Artificial intelligence algorithms and new approaches to wargame simulation

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Abstract

The Mission Planner is a decision-making toolset developed by NSC for Dstl currently applied at tactical level. It aims to support Dstl high intensity warfighting simulations by reducing or eliminating the need for complex pre-scripting or human-in-the-loop.

Different stochastic optimisation Artificial Intelligence (AI) techniques have been used (Genetic Programming and a novel implementation of Simulated Annealing). The algorithms have been employed in a generic architecture that allows simple application to different problems.

This flexibility allows the AI to generate plans against a reduced problem set (a Meta model) which represents only the essential elements of the full problem. The solution can then be evaluated against the full problem set, in this case SimBrig assessing brigade level land engagements. This approach has successfully overcome some of the limitations traditionally associated with the AI techniques used.

Formulating the problem in a novel way, using military-like syntax, means that the AI algorithms efficiently generate plans for tactical problems that resemble human-like decision making.

This paper presents the approach and techniques used in both the AI algorithms and the Meta wargame simulation.

Introduction

The Mission Planner is a decision-making toolset developed by NSC for use in Dstl high intensity warfighting simulations. It automatically develops plans for allocating forces in space and time in order to achieve a particular objective, in a situation of partial knowledge and where the enemy is also planning.

Traditionally Dstl models have approached such problems by building complex pre-scripted orders or by using a human-in-the-loop. These approaches can, in principle, represent human decision making in a reasonably accurate manner but at the cost of time (and therefore money) in the set up and/or running of the model. These constraints can severely limit their practical application.

The Mission Planner has been developed to use two different stochastic optimisation AI techniques in order to solve tactical problems in a number of wargames, so that they can play one or more sides. The programme of work was started to support the model CLARION, and the AI algorithms

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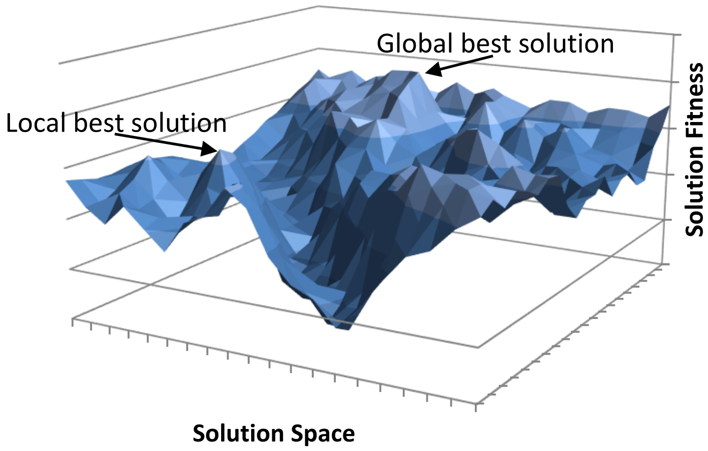
have been applied to: a proof-of-concept test bed (in order to better understand the capabilities and limitations of the algorithms employed), SimBrig and a bespoke brigade level land simulation, META.

Stochastic Optimisation

Stochastic Optimisation is a family of techniques for solving any generalised problem. These are often applied to complex problems, where it is impractical to go through all possible solutions (called the solution space) to determine the optimum. These techniques randomly explore a subset of the solution space in a rigorous mathematical fashion, to arrive at a "good" solution to the problem, though not necessarily guaranteed to be the best solution. An important aspect of these techniques is that they balance exploring avenues that offer promising results with searching the full solution space. Therefore they are able to find a globally "good" solution rather than the best solution in a local area of the solution space, as illustrated in the adjacent picture.



The general approach was first considered by H. Robbins and S. Monro (1951) and is summarised in J. C. Spall (2003).

Traditionally these techniques are applied to a wide range of problems, including wargaming (D. Jackson, 2005) timetabling (Zhao Le, et al., 2014) and scheduling (e.g. the travelling salesmen problem, V. Černý, 1985), game solutions (e.g. chess: A. Hauptman, M. Sipper 2005 and 2007; black gammon: Y. Azaria, M. Sipper, 2005; soccer bots: S. Luke, 1998; and robocode: Y. Shichel, et al. 2005) and circuit and antennae design (J.R. Koza et al., 1999, J. Lohn, et al., 2004).

Genetic Algorithm Overview

Genetic algorithms have a long history of use as an optimisation technique. N.A. Barricelli (1963) simulated evolution techniques to play a simple game, and the methods are described in books by A. Fraser, D. Burnell (1970).

The Genetic Algorithm technique has an abstract representation of a candidate solution to a problem, referred to as an Entity. This is typically a bit stream, a binary string of 0s and 1s. These are then translated into a solution to a specific problem by a process called decoding. For a wargame example, the 0s and 1s could translate to an order set:

- Move 000
- Attack 001
- Defend 010
- Support 011
- Retreat from 100

The following bits could represent input values to the order, for example the actor or target units, timings, areas etc.

An order sequence across the units in the wargame could then be built up from the bit stream.

This order set is then evaluated in a wargame model to obtain a “fitness measure”, a quantitative measure of how good the solution is.

A population of Entities is considered, randomly initialised.

This population is then evolved in generations, with parent solutions chosen by a method that mimics survival of the fittest, representing evolutionary pressure. Children are then generated by mutation and/or crossover of the bit streams of the parents.

A ‘best’ solution is then achieved after a number of generations.

The selection of parents is based on their measure of fitness, which enables the population to evolve to fitter solutions. The selection technique must maintain genetic diversity in order to arrive at a globally good solution, as a solution might have poor fitness, but consist of good elements that only need slight change to achieve a good result.

Tournament selection is one method that achieves this. When selecting a parent, first a number of candidates are chosen at random (regardless of their fitness). The best out of these is then selected. This ensures that a small number of well fitted but related entities are not always selected, swamping the population.

The fitness measure is core to all Stochastic Optimisation algorithms. A good measure of fitness allows algorithm to correctly apply selection pressure and ensures fittest elements of population are evolved.

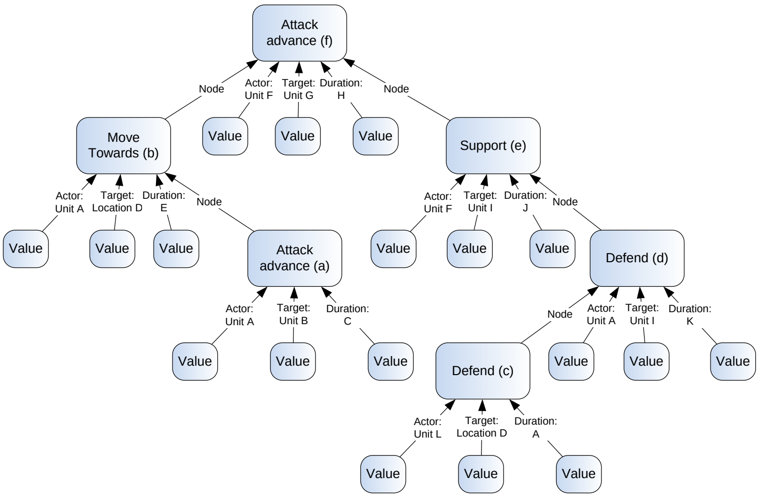
For the wargame example the fitness measure is obtained by first decoding an entity to an order set. These orders are then run through the evaluation wargame simulation and the results are assessed in terms of losses, achievements (positions held or denied from the enemy, or enemy losses or neutralisation), risk (enemy proximity and whether own units are mutually supporting), and efficiency (minimum resource consumption).

Great care should be taken that the fitness measure should be well understood and constrained, which can often be difficult in the case of “bad” solutions. A quantitative measure of success or fitness is important so as to properly select between two possible solutions and to allow the algorithm to navigate around “bad” solutions and explore the full solution space. This is most easily achieved by very clear and rigorous normalisation of all fitness measures and parameters.

It is important to note that Stochastic Optimisation techniques are notorious for finding loopholes in the logic of the evaluation model and metrics used for fitness measurement. This is because the algorithm has no understanding of the problem solved; as far as it is concerned it is simply swapping 0s and 1s and it has no concept as to why the resultant solution is good or bad.

Although this finding of loopholes is problematic if the goal is to find the “best” solution to a problem it can be advantageous. In particular by exposing the loopholes it provides a method of assisting in the verification and validation of complex models.

Genetic Programming



The first statement of modern "tree-based" genetic programming was given by N.L. Cramer (1985). The methods are described in J.R. Koza (1999) and R. Poli, et al. (2008).

Genetic Programming is a subset of Genetic Algorithms. The difference is that, instead of a bit stream of 0s and 1s, a candidate solution is made up of a node/input tree as illustrated in the adjacent example.

Assuming the simulation starts at a time T, the nodes translate as follows:

- Attack advance by actor unit A moving (and attacking if in range) target B, starting at time T ending at time T+C
- Unit A moves towards location D, starting at time T+C (the time actor A finishes its previous action represented by node a) finishing at time T+C+E
- Unit L moves towards (and defends if in range) location D starting at time T and ending at time T+A
- Unit A moves towards (and defends if in range) unit I, starting at time T+C+E (the time actor A finishes its previous action represented by node b) and ending at time T+C+E+K)
- Unit F moves towards (and supports if in range) unit I, starting at time T and ending at time T+J
- Unit F moves towards (and attacks if in range) target G, starting at time T+J (the time actor F finishes its previous action represented by node e) and ending at time T+J+H

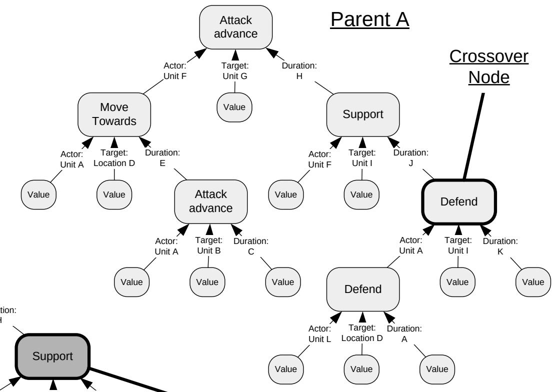
It is important to note that whilst a wargame example has been illustrated, in a Genetic Algorithm an entity is simply a node tree, each node having a number of input values and node children. The algorithm has no concept of what a node or input might mean, and it is only at the decoder stage that it is determined how each node translates to an order.

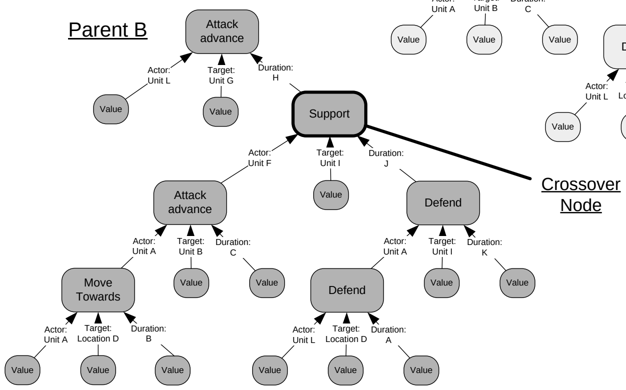
In principal, there is no difference between the mathematics of a bit stream Genetic Algorithm and a node tree Genetic Programming algorithm. However, it is much easier to write a decoder that efficiently translates the Entity, in its generic form, to a solution for a particular problem.

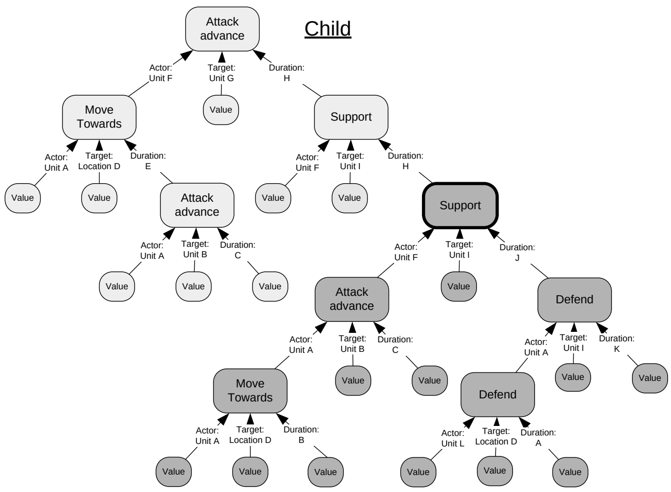
Algorithm efficiency is vital for any Stochastic Optimisation technique. Inefficient algorithms will not explore the solution space as convergence to a good solution requires a good probability of generating better solution from each generation otherwise potential improvements are lost. It is not the case that an inefficient algorithm will simply converge more slowly to a “good” solution; it might never converge at all.

An efficient algorithm must produce Entities with measurable fitness to allow comparison between Entities in order that the proper selection pressure is applied for evolution. “Bad” solutions are important in terms of the algorithm being able to explore the full solution space. There must, however, be a sensible measure of how “bad” these solutions are, so that the algorithm can navigate to better solutions. Therefore it is vital that Entities must always decode to a feasible solution (for example an order set) that can be measured, and that any change in the Entity (in its generic form) translates to a meaningful change in the translated solution.

This efficient decoding is much simpler for a node/input tree of a Genetic Programming algorithm than it is for a bit stream. However, it should be noted that there is no necessary difference between a Genetic Programming technique and a bit stream Genetic Algorithm with a well written decoder. If an Entity is always translated to a valid orders set, no matter how that Entity is randomly altered, then one would not expect a Genetic Programming algorithm to be significantly different from other Genetic Algorithms.







An example of a child entity generated from parent entities is illustrated in the adjacent figure.

The crossover nodes of each parent are chosen at random. The child is formed from the node tree above the crossover node of the first parent merged with the node tree below the crossover node of the second parent.

Simulated Annealing

Simulated Annealing is a well understood and efficient optimisation technique, which shares many similar elements to Genetic Algorithms. The earliest form of this algorithm is the Metropolis-Hastings algorithm, N. Metropolis, et al. (1953). The method is described in detail in W.H. Press (2007).

The concepts are analogous in form to annealing in metallurgy, a technique where heating and controlled cooling of a material increases the size of crystals and reduces defects in the atomic lattice. It uses the same mathematics as determining probability states given the thermodynamic free energy. As the Boltzmann distribution is mathematically well understood, the process is much better defined than the heuristic approach of Genetic Algorithms.

A candidate solution is considered, which can be formulated using the same generic representation as the Genetic approaches. A single solution is considered throughout the process, rather than a population. This solution is randomly perturbed to give a new solution. The probability that the newly generated solution will replace the current solution as the candidate solution is given by:

$$e^{-\frac{F_C - F_N}{T}}$$

where T is the "Temperature" and F is the Fitness measure of the new (N) or current (C) solutions.

Simulated Annealing has the concept of an annealing schedule, the Temperature T, analogous to the thermodynamic free energy of the system. It can be easily understood if the fitness measure is well constrained. This is best achieved by very clear and rigorous normalisation of all fitness measures and parameters. For example if the worst of all possible results has a fitness of 0 and the best of all possible results has a fitness of 100, then a temperature of 100 corresponds to a high probability that a poor solution will be chosen over a good one (albeit temporarily, to explore the full solution space), whereas a temperature of 1 will give a low probability.

The annealing schedule is the temperature profile used to generate the solution. Typically a high value of T is used initially for a given number of steps (or until a required convergence of changes in the fitness of the best solution found so far is reached). This allows "bad" solutions to be explored freely so that a wide region of the solution space is considered. The temperature is then lowered for a second round of steps, and so on. This reduction in T constrains the area considered, until finally the algorithm is considering refinements to the best solutions.

Simulated Annealing and Solution Perturbation

One of the main problems of the application of Simulated Annealing to gaming problems is how to perturb the candidate solution to obtain a new solution. Simulated Annealing is typically applied to problems where the free parameters are continuous and can be altered by a variable amount. Traditionally the solution should undergo large perturbations when considering large temperatures and small perturbations when considering low temperatures. A commonly held metric is that perturbations that accept the perturbed candidate solution about 50% of the time are most efficient.

However, the free parameters of a wargame problem are not continuous, but are discrete. Order sets can be randomly altered in discrete chunks of orders and order types. If the Entity solution is considered using the same Node/Input tree of the GP solution then an approach to controlling the scale of perturbation is much clearer. A perturbation can be applied either to a node (by randomly selecting a node in the tree for the current solution and replacing it with a randomly generated node tree) or to the input value(s) of a node (or nodes), as a simple random change. At high temperature, it is possible to favour Node perturbations (which represent a larger change to the solution than input changes) and also to favour nodes with many descendants. Input changes at high temperature would change multiple inputs. To the author's knowledge, such an approach has not been used before.

Seeding the initial population

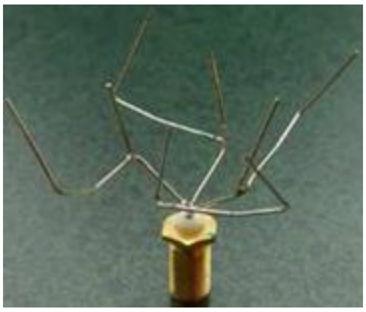
It is possible to seed the initial random population with an individual or group of individuals that represent a good starting point. These might be from the population obtained from previous runs of the algorithm for a situation that has now evolved, or, alternatively, they might be constructed by the user. There is a danger that if the seed individuals are much better than the randomly created trees, then their descendants can take over the population rapidly with a loss of genetic diversity. In these cases it is often more successful to control this diversity loss by initialising the whole population to either identical or mutated copies of the seed individuals.

The Mission planner toolset allows saving entity solutions (in their generic form) to a plan store. These stored plans represent a library of solutions that can then be used as seed solutions for future runs of the toolset.

Stochastic Optimisation, limitations

Stochastic Optimisation techniques, traditionally, have a number of limitations.

First, they are slow. Typically, for a brigade level problem, it might require evaluation of some tens of thousands of possible solutions to reach a reasonable solution. Even if each evaluation takes a millisecond this would mean the time taken for a solution would be measured in tens of seconds.



Also the algorithms have no concept or understanding as to why a solution might be good. This has a tendency of generating solutions in response to the exact detail of the problem posed, rather than necessarily a solution that is applicable to a wide range of problems. This makes these techniques excellent at, for example, circuit or antennae design (J.R. Koza et al., 1999, J. Lohn, et al., 2004), where they are able to come up with novel solutions that are not naturally intuitive, as illustrated in the adjacent figure. However they are not necessarily suitable for arriving at doctrinally correct solutions that reflect the perceived wisdom of, for example, the Staff Officers Handbook, for a wargame problem, unless heavily constrained.

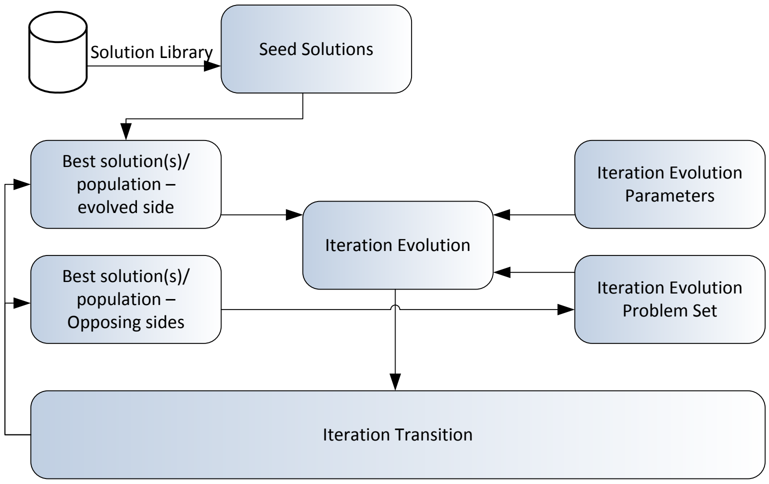
As discussed above Stochastic Optimisation techniques are also famous for exploiting loopholes in the problem posed. These might be in the fitness criteria by which a solution is assessed, or else in the logic of the evaluation model. This arises, again, from the fact that the algorithms have no concept or understanding as to why a solution is good.

Any implementation of these techniques will have to take into account these limitations, either accepting them, or finding solutions.

The Mission Planner addresses these limitations in a number of ways, detailed in the following sections. The first is to consider a solution against a range of plans, to ensure solutions are suited to a range of problems. The second is by using a military-like syntax for the decoding of order sets, allowing for efficient generation of plans that resemble human-like decision making. Lastly the generic form of the algorithms has been exploited to allow solving against a range of plan evaluators, including a reduced problem set (a Meta model). This represents only the essential elements of the full problem, enabling the use of algorithms that are both extremely robust and execute quickly.

Mission Planner

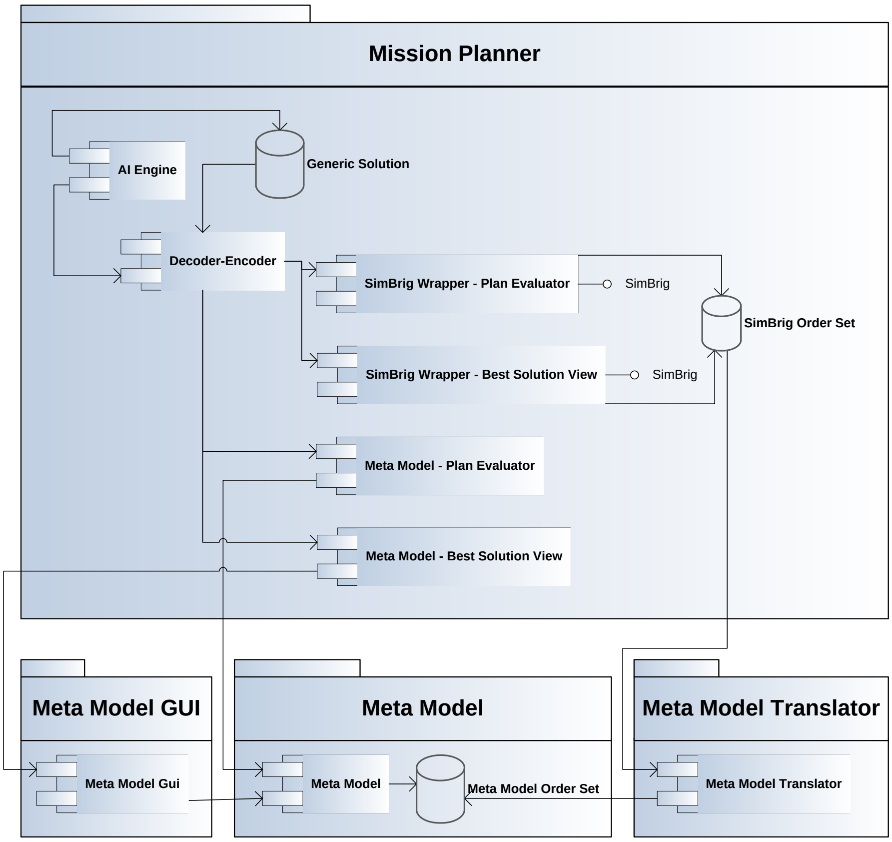
The mission planner is a toolset that applies the AI algorithms to a problem set in an iterative approach as illustrated in the figure below:



Each iteration evolves a full solution for a problem set, using the previous iteration's best solution(s) or solution population. The new iteration might change any of the following: the side being considered (for example in the first iteration generating Red plans and then in a second iteration generating plans for Blue to counter these), the AI algorithm control parameters (for example one iteration might set parameters that control the solution space more widely, whilst a second might set parameters to examine more closely the areas representing the best solutions), or a new set of problems could be considered that might, for example, represent a changing or evolving situation.

The first stage of each iteration is the retrieval of the entities that reflect the current best solution(s) or solution population for sides opposing the side that is going to be evolved in this iteration. These are then decoded to represent opposing plans. Also the best solution(s) or solution population is retrieved for the side being evolved. If the side being evolved has not been considered by any previous iteration then solution(s) or solution populations are generated at random or from a specified seed (or seeds) from the plan store.

The problem set consists of one or more scenarios. A generic solution is decoded as an order set for each of these scenarios, and the measure of fitness obtained for each. A final, overall fitness is obtained, weighting the fitness obtained for the best, worst and intermediate individual scores. This ensures that the solution obtained is good against a wide variety of problems and is not limited to the specific details of a single problem. It also permits solution of problems where there is uncertainty in the problem posed, for example, if Blue has does not have a clear view of Red forces, a number of scenarios could be considered.



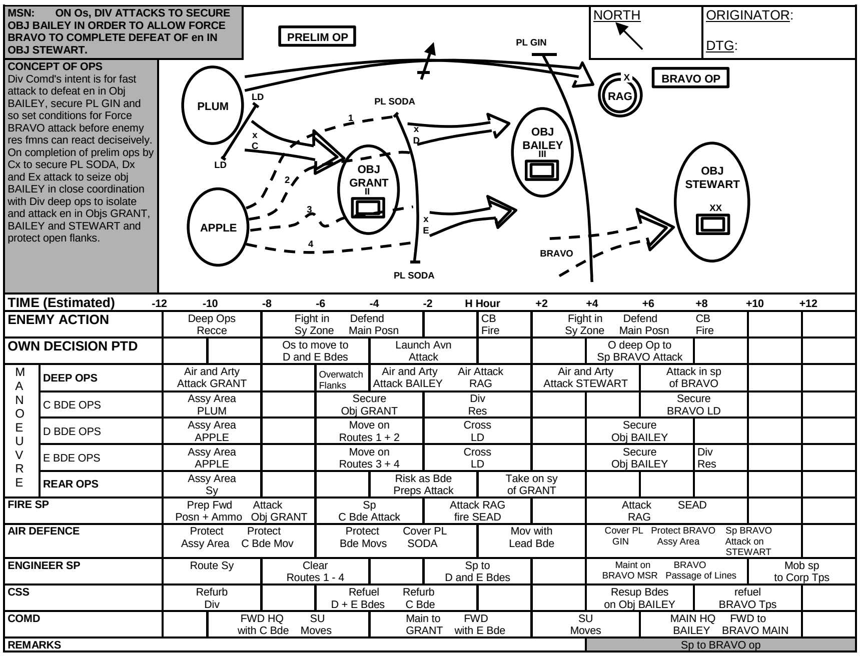
Mission Planner, Generic Architecture

As has been discussed, the AI algorithms work with a completely generic form of solution that can be applied to any problem. The only problem specific element is the decoder, which takes a solution, in its generic form, and translates it to a solution for a specific problem, in this case an order set for a wargame simulation. This specific solution is then evaluated to obtain a fitness score, which the AI algorithm then stores against the generic form of the solution to determine its use in exploring the full problem space.

The architecture of the Mission Planner exploits the generic nature of the algorithms employed to allow it to consider any problem, as illustrated in the above figure.

Decoders can be written in a plug and play fashion to consider problems of a completely different form. The inter-changeability of decoders means that one decoder can be used to assess solutions during the solution evolution process (the plan evaluator), whilst a different decoder can be used to view and assess the best solution arrived at (the solution view).

The adjacent figure demonstrates this with decoders for plan evaluation and solution views for both the META model and SimBrig



Military Syntax

The mission planner uses a military-like syntax for decoding of order sets, i.e. for translating a generic solution into an order set. This method is currently used for both the SimBrig and META decoders.

The concepts in a military synch matrix are used, an example of which is illustrated in the adjacent figure.

The nodes in the generic solution are translated into Areas and Timelines and Manoeuvre/Support orders. The inputs determine which locations correspond to each area in the solution, and the times of the timelines. Inputs for each Manoeuvre/Support order determine which areas and timelines are associated with that Manoeuvre/Support order.

In this way units naturally co-operate in time and space. By using this military syntax, the order set generated naturally looks human like. It also greatly enhances efficiency. For example, it can readily be seen that a “generically” good order set can be generated, which determines how units are to co-operate, by the way each unit’s orders are linked to areas and timelines. A solution that is good for one problem can be applied to a different problem simply by changing the specifics of the locations of the areas and the timings of the timelines. The AI algorithms will exploit such efficiencies when randomly generating solutions.

To the authors knowledge this is the first time that this approach has been used for Stochastic Optimisation algorithms applied to a wargame problem.

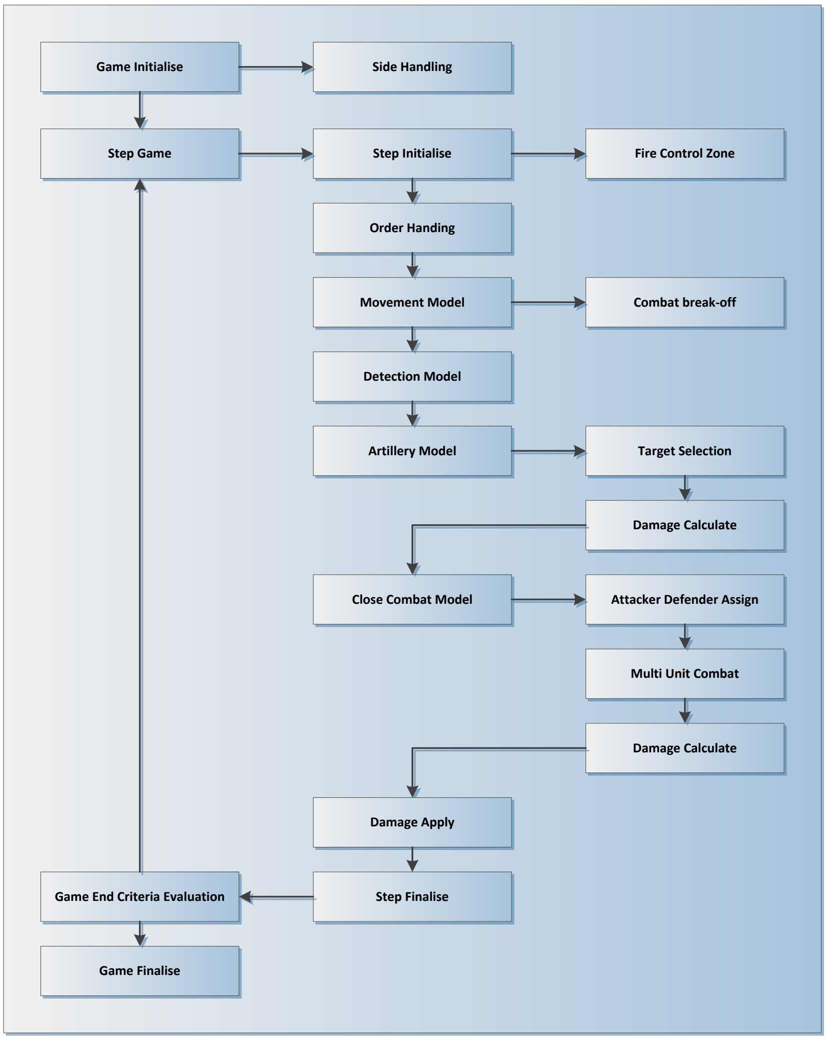
META

The META wargame model (Model for EngagemenT Analysis) is a bespoke model to evaluate a brigade level land engagement. It has been specifically developed to meet the requirements of the AI algorithms of the Mission Planner, which are for a plan evaluation model that is fast and robust, i.e. has no loopholes in the logic of its evaluation algorithms and that will also successfully evaluate all order sets, no matter how nonsensical they might seem. This is important for the AI algorithms, as they need to consider "bad" solutions, to be able to assign a quantitative measure of fitness to enable the algorithm to navigate to "good" solutions whilst still exploring the full solution space.

The guiding principle of the META model has been simplicity. The algorithms have been streamlined to represent only the essential elements of the full problem, in order to avoid unintentional complexity. The simplicity of the approach has also facilitated a clear and flexible model framework and architecture into which new algorithm modules might be added, or old ones replaced.

The figure below illustrates the META model elements.

As higher level land operations are being considered (in the first instance at brigade level), military forces are grouped together into aggregated units. A unit is defined by a type, representing both the size and military type/role, for example; British Infantry Battalion, British Tank Regiment etc.



The focus of the model is for an aggregation resolution of brigade level operations in terms of high intensity warfighting. There will therefore be a natural rhythm to the events that are evaluated, lending the system to a time stepped approach. Nevertheless to allow flexibility, as future components might consider operations on very different timescales, the model framework is implemented in such a way that event based processing may be easily added.

The simulation is multi-sided. To ensure that there is no overhead in terms of performance, as currently there is only the requirement to model two hostile sides, all sides are assumed to be hostile to each other, and do not share any intelligence detections. Therefore a side will only be aware of units that have been detected by its own units.

The fire control zone model is designed to control the operations of a side, defining a region and time during which one (or more) of the following are restricted:

- Artillery fire
    - Precision Artillery
    - General Artillery
- Close Combat
- Movement

The movement model is Arc/Node based in order to maintain compatibility with SimBrig.

A unit has a position that reflects either a Map-Node or location along an Arc.

An A* routing algorithm is included so that units take the quickest route between Map-Nodes.

Units exert zones of control that restrict the movement of enemy units.

The movement model takes into account the unit type, posture and terrain when determining movement rates and will also allow fixing by artillery for a period determined by the (moving) unit type.

Combat Break-off is modelled by units that are damaged passed a threshold value assuming a defensive posture. Moving units will attempt to retreat to the Map-Node they are coming from. Excepting this retreat the units undertake no further manoeuvre or offensive operations.

The detection model is, for the initial implementation, a visual model, with a detection range determined from the attacker and defender unit types, posture, facing and the terrain.

Wide Area Survey is simply modelled by allowing a side automatic detection of all enemy units.

The Artillery Model element controls target selection and damage calculation of artillery operations.

Target selection is either rule based, for artillery orders entered by the user, or freely chosen by the AI algorithm, allowing these algorithms to determine which unit represents the most suitable target.

Rule based target selection is based on a simple algorithm that identifies the enemy unit in range that corresponds to largest threat closest to a friendly unit.

The Close Combat model element controls the target selection and damage calculation of close combat operations. Close combat will occur when units of different sides are close enough, each type of unit having a close combat range associated with it.

Based on the operation the unit is currently undertaking, a unit will be defined as either attacking or defending when assessing the combat outcome.

If a unit can cause damage (either in an attacking or defending posture) to more than one unit it will select the largest (in terms of attrition capability). This allows that the combat units with the highest strength bear brunt of action – weaker combat units (such as artillery) that are supported properly will be defended. In any one time step, a unit will be allowed to damage one unit in its forward facing arc, and one unit in its flank facing arcs.

The focus of the Damage Calculation model (applied to both artillery and close combat damage resolution) is for an aggregation resolution of brigade level operations in terms of high intensity warfighting. Therefore a Lanchester-like damage algorithm is sufficient. Attrition rates are defined by unit type, similar to a BAMS representation. As unit type includes the size of unit represented, this will overcome the most obvious limitation of a Lanchester approach, in that suitable attrition rates can be defined to represent combat between units of significantly different size.

The damage algorithm takes into account the type and state of units engaged and engaging, as well as terrain and unit facings.

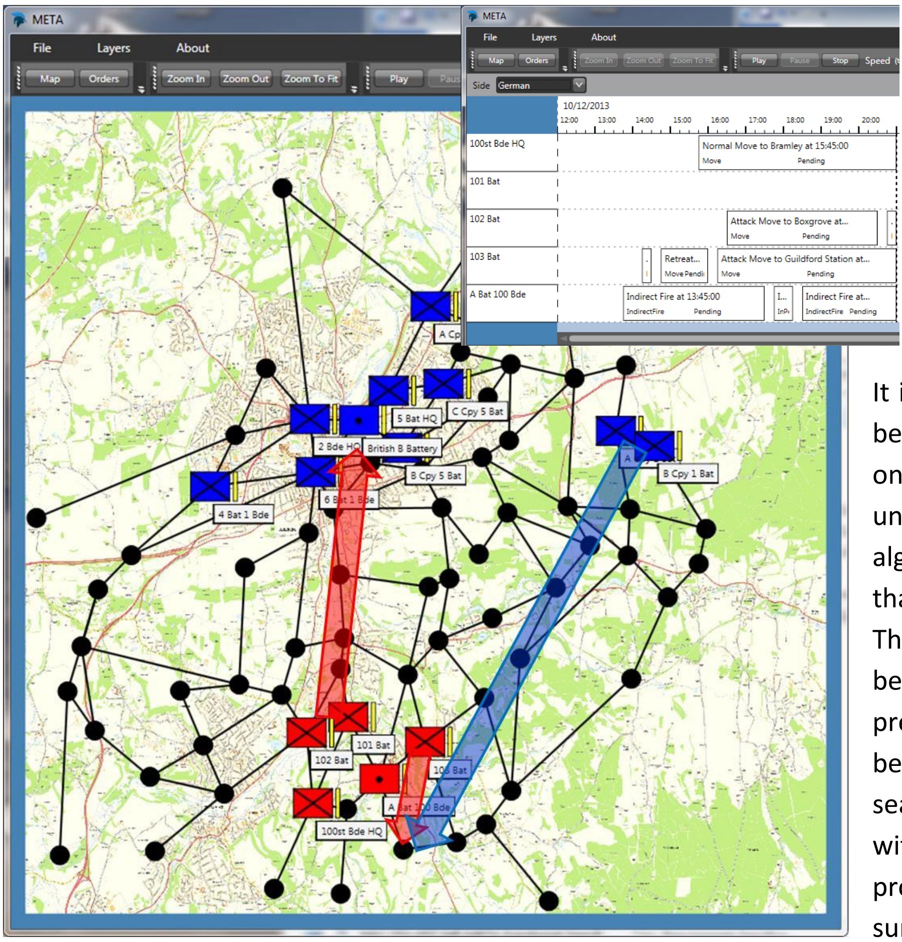
The application of damage occurs in a separate step, so that the order in which damage is calculated does not affect the results.

The data for the wargame has been drawn from a number of sources, including the British Army Battle Box, “The Stress of Battle” (D Rowland, 2006) and the PJHQ J5OA handy OA Guide.

To facilitate understanding of the model, data is interpreted in the most intuitive way possible. For example, attrition is defined in fractional loss per hour.

Results

Illustrated below is a brigade level problem, where The AI is controlling Red. Blue is defending locations in the North. Red is set objectives to defend itself in the south, and seize locations in the north. In 20 generations of 1000 entities it comes up with credible and robust plans, selecting suitable assets for the attack and defence and locating where it can exploit the flanks of blue units. On a modern machine (intel® Xeon® cpu e5-2620, 6 processors at 2 GhZ) this takes 5 minutes of processing, though rough plans can be achieved more quickly, 1 to 2 minutes.



It is interesting to note the difference between the two algorithms. Though only an initial investigation has been undertaken, the Simulated Annealing algorithm is clearly more efficient than the Genetic Programming. Though more analysis would have to be undertaken to confirm, the preliminary impression is that it is a better algorithm at balancing searching the wider solution space with honing in on areas offering promising results. This is not surprising given the well understood way in which the Simulating Annealing method explores the solution space, as opposed to the more heuristic Genetic Programming algorithm.

It should be noted that the Genetic Programming algorithm does seed solutions more elegantly, as it maintains elements of all seed solutions in the initial population, whereas the Simulated Annealing merely will use the best of all the seed solutions as applied to the current problem set, discarding the other seed solutions. It is not clear whether this disadvantage of seeding is simply theoretical. In practical terms it might have little impact, which would be quickly overcome by the efficiency of the algorithm.

Conclusions

It has been demonstrated that AI algorithms, such as Simulated Annealing and Genetic Programming can efficiently generate plans for tactical problems, in this case a brigade level land engagement, generating plans that resemble human-like decision making.

Two elements have been key to this success.

The first is the use of Military-like syntax in formulating the solutions the algorithms work with.

Secondly is that, utilising the generic nature of the AI algorithms, the toolset has been able to employ a “plug-and-play” architecture. This enables the use of a META model that allows the AI to generate plans against a reduced problem set which represents only the essential elements of the full problem. The solution generated can then be assessed against the full problem (for example SimBrig). This approach allows the META model to be simple, fast and robust, overcoming the traditional limitations of the AI techniques employed, which require the evaluation of many plans, and also have a tendency to exploit loopholes in the logic of the evaluation models.

The META model has also demonstrated a successful approach to wargame simulation. Concentrating on modelling only what is required for the problem considered, to a suitable level of detail, has enabled building a comprehensive and credible simulation of brigade level land engagements from scratch, achieved on a limited budget and timescale.

The Mission Planner will allow an exploration of a larger area of the potential solution space than can be explored by human scripting of behaviour. In particular it will allow for a wider range of possible Red reactions for particular courses of action and improve understanding of the value of information. The next step is imbed the Mission Planner within a model to test its ability to plan in a dynamic situation.

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Biography

Stephen graduated from Imperial College in 1994 with a PhD in Numerical and Theoretical Astrophysics. He continued his research interests at Imperial College as a Research Associate for a further 6 years. His papers in galactic plasma jet formation and high-energy cosmic ray acceleration enjoy success, and are still widely cited within the community. In 2000 Stephen joined NSC, working mainly in the field of artificial intelligence algorithms within war-gaming systems (both for NSC and Dstl programmes of work) and support of HQ commander and staff training exercises.

Simon graduated from Queen Mary and Westfield College in 1998 with a PhD in Astronomy. He continued his research interests at Queens University Belfast as a Research Fellow for a further 5 years. Simon’s research focused on mathematical modelling, in particular the dynamics of minor bodies of the Solar System. In 2003 Simon joined Dstl, working mainly in the field of campaign level simulation of combat operations. In order to improve these simulations he started investigating the use of artificial intelligence algorithms within war-gaming systems 6 years ago.