Research Advances in Automated Red Teaming

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Abstract

We present, combine and apply novel research advances to Automated Red Teaming (ART). ART is an automated vulnerability assessment tool which is employed to uncover the hard-to-predict and potentially critical elements of military operations. ART is principally based on the use of agent-based modelling/simulation, data farming and evolutionary computation. In this paper, we present two distinct computational methods to address multiple issues of ART: constraint handling and computing budget. These novel techniques originate from the research fields of evolutionary computation and cloud computing. These techniques are applied to a military toy model which was developed with the agent-based simulation platform MANA. We then discuss another potential bottleneck of ART: many-objective optimization. The aim of this research is to optimize ART to best assist defense experts in operational analysis and, ultimately, in critical decision making.

1. INTRODUCTION

To assist the military decision making process, Red Teaming (RT) [22, 28] was proposed as a vulnerability assessment tool which enables one to uncover the hard-to-predict and potentially disruptive elements of a military operation. Using this method, defense analysts may subsequently identify and resolve the weaknesses of tactical plans/defense systems. In typical (human-based) RT simulations, a defensive blue team is subjected to repeated attacks, where multiple scenarios may be examined, from a belligerent red team. RT has proved to be a valuable method to improve the robustness of operational tactics such as protecting key facilities (e.g., nuclear plants, military installations, etc.) [12].

Nevertheless RT is highly time-consuming where only a limited range of scenarios may be investigated due to practical constraints. Automated Red Teaming (ART) [26, 6] (or “objective-based data farming” [7]) was proposed to overcome this limitation by addressing RT in an automated manner using Evolutionary Agent-Based Simulations (EABS) [14]. EABSs are computational methods which can model the intricate and non-linear dynamics of warfare. EABSs utilize Evolutionary Computation (EC) techniques [10] to evolve simulation models to exhibit pre-specified/desirable output behaviors. Moreover, these EC techniques are commonly devised to solve multi-objective optimization problems as military operations are characterized with such multi-dimensional constraints which often conflict with each other.

In ART, the parameter values (e.g., troop clustering/cohesion, response to injured teammates, aggressiveness, stealthiness, etc.) defining the behavior or personality of the red team are evolved to optimize its efficiency (e.g., maximize damage to target facilities) against the blue team. Examples of ART systems which have been applied to military decision making include: ISAAC/EINStein [14], WISDOM [28] and NALEX [24].

Although ART has successfully been applied to a variety of military studies, we argue that significant issues still exist when using this tool. These issues are identified as follows:

1. Constraint handling: As mentioned earlier, specific parameter values of the red team are subjected to evolution in ART. Nevertheless no trade-off in cost has been introduced, as a result the evolutionary process may vary the parameter values regardless of their financial or practical cost. For example in [20], the optimal red team configuration was found with a value of 97% for “stealthiness”, this imposes hard practical constraints to real-life operations which may not always be easily achieved. Moreover, the evolutionary process may result in simulation models which are not plausible or more critically, valid. For example, we may consider the evolution of agents’ spatial coordinates in a three dimensional space, the ART process may result in positioning agents at invalid locations (e.g., within a wall or in the sky). This may dramatically limit the potential of ART in such circumstances.

2. Computing budget: ART (and more generally data farming) experiments typically require high performance computing facilities which availability and capabilities may not satisfy the user’s time constraints and experimental requirements. The ART user may thus be confronted with a “computing budget” issue which may
limit the scale of the ART experiments. This would consequently affect the insights that may be gained using ART.

To address the above ART issues, we have developed novel computational techniques which originate from the rapidly growing research fields of evolutionary computation (more specifically, evolutionary multi-objective optimization) and cloud computing. To assist this research we employ the ART framework which was developed by Singapore DSO national laboratories [6]. In the remainder of this paper, we first present our novel techniques and then, apply them to a military toy model which was developed using the agent-based simulation platform MANA [18]. Following on from this, we discuss another research issue limiting the ART’s potential: many-objective optimization.

2. CONSTRAINT HANDLING

As introduced earlier, constraint handling has not been investigated in ART. We first identify the existing classes of constraints that may be encountered when performing ART experiments:

1. Cost trade-off: In typical ART experiments, specific parameter values are selected to be subjected to the evolutionary process. For each parameter, boundary value ranges are manually set and define the search space. As devised, the system would evolve/vary the parameter values within the associated ranges regardless of their potential cost. When evolving the red team’s behavioral parameters such as the agents’ stealthiness and speed or the number of red agents, ART would commonly maximize the value for these parameters, as this would usually increase red’s chances to break blue. No consideration is given to the practical/financial costs involved in increasing the agents’ stealthiness or speed. In such cases, the evolutionary search would provide insights of limited interest as the results could have been easily predicted (or could be hardly implementable in military operations). This lack of a secondary dimension addressing cost is thus a critical drawback which depreciates ART for real-world operations.

2. Simulation model validity: Although the evolvable parameter values are bounded by ranges, the generation of invalid/unrealistic models (due to the parameter values) during the evolutionary search may still occur. Indeed, the value ranges are set globally and do not account for local model/environmental factors. For instance, we may consider varying the initial spatial coordinates $x$, $y$ of an agent $A$ in a two dimensional space. The coordinates’ ranges are set globally (e.g., $A_x \in [20, 100]$ and $B_y \in [50, 100]$), A may thus be automatically positioned by ART anywhere within this region denoted by $R$. Nevertheless, if a rectangular obstacle $O$ (e.g., a wall) with dimension $10 \times 1$ is to be occurring in $R$, then $A$ could potentially be placed within the wall $O$ through random mutations during the evolutionary search. As a result, an invalid model would have been generated. Moreover, unrealistic models could also be generated due to potential interactions between the evolvable parameters. For example, let us consider an agent $B$ with speed $B_s$ and weight $B_w$. Here $B_s$ and $B_w$ could potentially interact with each other with $B_w$ limiting the maximal value of $B_s$. In such cases, ART cannot currently address this constraint due to interactions between parameters and would produce invalid and unrealistic simulation models/solutions.

To our knowledge, the above constraints have never been addressed in ART studies. We propose the following solutions to tackle these issues.

1. To address the cost trade-off constraint we suggest that additional objectives to the evolutionary search could be introduced to reflect the cost of the parameter values. For instance, the objectives of an ART experiment could include: 1) maximize blue casualties, 2) minimize red casualties and 3) minimize red stealthiness. Here, we assume that red stealthiness is associated with some cost (i.e., as red stealthiness increases, the cost of achieving this level of stealthiness increases accordingly) and we therefore wish to minimize this cost through minimizing the value of red stealthiness. Similarly, further parameters/objectives could be devised to account for further cost constraints. Finally, although addressing cost trade-off constraint through introducing additional objectives can be easily conducted/implemented, this affects the complexity of the evolutionary search. Solving many-objective optimization problems is a difficult task [15] which suggests that the current proposed method should be employed with parsimony. This many-objective optimization issue is further discussed in Section 5.

2. The simulation model validity constraint is model dependent and requires modifications of both the simulation platform and ART’s EA. To tackle model validity, we propose the introduction of a penalty function (returned by the simulation platform) which would reflect the validity of a model. A validity metric is introduced to measure the model error distance. For instance let us consider an agent being positioned by ART under the ground level: this would be relatively less erroneous if the agent is placed in the water and not in solid matter. Our solution does not attempt to reject or “repair” the
invalid simulation models but rather exploit the information carried by the invalid models/solutions and subsequently attempt to minimize the model error distance (which is here introduced as an additional EA objective). A motivation for this proposal is that EAs are stochastic search techniques, if we were to automatically reject (or repair if possible, however this would have a significant computational impact) invalid solutions then this might lead the EA to be stuck in local optima (especially in problems with disjoint search space) [11, 27].

In Section 4., we illustrate constraint handling by implementing our cost trade-off constraint solution and applying it to a toy model. The simulation model validity constraint is currently being investigated in collaboration with the MANA developers from the New Zealand Defence Technology Agency.

The above proposed solutions are essentially based on the introduction of further objectives to be solved by the EA. Nevertheless, as mentioned earlier, this impacts the complexity of the evolutionary search. To cope with the increased search complexity and computational requirements, we investigate the use of cloud computing techniques. This is presented in the following section.

3. COMPUTING BUDGET

Conducting ART experiments requires a significant amount of computing power (i.e., high performance computing facilities) to evaluate simulation models across a large search space. Moreover, ART experiments are typically conducted in an infrequent fashion and may occur when the computing facilities are not fully available. The user may thus be confronted with a computing budget limiting the use of ART techniques. We propose the use of the cloud computing paradigm to address these budget and flexibility issues.

Cloud computing [5] is a novel high performance computing paradigm in which computing capabilities are provided as a service via the Internet. This approach enables users to access computing services without requiring expertise in the technology that supports them.

The key benefits of cloud computing are identified as follows:

- **Reduced Cost**: Cloud computing infrastructures are typically provided by a third-party and do not need to be purchased for infrequent computing tasks. Users pay for the resources on a utility computing basis. This enables users with limited financial and computing resources to exploit high performance computing facilities (e.g., the Amazon Elastic Compute Cloud) without having to invest into personal and expensive computing facilities.

- **Scalability**: Multiple computing “clouds” (which can be distant from each other) can be aggregated to form a single virtual entity enabling users to conduct very large scale experiments. The computing resources are dynamically provided and self-managed by the cloud computing server.

We adapted the DSO’s ART framework to support cloud computing facilities. During the execution of ART experiments, the simulation model variants are dynamically distributed by the cloud computing server to the nodes. Results are then collated and sent back to ART for evaluation. From the user’s point of view, no technical expertise or setting is necessary to exploit the cloud computing facilities.

Future work includes the implementation of a novel job scheduler (based on the Apache Hadoop framework) to optimize the allocation/distribution of ART jobs (using techniques such as [19]) to further best exploit the user’s computing budget. In the next section, we employ our cloud computing compliant ART framework (in combination of the method presented in Section 2.) to conduct the ART experiments.

4. A MILITARY TOY MODEL

To illustrate the techniques presented earlier, we use a MANA toy model and conduct ART experiments using DSO’s ART framework.

4.1. The Scenario

An urban area of operations is considered. A town market is modeled where a first infantry squad (Blue) adopts a static position and is defending a key position located in the center of the market. Blue is partially hidden within the compounds of surrounding buildings. A second mobile squad (Red), initially located outside the market, attacks Blue to overtake its position. Both squads are equally attired in terms of offensive and defensive equipments. No civilians are considered in this scenario.

4.2. The model

Our toy model is developed using MANA, an agent-based simulation platform which was created by the New Zealand Defence Technology Agency to model and simulate defense related scenarios in which the properties of the environment and agents can be specified. It has the capability to model complex relationships and interactions between agents as well as different environmental conditions. This system has been employed to examine various scenarios such as managing civil violence [29], countering improvised explosive devices [1] and protecting the U.S. border [2].

Fig. 1 depicts the MANA model of our scenario introduced in the previous section.

Table 1 summarizes the model parameters of Blue. The values of these parameters are fixed and do not vary during the evolutionary experiments.
Figure 1. A military toy model. MANA version 3.2.2 was employed to model this scenario. This model was adapted from an unpublished study originally conducted by David Gallinan, a MANA developer from New Zealand Defence and Technology Agency.

Table 1. Blue Force fixed parameters

<table>
<thead>
<tr>
<th>Property</th>
<th>MANA Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of soldiers</td>
<td>15</td>
</tr>
<tr>
<td>Individual aggressiveness</td>
<td>15</td>
</tr>
<tr>
<td>Response to injured friends</td>
<td>10</td>
</tr>
<tr>
<td>Cohesion</td>
<td>15</td>
</tr>
<tr>
<td>Concealment rate</td>
<td>50%</td>
</tr>
</tbody>
</table>

Cohesion determines the propensity of the soldiers to remain unified within the squad formation. Concealment rate addresses the level of cover/stealthiness of Blue (here, Blue is partially hidden).

4.3. Measures of effectiveness

The principle measures of effectiveness (or mission objectives) are: 1) maximize Blue causalities, 2) minimize Red causalities, 3) minimize the number of deployed Red agents and 4) minimize Red stealthiness. These objectives are addressed with equal importance and explicitly (i.e., no linear combination or weighted sum of objectives is conducted) by the ART’s evolutionary algorithm. Objectives 3 and 4 are devised to set a cost/constraint upon the number of Red agents and their level of stealthiness, i.e., as the number of deployed Red agents increases, the cost of the Red operation increases accordingly; objective 3 is thus set to minimize this cost.

4.4. The ART framework

Singapore DSO national laboratories’ ART framework is a modular system allowing us to incorporate our novel techniques. Detailed description of the framework is provided by Choo et al. [6].

Figure 2. The ART Framework

The modules depicted in Fig. 2 act as wrappers for the ART controller to access and amend the inputs to the simulation model. These modules are designed as external libraries which are loaded during runtime. The interface module controls the input display from which the users can set parameters to be considered for an ART experiment. The ART controller handles the communications between the different modules. The output module is responsible for collating, formatting and creating the result files. The simulation software module supports for the simulation platform to be employed (e.g., MANA, Pythagoras [3], etc). The search algorithm module specifies the different heuristic algorithms available to ART (e.g., NSGA-II [8], SPEA2 [31], MOBCO [23] or PSO [16]). Finally, the computing infrastructure module handles the different types of supported computing facilities by ART (e.g., stand alone computer, Condor [21] or Hadoop/cloud computing [4]).

The above system is here employed to conduct the experiments as its modular nature facilitates the incorporation of new heuristic algorithms and (grid) computing techniques.

4.5. Experiments

Two series of experiments are conducted to outline the effects of incorporating constraint handling using cloud computing facilities. These experiments are conducted using a cloud computing cluster located in Singapore. This cloud computer was based on the Hadoop framework and utilizes a cluster of laboratory workstations.

Table 2 lists the evolutionary experiment parameters. The NSGA-II population size and number of generations indicate that $50 \times 100 = 5000$ distinct MANA simulation models are generated and evaluated during the evolutionary experiment. Each distinct simulation model is executed/replicated...
Table 2. Evolutionary simulation parameters.

<table>
<thead>
<tr>
<th>Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation engine</td>
<td>MANA</td>
</tr>
<tr>
<td>Evolutionary algorithm</td>
<td>NSGA-II [8]</td>
</tr>
<tr>
<td>NSGA-II population size</td>
<td>100</td>
</tr>
<tr>
<td>NSGA-II crossover rate</td>
<td>0.9</td>
</tr>
<tr>
<td>NSGA-II mutation probability</td>
<td>0.2</td>
</tr>
<tr>
<td>NSGA-II number of generation</td>
<td>50</td>
</tr>
<tr>
<td>NSGA-II objective 1</td>
<td>Maximize Blue casualty</td>
</tr>
<tr>
<td>NSGA-II objective 2</td>
<td>Minimize Red casualty</td>
</tr>
</tbody>
</table>

30 times to account for statistical fluctuations. The NSGA-II parameter values were set according to previous experiments in which such values are commonly employed. However, this does not guarantee that these values are (near) optimal to solve the present ART problem.

Table 3. Evolvable Red parameters.

<table>
<thead>
<tr>
<th>Red property</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of soldiers</td>
<td>5</td>
<td>15</td>
</tr>
<tr>
<td>Stealthiness</td>
<td>0</td>
<td>99</td>
</tr>
<tr>
<td>Cohesion</td>
<td>-100</td>
<td>100</td>
</tr>
<tr>
<td>Response to injured friends</td>
<td>-100</td>
<td>100</td>
</tr>
<tr>
<td>Individual aggressiveness</td>
<td>-100</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 3 enumerates the Red parameters that are subjected to evolution. The parameter values may vary within the boundary values as set by the min and max figures. Stealthiness has a max value of 99, as 100 would indicate that Red is invisible.

Table 4. Evolutionary simulation results with no constraint handling using NSGA-II with 2 objectives: maximize Blue casualties and minimize Red casualties.

<table>
<thead>
<tr>
<th>Property</th>
<th>Final value</th>
<th>mean</th>
<th>var.</th>
<th>CI 90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Red soldiers</td>
<td>12.35</td>
<td>±3.32</td>
<td>±0.55</td>
<td></td>
</tr>
<tr>
<td>Red stealthiness</td>
<td>98.44</td>
<td>±0.28</td>
<td>±0.05</td>
<td></td>
</tr>
<tr>
<td>Red cohesion</td>
<td>14.45</td>
<td>±6.92</td>
<td>±10.35</td>
<td></td>
</tr>
<tr>
<td>Red response to inj. friends</td>
<td>18.15</td>
<td>±5.37</td>
<td>±9.11</td>
<td></td>
</tr>
<tr>
<td>Red aggressiveness</td>
<td>-24.29</td>
<td>±78.34</td>
<td>±12.89</td>
<td></td>
</tr>
<tr>
<td>Blue casualty</td>
<td>12.12</td>
<td>±3.41</td>
<td>±0.56</td>
<td></td>
</tr>
<tr>
<td>Red casualty</td>
<td>1.05</td>
<td>±0.51</td>
<td>±0.08</td>
<td></td>
</tr>
</tbody>
</table>

Table 4 presents the results of the evolutionary experiment where no constraints were devised over the number of Red agents and stealthiness. The objectives of this experiment were to maximize the number of Blue casualties and minimize the number of Red casualties. The values presented in Table 4 and 5 depict the variability of solutions across the final population sets generated by the evolutionary experiments.

Figure 3. Final set of solutions generated by the evolutionary experiment with no constraint handling.

It may be observed that the evolutionary search successfully converged towards a set of optimal solutions (Fig. 3) accounting for the compromise between the number of Blue casualties and the number of Red casualties. The values for Red cohesion, response to injured friends and aggressiveness present relatively high variances. A potential reason for this phenomenon is the high value for Red stealthiness (98.44). These results indicate that Red stealthiness is the key factor optimizing the mission’s objectives. In other words, if the value for Red stealthiness is high enough, then the complementary parameters do not impact significantly the outcomes of the simulations (explaining the high variances observed for these complementary parameters).

Table 5. Evolutionary simulation results with constraint handling using NSGA-II with 4 objectives: maximize Blue casualties, minimize Red casualties, minimize number of Red agents and minimize Red stealthiness.

<table>
<thead>
<tr>
<th>Property</th>
<th>Final value</th>
<th>mean</th>
<th>var.</th>
<th>CI 90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red cohesion</td>
<td>65.27</td>
<td>±17.03</td>
<td>±2.80</td>
<td></td>
</tr>
<tr>
<td>Red response to inj. friends</td>
<td>-13.96</td>
<td>±61.02</td>
<td>±10.04</td>
<td></td>
</tr>
<tr>
<td>Red aggressiveness</td>
<td>-71.33</td>
<td>±61.30</td>
<td>±10.08</td>
<td></td>
</tr>
<tr>
<td>Red stealthiness</td>
<td>50.07</td>
<td>±34.12</td>
<td>±5.61</td>
<td></td>
</tr>
<tr>
<td>Number of Red soldiers</td>
<td>10.08</td>
<td>±3.16</td>
<td>±0.52</td>
<td></td>
</tr>
<tr>
<td>Blue casualty</td>
<td>8.16</td>
<td>±3.44</td>
<td>±0.57</td>
<td></td>
</tr>
<tr>
<td>Red casualty</td>
<td>5.46</td>
<td>±2.73</td>
<td>±0.45</td>
<td></td>
</tr>
</tbody>
</table>

In the second experiment, two objectives are added to address cost trade-off constraints: minimize the number of deployed Red agents and minimize Red stealthiness. In Table 5 we observe that: although a trend exists (when compared with previous results) where both the average Red stealthiness and squad size are effectively decreased, relatively high variances exist for all parameter values. This suggests that the current simplistic quantitative analysis may not be address-
ing the results adequately and prevent a better understanding of the results. Nevertheless, when examining the final simulation models individually using the MANA front end, we noted some unexpected phenomena which are here described qualitatively:

- The value for Red aggressiveness was typically negative. The Red forces would first converge towards Blue’s position and then avoid direct contact with Blue. Red would spread around the central target position. This may promote the minimization of Red casualty, especially when considering a low value for Red stealthiness (which naturally conflicts with the goal of minimizing the number of Red casualty).
- Red cohesion was always positive, the spreading of Red around the target position was conducted in a “unified fashion” where Red would remain in squad formations. This cohesiveness optimized the Red chances to both maximize Blue casualties and minimize Red casualties.

Moreover when examining the interactions between specific parameters (see Fig. 4), particular trends were observed suggesting the existence of key interactions in the simulation outcomes.

Figure 4. Interactions between parameters.

Although some interesting unexpected outcomes were observed, further analytical studies remain necessary as the experimental data present very high variances. We propose two hypotheses to explain those variances in the data:

1. It is first conjectured that interactions between the parameters exist (as suggested in Fig. 4), this may result in the formation of distinct clusters of solution (where the average parameter values would vary significantly from one cluster to another). These classes of solution would be hidden by the simplistic analysis conducted and presented above.

2. The evolutionary search did not reach convergence. The above data would therefore result from the exploration phase of the search where a high diversity of solution may still be occurring.

Future work, involving data mining techniques [13] and analysis of the dynamics of the evolutionary search could illuminate the above experimental results.

5. DISCUSSION

In this section, we discuss an additional potential major issue of ART: many-objective optimization. Solving real world problems commonly involves the simultaneous optimization of many objectives which often conflict with each other. In order to solve these many-objective combinatorial or numerical optimization problems, several heuristic algorithms have been proposed.

These heuristic algorithms can be classified into two main categories: evolutionary algorithms (EAs) [10] and swarm intelligence based algorithms (SAs) [9]. Both families of techniques are inspired by real phenomena occurring in nature. EAs simulate natural evolution by evolving species through the variation/recombination of genetic material. Whereas SAs exploit the collective intelligence exhibited in the group behavior of social entities such as bird flocks, ant and bee colonies.

Two multi-objective EAs (MOEAs) have been implemented within the Singapore DSO national laboratories’s ART framework: Non-dominated Sorting Algorithm II (NSGA-II) [8], Strength Pareto Evolutionary Algorithm II (SPEA II) [31]. In addition this framework supports two SAs: Multi-objective Bee Colony Algorithm (MOBCO) [23] and Particle Swarm Optimization (PSO) [16]. Although these heuristic algorithms have been successfully applied to both numerical benchmark problems (e.g., ZDT [30]) and ART problems, they suffer from one major constraint: they do not scale well against many (i.e., 4+) objective optimization problems where the performances may collapse and become equivalent to random search techniques [17]. However tactical operational plans may often include 4+ objectives [14].
Several substitute distance based approaches [25] (i.e., sub-vector dominance, ε-dominance, fuzzy Pareto dominance and sub-objective dominance count) have also been proposed to accommodate such many-objective optimization problems. In order to identify the limitations and suitability of multi-objective EAs in ART, we suggest the realization of comparative studies where these methods (including weighted sum of objectives techniques) are evaluated against a benchmark composed of optimization problems with an increasing number of objectives. According to the user’s requirements and based on this evaluation, a satisfactory search method could then be selected. This also suggests that a modular approach to EABS, where multiple EAs are available, would be advantageous.

6. CONCLUSION

Key issues of Automated Red Teaming were identified and discussed: constraint handling and computing budget. We argued that for both of these issues, significant drawbacks currently exist and limit the potential of ART to assist in military decision making. To resolve these issues, we proposed novel techniques originating from the fields of evolutionary computation and cloud computing. Cost trade-off Constraint handling was addressed through the addition of objectives to be achieved in the ART experiments. We proposed the exploitation of the cloud computing paradigm to resolve the ART’s computing budget issues. These techniques were combined and evaluated using a military toy model which was developed using the MANA platform. Experimental results suggested the potential benefits of our proposed techniques to further enhance the ART method. We then discussed the critical problem of handling many-objective optimization problems with current heuristic techniques. For further work we plan to: 1) analyze in detail the experimental results using data mining techniques, 2) to investigate model validity constraints, 3) to optimize job allocation when using cloud computing facilities, and 4) to develop new heuristic techniques capable of efficiently address many-objective ART problems.

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