Decision Support for Simulation-Based Operation Planning

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ABSTRACT

In this paper, we develop methods for analyzing large amounts of data from a military ground combat simulation system. Through a series of processes, we focus the big data set on situations that correspond to important questions and show advantageous outcomes. The result is a decision support methodology that provides commanders with results that answer specific questions of interest, such as what the consequences for the Blue side are in various Red scenarios or what a particular Blue force can withstand. This approach is a step toward taking the traditional data farming methodology from its analytical view into a prescriptive operation planning context and a decision making mode.

Keywords: decision support, MCDM, data analysis, information fusion, data farming, big data analytics, prescriptive analytics, operation planning

1. INTRODUCTION

In this paper, we develop methods for analyzing large amounts of output data from simulations in a multiple-criteria decision support system focused on answering a commander's specific questions regarding force configuration, outcomes, etc., in military operation planning.

We assume data farming [1] simulations with multiple evaluation criteria have taken place. Before addressing the commander's decision support, we must perform the multiple-criteria analysis and focus the entire data set such that it provides answers to specific questions of importance.

To provide decision support for a commander's specific questions in operation planning, we perform a sequence of process steps at several levels. From a top-level perspective, we first do scenario development, modelling, and simulation, followed by data analysis and decision support in a data farming approach. The final step of decision support goes a step beyond what is traditionally performed in statistical analysis within data farming. We think of this as data farming's decision support mode. In the operation planning problem that we study we have up to ten different measures of effectiveness (MOE). Thus, we need to manage a multiple-criteria decision making (MCDM) process. This is handled by preference analysis of the MOEs, followed by a Monte Carlo weight assignment process. With this approach we can avoid the difficult problem of weight assignment by human analysts and decision makers, although final adjustments by analysts may be necessary. With these two processes completed, we can focus on decision support. We further divide decision support into three sub-processes: one the *Analyst View* process, which is similar to the traditional statistical analysis usually performed in data farming; one the *Commander's Overview* process, which is focused on the big picture of how to win in military combat; and one the *Commander's Specific Questions* process, focusing on more specific questions of when we will win in different specific situations. Our focus in this paper is on the *Commander's Specific Questions* process. All other processes are discussed in other papers [4][12].

In Sec. 2 we give a short overview of the data farming approach used to perform the simulations. The ground warfare scenario under study is described in Sec. 3. The main focus of this paper is Sec. 4, where we develop methods for data analysis and decision support for a commander. We begin with a process overview description that puts the work of this paper into the context of previous work, and then move to the commander's specific questions, which are answered through a series of statistical and visualization methods for specific subsets of all simulation runs. Finally, the conclusions are presented (Sec. 5).

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2. DATA FARMING

Data farming [1] is a process aimed at maximizing the information available from a large set of data. The focus is on trying to produce a sufficiently complete landscape of potential outcomes rather than on identifying an individual response. In addition to identifying significant effects and relationships between input parameters, attention is also focused on detecting possible anomalies and including them in the decisions.

Data farming aims to provide insights into the problem formulations and is an iterative process consisting of a "loop of loops"; see Figure 1. In this paper our focus is on data analysis and data visualization within operation planning.

There is perhaps no optimal decision possible in a system where there are opponents acting in their own interests, but the notion is that more informed decisions can be made because the decision maker is allowed to understand the landscape of possibilities.

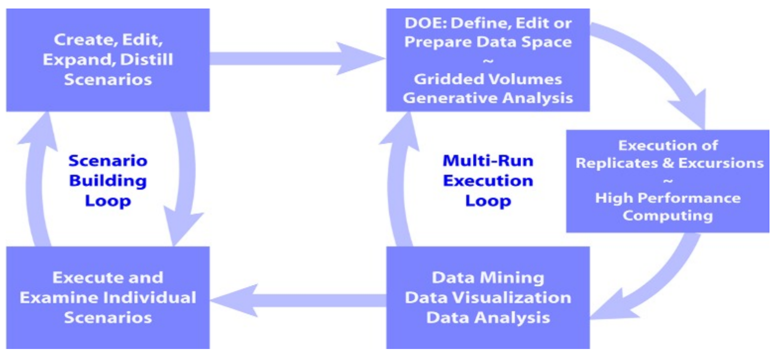

Figure 1. Scenario development and experimentation loop [1].

Based on the characteristics of the problem to be solved, there is a need for modeling nonlinearities, abstractions and influence between the various parts of the problem in a functional way. It is the combination of simple, efficient, and abstract models, as well as high performance computing, together with effective experiment design, that enables quick exploration of a solution space. Simple models make it easier to manage a large number of simulation runs, which enables exploration of a large parameter and value space and allows for the investigation of the solution space. The result is a landscape of outputs, which can then be used to analyze trends, detect anomalies and to generate insights regarding multiple parameter dimensions. In addition to identifying the general characteristics, the analysis also strives to provide understanding of the spread and central tendencies as well as to elucidate internal parameter relationships and thresholds.

The core of data farming is based on a rich and diverse array of different simulation runs that are carried out on computers to check different assumptions, to gain new insights into relevant relationships, as well as to obtain more robust statements on opportunities and risks in specific mission situations. This is achieved by systematically varying the different parameter values for the input parameters that are assumed to be crucial to the measures of effectiveness.

As mentioned, our focus is on data analysis and data visualization and how we can use the data farming approach for decision-making in general and, specifically, for decision support to a commander in operation planning.

3. SCENARIO

3.1 Scenario Overview

One of the initial tasks is to investigate how a combat sequence in a scenario proceeds to establish the foundation for developing a simulation model. This investigation is performed using war gaming [2], which helps us to produce key parameters and decision situations. We begin the process by defining different concepts, such as scenarios and events. Next, we break down a game situation into various events to come up with different ways to identify parameters, decision rules and actions. Based on this, we develop a scenario using war gaming on a map. We analyze the course of the game, followed by suggestions on how the scenario and the identified decision situations can be described in terms of simulation parameters. Because we plan to employ the data farming method, we need to be able to create different versions of the scenario to act as input to our simulation runs. Hence, when modelling the scenario, we need a set of general variables that can be used for all versions of it and a set of scenario-specific variables that depend on the current scenario terrain, types of units, tasks, and situations requiring tactical decisions.

To model the scenario, it is important to broaden the space of possible decisions that the simulated unit leaders can make and the actions that the simulated units can take. Again, the reason is to avoid missing any possible and interesting situations when running simulations using a data farming approach. However, we initially choose mainly the decision and policy options identified during a portion of the war game. The idea is that, in the future, the scenario model will be enhanced until the entire course of the game with all the actors can be modelled. Continued games will also provide additional data for the parameters that are important to the simulation and the interactions between different actors that may be relevant in the simulation.

Typically, a scenario in the context of the operation planning games is a description of the roles of different actors and their activities extended over a long period of time and over large areas. We initially focus on a smaller part of a scenario where only a few actors are active. This is called a vignette, which consists of a number of events together with actors who perform some specific activities, such as moving forward, reconnaissance, opening fire, etc.

The initial vignette includes a limited ground combat situation. Hence, the vignette used in our work unfolds in the context of defense against an armored attack, where an attack has been going on for a number of days before the start of the vignette. In this situation Red forces have air-dropped a parachute battalion at an airport and are in battle with a Blue force mechanized battalion reinforced with a tank company.

A new air-drop of a second Red force parachute battalion occurs in the areas around Gimo (see Figure 2).

Figure 2. Scenario map.

The task of this unit is to move south towards the airport to support the first Red parachute battalion in ensuring that the airport stays open for the landing of transport aircraft carrying new military units. At the same time, a second Blue mechanized battalion has regrouped and is positioned in the northern part of Uppsala. The task of this battalion is to prevent the Red forces from reaching the airport further south.

This part of the scenario is the focus of our simulation. The organization of the forces (Order of Battle - ORBAT) is as follows: a mechanized battalion on the Blue side and a parachute battalion on the Red side. In this example, these units are organized as described in Figure 3 and Figure 4. The units are simplified for several reasons.

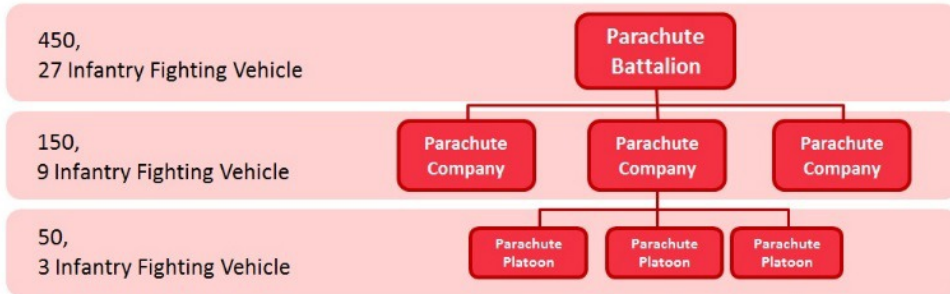

Figure 3. Red order of battle.

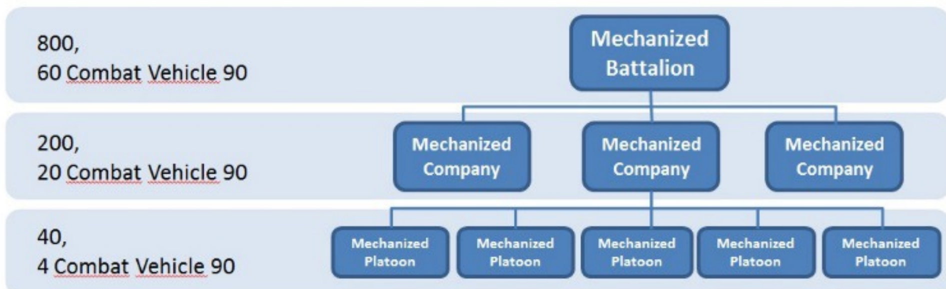

Figure 4. Blue order of battle.

3.2 Simulation Framework and Set-up

We use the *Flexible Analysis and Mission Effectiveness System* (FLAMES) simulation framework [3] in our work. In this framework, a basic template actor that comes with the framework can be modified to match the physical and behavioral characteristics of the actors in our vignette. Technical details on the components in the simulation can be found in [4].

The vignette we currently use is extended compared to [4] by including Main Battle Tanks 122 (Strv122) to support the armored personnel carriers (APCs) Combat Vehicle 90 (Strf90), already in the vignette, on the Blue side. On the Red side we added BMD-3 and BMD-3 with anti-tank guided missile (ATGM) launch capability to the BMP-1 APC already in the vignette. The Blue platoons are either pure Strf90 or Strv122 platoons with four vehicles each, whereas the Red platoons are of three different types: pure BMP-1 or BMD-3, or mixed platoons with two BMP-1 and one BMD-3, or two BMD-3 and one BMD-3 ATGM, with three vehicles in each platoon. Tanks have heavier firing capability and are more robust when being shot at, according to specific munition and damage models. We have also added artillery with up to three mortar units that may fire terminally guided ammunition.

The challenge is that the variations of input parameter values must be selected in such a way so that there is no combinatorial explosion. To support data farming we have created software which depends on FLAMES running the scenarios in batch mode. This software first produces an input file containing permutations of our basic scenario, which is performed by randomizing between minimum and maximum values for each scenario variable; see Table 1. These ranges are selected so they match the expected values for each parameter in a real situation.

In the present experiment we have 40 000 permutated scenarios, where each scenario is run four times with identical initial conditions but with different simulation seeds, making a total of 160 000 runs. The four different seed values give slight random Monte Carlo variations within each simulation group with identical input parameters.

Table 1. Input Scenario Variables with Value ranges

Scenario variable	Value range
Number of Blue Combat Vehicle 90 (Strf90) that are active	0–108
Number of Blue Main Battle Tank 122 (Strv122) that are active	0–36
Number of Ammunition for Blue Combat Vehicle 90	60–120
Number of Ammunition for Blue Main Battle Tank 122 (Strv122)	8–24
Number of Blue Mortar Units (BMU) that are active	0–3
Blue Mortar Shell end phase Homing Radius (SHR)	30–120 m (in 30 m steps)
Blue Mortar Shell Probability of Kill (SPK)	0.2–0.8 (in 0.2 steps)
Sensor range for Blue (BSR) and Red (RSR) units	1500–2500 m
Number of Red BMP-1 that are active	0–26
Number of Red BMD-3 that are active	0–17
Number of Red BMD-3-Missile that are active	0–2
Routes that the Red units can take	Predefined routes 1, 2, 3

4. DECISION SUPPORT FOR THE COMMANDER

4.1 Decision Support Process Overview

The decision support processes are focused on identifying the most effective plan instances as evaluated by all measures of effectiveness (MOEs). When there are several MOEs, we are faced with an MCDM problem when assessing which plan instances are most preferred.

To find the best simulations we must rank all simulation runs based on their MOEs. Thus, we need to assign weights to these measures. In some special situations there might be sufficiently accurate knowledge of which parameter inputs and simulation outputs are most important to optimize to obtain a preferred outcome. When this is the case it may be possible to directly assign weights to the different MOEs. However, this is usually not the case and is often a difficult problem for decision makers. As an alternative approach, we may let them express preferences on the relative importance between different MOEs, or between any two disjoint subsets of MOEs.

In [5] we developed a preference-ranking approach as an extension to Utkin's [6] preference assignment method that is focused on finding the preferred order of importance of all MOEs from the preference assignments made by the decision makers. This extension uses interpolation in belief-plausibility intervals [7] regarding the obtained degree of preference of all different MOEs and delivers a complete ranking of all MOEs. The method accepts any number of preference expressions regarding the MOEs from any number of decision makers. For example, an expression such as *"MOE_i is more important than MOE_j"*; $MOE_i \succcurlyeq MOE_j$, or an expression regarding two different subsets of MOEs such as *"MOE_i and MOE_j are more important than MOE_k and MOE_l"*; $\{MOE_i, MOE_j\} \succcurlyeq \{MOE_k, MOE_l\}$.

Each MOE is ranked by

$$\frac{1}{2}\left[Bel_{\{i\}\Theta}(\{MOE_i\} \succcurlyeq \Theta) + Pls_{\{i\}\Theta}(\{MOE_i\} \succcurlyeq \Theta)\right] \tag{1}$$

where *Bel* and *Pls* are the belief and plausibility, respectively, and $\Theta = \{MOE_i\}$, see [5] for details.

The preference-ranking approach has been further extended to allow partial preference ranking of MOEs [8] using belief function theory [9–11]. Partial rankings of MOEs have higher belief-plausibility but less information value. It may be beneficial when the belief-plausibility is too low for the best complete rankings of MOEs. However, in this paper we use the complete ranking method [5].

Using the preference order for all MOEs, we adopt a Monte Carlo approach to assign weights for these MOEs. We randomly assign weights that abide by the preferred order of the MOEs; i.e., the most preferred measure will be weighted higher than the second most preferred measure, etc. Using a Monte Carlo approach, we provide alternative weight assignments for all measures, yielding alternative rankings of all simulations. The simulations with the highest average ranking are the most preferred.

With this methodology we obtain a ranking of all plans and can then analyze the best plans to learn which combination of parameter ranges leads to success. A process overview is provided in Figure 5.

Figure 5. Process overview.

The last process step, *Decision Support,* in Fig. 5 can be split into three sub-processes (Figure 6). They are,

- The *Analyst View* [4], where all data are statistically analyzed by an analyst who may prepare specific questions to be answered,
- The *Commander's Overview,* where the best simulations leading to Blue success are analyzed to provide information regarding the number of input parameters needed to explain the result, which parameters these are, and what values these parameters should assume in order for Blue to achieve success,
- The *Commander's Specific Questions,* where subsets of simulations are analyzed by looking at a subset of parameter values for some Red parameters or for some Blue parameters.

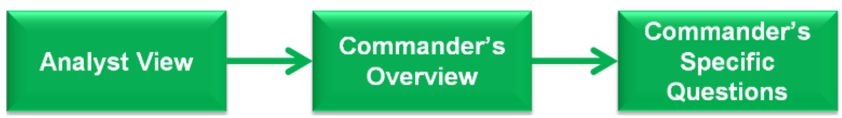

Figure 6. Three components of decision support.

In the Analyst View we may use Heat Maps to study variation of MOEs in relation to two input parameters. In the first row of Figure 7 we observe Red and Blue losses in relation to the number of platoons on each side. In the second row we observe how Red losses increase when some Combat Vehicles are exchange for Main Battle Tanks. The last row presents losses depending on the chosen avenue of approach for Red. Clearly, approach number 2 is worse for the Red side.

The focus in this paper is, however, on the Commander's Specific Questions. The approaches taken in the Analyst View are developed in [4], and the approaches taken in the Commander's Overview are developed in [12].

When analyzing the entire data set, we vary all input parameters independently, both concerning the Red side and the Blue side. Such an analysis is an unrestricted data exploration and is usually a good first step to obtain an overview of the entire data set. This is what was performed in the Analyst View [4]. However, if we want to answer more specific questions of interest to the Blue-side decision maker, we should also restrict the data set to specific subsets that match those questions. An obvious choice is to begin with restricting some of the input parameters on the Red side, e.g., the size and composition of the Red force.

We begin by imposing restrictions upon the entire data set to study different Red Scenarios (Sec. 4.2) and then specialize by viewing the best 2000 simulations found by the MCDM and preference analysis to study a specific Blue Scenario (Sec. 4.3). While the first answers the commander's specific questions regarding what the consequences for the Blue side are in different Red scenarios, the latter answers the commander's specific questions regarding what a particular Blue force can withstand.

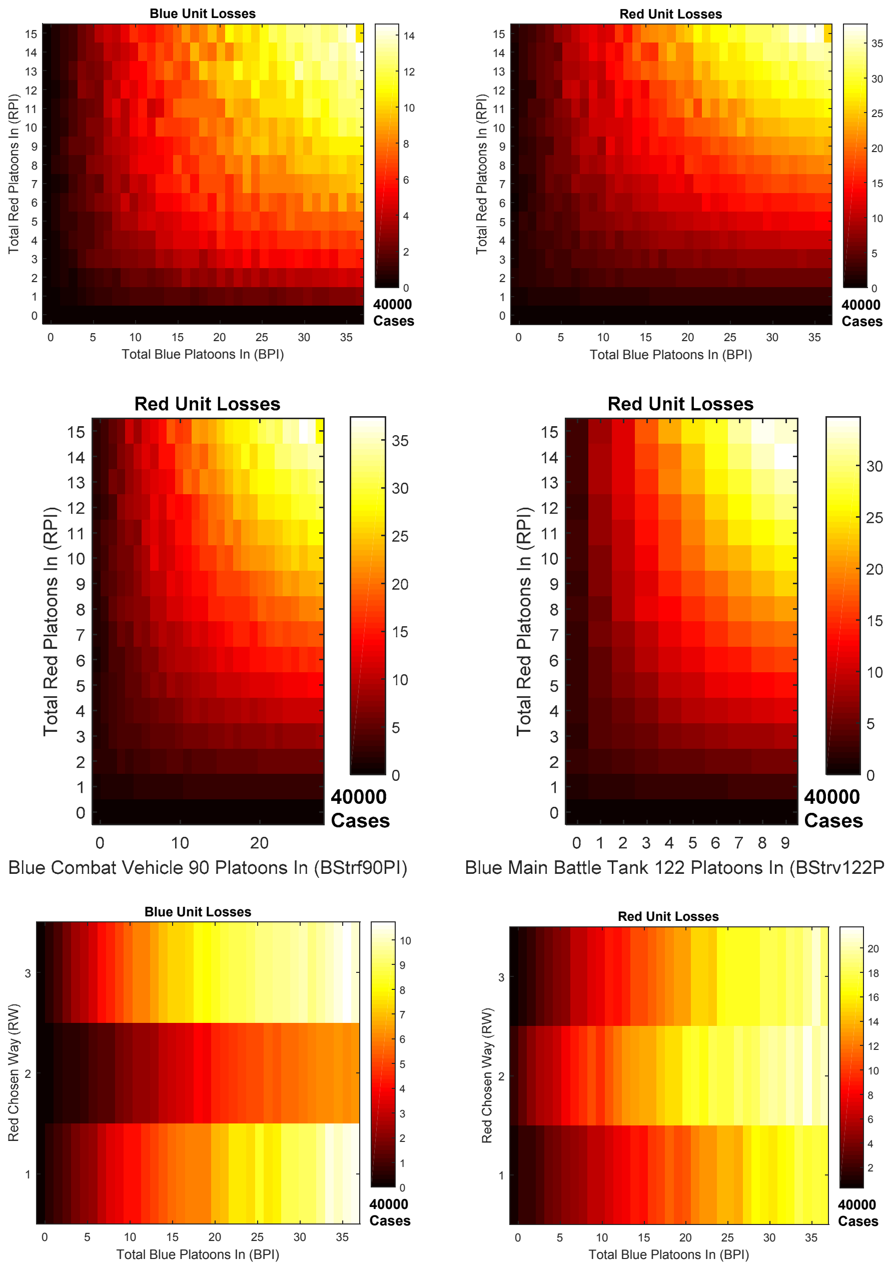

Figure 7. A heat map view of losses on Blue (*left*) and Red (*right*) losses for a few parameters.

4.2 Commander's Specific Questions for Red Scenarios

After having acquired simulation output from 10 000 random permutations of all input scenario variables, we must choose an approach to analyze the output. There are, of course, many approaches to this, depending on what we want to achieve. Assuming that the previous steps have been performed, we focus on the *Commander's Specific Questions* in Figure 6. This is the last view of the simulation results focused on finding answers to a selection of specific questions. Because many scenario variables are varied simultaneously, we select a subset of all simulation runs by fixing some of the input parameters at certain values or in narrow ranges, while investigating the behavior of others over full ranges. This is performed because trends are difficult to observe when all parameters vary over full ranges simultaneously in data farming.

The two main visualization approaches we will take in this paper are *Heat maps* and *Box plots,* to be described in the following.

Heat Maps of Red Units Breaking Through a Defense Line and Red Unit Losses

One way to simultaneously vary two input parameters and study the behavior of an output parameter is to use 3D histograms with the input scenario variables on the *x*- and *y*-axes, and a dependent output scenario variable on the *z*-axis. Alternatively, we color-code the *z*-value and observe the histogram from above as a heat map. In combination with different filters on some of the other scenario input variables, fixing input parameters to certain values or in narrow value ranges gives a good overview of the degree to which the *x*- and *y*-values correlate for particular subsets of simulations.

Below, we draw heat maps of *Red Units Finish* (RUF) (i.e., the number of Red units that break through a defense line defended by Blue units), and *Red Unit Losses*. Generally in the heat maps *no data* cells (i.e., when there are zero simulations with a certain combination of *x*- and *y*-values) are colored gray. If several simulations have the same *x*- and *y*-values, their *z*-values are averaged before display. We draw below one heat map each for three different filters on number of Red platoons, (Figures 8–13) where the sum of all Red platoons equals 6, 10 and 14, respectively.

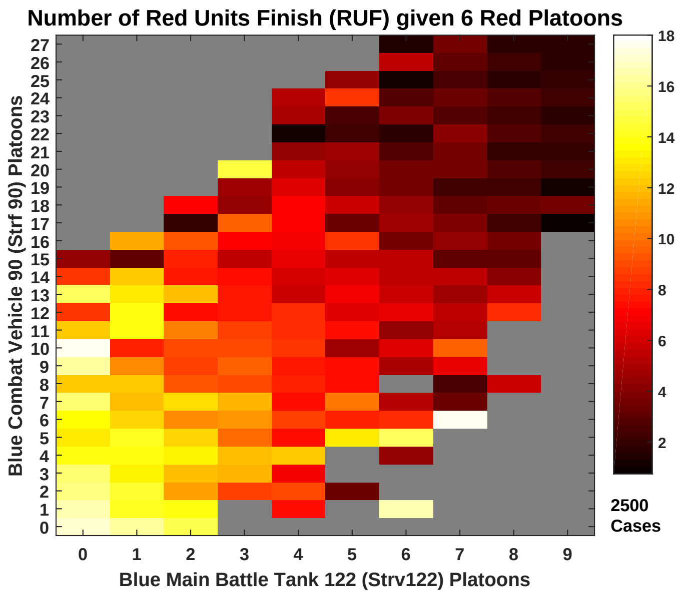

Figure 8. Number of Red units given six Red platoons that manages to bypass a defense line defended by the Blue side.

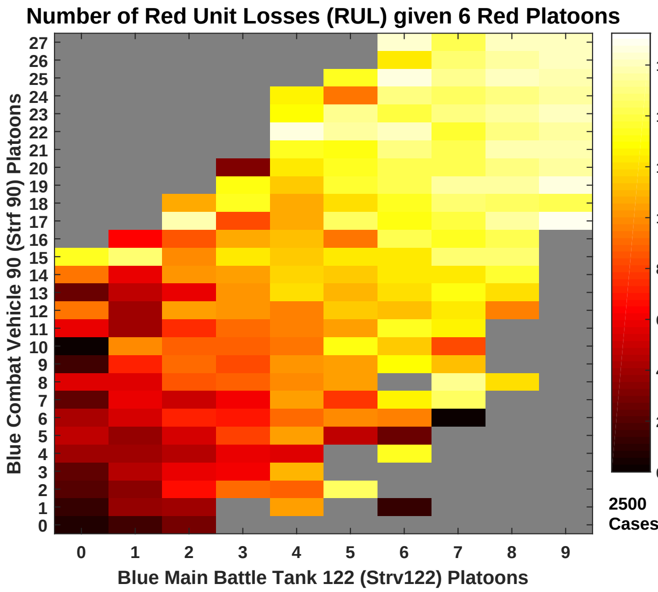

Figure 9. Number of Red units given six Red platoons that get destroyed by the Blue side.

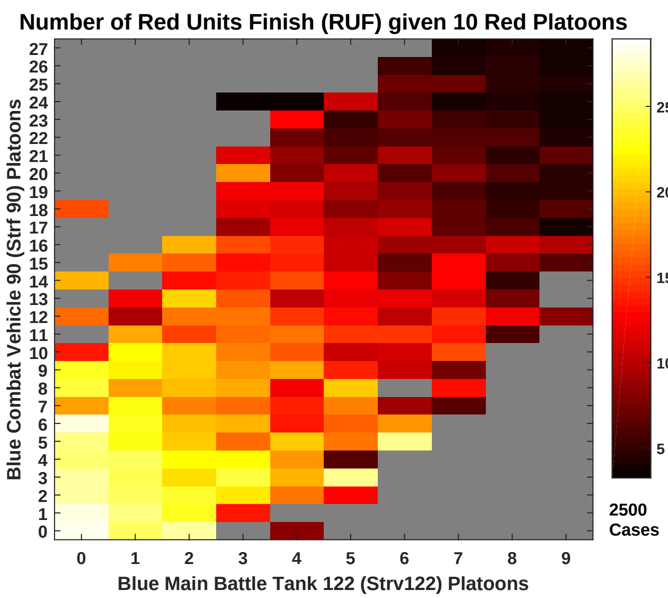

Figure 10. Number of Red units given ten Red platoons that manages to bypass a defense line defended by the Blue side.

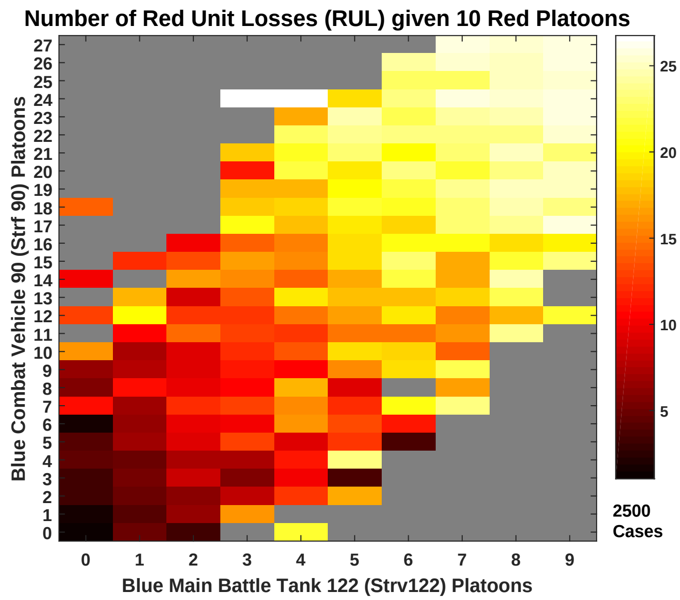

Figure 11. Number of Red units given ten Red platoons that get destroyed by the Blue side.

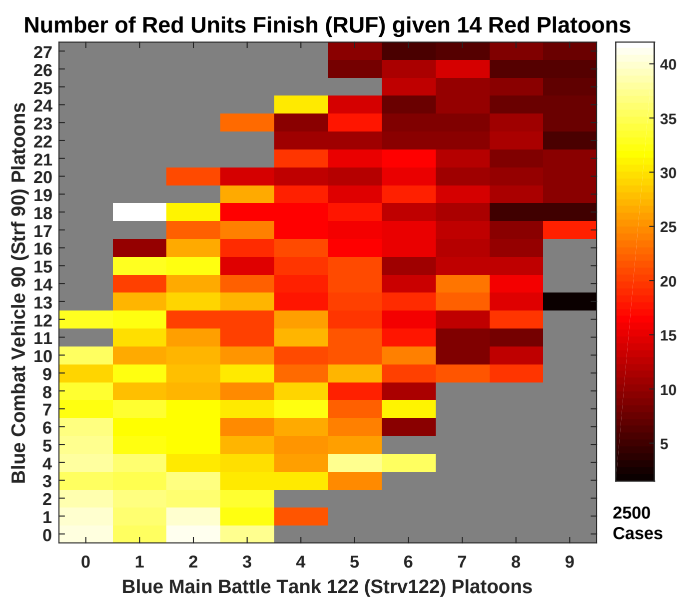

Figure 12. Number of Red units given 14 Red platoons that manages to bypass a defense line defended by the Blue side.

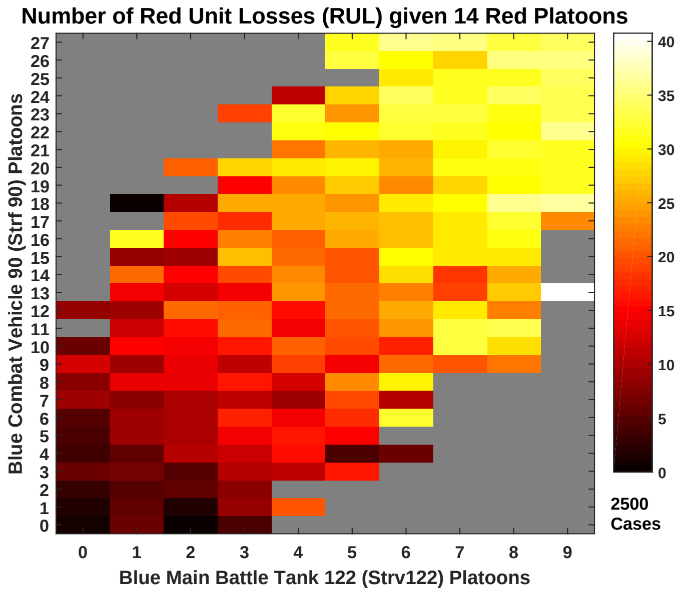

Figure 13. Number of Red units given 14 Red platoons that get destroyed by the Blue side.

The distribution of lighter colors shows that more Red units avoid getting destroyed by Blue units and make it to the *finish line* when their number is larger, especially for low numbers of Blue units. The opposite is observed for the *Red Unit Losses.* Both are, of course, what could be expected.

We may instead of absolute values display *relative values*, such as the percentage of Red losses. This makes it easier to use the whole simulation dataset, see Figure 14.

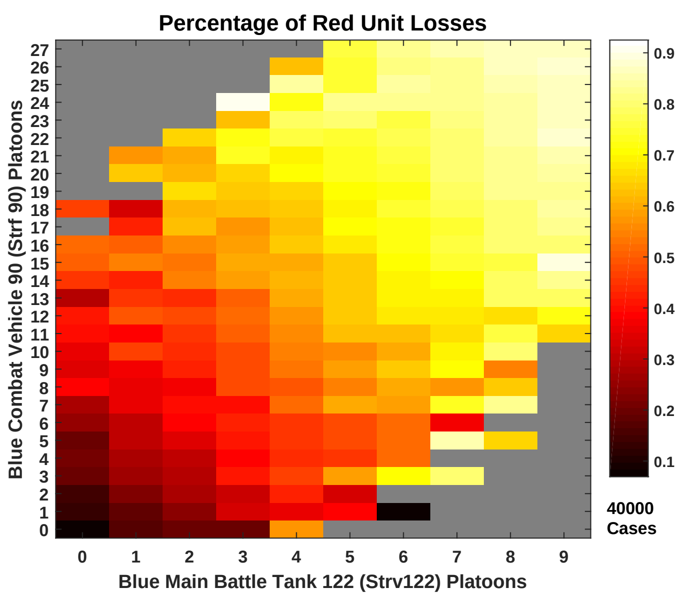

Figure 14. Relative number of Red units that get destroyed by the Blue side.

We may also check the effect of the artillery (mortars). Up to three mortars can be active in each simulation, and they may fire one or two *salvos* of ten shells each. The shells are modelled with varying *probability of kill* as well as varying ability to *home in within different radii* against a target in the final phase of flight, see Figures 15–17. In all three figures, we observe simulations that have ten Red platoons and no Blue platoons, only Blue mortar units. This leaves us with 61 cases from of a total of 40 000. This is done to observe Red losses from artillery.

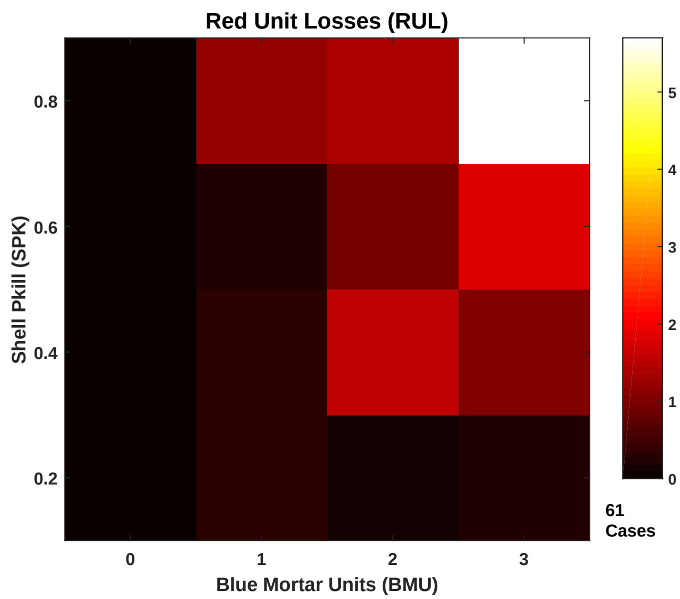

Figure 15. Red unit losses from mortars firing shells with different probability of kill.

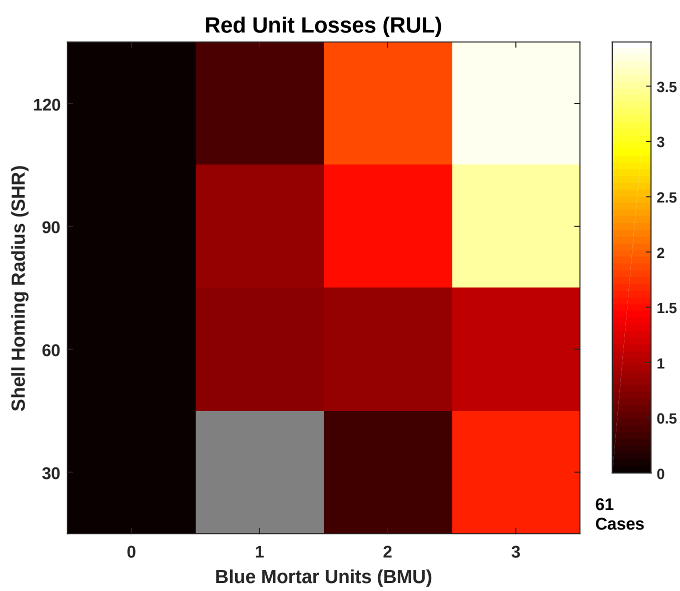

Figure 16. Red units from mortars firing shells with different ability to deviate from ballistic trajectory and hit targets outside it.

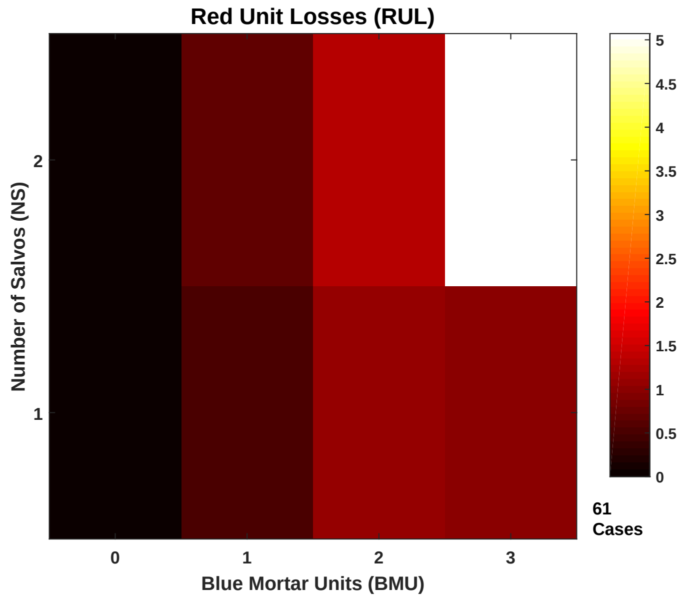

Figure 17. Red units from mortar firing one or two salvos with ten shells in each salvo.

Box Plots of Blue Losses

Data can spread along an output dimension due to its dependencies on many other dimensions that are allowed to vary simultaneously within a dataset. For instance, above, the *type* of Red platoons can vary randomly because no filter is set on platoon types. In addition, a spread normally occurs due to random Monte Carlo effects in the simulation. One approach to observing the spread in the data is to use box plots for output variables.

In the box plots below, the horizontal Red line within a box is its median value and the upper and lower edges of a box are the upper and lower quartiles. Thus, each box contains 50% of all output data for that *x*-value. Outside of the box, the dashed *whiskers* extend approximately 1.5 times the distance between the two quartiles. This frames approximately ±2.7σ, with 99.3% of the data within the whiskers if the data are normally distributed. Outside the whiskers, data points are considered outliers and are individually plotted as red "+" signs.

In Figures 18 to 20 we study the spread in *Blue Unit Losses* (BUL) for different numbers of Blue platoons entering a vignette. We draw one box plot each for the same three different filters used for the heat maps.

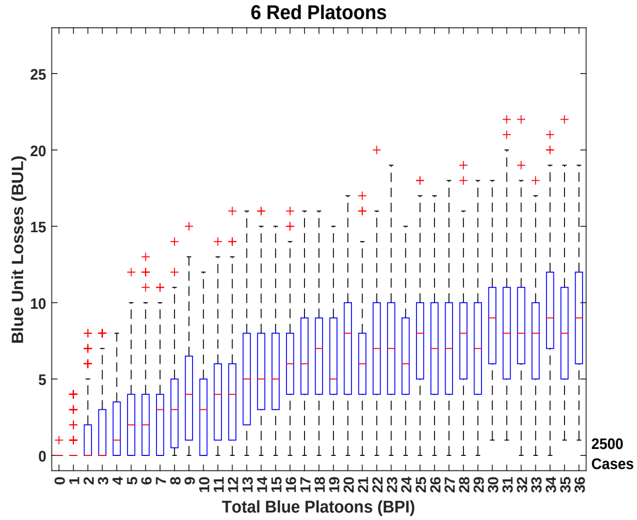

Figure 18. Numbers of lost (destroyed) Blue units attacked by 6 Red platoons as a function of number of Blue platoons that are in defending position (2500 simulation cases).

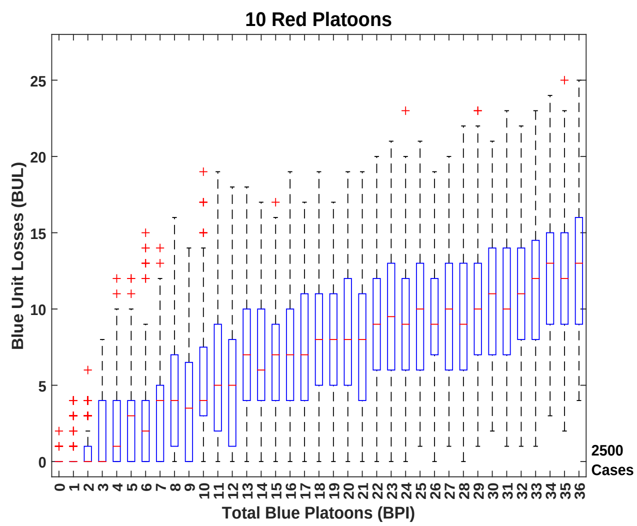

Figure 19. Numbers of lost (destroyed) Blue units attacked by 10 Red platoons as a function of number of Blue platoons that are in defending position (2500 simulation cases).

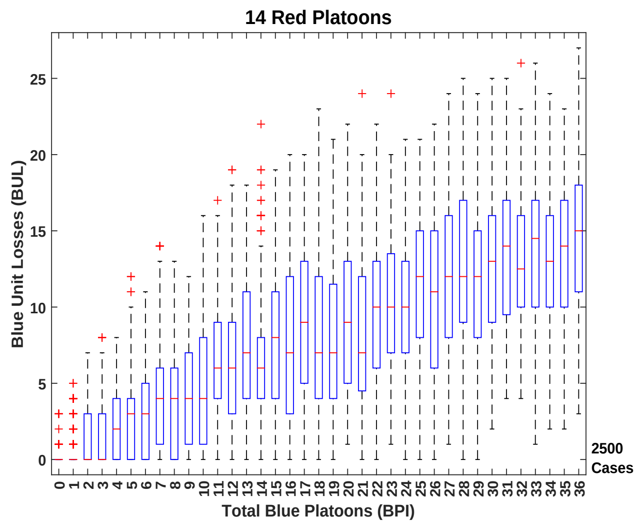

Figure 20. Numbers of lost (destroyed) Blue units attacked by 14 Red platoons as a function of number of Blue platoons that are in defending position (2500 simulation cases).

The main trend observed is that the more numerous the Blue side is (along the *x*-axis in each box plot), the more Blue units are lost (sic!). The simple explanation is that there are then more targets for the Red units to shoot at. BUL also increase, as expected, when being attacked by a more numerous enemy as seen step-wise in Figures 10–12. The spread of BUL is due to Monte Carlo effects causing spread within each simulation case, as well as other input parameters being allowed to vary, e.g., the combination of Red units with different firepower. To check the influence of this last effect, we will in Sec. 4.3 turn back to heat maps and study the effect on three output parameters as functions of the number of Red units of two different types.

Before that, we can in a similar manner observe the spread of Red unit losses due to the effect of Blue artillery (Figures 21 and 22).

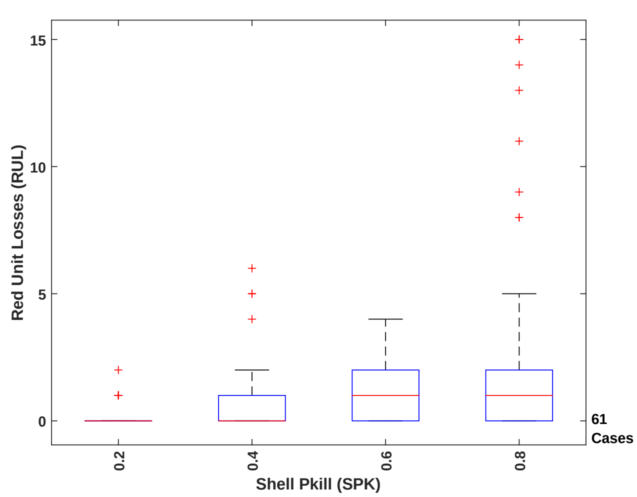

Figure 21. The spread in Red unit losses due to varying mortar probability of kill.

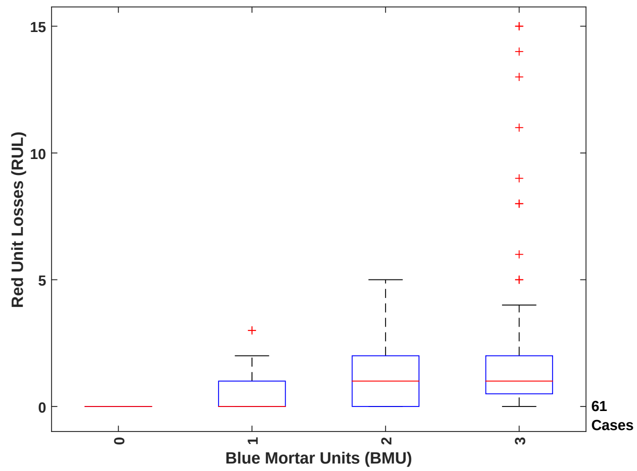

Figure 22. The spread in Red unit losses due to varying number of mortars.

4.3 Commander's Questions for a Specific Blue Force

We now put the number of two different Red force components along the *x*- and *y*-axes. We also narrow the variation on the Blue side by setting a lower limit on them, such as only showing results from simulations containing at least six Blue tanks Strv122, as a case study of specific interest. Below we look at three different output scenario variables; *Red Units Finished* (RUF), *Blue Unit Losses* (BUL) and *Red Unit Losses* (RUL).

For RUF in Figure 23, the largest value is found in the upper right. The greatest effect is seen in the right column, with two additional Red missile platoons that contributes significantly to the ability of Red units to pass the defense line.

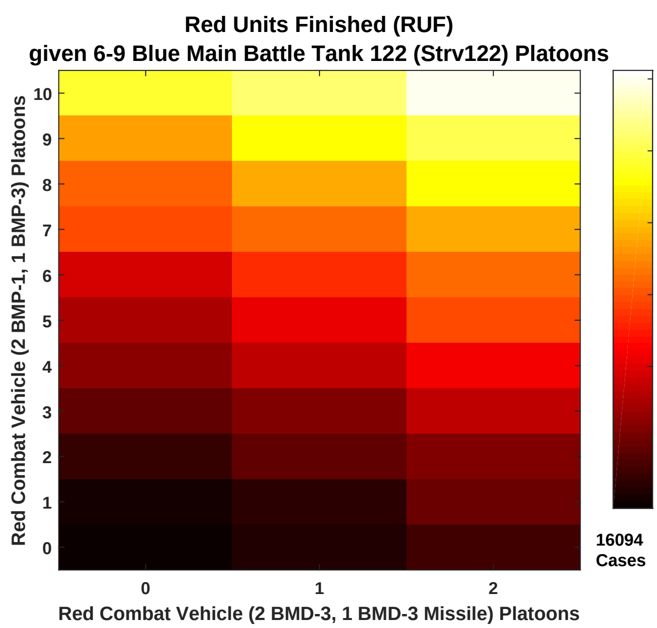

Figure 23. Number of Red units bypassing the Blue defense line in simulations with six to nine Main Battle Tank (Strv122) platoons.

For BUL (Figure 24), the left column is most prominent: no heavy Red platoons ($x = 0$) require a high number of lighter Red platoons ($y > 6$) to achieve a high impact on the Blue side. With two Red platoons armed with missiles they achieve the same effect as three Red platoons without missiles.

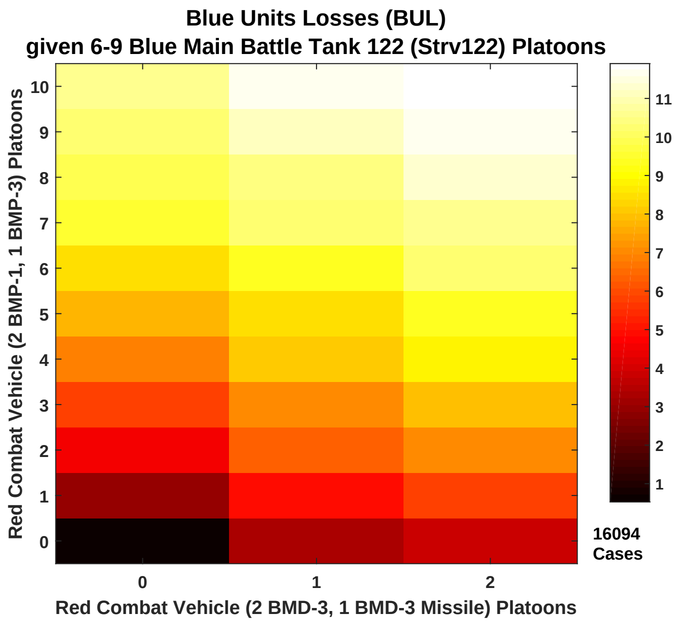

Figure 24. Number of Blue units lost for the Blue defense in simulations with six to nine Main Battle Tank (Strv122) platoons.

For RUL (Figure 25), we see a similar trend, which could be explained by the greater number of Red units and the greater number of targets for the Red side. However, no major decline in RUL is seen when some Red platoons are armed with missiles. This is easy to observe at the along the line ({0, 2}, {1, 1}, {2, 0}) where the cells of the heat maps have the color.

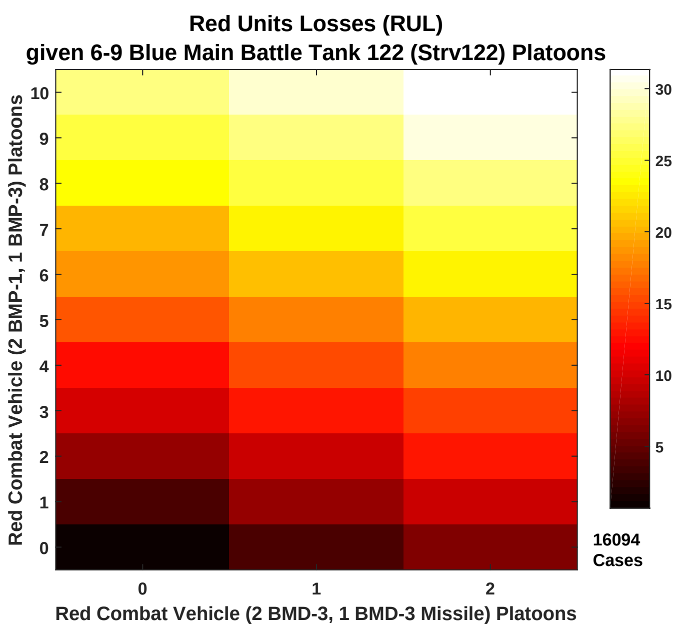

Figure 25. Number of Red units lost for the Blue defense in simulations with six to nine Main Battle Tank (Strv122) platoons.

If we want to study the effect of the missile units in more detail, we can extract the number of destroyed Blue units in each simulation due to missile strikes. We plot that MOE in two ways; in a box plot as a function of number of missile platoons in the simulations, and as histograms for those simulations that contained one and two missile platoons, respectively, see Figure 26. We observe in the box plot a slight increase of destroyed Blue units; the median is 1 in simulations with two missile platoons. In the histograms, we observe that the bars are slightly more adjusted to higher Blue losses. Especially the frequency of two and three losses increase.

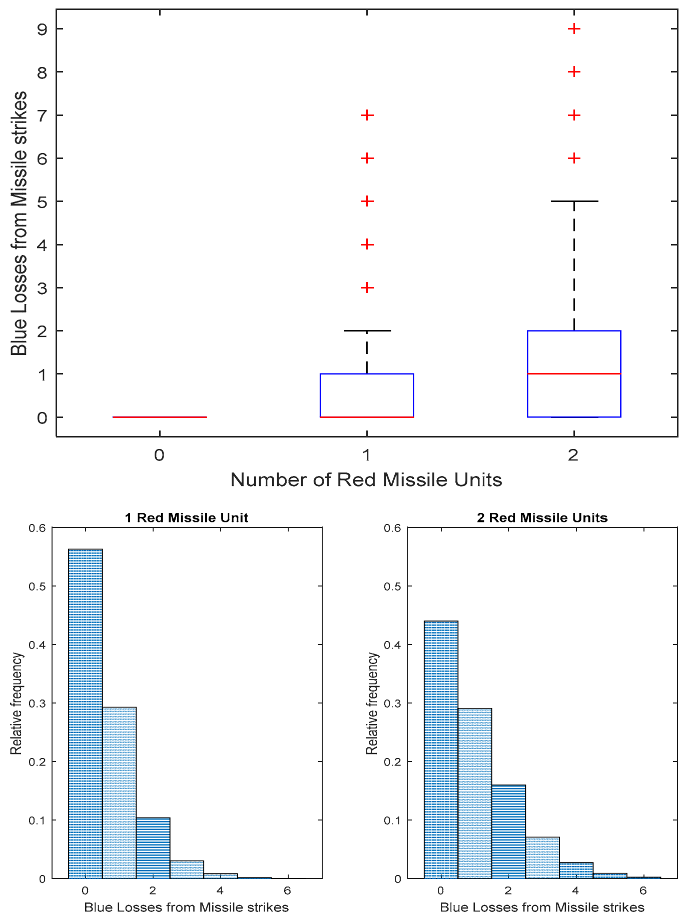

Figure 26. Going deeper into the effect of the heavier Red missile units. Specific Blue losses due to missile strikes are studied here. The histogram bars should be interpreted as the relative frequency of simulations where 0–6 Blue units were destroyed due to missile strikes. I.e., in 57% of the simulations where there was one Red missile platoon, no Blue units were destroyed by missiles.

Using the preference-based ranking procedure [5], we rank all simulations according to the most advantageous outcomes for the Blue defending side. We use the ranking preference order of [5], i.e.,

$$BUL \succcurlyeq RUL \succcurlyeq RUF \succcurlyeq RPI \succcurlyeq BPI, \tag{2}$$

where RPI and BPI are the number of Red and Blue platoons that enter the scenario. BUL has the highest preference to be optimized (minimized), then RUL is to be optimized (maximized), followed by RUF (minimized), RPI (maximized) and BPI (minimized). The two last directions of optimization should be to be explained; achieving a particular outcome with few Blue units rather than many is a greater achievement.

Filtering out the 2000 *best* simulations (in the eyes of the Blue side), we visualize the remaining data and compare it to earlier figures. As an example, we show in Figure 16 the same situation as in Figure 8, but with the smaller more specific data set.

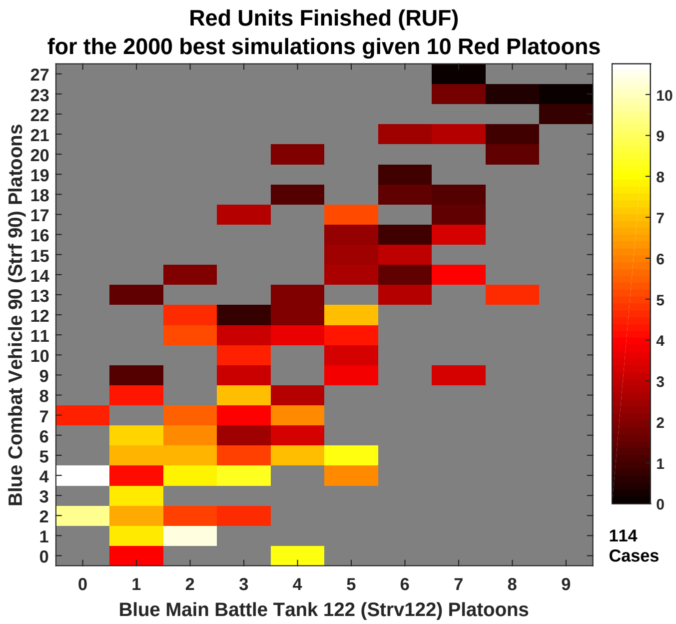

Figure 27. The same heat map as in Figure 10, when only the 2000 simulations with most advantageous outcome for the Blue side are kept before filtering out those of them that have ten Red platoons (this filtering leaves 114 simulation cases).

We notice that far fewer Red units pass the defense line (generally darker colors) for ten Red platoons and the same combinations of Blue platoons in a simulation. The number of data points is of course much smaller, 114 simulation runs altogether, as we only analyze those simulations among the best 2000 that have exactly ten Red platoons in the data farming input setup.

The simulations performed cover the ranges of input parameters as uniformly as possible. After keeping only the highest ranked simulations, it should be possible to see which ranges of input parameters are most favorable for the Blue side. In Figure 28, we have chosen some input parameters and study their distribution for the same 2000 best plans as above.

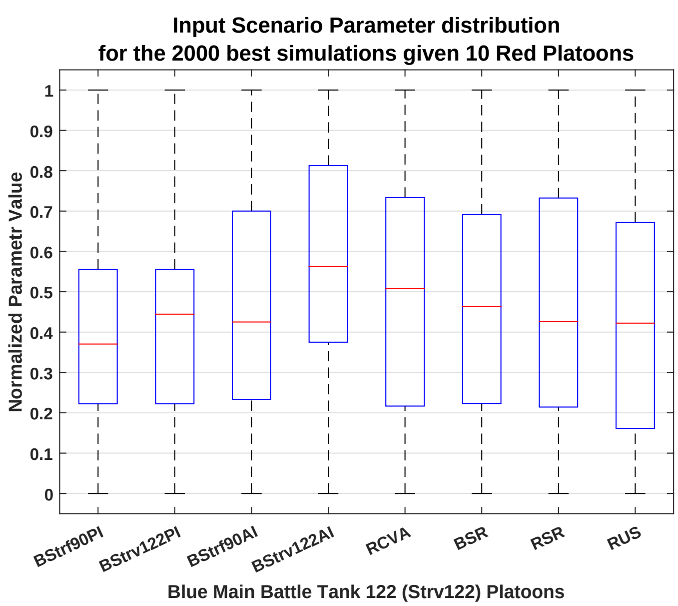

Figure 28. The distribution of input parameter values (normalized 0-1) for the 2000 simulations with most advantageous outcome for the Blue side (114 simulation cases).

We observe that it is advantageous to use approximately 0.4 (median value) of the maximum amounts of Blue units (BStrf90PI are APC platoons, BStrv122PI are tank platoons), as observed from the two leftmost boxes. More Blue units offer more targets for the Red side to engage, and we have put priority on minimizing BUL, not maximizing RUL. Thus, this view of the data, including establishing the preference order, is an example of the *Commander's Specific Questions*.

Some additional examples of specific questions that can be drawn from a focused data set are (observations from Figure 28): The amount of ammunition (suffix AI and A) is more important for the Blue tanks than for the Blue APC's. This is probably the case since the tanks has less and may deplete their ammunition depot before the simulation ends.

The sensor ranges (BSR, RSR) show a rather uniformly distributed spread (median close to approximately 50%, quartiles at approximately 25% and 75%), which indicates that there is no real effect when varying them, which is also confirmed when studying them in heat maps (not included in this paper). The terrain model used in the vignettes are scattered with forested and partly hilly areas mixed with open land. This means that the lines–of–sight for the units' sensors are often limited by vegetation and terrain.

Additional ways to analyze and visualize information for decision support in operation planning are discussed in [13]. While the current paper focuses on operation planning based on tactical level simulation in ground warfare, [13] focuses on operation planning with an operational level simulation of an expedition.

5. CONCLUSIONS

We presented a process view of data analysis, where we develop and use ranking methods to identify the most advantageous simulation runs and use them to focus the data set such that specific questions regarding topics of interest to a decision maker can be put forward and answered. We think that this approach is a first step towards taking the data farming methodology from its traditional analytical view into an operation planning context and a decision-making mode.

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