetected.

MANA was employed post-activity to more thoroughly explore the effectiveness of the force structure. This was done by first using MANA to vary sensor placements and reduce the size of the area of operation (AO) until a maximum coverage rate was achieved. This was then employed against different enemy courses of action (random approaches).

The results indicated that too much emphasis in the original wargame had gone in to monitoring roads, and that the enemy force had exploited terrain features to avoid detection by going off-road. With revised sensor placements and the use of a slightly smaller AO size, MANA results suggested there was a 99% probability of detecting all the insurgents. Ground surveillance radar was found to be the most critical sensor to have (it contributed to 57% of the overall detections) and it was also useful for cueing the light armoured vehicles that were used to intercept Red. The UAV was found to be best utilised by using it to cover radar dead zones and to track contacts that moved through terrain where vehicles were unable to go.

The conclusion was that the proposed force structure appeared to be adequate for the given screening operation, but that some sensors had not been placed well during the original wargame. This highlighted the need for a more thorough intelligence preparation of the battlefield process.

4.3. Maritime Force Protection (Anderson 2012)

This study gives an example of how the data farming process and the inspection of extreme outliers can be used to gain tactical insights.

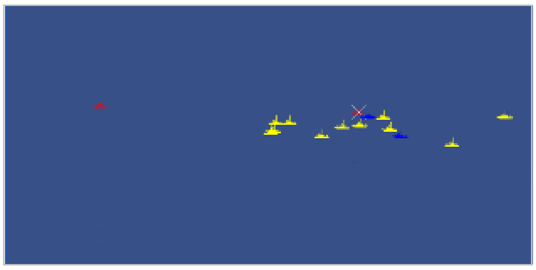

Figure 11: MANA anti-submarine warfare study

In this study, MANA was used to explore an anti-submarine warfare (ASW) scenario. In the scenario, warships must escort a convoy of 15 high value units (HVU) through a constrained waterway in which two enemy submarines were operating.

A baseline model was first run 500 times to determine the approximate number of Blue frigates required to protect the convoy. The main measures of effectiveness considered were the probability of raid annihilation (PRA) and the average number of HVU lost.

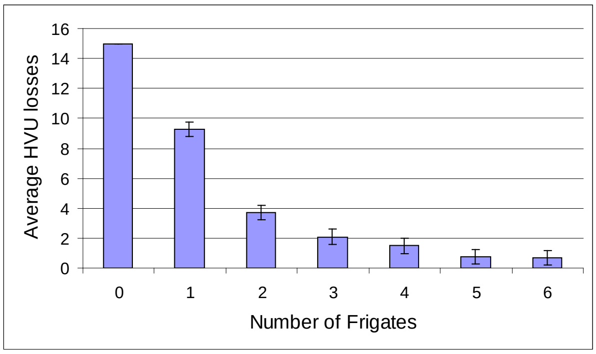

Figure 12: Baseline scenario results

The baseline model results suggested that four or more frigates were required to achieve a 100% PRA and that there was then a diminishing return on adding more frigates (having more than four frigates still resulted in the loss of at least one HVU). This was because Blue did not usually detect Red until after it launched a torpedo. A recommendation was therefore made to consider giving the HVUs their own torpedo counter-measures (e.g. towed decoys).

The inspection of statistical outliers also revealed key behaviours (tactics) that appeared to work well for both sides. For example, Red generally did better if it neutralised a frigate early in the scenario or if one sub could 'distract' frigates away from the convoy. Red also did well when it waited downstream for the high value units rather than closing in on them. Blue generally did better when the HVU convoy were clustered together and the frigates dispersed evenly around them.

A data-farming process was then employed, in which the baseline model was re-run multiple times across a wide range of incremental parameter changes. The entity parameters that were varied included; sensor and weapon ranges, weapon kill probabilities, firing time delays, speeds and starting positions. Regression analysis then indicated that detection range was the most critical parameter for Blue to have over Red, followed by weapon range, weapon kill probability and weapon firing cycle delay time.

5. SUMMARY

MANA has proven to be a highly flexible tool that has enabled DTA to conduct studies across a wide range of research areas of interest to the NZDF. Its rapid set up and turn around time has also made it a popular tool with the international analysis community.

In general, DTA has found that using MANA in conjunction with the data farming process can be extremely useful for gaining a better understanding of the key issues affecting the systems we are given to study. This has proved to be particularly useful to guide further research priorities and/or more in-depth modelling and simulation tools (Anderson 2012).

Because MANA also often produces a wider distribution of possible outcomes than other types of models, value can be gained from exploring extreme outliers and the interactions or events that led to their occurrence. MANA can also produce emergent behaviour that the analyst may not have previously considered. These types of insights can be particularly useful when analysing asymmetric warfare and counter-insurgency scenarios.

ACKNOWLEDGMENTS

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REFERENCES

Lauren, M.K. 1999, *Characterising the Difference between Complex Adaptive and Conventional Combat Models*, DOTSE Report 169, NR 1335, Auckland, New Zealand.

Anderson, M.A. Galligan, D.P and Lauren, M.K. 2004, *Map Aware Non-Uniform Automata (MANA) Users Manual*, DTA Technical Note 2004/2, NR 1397, Auckland, New Zealand.

McIntosh, G.C. 2004, *Strategies for Emergency Food Distribution Investigated Using Cellular Automata*, DTA Report 200, NR 1399, Auckland, New Zealand.

Anderson, M.A. 2008, *Exploring a Rural Guard Scenario using MANA*, DTA Report 246, NR 1458, Auckland, New Zealand.

Anderson, M.A. 2012, *A New Zealand Approach to Maritime Combat Analysis*, DTA Report 368, NR 1427, Auckland, New Zealand.

AUTHORS BIOGRAPHY

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