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Game Theory, Adaptation, and Genetic Programming: Some Perspectives on Operations Research for Counter-IED

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Game Theory, Adaptation, and Genetic Programming: Some Perspectives on Operations Research for Counter-IED

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Abstract

This paper explores Operations Research issues in the response to Improvised Explosive Devices (IEDs), using the concept of a "fitness landscape." In particular, we examine optimisation approaches that assume a fixed fitness landscape for Blue actions; game-theoretic approaches where fitness is associated with the combination of Red and Blue actions; and approaches that assume fitness landscapes are constantly changing as a result of Red and Blue adaptivity. In particular, we examine the use of genetic programming. We discuss the strengths and weaknesses of these approaches with respect to an illustrative simulation model, and present experiments suggesting that genetic programming is a promising mechanism for exploring adaptivity in such simulation models.

1. Introduction: IEDs

Improvised Explosive Devices (IEDs) have had a significant impact on recent military operations by a number of countries (JIEDDO, 2008; Zorpette, 2008a, 2008b). For example, Figure 1 shows the impact of an IED blast.[1] As well as causing deaths, IEDs are also responsible for many injuries. They remain an issue in several ongoing conflicts.

Insurgents may construct and place IEDs in a number of different ways, and may trigger them either directly (by using a radio or command wire), or indirectly (when the victim activates a pressure plate or infrared sensor).

The ongoing IED problem leads to a need for effective Counter-IED Operations Research (OR). In this paper we use a simple agent-based simulation, written in Java, to illustrate the strengths and weaknesses of OR approaches based on **optimisation**, on **game theory**, and on **adaptation**. An important case of the latter is the use of **genetic programming**.

Figure 1: IED aftermath: a Stryker vehicle overturned by a buried IED blast (photo from www.army.mil)

2. A Simple Simulation Model

As an illustration of some of the Operations Research (OR) issues involved in analysing Counter-IED operations, we have constructed the very simple agent-based simulation shown in Figure 2.

[1] All data in this paper is taken from open sources, such as books, journals and the Internet.

This simulation is not intended to accurately represent real-world IEDs or Counter-IED activities, but rather to illuminate the Operations Research issues they raise.

In this simple model, Blue agents must traverse a 20×20 grid from left to right. The grid contains four kinds of terrain: a gently curving **road**, a meandering **path**, a large expanse of **sand**, and randomly-placed **rocky** areas.

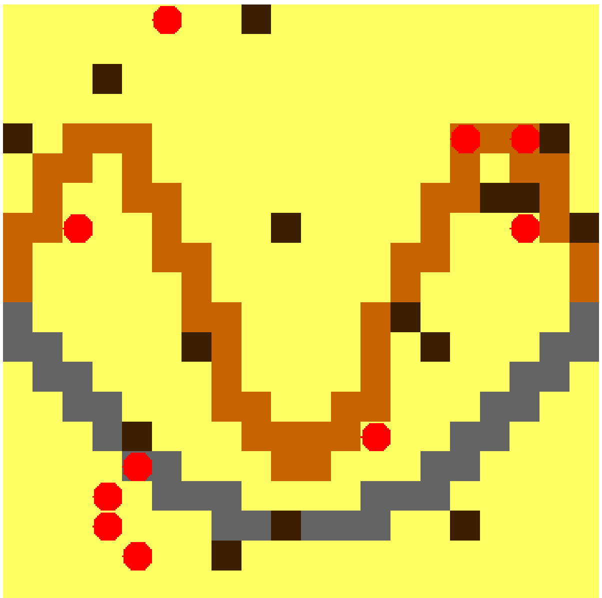

Figure 2: Our simple agent-based simulation. Grid cells are coloured yellow (sand), grey (the curving road), light brown (the meandering path), or dark brown (rocky areas). Red circles show IEDs, which are invisible to the Blue agents. The Blue agents begin at the middle left, and must travel to the right-hand side of the region, while avoiding the IEDs.

3. Optimisation

Although the simulation shown in Figure 2 is very simple, it illustrates the basic dilemma faced by Blue forces in a Counter-IED context: which Blue strategy gives the best chance of survival? For experimental purposes, we began by considering four Blue strategies: a **direct** strategy of moving only to the right, and three terrain-based strategies (**sand**, **path**, and **road**) where Blue agents prefer to move along a specific kind of terrain, leaving it only when they are forced to.

In real life, Blue strategies include the selection of IED-resistant vehicles (JIEDDO, 2008; Zorpette, 2008a). They also include countermeasures to prevent the operation of infrared (Zorpette 2008a, p 27) or radio triggers. An example radio countermeasure is the US CREW (Counter Radio-controlled-IED EW) system (JIEDDO 2008, p 11).

Culvert denial systems such as the US Terrapin (JIEDDO 2008, p 10) can also form part of a Blue strategy, as can detection devices, such as the US Fido (Zorpette 2008a, p 29), or ground penetrating radar systems such as the US Husky (JIEDDO 2008, p 10).

Less concrete Blue strategies include route planning; Standard Operating Procedures (SOPs), such as IED disposal techniques; intelligence-gathering activities for locating IEDS; and the full range of counterinsurgency (COIN) operations (US Army, 2006) which help to prevent IEDs from being placed.

Although our simple agent-based simulation does not capture the complexity of the full range of real-world strategies, it is sufficient to illustrate the basic optimisation approach to

Operations Research. A range of Blue strategies is simulated (four in this case), and results are plotted as in Figure 3.

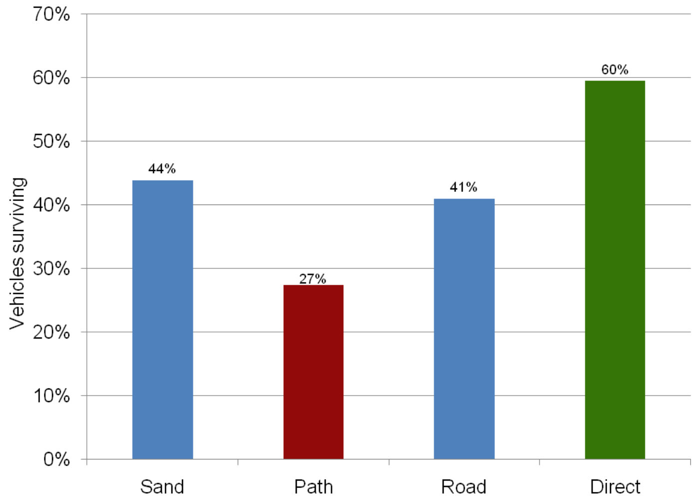

Figure 3: Performance of 4 Blue strategies against randomly-placed IEDs (averaged over 100,000 simulated Blue trips, each on a grid like Figure 2, but with different randomly-placed IEDs and rocky areas).

Where the space of Blue strategies is conceived of as two-dimensional, such a plot is called a "fitness landscape" (Ilachinski, 2004, p 503). If the range of possible Blue strategies is large, finding the optimum point on the fitness landscape may require sophisticated search techniques (Goldberg, 1989; Hecht-Nielsen, 1990).

In the case of Figure 3, however, it is clear that travelling along the meandering path is the worst strategy, with only 27.4% of Blue vehicles getting through, and the direct route is the best strategy, with 59.5% of vehicles getting through. These results are explained by the fact that, for this simple simulation, the shortest route is least likely to encounter an IED.

3.1. Weaknesses of the Optimisation Approach

The main weakness of this naive optimisation approach is that it assumes a single fixed strategy for the Red (insurgent) side. IEDs are, by definition, improvised and ever-changing, at least over the longer term. Insurgents placing IEDs deliberately choose the strategies which they believe will be most destructive. The simplistic answers suggested by plots like Figure 3 are therefore inadequate, because they ignore the mind of the enemy.

4. Game Theory

Incorporating the enemy's ability to choose brings the problem into the domain of *game theory*. For experimental purposes, we provide six possible Red strategies: four terrain-based strategies (where IEDs are placed preferentially on **sand**, **path**, **road**, or **rocky** squares), one strategy where IEDs are placed preferentially in the **central** region of the grid, and one strategy where IEDs are placed **randomly** as they were in Section 3.

In real life, Red strategies include the choice of IED type (buried, explosively formed penetrator, etc.), of triggering device (radio, mobile phone, command wire, pressure plate, infrared sensor, etc.), of placement options, of camouflage options, and of possible decoy devices.

In our simulated region, as in real life, the outcome of a Blue trip is a combination of the chosen Blue strategy for driving and the chosen Red strategy for IED placement. Table 1 shows the percentage of Blue vehicles getting through, averaged over 100,000 simulated trips. The row corresponding to Red's "random" strategy contains precisely the numbers in Figure 3.

Some of the combinations in Table 1 are particularly good for Blue. If Blue takes the road, for example, and Red places IEDs on the path, on the sand, or in the central region, then at least 93% of the vehicles will get through, with the exceptions resulting from cases where Blue strays off the road to avoid a rocky area. However, Blue cannot count on such a felicitous combination. If Blue and Red make the same choice of the path or the road, for example, then less than 1% of the vehicles will get through.

Table 1: Percentage of vehicles getting through for combinations of Red and Blue strategies (averaged over 100,000 simulated Blue trips).

Red Strategies	Blue Strategies: Sand	Path	Road	Direct
Sand	37%	87%	93%	63%
Path	70%	0%	94%	41%
Road	66%	65%	1%	49%
Rock	81%	54%	66%	59%
Central	26%	10%	94%	19%
Random	44%	27%	41%	60%

Game theory assumes that Red and Blue choose their strategies independently, and takes account of the intelligence of both sides. Linear programming can be used to find a strategy (or probabilistic choice of strategies) yielding the best possible result against a totally rational opponent (Taha, 1992). Game theory was used in World War II for planning anti-submarine operations (Leonard, 1992), and in recent times has also been applied to the IED problem (Washburn, 2006).

Applying the standard linear programming techniques to Table 1 yields the solution shown in Table 2. The optimal solution for both sides is a probabilistic choice of strategies (or "mixed strategy"). The Blue strategy guarantees an expected chance of getting through of at least 45.0%. The Red strategy guarantees an expected chance of getting through of at most 45.0%.

Table 2: Optimal solution for the game in Table 1, with each side making a probabilistic choice amongst three strategies. An expected 45.0% chance of vehicles getting through is the best that both sides can hope for against a totally rational opponent.

Red	Blue Strategies and probabilities: **Sand** 0.58	**Road** 0.29	**Direct** 0.12
Road 0.28	66%	1%	49%
Central 0.29	26%	94%	19%
Random 0.44	44%	41%	60%

4.1. Weaknesses of the Game Theory Approach

One weakness of the kind of analysis presented in Table 1 is that it assumes that the full range of possible Red and Blue strategies is known *a priori*, and that the percentages in the table are also known to both sides. In fact, being improvised, Red IED strategies are constantly being developed, as are Blue countermeasures against them and Red counter-countermeasures. Furthermore, the real-world equivalent of the percentages in Table 1 may be estimated ahead of time, but can only be known with certainty by experience. A solution like the one in Table 2 is therefore difficult to achieve in practice.

In addition, although the "mixed strategy" in Table 2 is expressed in probabilistic terms, it in fact applies only to a single trip, where neither side has any idea of the opponent's strategy. However, the counter-IED problem is an *iterated game*, involving a sequence of multiple trips. Information about the opponent's past strategies provides significant information about their future actions (even if the information is not totally certain). This is particularly true because neither side can switch strategies instantaneously. It takes time to develop and disseminate new Standard Operating Procedures (SOPs), and it also takes time to develop new equipment, such as new vehicles. We will examine the issue of iterated strategies further in Section 5.

4.2. Counterinsurgency and Nonzero-Sum Games

The analysis in Table 1 presents the counter-IED problem as a *zero-sum game*, where Blue is trying to minimise losses and Red to maximise them. While this may be adequate in the short term, in the long term counter-IED operations are part of the larger arena of counterinsurgency (COIN) operations, which are decidedly *nonzero-sum*.

The goal of counterinsurgency operations is a win/win solution where the insurgency diminishes because the concerns of potential insurgents are met. For example, during the Philippine communist insurgency of the 1950s, Defence Secretary (and later President) Ramon Magsaysay shrank support for the communist guerrillas by instructing Blue forces to provide aid, medical assistance, and legal advice to villagers (Joes, 2008). Conversely, as the US Army/Marine Corps counterinsurgency field manual indicates, an aggressively zero-sum approach may be ineffective (US Army, 2006: 1-45), in that individuals who have been negatively impacted by counterinsurgency operations may join the insurgency, rather than support government forces (Chiarelli and Michaelis 2005, p 6).

For nonzero-sum games, the equivalent of the optimal "mixed strategy" in Table 2 is a *Nash equilibrium*. However, as is well-known, a Nash equilibrium may not be *Pareto optimal*, that is, it may miss win/win solutions which are better for both sides (Poundstone, 1992; Morris, 1994, p. 127). Within nonzero-sum games such as counterinsurgency, mathematical analysis is often less important than developing an understanding of the social concerns of both sides, and creating an atmosphere of mutual trust in which a win/win solution can be accepted by a large majority of the participants. This may involve Operations Research focussed on network analysis and course-of-action ontologies (Darr *et al.*, 2010).

5. Adaptation

An important aspect of IEDs is that they are, as we have said, improvised and (in the long term) constantly changing. In response to Blue countermeasures, Red counter-countermeasures will be developed.

Even very sophisticated countermeasures may be negated by inexpensive or improvised counter-countermeasures (Zorpette 2008a, p 30). Insurgents also adapt the design and placement of IEDs in response to Blue tactics (Zorpette 2008b, p 38). Consequently, as the US Army/Marine Corps counterinsurgency field manual notes:

> "*Competent insurgents are adaptive. … Insurgents quickly adjust to successful COIN practices and rapidly disseminate information throughout the insurgency. … Effective*

leaders at all levels avoid complacency and are at least as adaptive as their enemies. … Constantly developing new practices is essential." (US Army, 2006: 1-155)

Carley & Svoboda (1996) note the value of formal computational models for studying organisational behaviour and, more specifically, organisational adaptation. It is difficult to explore innovation and adaptation in detail within a simulation model as simple as the one in Figure 2, but we begin by constructing a variation of the game-theoretic approach presented in Section 4, suitable for preliminary investigation. In this model, Blue chooses from the four strategies in Table 1, with a bias towards strategies that have worked well in the last 20 trips. Red makes a similar choice from the six Red strategies in Table 1.

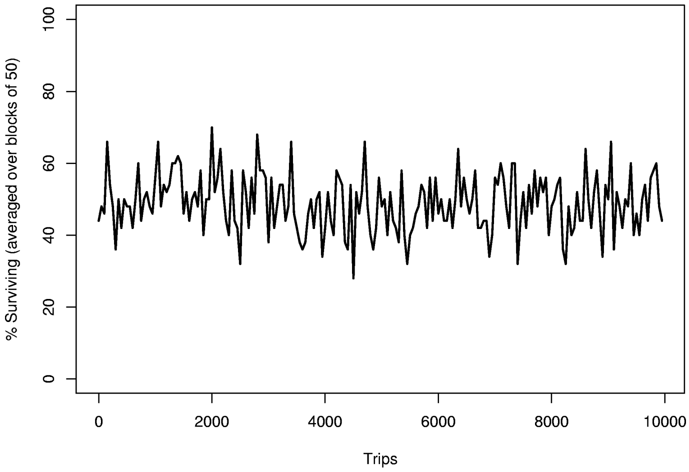

Figure 4: Results of Red and Blue adaptation over 10,000 trips (averages over groups of 50 trips).

Figure 4 shows the results of this simple form of adaptivity. The number of Blue vehicles getting through oscillates between 28% and 70%, with a mean of 48.8%. Auto-correlation analysis (Figure 5) suggests that Figure 4 consists of a considerable amount of random noise overlaid on an irregular oscillation with a period of about 700 trips. In other words, after about 350 trips Red (or Blue) is able to detect and exploit a pattern in the other party's actions, and temporarily gain a slight upper hand. After another 350 or so trips, Blue (or Red) will in turn find a successful counter-response. The alternation between Red and Blue advantage continues throughout this iterated game.

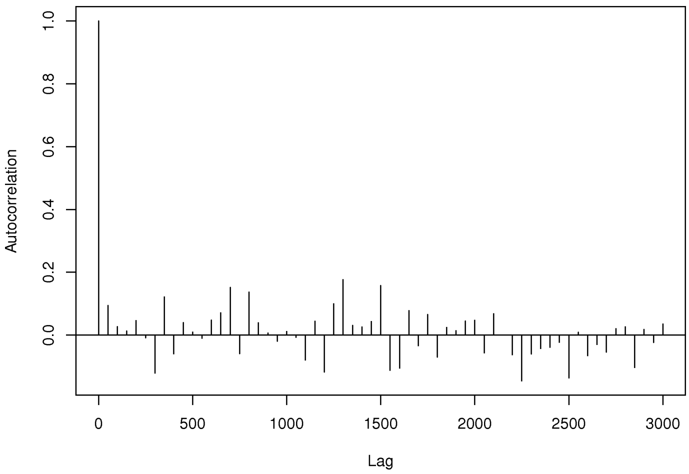

Figure 5: Autocorrelation plot for Figure 4, showing an initial trough at 350, corresponding to half of the underlying period.

Figure 4 reflects a situation where Red and Blue are equally adaptive. We varied this in a further experiment by giving Red and/or Blue a 100-trip delay in responding to past events. In other words, instead of using strategies that worked well for trips at time *t*–20 to *t*–1, the delayed party responded to trips at time *t*–120 to *t*–101. Figure 6 shows the results. When both sides are equally adaptive, around 50% of vehicles get through, but this increases to 55.5% when Blue is more adaptive, i.e. Blue is “inside the OODA loop” of Red (Brehmer 2005). It drops to 46.1% when Red is more adaptive.

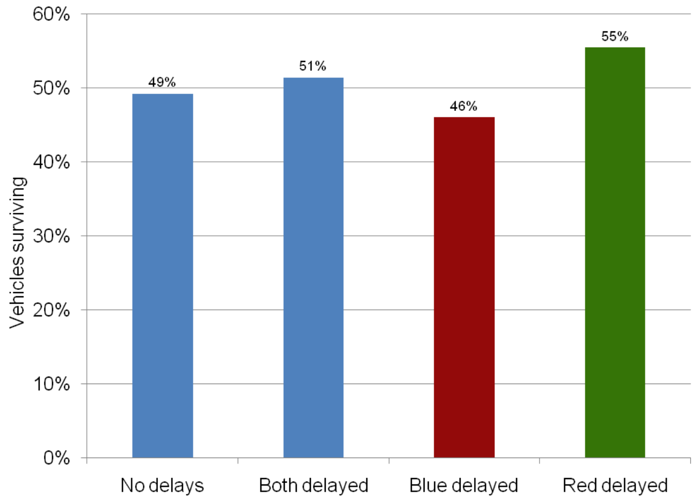

Figure 6: Results for reducing Red and/or Blue adaptivity by a delay factor. The delayed party does significantly worse (differences between colours statistically significant by χ^2 at the 10^{-15} level or better).

6. Genetic Programming

A somewhat more realistic simulation model allows Red and Blue to innovate new strategies using *genetic programming* (Koza *et al*. 2003). This technique has had several applications. Angeline & Pollack (1993), for example, use it to evolve strategies for the simple game Tic-Tac-Toe (Noughts and Crosses). We have constructed a simple Java-based genetic programming system where Red and Blue can develop plans which generalise the strategies of Table 1. Innovation is now possible: it results from a process of mutations and combinations of existing plans. Learning results from eliminating unsuccessful plans.

Blue strategies consist of rules for moving from a given square, and include the three simple strategies ***Move-up***, ***Move-down***, and ***Move-right***. Repeated, ***Move-right*** is the “Direct” strategy of Sections 3 and 4, while repeatedly executing ***Move-down*** results in travel along the bottom edge of the simulation region. Given strategies S_1, S_2, S_3, and S_4, the following more complex strategies are possible:

- ***Select*** S_1 S_2 S_3 S_4, choosing S_i depending on whether the current square is sand, path, road, or rock;
- ***Up*** S_1 S_2 S_3 S_4, choosing S_i depending on whether the square up from current is sand, path, road, or rock;
- ***Down*** S_1 S_2 S_3 S_4, choosing S_i depending on whether the square below current is sand, path, road, or rock;
- ***Right*** S_1 S_2 S_3 S_4, choosing S_i depending on whether the square to the right of current is sand, path, road, or rock;
- ***History*** S_1 S_2 S_3, choosing S_i depending on whether the last move was up, down, or right;
- ***Prefer T***, selecting movement onto terrain *T* (sand, path, road, or rock);
- ***Avoid T***, selecting movement not onto terrain *T*.

Red strategies consist of rules for deciding whether to plant an IED on a given square, and include the simple strategies ***Yes*** and ***No***. On their own, these have the effect of the "Random" strategy of Section 4, since they imply equal probabilities across the whole grid. Given strategies S_1, S_2, S_3, and S_4, the following more complex strategies are possible:

- ***Select*** $\boldsymbol{S_1\ S_2\ S_3\ S_4}$, choosing S_i depending on whether the current square is sand, path, road, or rock;
- ***Up*** $\boldsymbol{S_1\ S_2\ S_3\ S_4}$, choosing S_i depending on whether the square up from current is sand, path, road, or rock;
- ***Down*** $\boldsymbol{S_1\ S_2\ S_3\ S_4}$, choosing S_i depending on whether the square below current is sand, path, road, or rock;
- ***Right*** $\boldsymbol{S_1\ S_2\ S_3\ S_4}$, choosing S_i depending on whether the square to the right of current is sand, path, road, or rock;
- ***Prefer R***, preferring placement in a region R, such as the centre.

The genetic programming process can mutate one strategy into another, or "cross" two strategies by replacing a substrategy of the first by the second. Strategies are deemed "fitter" than others if they succeed more often against the enemy, and unfit strategies are progressively replaced by new "children" of the genetic programming process.

One example run ended with the most popular out of a population of 40 Blue strategies being ***Move-down*** (with the effect of "travel along the bottom edge"), and the most popular Red counter-strategy being ***Prefer not-centre*** (with the effect of "randomly, anywhere except the central region"). In the long run, such simple strategies usually win out over specialised strategies such as ***Select Move-right Move-up Move-down Move-right***, since the opposition strategy does not generally remain constant long enough for sophisticated counter-counter-strategies to evolve. In other words, the simple strategies are usually more robust. However, various complex strategies do often "lead the pack" for limited periods of time.

Figure 7 shows the result of the genetic programming model. Blue vehicles getting through oscillate between 32% and 76%, with a mean of 52.8%. Oscillations have a period similar to those of Figure 4, although with slightly less random noise.

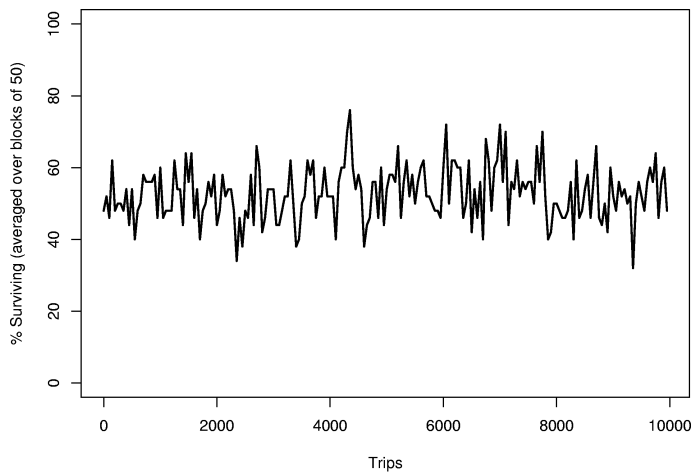

Figure 7: Results of Red and Blue adaptation over 10,000 trips using genetic programming (averages over groups of 50 trips).

The similar behaviour indicates that the simpler adaptivity model was in fact adequate for drawing the conclusions that were made: that adaptivity leads to oscillations, as first one side and then the other gains an edge; and that the side which adapts more rapidly has an overall advantage. For more complex problems, we would expect the benefits of genetic programming's greater realism to become apparent. For example, Luke & Spector (1996), in their simulation of hunting lions, show that genetic programming can be used to study blue/blue or red/red cooperation in the context of a wider blue/red conflict.

Genetic programming is a promising model of social and organisational adaptation, because such adaptation can be understood as a process of transmitting and modifying "memes" (Dawkins, 1989; Gabora, 1995; Boal & Schultz, 2007). As Weeks & Galunic (2003) point out:

> "*Memes are the replicators in cultural evolution. They are modes of thought (ideas, assumptions, values, beliefs, and know-how) that when they are enacted (as language and behavior and other forms of expression) create the macro-level patterns of culture. … Memes are the genes of culture*."

Because genetic programs express beliefs, decision procedures, etc. in a formal language, they can in particular represent memes, and genetic programming can therefore model, albeit at a coarse-grain level, the process of social and organisational adaptation through meme evolution. It is a more general approach than the evolutionary adaptation of neural networks, which we have used in earlier work (Dekker, 2011).

Returning to our experiment, Figure 8 shows the result of making one or other side less adaptive, using a smaller population in the genetic programming, and less frequent learning. As in Figure 6, the less adaptive side succeeds less often, overall. However, the differences are greater than those of Figure 6, with a spread of 16.8%, rather than 9.4%, in the results.

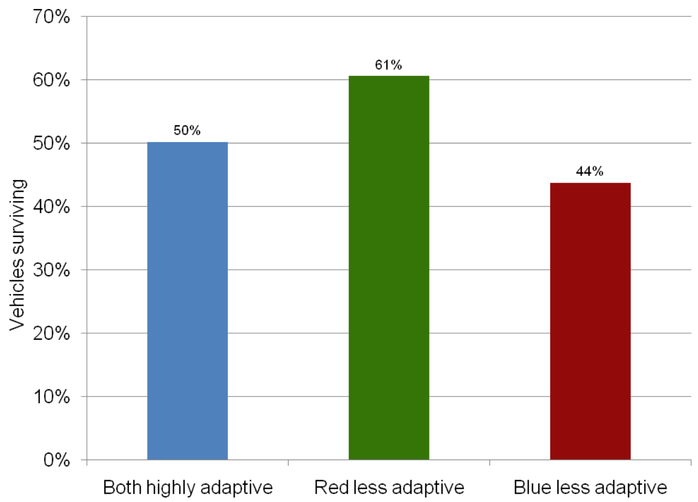

Figure 8: Results for reducing Red or Blue adaptivity using genetic programming (averages over 20 runs each). The less adaptive party does significantly worse (differences between colours are statistically significant by ANOVA at the 10^{-3} level or better).

Investigating the extent of this advantage in the real world would, of course, require a more realistic model than the one in Figure 2. However, our results suggest that genetic programming is a promising way of studying real-world adaptivity in such a more realistic model.

7. Discussion

In this paper, we have used the simple agent-based simulation in Figure 2 to briefly survey Operations Research issues associated with counter-IED activities.

While it is possible to assume a fixed Red strategy and optimise against it, as in Section 3, this fails to capture the improvised nature of IEDs. The game-theoretic approach in Section 4 captures the fact that Red is an intelligent opponent, but it still does not recognize the ever-changing nature of the IED threat, and the nonzero-sum aspect of counterinsurgency operations.

Doing justice to the IED threat requires incorporating adaptivity into the model, so that Red and Blue are, in a sense, optimising on a fitness landscape which constantly changes as the opponent adapts. Figure 6 and Figure 8 highlight the fact that in such a contest, the most rapidly adapting side has an advantage. This conclusion reinforces other work on adaptive learning (Spaans *et al*. 2009). Our results also suggest that genetic programming is a promising way of studying real-world adaptivity, because of its ability to simulate the innovation and evolution of organisational "memes."

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