Scythe

Proceedings and Bulletin of the International Data Farming Community

Issue 9 - Workshop 21

Proceedings and Bulletin of the International Data Farming Community

Table of Contents

Scythe

Proceedings and Bulletin of the International Data Farming Community

It is appropriate that the publication supporting the International Data Farming Workshop is named after a farming implement. In farming, a scythe is used to clear and harvest. We hope that the "Scythe" will perform a similar role for our data farming community by being a tool to help prepare for our data farming efforts and harvest the results. The Scythe is provided to all attendees of the Workshops. Electronic copies may be obtained from harvest.nps.edu. Please contact the editors for additional paper copies.

The Scythe consists primarily of team reports written by the team members on activity, analysis, and results in their team during the workshop from their perspective. Please let us know what you think of this ninth prototypical issue. Articles, ideas for articles and material, and any commentary are always appreciated.

International Data Farming Community Workshop 21 Program Committee

International Data Farming Community Overview

The International Data Farming Community is a consortium of researchers interested in the study of *Data Farming*, its methodologies, applications, tools, and evolution.

The primary venue for the Community is the biannual International Data Farming Workshops, where researchers participate in team-oriented model development, experimental design, and analysis using high performance computing resources... that is, Data Farming.

Scythe, *Proceedings and Bulletin of the International Data Farming Community*, Issue 9, Workshop 21 Publication date: March 2011

Bulletin Editors

Gary Horne: .... gehorne@nps.edu
Ted Meyer: .... temeyer@nps.edu

IDFW 21:
"EXPLORATION"

by Gary Horne
Naval Postgraduate School

International Data Farming Workshop. Number 21 was held in Lisbon from September 19th through 24th, 2010. This workshop was the first we have held in Portugal and it was a magnficent treat to be there! Our theme was "Exploration" as might be expected with Portugal being the home of many great explorers in our history and the starting point for many great adventures. We had eight teams and our goal during the week was, as usual, to work in these teams using data farming methods to explore our important questions.

On behalf of our host, Colonel Fernando Freire from the Portuguese Military Academy, I would like to express our thanks to the team leaders, the plenary speakers, and all of the participants in IDFW 21! And, of course, a large Thank You to Fernando and all of the folks from Portugal who worked so hard to make IDFW 21 a world-class event!

This issue, our ninth, of The Scythe contains a summary of each work team effort. And, as always, the other materials from this workshop are available online at http://harvest.nps.edu along with electronic copies of this issue of The Scythe. The plan continues to be to hold even-numbered workshops once a year in Monterey with odd-numbered workshops taking place at international venues. So looking ahead, our Data Farming community will be in Monterey from the 20th through the-25th of March 2011for our next workshop, International Data Farming Workshop 22. And for those of you who like to plan a little more in advance, International Data Farming Workshop 23 will be held in Finland from the 18th through the-23rd of September 2011. We hope to see you at both!

Gary Horne

Team 1: Analyzing Forecasted Pirate Probabilities to Exploit Meteorological and Intelligence Parameters Through Data Farming

TEAM 1 MEMBERS

Esher, Leslie LT
Lednicky, Eric, CDR
Miranda, Sofia LT
Regnier, Eva Dr.
Sanchez, Paul Dr.
Upton, Steve Mr.
Naval Postgraduate School, US

INTRODUCTION

In the course of recent history, the instability and lack of government in Somalia have caused a rapid increase in pirate activity within the Somali Basin Region (SBR) and the Gulf of Aden (GoA). The United States and multi-national military forces, combining the U.S. Naval Forces Central Command (USNAVCENT), U.S. Fifth Fleet and units from over 20 international partners under the leadership of Vice Admiral William Gortney, has been tasked with finding a solution to deter and eliminate pirating within the GoA and SBR.

Piracy may seem to be a very simple opportunistic form of robbery, but when the top layer is removed a more complicated and intricate problem is revealed. The Combined Maritime Forces (CMF) Assessment Team and Maritime Security Operations (MSO) are actively pursuing ways to mitigate pirating of neutral vessels. Neutral vessels can be defined as shipping vessels, commercial tankers, sailing vessels, fishing vessels, and yachts. The CMF team and MSO shop are working together to patrol the 2.5 million square miles of vulnerable waters between the coast of Somalia and India. Due to the large ransoms being gained by pirating neutral vessels, piracy has spread across the globe and particularly to the western side of Africa in the Gulf of Guinea, U.S. Seventh Fleet operating waters.

For these reasons and more, the Big Three: the North Atlantic Treaty Organization (NATO), the European Union (EU), and the United States (US), are actively seeking additional tools to help strategically place their military ships. This tool should be able to predict at what date time group (DTG) and at what location (longitude/latitude) the probability of a pirate attack is high. Having this vital information will enable the Big Three to provide each military vessel's Commanding Officer a better chance to interdict a Pirate Action Group (PAG) before an attack occurs or patrol and deter piracy in a location that has a high probability of a pirate attack. A PAG is a group of pirate skiffs that attach to a mother skiff for operational longevity.

A pirate prediction tool may save NATO, EU, and US military forces time, money, and resources. The Next Generation Piracy Performance Surface Model (PPS-Next) is a predictive tool developed by Dr James Hansen, Naval Research Laboratory-Monterey, in partnership with the Naval Meteorology and Oceanography Command (NMOC) at Stennis Space Center and the Naval Postgraduate School (NPS) Operations Research (OR) Department. PPS-Next dynamically couples pirate Concept of Operations (CONOPS), defined by intelligence (INTEL) gained on pirate activity, with meteorological activity (METOC), such as waves, winds, drift, and currents, to forecast relative risk of pirate activity at a given DTG, latitude and longitude.

Simulated Pirate Behavior

The new version of PPS-Next, updated since the analysis from IDFW-20, is very different in the simulation of pirate behavior. In IDFW-20, the simulated pirate motored to a waypoint and then drifted with the current. The simulated pirate would complete a pre-determined mission length, and then transit back to its origin (Esher et al, 2010).

Advancements have been made to PPS-Next to increase the operational usefulness of the model for CMF Assessment Team, NATO partners, and commercial shipping companies. This model provides the operator with the ability to map PAGs' proposed area of operations to Google earth with the addition of real METOC conditions, while giving the pirates certain behaviors (defined in Table 1) that will impact the way the PAGs move from their base waypoint distribution to their operating waypoint distribution.

Determining the most influential independent variables will allow the developers to set parameters to reduce run time and capture the driving factors and help operators to concentrate their intelligence efforts on these important areas. If METOC conditions prove to be the driving factors, then particular attention should be given to monitoring military operational attributes in correlation to METOC.

Design of PPS-Next Experiment

To capture the effects of all variables and interactions among them, we used a Nearly Orthogonal Latin Hypercube (NOLH) design (Cioppa & Lucas, 2007; Cioppa, 2002), with four rotational designs.

Table 1 lists the independent variables that were varied in the simulation and their corresponding minimum and maximum values. For many of the independent variables, their standard deviations (StDev) were also varied. For the StDevs, we elected to make their minimum and maximum values a proportion of the mean values of the underlying parameter.

A brief description of each of the independent variables is as follows: mission length is the mean length of time that a PAG is active in the simulation; the number of bases is the total number of sea or land bases that pirates operate from; pirate skiff speed is the mean speed that a PAG is expected to sustain during the transit and searching patterns [this does not include attacking speed]; mean drift current is the factor by which the velocity of the currents impacts the velocity of the skiff; mean drift wind is the factor by which the velocity of the winds affects skiff velocity; mean wind threshold is the mean wind threshold below which a PAG can operate; mean wave threshold is the mean wave threshold below which a PAG can operate; minimum (maximum) iweather is the minimum (maximum) probability that a PAG has knowledge of adverse weather conditions before the PAG leaves their starting waypoint, in the event the PAG does not know about weather conditions and encounters adverse weather their mission will be terminated; pirate search pattern is equal to 0 if the PAG has a drifting search, 1 if the PAG has a random walk, and 2 if the PAG has a zigzag search pattern; number of tracks is the number of PAGs replicated during a 24 hour simulation time step period; model time step is the incremental time-steps the code uses, which affects run time, but can cause simulation instability if a poor value is chosen; pirate hits is either a 0 if no hits occurred or a 1 if a pirate hit occurred [the pirate hit would be an observed attack that occurred in a simulated area and the probabilities would be updated based on the simulated probabilities and the actual hit (successful/attempt/unsuccessful/etc).

Independent Variable	Type, >0	Min Value	Max Value
Mission Length (hours)	Integer	72.0	600.0
Mission Length StDev[3]	Integer	(1/6)	(1/6)
Number of Bases	Integer	10.0	30.0
Pirate Skiff Speed (knots)	Integer	3.0	10.0
Pirate Skiff Speed StDev[3]	Integer	0.0	(1/4)
Mean Drift Current (knots)	Integer	0.5	1.0
Mean Drift Current StDev[3]	Continuous	(1/6)	(1/6)
Mean Drift Wind (knots)	Continuous	0.0	0.5
Mean Drift Wind StDev[3]	Continuous	(1/4)	(1/4)
Mean Wind Threshold (knots)	Continuous	22.0	28.0
Mean Wind Current StDev[3]	Continuous	(1/8)	(1/8)
Mean Wave Threshold (knots)	Continuous	3	9
Mean Wave Threshold StDev[3]	Continuous	(1/3)	(1/3)
Iweather_min (Probability)	Continuous	1-iweather_ max	1-iweather_ max
Iweather_max (Probabilty)	Continuous	0.5	1
Pirate Search Pattern (categorical variable, 0, 1, or 2)	Categorical (Nominal)	0	2
Number of Tracks	Integer	128	128
Model Time Step[3] (days)	Continuous	0.2	0.2
Pirate Hits (Binary, yes=1 or no=0)	Categorical (Nominal)	0	1

Table 1: Independent variables with their corresponding minimum and maximum values used in the Cioppa & Lucas Nearly Orthogonal Latin Hypercube design that was downloaded from the SEED Center website.

1. The first column is a list of the independent variables that will be modeled in the simulation.
2. The second column is the mathematical description of the numbers to delineate between continuous and integer numbers.

This team faced many challenge but the most challenging was translating our design of experiment (DOE) into the input format that the PPS-Next code requires. PPS-Next is written in Python (x,y) 2.6.5.3 and we were running the code in Python (x,y) 2.6.6.0; version control was extremely important. When the code ran to completion with the DOE, the probability field outputs then need to be transferred to MATLAB for mathematical comparison and inputted into JMP 9.0 for statistical analysis.

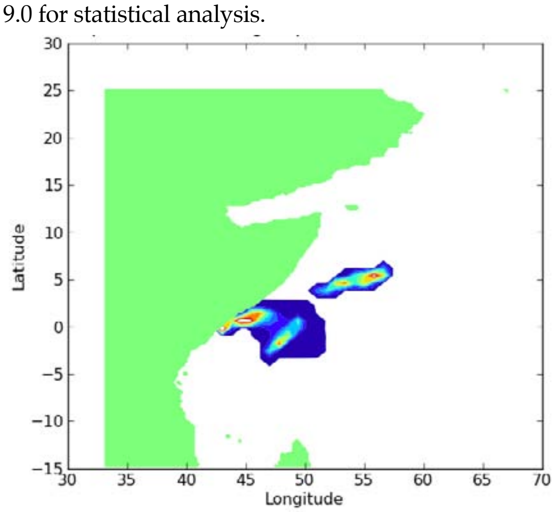


Figure 1: Sample output from the PPS-Next base-case scenario. The plot shows the simulated distribution of pirate action groups within the Somali Basin Region. The darker red colors are indicative of a higher probability of a pirate being in this latitude and longitude areas of low probability are dark blue.

Description of Scenario

PPS-Next is a framework that generates Monte-Carlo simulations of pirate behavior and interprets these results probabilistically. Simulations are affected by five key distributions: real-time meteorological and oceanographic forecasts, information about the impact of meteorological and oceanographic conditions on a PAG (skiff and/or mother dhow), information about the distributions of locations and times from which the PAG begins their missions, information about the length of time and distribution of locations in which a PAG can operate, and known (unknown) intelligence about the PAG's CONOPS for targeting neutral vessels (i.e. commercial shipping, sailing vessel, yacht, fishing vessel, chemical tanker). Individual PAG replicates are given attributes that are randomly drawn from the key distributions before executing a mission. Due to limited INTEL on PAG operating areas a large numbers of replicates are run daily and this output is then archived. The resulting collections of PAG trajectories are used to define PAG densities as a function of forecast lead. PAG attack probabilities are obtained by convolving the results with commercial shipping densities and additional meteorological and oceanographic constraints.

Figure 2 shows the normalized pirate probabilities over a 48-hour period. This figure is a 3-D replication of the plot in Figure 1 with the land masses not represented.

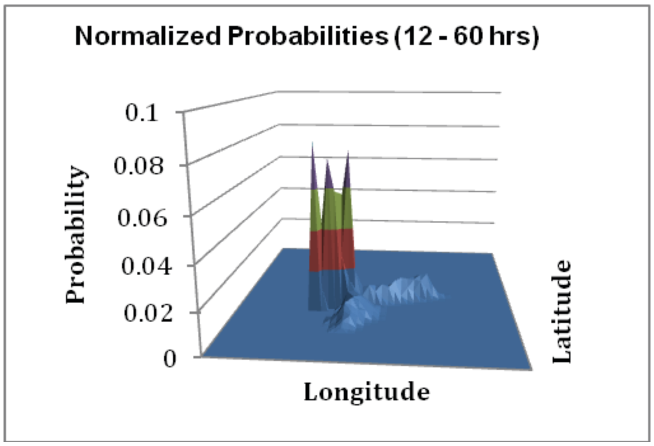


Figure 2: Normalized by summing over the pirate probabilities for the simulated period of 12 hours through 60 hours.

RESULTS AND ANALYSIS

The greatest challenge for this Team was creating a link between the world of Data Farming and the simulation, PPS-Next. This complexity led to slow progress while attempting to conduct simulation runs with the independent variables from Table 1 in a four rotational design of the NOLH. PPS-Next was initially designed to run on the high performance computers at the Naval Oceanographic Office (NAVO) in Mississippi with the ability to be used at the CMF Headquarters in Bahrain and eventually extending its capabilities to commercial shipping companies. Prior to IDFW-21, PPS-Next had only been tested on a single base-case scenario; therefore, the combinations of input parameters generated as part of the space-filling NOLH design in many cases created errors that PPS-Next could not recover from. In operational usage, users will have the ability to modify many of the variables – such as waypoint distributions. Therefore, by pushing the limits of the model we allowed the developer to modify the code to make it more resistant to problematic input combinations. Despite simulation runs not being completed during the duration of IDFW 21, the missing link to the puzzle was solved after the workshop and simulation runs from this NOLH design were completed.

During IDFW 20, we examined different ways to measure the output, and used nine output metrics as shown in the table below (Esher et al., 2010), and these were used to analyze IDFW 21 results.

Dependent Variable
Root Mean Square Error (RMSE)
Smoothed RMSE
Maximum Difference
Smoothed Maximum Difference
Inner RMSE
Inner Smoothed RMSE
Inner Smoothed Maximum Difference
Mean 50th Percentile
Smoothed Mean 50th Percentile

Table 2: Output Metrics

There is no clear-cut best way to summarize the quality or variations in PPS-Next output. During IDFW 21, the team discussed new ways to measure the simulation output. We explored smoothing the PPS-next output, which is very narrowly distributed to find the "sweet spot" where the output is being accurately measured without losing any of its validity.

We received historical pirate data from the Naval Research Laboratory (NRL) at Stennis Space Center along the Mississippi Gulf Coast. The data was read into JMP 8.0, statistical analysis software, to explore commonality amongst historical pirate attacks. The data received had many pertinent areas that were not accounted for or data was unavailable; for this reason, we decided that there were not enough data points to accurately conclude a proper analysis through common trends and trend lines, regression/partition trees, or generalized/linear models.

We also highlighted areas of analytical discussion and approaches:

- We discussed the Validation, Verification, and Accreditation (VV&A) of PPS-Next.
- In future simulation runs, we looked to altering the time step (dt) in the NOLH to find the "sweet spot" that would provide the same accuracy and conciseness without the omission of important details.
- We discussed how and when we could compare PPS-Next against historical attacks and historical METOC conditions. This analysis is complicated because the real METOC conditions from historical attacks are not kept in a database.
- For future analysis, we discussed looking at a using not only a rotational design but also the advantages of using a robust design as defined by Taguchi with the use of indicator variables when analyzing PPS-Next.
- When attempting to run PPS-Next we came across some areas where the definitions for certain independent variables were not as clearly defined as

assumed; therefore, we discussed the disadvantages and precautionary measures for using a model that has not been developed by anyone on the team.

- PPS-Next is written in Python (x,y) 2.6.5.3 and the code was very sensitive to the differing version of Python (x,y) that were used. In operational use, this may cause extensive frustration for the operator of PPS-Next. Caution should be used when using a computer language that is as fragile as Python (x,y) as this adds unnecessary loss of time and resources in code troubleshooting.

CONCLUSIONS

PPS-Next, the Next Generation Piracy Performance Surface Model, is being constructed to supersede the current Piracy Performance Surface model, PPS, for the US Military Fleet, NATO Militaries, and the European Union. The product will be invaluable for use by the Combined Maritime Forces and Maritime Security Operations, headquartered in Bahrain, for allocation of military assets in offensive and defensive measures and also to provide commercial shipping companies with a forward warning tool.

REFERENCES

[1] Sanchez, S. M. 2005. “Work Smarter, not harder: Guidelines for designing simulation experiments,” Proceedings of the 2005 Winter Simulation Conference, pp. 69-82. Software and references available at http://harvest.nps.edu.

[2] Cioppa, T.M. & Lucas, T.W. 2007. Efficient Nearly Orthogonal and Space-Filling Latin Hypercubes. Technometrics 49(1): 45-55.

[3] Cioppa, T.M., 2002. “Efficient Nearly Orthogonal and Space-filling Experimental Designs for High-dimensional Complex Models”, PhD Thesis, Department of Operations Research, Naval Postgraduate School, Monterey, CA.

[4] Design of experiments via taguchi methods: orthogonal arrays. 2007. In Wikipedia, the free encyclopedia. Retrieved from http://controls.engin.umich.edu/wiki/index.php/Design_of_experiments_via_taguchi_methods:_orthogonal_arrays (2010, October 18) .

[5] Esher, L., Hall, S., Hansen, J., Regnier, E., Sanchez, P. & Singham, D. 2010. Anti-Piracy and Terror Reduction: Simulating Pirate Behavior to Exploit Environmental Information. Scythe Proceedings and Bulletin of the International Data Farming Community (Scythe 8, report from IDFW 20 Team 14).

[6] Hutchinson, T. A. 2007. An Adaptive Time-Step for Increased Model Efficiency. Retrieved from http://www.mmm.ucar.edu/wrf/users/workshops/WS2007/abstracts/9-4_Hutchinson.pdf (2010, October 19)

[7] Sanchez, P. J. and Sanchez, S. M. 2005. “Very Large Fractional Factorial and Central Composite Designs.”

[8] ACM Transactions on Modeling and Computer Simulation, 15(4): 362-377.

[9] Software Downloads, SEED Center for Data Farming, http://harvest.nps.edu/.

[10] Vieira Junior, H., Sanchez, S. M., Kienitz, K. H., and Belderrain, M. C. N. 2010. Generating and Improving Orthogonal Designs by Using Mixed Integer Programming. Submitted to Journal of the Royal Statistical Society, Series B (Statistical Methodology).

Team 2: Robust Port Security

TEAM 2 MEMBERS

Ka-Yoon Wong
Anderson, Ben LT
Lorenzen, Jesse LT
Macaskill, Jonathan LT
Thompson, Meredith
Naval Postgraduate School, US

Decraene, James
Nanyang Technological University, Singapore

Lobo, Victor
Portuguese Naval Academy, Portugal

Loechel, Alexander
University der Bundeswehr, Germany

Schubert, Johan
Swedish Defence Research Agency, Sweden

INTRODUCTION

Nearly a decade after the highly publicized small boat attacks against the USS Cole (in 2000) and M/V Limburg (in 2002) in Yemen, small vessels continue to pose a security threat to ports worldwide. At ports, small vessels frequently operate in close proximity to important maritime infrastructure, such as bridges and petrochemical plants, and to passenger and military ships. (Department of Homeland Security, Small Vessel Security Strategy, 2008)

An attacker can be easily camouflaged among innocent small vessel traffic and avoid detection by being in the crowd, all the while approaching its desired target undetected and unopposed. When the attacker finally decides to execute the attack, separating from the main traffic to speed toward its target, there is only a narrow time window for an effective defender response.

Two factors confound the defense against such attacks. The first is the lack of warning, which leads to the inability of a defender to anticipate the true target of the attack from among the many possible targets and hence is unable to pre-position any assets to protect the target. The second factor is that the effort to classify the malicious intention of a would-be attacker is non-trivial, since the attacker would look like an innocent vessel from afar. Conceivably, a further difficulty the defender would face is the restriction of maneuver space for an interception attempt in a shipping channel with high traffic, especially if the terrorist boat weaves in and out among the innocent vessels.

The objective of the study is to explore the effects of neutrals on the effectiveness of the defender's deterrence and interdiction operations against a small boat attack in a port environment. The goal of the team was to identify robust employment tactics of port security forces to detect, defend and/or intercept a spectrum of threats and adversary tactics, through the use of MANA and a red-teaming process.

Scenario and Modeling

The Port of Lisbon was chosen for the study scenario. Lisbon is a wealthy and important city, with its busy port contributing significantly to commerce and trade. The city of Lisbon is also a key tourist icon in Portugal, being one of the oldest cities of the world, richly endowed with history dating from the Neolithic era, and is also home to two UNESCO World Heritage Sites – Belém Tower and Jerónimos Monastery (Wikipedia). The city and port present many potential targets for terrorists to strike from the sea and, together with the high volume of traffic in a narrow straits, poses a challenge for the navy and maritime police to defend.

A busy section of the Tagus River at Lisbon, of approximately 10 by 5 km, was modelled (see Figure 1). Initial

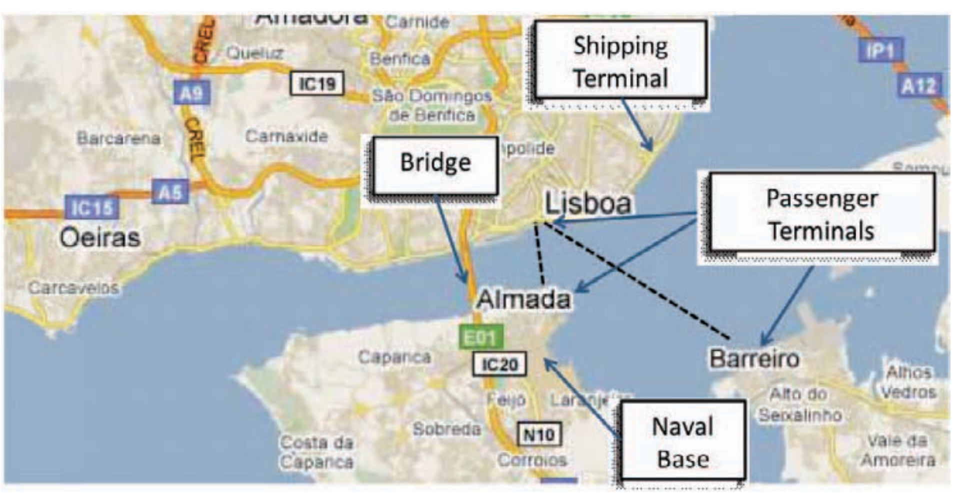


Figure 1: Port of Lisbon

runs with the terrain map crashed due to insufficient pixels, but this issue was overcome by increasing the pixel resolution.

Three types of agents are modelled:

- **Neutrals**: Commercial and recreational shipping traffic (neutral vessels) ply the channel in the center of the straits.
- **Attacker**: The attacker is presumed to employ a speedboat in the 20-foot class, such as the Baja Outlaw 20, and is capable of carrying 4 to 6 persons, or a few hundred pounds of explosives, at high speeds. The attacker seeks to be camouflaged among traffic, entering the region from the west, and joining the stream of neutral vessel traffic.
  One intention of the team was to model the attacker's ability to randomly choose a target along the coast to attack. However, due to the complexity of modelling and calibrating the behaviour of the neutral vessels, which consumed most of the time at the workshop, this objective was set aside. Instead, the attacker was given just one target – the naval base on the east of the area of operations considered.
  If the attacker boat is unopposed in its approach to the target, it will follow the shipping traffic until it reaches the shortest path to the target, at which point the attacker will speed up to maximum speed and execute a strike. This modus operandi simulates a high level of surprise that can be accorded to the attacker.
- **Defender**: The defending boats are assumed to be patrol boats equivalent to the SAFE Boat International Defender class boat, widely used by the US Coast Guard. They are tasked to perform random checks on vessels in the channel, and are either deployed in a barrier patrol profile or to sweep the channel (see Figure 2).

Figure 2: Patrol Locations and Attacker's Target

Agent Interactions

Each patrol boat selects a neutral vessel within its sensor range at random, proceeds toward it and stops the vessel for inspection. The inspection takes 5 minutes to complete, after which the vessel will be tagged as a non-threatening vessel and will not be stopped if it later meets other patrol boats.

During an inspection, the patrol boat will be unable to classify any other vessel in its sensor range. After an inspection, the patrol boat will travel for 5 minutes before looking for the next vessel to inspect, to avoid getting fixed in a single location. These two 5 minute gaps potentially allow for an attacker to sneak past the patrol boats.

On the other hand, if the patrol boat stops and inspects an attacker boat, the attacker will be known immediately, and the interception will be counted a success. If the attacker sees the patrol boat, it will speed up and attempt to outrun the defending patrol boat, and head for its target. The patrol boat will give chase and attempt to stop the attacker. However, the attacker has a head-start that leads to an advantage in the chase (since the maximum speeds of both boats are the same).

Experiment Setup

The probability of at least 1 successful attack is used as the Measure of Effectiveness (MOE) in this study. A small experiment was designed to verify the model in the workshop, using the factor and level settings given in Table 1.

Factors	Levels
Number of Neutrals	8 - 20
Number of Blue patrol boats	1 - 3
Number of Red attackers	1 - 3
Speed of Blue patrols	Patrol speed: 10 - 30 kts (Max: 40 kts)
Evasive Speed of Red Attackers	40 kts (Fixed)
Sensor Range	Det: 3000 - 6000 m Class: 200 - 1000 m

Table 1: Factors and Levels

The Nearly Orthogonal Latin Hypercube design of experiments spreadsheet was used to obtain 33 design points (NOLH spreadsheet, downloaded from harvest.nps.edu), and 50 replications of each design point were run.

RESULTS AND ANALYSIS

We anticipated the effects of the factors as follows:

Factor	Proportion of Successful Attacks
More patrols	Reduced
More attackers	Increased
Longer sensor range	Reduced
Speed of patrols	Increased
More neutral shipping	Increased

Table 2: Anticipated Factor Effects on the MOE

The simulation results were analyzed through a partition tree followed by a logistic fit (see Figure 3), yielding two unexpected findings. We found that the speed of patrols had marginal effect on the proportion of successful attacks, and a surprise finding that more neutrals had resulted in a higher probability of detection.

Scrutiny of the simulation showed that due to the higher volume of traffic, the patrol boats were spending more time in the centre of the channel. Since the route the attacker takes passes through the center of the channel, the chance of a patrol detecting the attacker was higher. We rationalized that this artifact was a model-specific issue.

Conclusion

Within the short span of the workshop, the team managed to assemble and verify a basic model for exploring the defense against small boat attacks in the complex environment of a port. This experiment opens the way for further study by detailing the scenario and providing the building blocks of agent behavior in a MANA model.

REFERENCES

[1] Department of Homeland Security, United States (2008). Small Vessel Security Strategy. Retrieved from www.dhs.gov/xlibrary/assets/small-vessel-security-strategy.pdf

[2] Wikipedia. Lisbon. http://en.wikipedia.org/wiki/Lisbon

[3] Software Downloads, SEED Center for Data Farming, http://harvest.nps.edu/

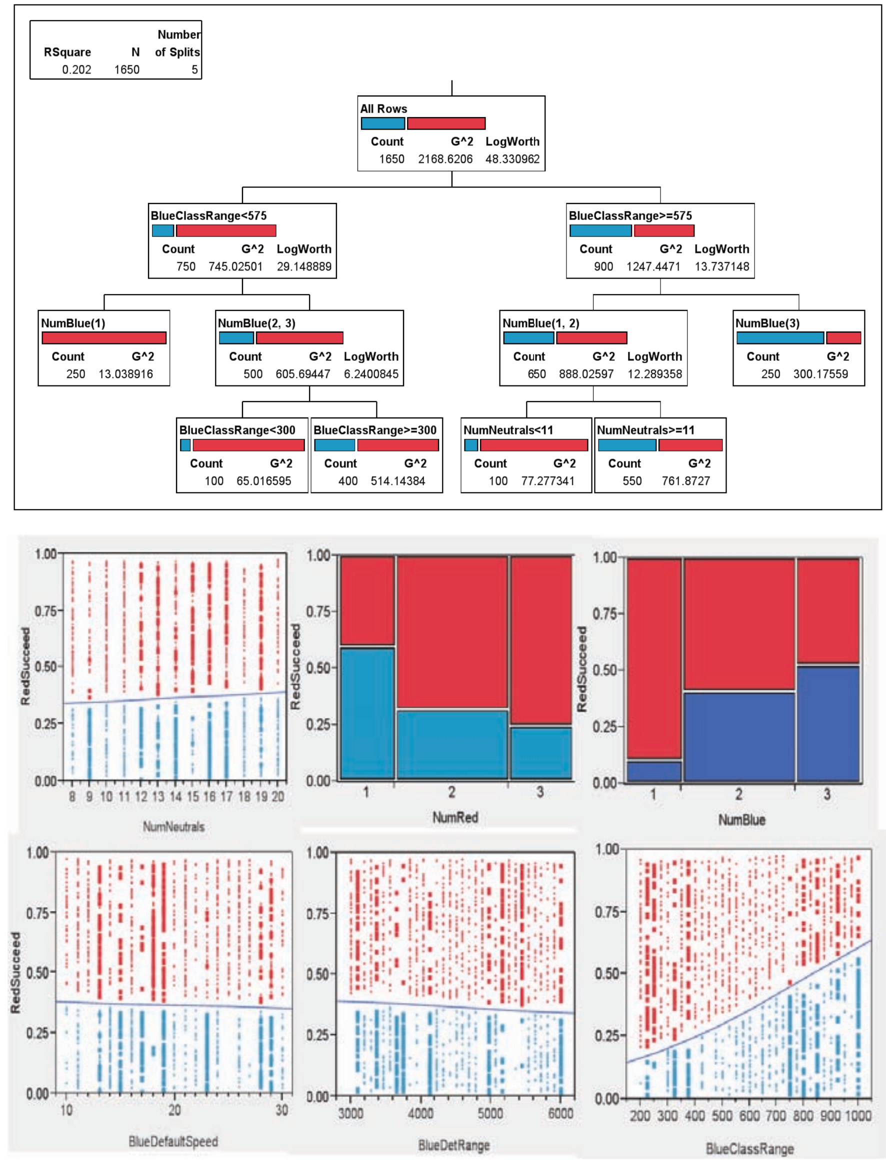


Figure 3: Partition Tree and Logistic FiT

Team 3: Data Farming the Agent-Based ELICIT (abELICIT) Model

TEAM 3 MEMBERS

Stephen C. Upton
Laura Whitney
Prof. Susan Sanchez
Naval Postgraduate School, US

Stephen M. Robinson
University of Wisconsin-Madison, US

LTC Fernando Freire
Portuguese Armed Forces, Portugal

Marco Manso
EDISOFT S.A., Portugal

INTRODUCTION

ELICIT (Experimental Laboratory for the Investigation of Collaboration, Information-sharing and Trust) is a research and experimentation program developed for the US DOD CCRP (Command and Control Research Program) to conduct research related with collaboration, information sharing and trust in organizations. The ELICIT platform is an experimentation environment supported by software tools and procedures that allows instantiating different C2 approaches and observation of behaviors and dynamics in the information, cognitive and social domains. Agent-based ELICIT (abELICIT) is the agent-based functionality of the ELICIT platform, and allows a researcher to conduct human-only, agent-only or hybrid human and agent experiments. The version used in this workshop was version 2.4; we focused on running experiments using software agents only.

To explore the vast input space of the abELICIT model and understand how changes in the input variables affect various output metrics, e.g., how shared awareness affects agility of a C2 approach, the CCRP ELICIT team and the international ELICIT CoI (Community of Interest) will benefit from an automated data farming capability within the ELICIT platform. Toward that end, the abELICIT data farming team first conducted an experiment aimed at understanding the ordering effects of "factoids", i.e., when specific information reaches agents, and how that might impact several metrics of interest. Additionally, we were interested in observing how ordering of the factoids makes a difference while agent parameters are systematically varied, as well as looking at different kinds of ordering, based on the types and impacts of the factoids.

Initially, our goals during the workshop were to continue analysis of the initial experiment, identify a set of possible next steps, to learn and understand a little more of what abELICIT is and how it is used by the ELICIT CoI, and where our work can positively impact the community. We set aside the original goal of continuing the analysis of the initial experiment and instead set an additional goal to conduct a simple exploratory data farming experiment using abELICIT. This would allow us to demonstrate proof-of-concept and to get a feel for the necessary mechanics in setting up and conducting a data farming experiment with abELICIT, as well as continuing to learn more about abELICIT functionality.

We next give an overview of abELICIT functionality. Following that is a description of our data farming experiment, a note on the illustrative results and analysis, and a summary concludes the paper.

abELICIT Overview

Within an abELICIT experiment (also applies to an ELICIT experiment), the problem the agents need to solve is collectively determining the where, what, when, and who of a future, fictitious terrorist attack. Information on this attack is contained in a set of "factoids", with each factoid containing information relevant to one aspect of the attack. To whom and when the factoids are distributed to the agents is a function of the individual experiment. The agents then process the factoids received to determine, among other things, whether to share that information with other agents it is connected to, or to post or pull factoids from a notional website dedicated to a particular aspect of the problem. For abELICIT, whether and when the agents have solved the problem is determined by processing the log files after the run is completed.

Software agents may be parameterized according to 54 parameters that determine, among other aspects, the way they process information, build awareness, socialize and identify, as illustrated in Figure 1. Whether to share, how often to share, and the likelihood to seek information are all examples of agent parameters that can be varied. A number of parameters are associated with the amount of time a particular action takes, e.g., how long it takes to share or post a factoid once the agent determines it will share or post. Finally, there are a few Boolean (on/off, true/false) parameters such as whether the agent is a guesser or a hoarder of factoids.

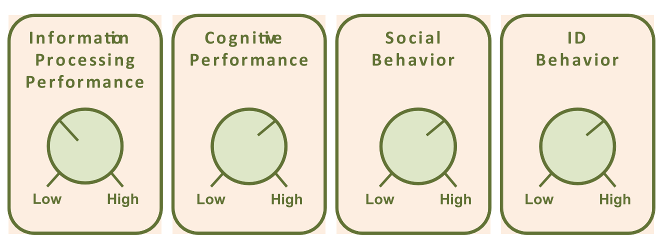


Figure 1: Parameterizing Agent Characteristics

For more detailed information about abELICIT, refer to (Ruddy 2009, Ruddy 2010).

Experiments

To gain familiarity with abELICIT, help design our initial experiment, and determine a small subset of the parameters to focus on, the team went through each of the 54 agent parameters, categorized them into the four broad categories depicted in Figure 1, and then prioritized them according to how we thought they may impact performance. We decided to focus on 7 parameters to characterize two types of agent behaviors, and used those in conjunction the two available organizational structures of HIERARCHY and EDGE (provided as examples on the ELICIT server). These 7 parameters were: postedTypes, sharedTypes, propensityToShare, shareWith, shareWithWebSites, propensityToSeek, and primary area of interest (more details on all the parameters can be found in Ruddy 2010).

The experiments were designed to test performance of (a) Traditional HIERARCHY and (b) EDGE organizations when their constituent members are either: (i) TYPE 1: highly specialized (task focused), share/post sporadically and strictly within hierarchical chain; or (ii) TYPE-2: flexible across tasks, share/post, share/post often and across all members. (More information on differing C2 approaches and Hierarchy and Edge organizations can be found in, e.g., Alberts 2003 and Alberts 2006).

The four possible combinations of two organizational structures (HIERARCHY and EDGE) with two agent behaviors (TYPE 1 and TYPE 2) resulted in the 2x2 design of experiments matrix presented in Table 1. Hierarchy 1 (H-1) and Edge 1 (E-1) are the “usual” Hierarchy and Edge organizational structures, with Hierarchy 2 (H-2) and Edge 2 (E-2) being hybrid structures.

	Agent Behavior	
Organizational Structure	**Hierarchy 1** Agent Behavior 1: •Specialized per working space (who, what, when, where) •Share/post within team •Including team leader and cross team coordinator	**Hierarchy 2** Agent Behavior 2: •Flexible working space (who, what, when, where) •Share/post with all agents
	Edge 2 Agent Behavior 1: •Specialized per working space (who, what, when, where) •Share/post within team •Including team leader and cross team coordinator	**Edge 1** Agent Behavior 2: •Flexible working space (who, what, when, where) •Share/post with all agents

Table 1: Design of Experiments

Four runs, one run for each of the combinations (designs) above, were conducted, comprising a total of 68 agents (17 agents per run) and 2 organizational configuration files. We first created a spreadsheet that listed the 68 agents with their settings for the 7 agent parameters, keeping the other 47 agent parameters fixed. We then created a script (in the computer language R) to generate the 68 agent files, combined that with the organizational files and other supporting files for an abELICIT run, and submitted the runs to the ELICIT server. After the runs were completed, we downloaded the ELICIT log files and post-processed them to extract the data.

Results and Analysis

Unfortunately, and perhaps not surprisingly given our crude settings, the results obtained were not within valid ranges. For example, organizational effectiveness could not be determined since agents didn’t provided identifies. TYPE-2 agents did an enormous number of shares (a total of 13328 - we assumed it was a consequence of setting the ‘propensityToShare’ parameters) and no pull actions. The fact that TYPE-1 agents in the hierarchy didn’t perform post actions is also a matter that needs investigating. Agents also displayed a consistent and highly symmetrical behavior (e.g., same number of shares sent and received).

The lack of validity for this data set was likely due to the team’s inexperience with abELICIT, the specific selection of agent parameters to vary and their ranges, and the setting of the other, fixed agent parameters. However, our main goal for this workshop was one of understanding the data farming mechanics for abELICIT and not a focus on any particular results, and we believe we succeeded in that goal. It is clear, though, that it is crucial in future work to determine adequate ranges of agents’ parameters and their interaction with other agent characteristics (Figure 1) so that runs yield valid results. Nonetheless, a deeper look into these particular results and why the results were outside seemingly valid ranges might prove useful.

Nevertheless, to further explore the data and the types of analyses that could be obtained, we looked at three sociograms that provide a visualization of the social-networks generated by these illustrative experiments: Traditional Hierarchy with TYPE-1 agents (Figure 2), EDGE with TYPE-2 agents (Figure 3) and EDGE with TYPE-1 agents (Figure 4). These and other tools, applied to data from experiments across a wider range of allowable configurations, could provide great insight into which of the agents’ parameters, and their interactions, have the most effect on outcome metrics. [Note: post-processing of the data and the construction of these graphs were graciously made by Marco Manso and the set of tools he previously developed to examine ELICIT output (Manso and B. Manso, 2010) and (Manso and M. Manso, 2010).]

In the figures below, the yellow nodes are the websites (WHO, WHAT, WHEN and WHERE), and the other colored nodes are the agents (different colors represent the roles in the organization, and the node labels reflect notional names for the agents). The edges or lines between the nodes represent connectivity between the nodes, and the width of the edge indicates the amount of sharing of factoids (with other connected agents) or the posting or pushing of factoids (with websites).

Figure 2 is a traditional HIERARCHY with TYPE-1 agents (the H-1 setting described above). The red colored nodes are team members, the purple colored nodes are team leaders, and the aqua colored node is the Cross-team coordinator. Team member, Team leader, and Cross-team coordinator are specific agent roles in ELICIT and abELICIT. In this case, there are some links that are missing, e.g., there should be links connecting Sam-WHERE and Sidney-WHERE, and similarly for the WHEN node. There also appears to be more connections between agents than we might expect for the HIERARCHY organization. This type of visualization is beneficial for easily discovering these types of anomalies.

On the other hand, trying to make sense of the connections in Figure 3 would be challenging. In this case, corresponding to E-1 setting above, all agents are linked to all websites and each other, illustrating a fully connected network.

Finally, in Figure 4, we have a hybrid structure, corresponding to the E-2 setting above, which uses an EDGE organizational structure with HIERARCHICAL agent behaviors. Again, more work would need to be done in order to determine the implications of these differing structures and to explain these particular outcomes.

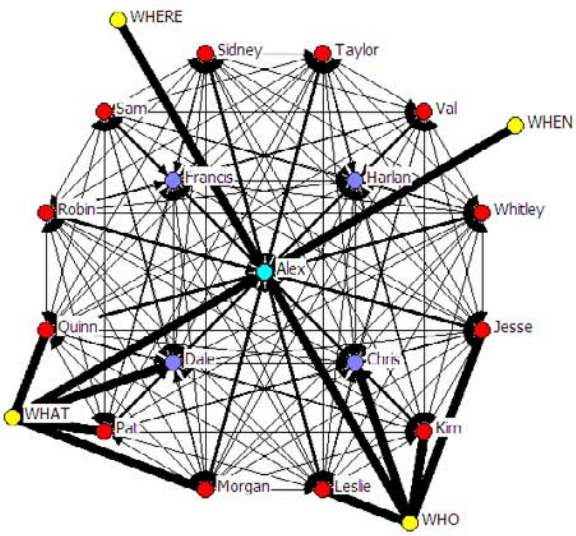


Figure 2: Traditional Hierarchy with TYPE-1 agents

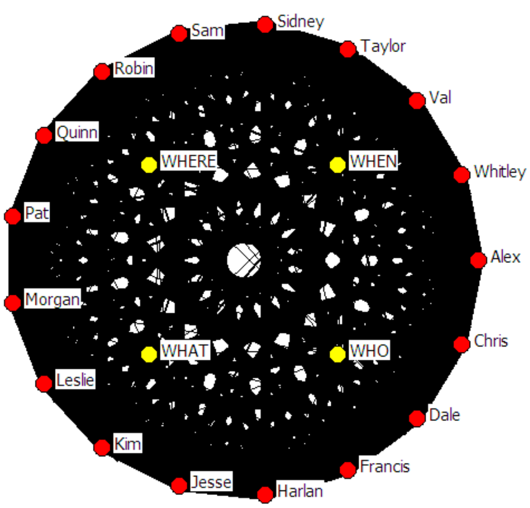


Figure 3: EDGE with TYPE-2 agents

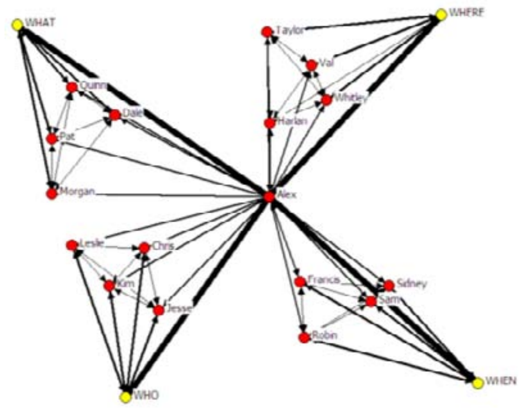


Figure 4: EDGE with TYPE-1 agents

SUMMARY

During IDFW 21, the abELICIT team (Team 3) learned more about the ELICIT platform and the agent-based functionality in abELICIT. Starting with an overall introduction of ELICIT and abELICIT, the team then proceeded to prioritize the 54 agent configuration parameters, ranking the parameters based on their expected influence on several outcome measures. We discussed a first data farming experiment using a 22 full-factorial design (4 runs), comparing a classic C2 hierarchy and an edge organization, and hybrids of those. This experiment was used to illustrate the data farming process and as a means to become familiar with the mechanics of making an abELICIT batch run. We then constructed 68 agent configuration files (17 agents * 4 runs) and an agent batch file and submitted those runs through the ELICIT server. We downloaded the data and began the analysis of that data by workshop end.

REFERENCES

[1] Alberts, David S. and Hayes, Richard E. 2003. Power to the Edge. Available at http://www.dodccrp.org

[2] Alberts, David S. and Hayes, Richard E. 2006. Understanding Command and Control. Available at http://www.dodccrp.org

[3] Ruddy, M., Wynn, D. and McEver, Jimmie. 2009. “Instantiation of a Sensemaking Agent for use with ELICIT Experimentation”, 14th ICCRTS.

[4] Ruddy, M. 2010. “ELICIT 2.4 Web-based Software Guide For Human Experiment Directors with abELICIT Appendix”.

[5] Manso, Marco and Manso, Bárbara. “N2C2M2 Experimentation And Validation: Understanding Its C2 Approaches And Implications”, 15th ICCRTS.

[6] Manso, Bárbara and Manso, Marco. “Know The Network, Knit The Network: Applying SNA To N2C2 Maturity Model Experiment”, 15th ICCRTS.

Team 4: Evaluation of Electro-optical Sensor Systems in Network Centric Operations Using ABSEM 0.5

TEAM 4 MEMBERS

André Geiger
Bundeswehr Procurement Office, DEU

Choo Chwee Seng
DSO, SGP

Tom Donnelly Ph.D.
jmp, US

LtCol Tom Erlenbruch
Bundeswehr Army Office, DEU

Daniel Kallfass
Dr. Klaus-Peter Schwierz
Gudrun Wagner
Cassidian, DEU

LtCol Stephan Seichter
Bundeswehr Transformation Center, DEU

INTRODUCTION

During the last few years, on behalf of the Bundeswehr, the Bundeswehr Procurement Office, and the Bundeswehr Centre for Transformation, Cassidian (formerly EADS) has been working on the development of two agent-based simulation models: First, the model PAX, that concentrates on studying peace support operations and focuses on analyzing aggression emergence within civilian groups. Secondly, the model ABSEM, which is an agent-based model that concentrates on modeling complex technical systems with a detailed physical approach and thus allowing to analyze the combination of various sensor and effector systems in NCO.

At IDFW 21, the main focus was to analyze sensor systems and different tactics, techniques and procedures (TTP) in NCO.

One military scenario was modeled, which focused on questions in the context of convoy protection. Different realistic asymmetric threat situations were simulated and different action alternatives with variable TTPs were analyzed and compared to each other.

Figure 1: TIGER HELICOPTER

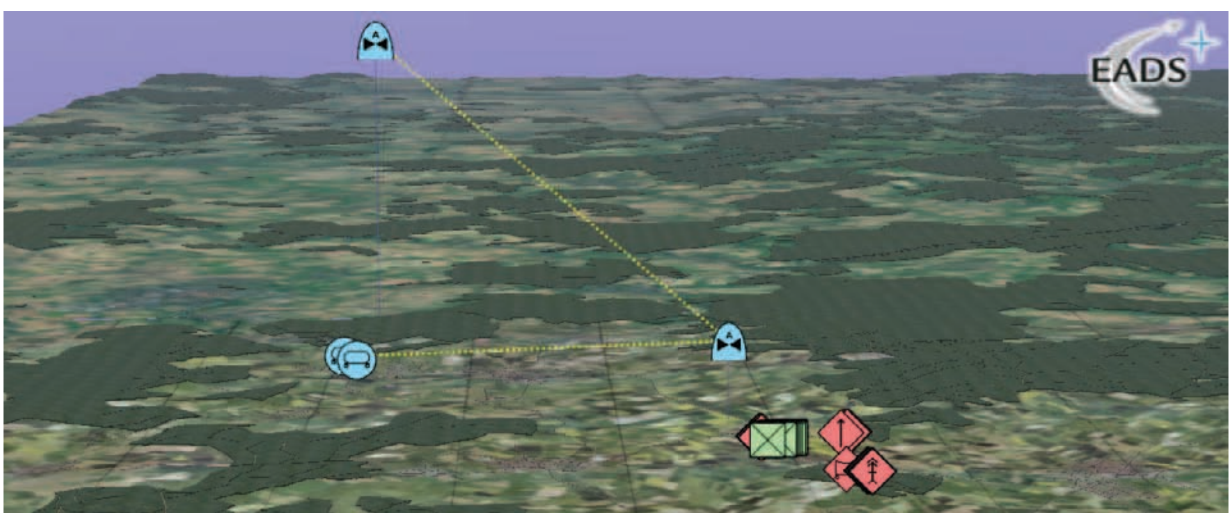


Figure 2: Convoy ambush scenario

Scenario Description

A Convoy consisting of transport trucks and an armored infantry platoon moves on a main line of communication. An alternative route has been reconnoitered. 2 TIGER helicopters are deployed for convoy protection using the ground escort technique.

Insurgents (INS) prepared an ambush along the LoC with two INS groups hidden on both sides of the road. The INS are equipped with sub-machine guns and RPGs. A third INS group with pickup trucks is hiding about 3 km away from the ambush. This group is also equipped with mortars mounted on pickup trucks to support the other INS groups with indirect fire.

If the convoy or the helicopters identify the ambush situation, the convoy will use the alternative route and avoid the ambush.

Data Farming Questions and Parameters

The main analysis question to explore was how the flight pattern of the two helicopters would effect the identification of INS.

To answer this question simulation parameters of the own troops (BLUE) and the INS (RED) were varied.

It was important to ensure that only input data was changed, which was meaningful to the simulation scenario and needed to answer the data farming question.

To compare data farming results two measures of effectiveness (MoE) were defined:

a. MoE 1: Distance of first convoy vehicle to INS 1 when on TIGER identifies the first INS

b. MoE 2: Proportion of identified INS by both TIGERS at the end of the simulation (convoy reaches intersection with the alternative route)

BLUE Farming Parameters	Min	Max
Difference of TIGER speed to convoy speed (km/h)	20	100
Helicopter height above ground (m)	200	1600
First helicopter distance to convoy (m)	0	6000
Convoy speed (km/h)	20	50

Table 1: BLUE Farming Parameters

RED Farming Parameters	Min	Max
Number of INS in each group	10	40
INS camouflage level	0	100

Table 2: RED Farming Parameters

Analysis

The team used a two prong approach to farm data:

a. Despite only having 6 input parameters we used an NOLH design with 65 unique trials. This design was chosen to a high density of data points within the design space.

   At each design points we ran 100 replications.

b. Use a fully gridded design to compute results for a validation data set.

The simulation results were divided into two data sets to analyze both MoE's independently. During the workshop we were only able to analyze the data set for MoE 2.

In a first step we checked the input data to make sure that we did not make any mistakes in the experiment setup. The following figure shows an example for the distribution of input data for relative TIGER speed.

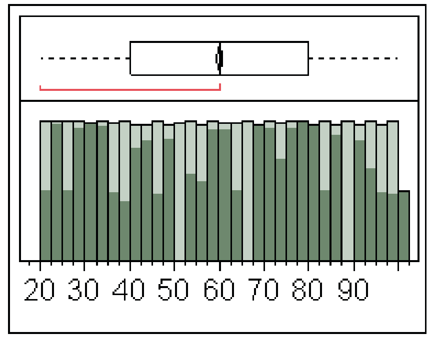


Figure 3: Distribution of input data for relative Tiger speed

In the next step we built a regression model based on the results of the NOLH design to forecast results and to easily show dependencies. We started by using partition trees to identify the main contributing factors. Figure 4 shows the main factors after 31 splits.

Column Contributions

Term	Number of Splits	SS
TigerSpeedRelative	3	0.41802371
TigerHeight	8	12.8738769
Tiger1_Distance	2	0.14791312
ConvoySpeed	4	3.1968188
num_INS2_AK47	7	0.81823484
InsurgentCamouflage	7	908.650834
Total	31	926.105701

Figure 4: Main contributing factors

Because the INS camouflage level contibuted more , by far, than any other factor we computed another decision tree, eliminating the influence of INS factors (Figure 5).

Column Contributions

Term	Number of Splits	SS
TigerSpeedRelative	7	448.820034
TigerHeight	3	226.622811
Tiger1_Distance	3	178.174225
ConvoySpeed	1	35.2415044
num_INS2_AK47	0	0
InsurgentCamouflage	0	0
Total	14	888.858574

Figure 5: Main BLUE contributing factors

From both results we could identify the following factors as contributing to our regression model:

a. INS camouflage level

b. Relative TIGER speed

c. TIGER height above ground

d. TIGER distance to convoy

e. Number of INS

To build the model we used a stepwise regression with those factors and only kept terms in the model that improved R2. We chose to build a quadratic model with two term interactions.

The prediction profiler shows how changes in one of the factors, in this case the INS camouflage level, change the influence of the other factors.

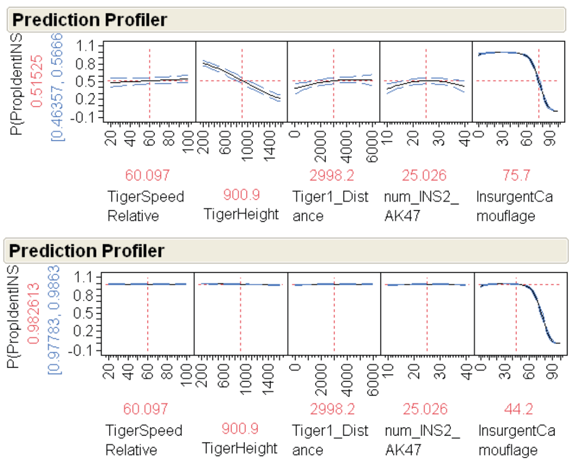


Figure 6: Prediction profiler for the regression model

We validated the regression model with the validation data set and could show that it provides reasonable predictions.

RESULTS

We were able to build a regression model, to validate it using an independent data set and to show that all factors in the model were significant.

The main findings are that our tactics, techniques and procedures only make a difference when the insurgents are well camouflaged. Otherwise the well advanced TIGER sensor can identify them independently from its flight pattern.

For well camouflaged INS we identified the helicopter elevation above ground as the most important factor. A lower flight elevation leads to a greater possibility of enemy detection. This factor is so important in the model because it shows up as a quadratic term and in many tow way interactions with other contributing factors.

Further important factors are relative TIGER speed, distance of the TIGER to the convoy, and the convoy speed.

CONCLUSIONS

For team 4 this was a very successful workshop since we were able to set up a complex scenario in ABSEM and to conduct multiple simulation runs on our computer cluster using as well NOLH as fully gridded designs. The analysis let to the identification of main factors in a convoy protection scenario. This allows us to focus future live exercises on main TTPs for convoy protection using helicopters.

Authors

Gudrun Wagner, Cassidian, DEU

LtCol Thomas Erlenbruch, Army Office, DEU

REFERENCES

[1] Sanchez, S. M. 2005. "Work Smarter, not harder: Guidelines for designing simulation experiments," Proceedings of the 2005 Winter Simulation Conference, pp. 69-82. Software and references available at http://harvest.nps.edu

[2] Brandstein, A. G. and Horne, G. E. 1998. "Data Farming: A Meta-Technique for Research in the 21st Century," Maneuver Warfare Science 1998, pp. 93-99. USMC: Washington, D.C.,

[3] Cioppa, T.M., 2002. "Efficient Nearly Orthogonal and Space-filling Experimental Designs for High-dimensional Complex Models", PhD Thesis, Department of Operations Research, Naval Postgraduate School, Monterey, CA.

[4] Software Downloads, SEED Center for Data Farming, http://harvest.nps.edu/

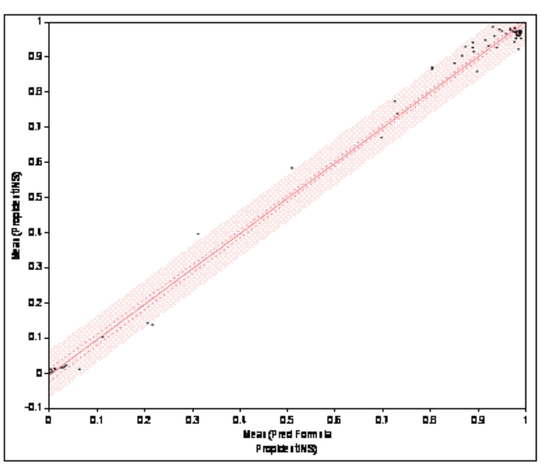


Figure 7: Fitting the model

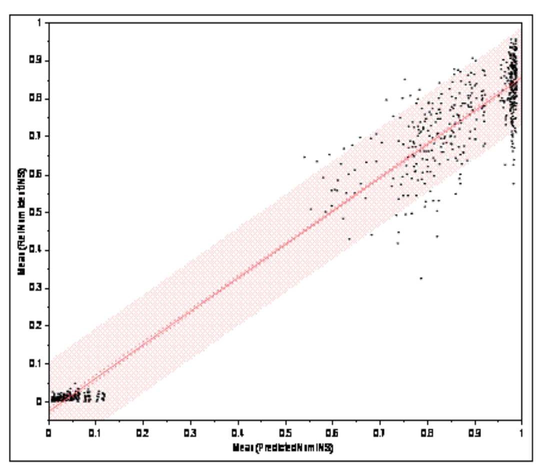


Figure 8: Validating the model

IDFW 21 Poster Session

IDFW 21 Teams

[5]

Team 5: Data Farming with SANDIS Software Applied to Mortar Vehicle Support for Convoys

TEAM 5 MEMBERS

Bruun R. S.
Solute Oy, Finland

Hämäläinen J. S.
Lappi E. I.,
PVTT, Finland

Lesnowicz Jr E. J.,
Naval Postgraduate School, US

INTRODUCTION

Data farming is a powerful tool for analyzing complex problems numerically. Our goal is to apply data farming methodology using the SANDIS combat model (see Lappi, 2008) to effectively study alternative scenarios. In order to do that, we introduce a rather simple scenario where a convoy supported by mortar vehicles comes under attack. The data farming is realized by collecting data from batch runs in which simulations are done with different initial parameters of a given battle situation. The results of the differently parameterized cases are the losses caused during the scenario.

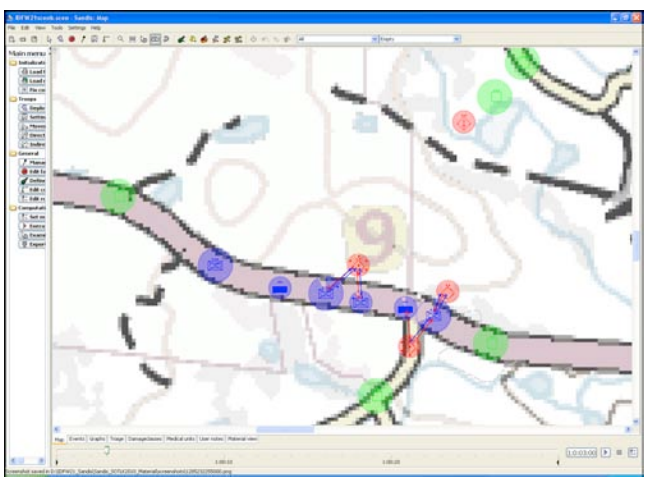


Figure 1. The scenario after blue and red have started the firefight. Blue circles correspond to the convoy, red to the attacking force and green to civilian groups.

Description of Scenario

This work is continuation for an earlier convoy study (Lindberg et al., 2009) which focused on the effects of mortar support for convoys. Here we examine the sensitivity of the results to certain parameters. Also, we add civil parts to the scenario and modify the convoy, equipment and attacking force. The scenario consists of an attacking red force, a blue force convoy with escorting mortar vehicles, and civilian parts. The convoy advances along a narrow road through a forest, which makes passing of stopped vehicles difficult. The civilians are wandering in the forest and on the roads without any reaction to the fighting. The case study begins when the convoy is stopped and attacked by the red force. The set up is presented in Figure 1 and the personnel, vehicles and weapons used are listed in Table 1.

Part	Blue Force	Red Force	Civil Part
Vehicles and weapons	3 Platoons with 3 Infantry Fighting Vehicles, carrying 7 men per vehicle, and one mortar vehicle with a 120 mm advanced mortar system.	3 Cells with 15 men, 6xRPG-7 (rocket propelled grenade).	
	2 Truck platoons of three trucks with two personnel.	1 Cell with 6 men, two 81 mm mortars and off-road vehicles	
Persons and personal weapons	All soldiers have assault rifles.	All soldiers have assault rifles.	5 groups of ten unarmed persons.

Table 1. A list of personnel, weapons and vehicles of the parties in the scenario.

Data farming using SANDIS

Simulations implemented with the SANDIS software are calculated in batch runs. Data farming is done by varying selected parameters of interesting events, in this case the parameters of mortar fire after the convoy has stopped. We shall study the effect of the response times of the mortars, variations in hit probability and the amount of ammunition.

The amount of ammunition is given as the number of single shots in a minute for a five minute period (for the 1st and 2nd platoon) or number of strikes (10 rounds per minute) for the 3rd platoon. The variation in accuracy is implemented as additional deviation to the deviation already present in the artillery model used (see Heininen, 2006 and Saira et al., 2008).

The scenario starts when the convoy has stopped, and the possible losses due to the stopping of the convoy are not taken into account. The next figure presents the workflow of this study.

Scenario timeline	Event
0	Convoy encounters an obstacle and the head of the convoy stops.
1	Red force opens fire to the headand middle of the convoy.
2	Blue force infantry opens fire at the attacking force
(3-7)+response parameter	Two blue force platoons under attack use mortars against ambushing red cells using single shots with a varying response time and amount of grenades.
5	Red force uses mortars against the 2nd blue platoon
6 + response parameter	3rd platoon's mortar opens fire at a red cell with 10 round strikes.
10	Red uses a mortar against the head of the convoy.
(12-16)+response parameter	3rd platoon's blue mortars fire at the red mortars. Two blue force platoons under attack use their mortar vehicles against ambushing red cells with 1-4 single shots per target and a varying delay.

Table 2. The basic scenario timelines which will be varied during the data farming.

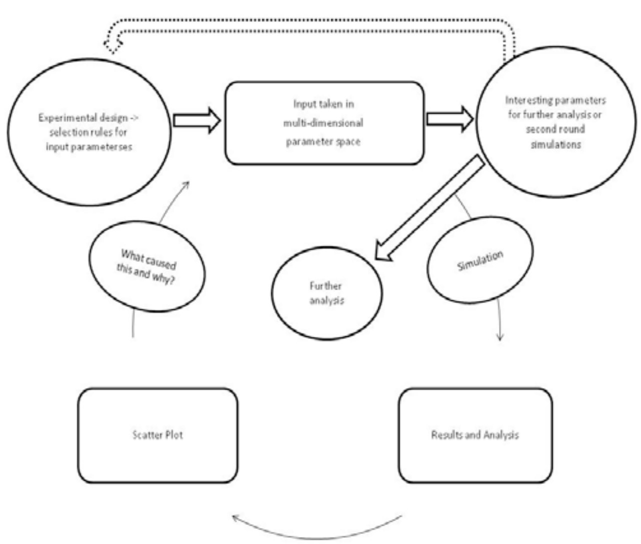


Figure 2. Graphical view of our simulation procedure.

Six independent parameters are considered: the number of rounds (10n, n=1,2), response time (0-4 min), firing and accuracy (additional deviation of 8 to 30m) of the 3rd platoon, the number of rounds shot (1-4) by the mortar vehicles of the 1st and 2nd blue platoons at a selected target at a given time, response time (0-2 min) and accuracy (additional deviation of 2 to 4 meters) of the vehicles of the 1st and 2nd blue platoons .

Two sets of 251 simulations were run, followed by a set of 128 runs in the neighborhood of the best results. In the first set of runs the number of rounds fired at each located target was 1 or 2, and in the second set 3 or 4. In addition, the accuracy modifiers were multiplied by 1.5 for the second set of runs. The third set was a further study of parameters around the three most suitable parameter vectors given in table 3.

Number of 10 rounds strikes by 3rd platoon	2	2	1
Response time parameter of 3rd platoon	0	0	1
Variation of accuracy of 3rd platoon	26,3	8,2	29,3
Number of grenades per close support target of 1st and 2nd platoon	3	3	3
Response time parameter of 1st an 2nd platoon	1	1	1
Variation of accuracy of 1st and 2nd platoon	4,0	3,1	2,5

Table 3. Parameters which resulted in the least losses for blue and civilian parts in the first and second simulation sets.

RESULTS AND ANALYSIS

In total 632 different simulations were run. In order to find the most interesting parameters, we began our analysis by looking at the losses of blue and civilian parts in the first two sets of runs, where the essential difference appeared to be the amount of grenades shot by the vehicles in the 1st and 2nd platoon. These losses are shown as a scatter plot in Figure 3.

The results of the two initial sets show that using more rounds yield better results even with lesser accuracy. To find parameters that gave even better results, a set of 128 simulations was run using parameters in the neighborhood of the best results in the initial sets, i.e. those in the lower left corner in Figure 3. The results of the third set are shown in Figure 4.

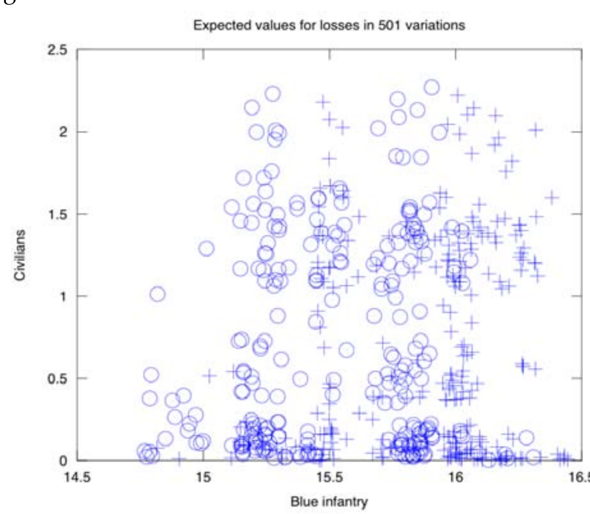


Figure 3. Scatter plot of the blue losses versus civilian losses. Markings with a + correspond to the first setup, where the number of rounds is either 1 or 2, and markings with a o correspond to setups where 3 or 4 rounds were used In the second set the variation of accuracy was also bigger.

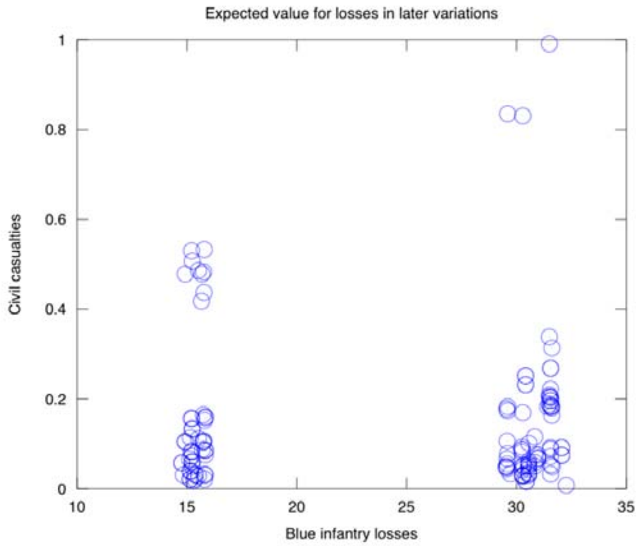


Figure 4. Scatter plot of the blue losses versus civilian losses of simulations made around the best parameters found in first runs.

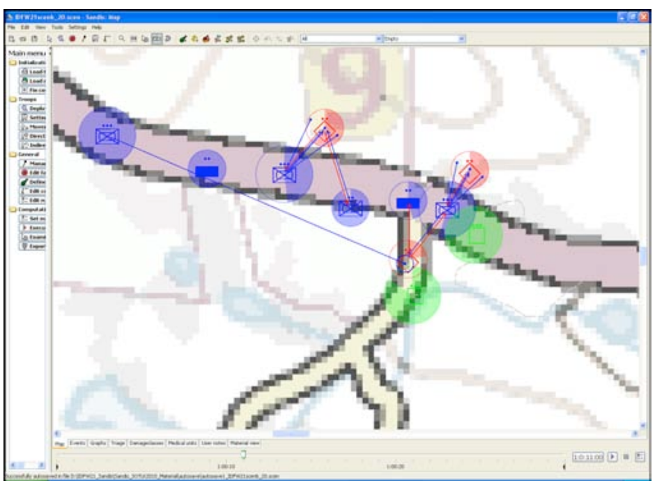


Figure 5. Screenshot taken from a scenario variation where the 3rd platoon's mortar fires (blue line pointing at the red and green circles in the picture) and hits the civilians.

In the scenario, one group of civilians ventured close to a red unit at the eleventh minute of scenario time, which resulted in the most civilian casualties, see Figure 5.

Finally, we examined correlations between the studied parameters and blue losses. The biggest correlations are presented in Figure 6.

There is no strong correlation between the losses and any single studied parameter. However, we observed from the best parameter combinations that a short response time for the 3rd platoon, combined with shooting three rounds with the 1st and 2nd platoons gave optimal results. The extreme points, i.e. the variations with least or most losses, are explained only by a rather complicated combination of parameters, leaving open questions for further study.

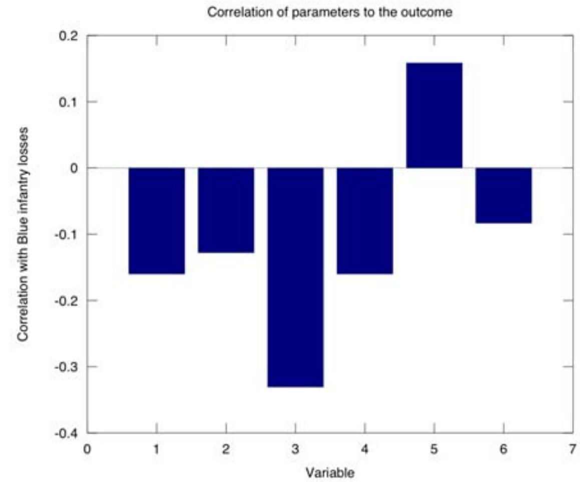


Figure 6. The parameters with the greatest correlation with blue losses. Parameters in the figure are: Number of 10 round strikes by the 3rd platoon (1), Response time parameter of the 3rd platoon (2), Variation of accuracy of the 3rd platoon (3), Number of rounds per close support target of the 1st and 2nd platoons (4), Response parameter of the 1st an 2nd platoons (5) and Variation of accuracy of the 1st and 2nd platoons (6).

CONCLUSIONS

Convoy security was studied and a data farming experiment with SANDIS software was performed. The considered case study shows us that data farming can be done using SANDIS, as long as the operator takes care that the parameters stay realistic in terms of a given scenario. It can be said that advanced mortar vehicles gave convoy a useful indirect fire capability. No red teaming was done in this case, so the optimal parameters apply only to the given scenario, in which the fast response time and reasonable spreading of the rounds to the target area seemed to be the essential parameters. Obtained results support further data farming studies with SANDIS in different topics with bigger scenarios and parameter sets.

Acknowledgements

Authors express their gratitude to Dr Bernt Åkesson and Mr. Ville Pettersson for their support to the work done for this paper.

REFERENCES

[1] Lappi E. 2008. "SANDIS – operation analysis software for comparative analysis," Proc. of 2nd Military Analysis Symposium, 2008, Stockholm.

[2] Lindberg A., Liukko T., Arpiainen J., and Hämäläinen J. 2009 "Suitability of Sandis Software to Small Scale Military Problems- A Case Study:Does the use of Mortar Reduce Convoy Vulnerability in an Asymmetric Warfare Situation ," Proc. of the 3rd International Sandis Workshop, PVTT Publications, No 19, 2009, pp. 14-22, Valkeakoski.

[3] Heininen T. 2006. "A method to calculate the lethality of fragmenting ammunition," in Lanchester and Beyond, PVTT Publications, No 11, 2006, pp. 19-30, Riihimäki.

[4] Saira O.-P., Lappi E. Pottonen O. Åkesson B. M. and Vulli M. 2008. "Simulating Indirect Fire – A Numerical Model and Validation through Field Tests," in Proc. of 2nd Military Analysis Symposium, 2008, Stockholm.

Plenaries

Tuesday

Data Farming for New Members and History of Data Farming – Gary Horne and Klaus-Peter Schwierz

New Capabilities in JMP 9 Useful for analyzing IDFW Data – Tom Donnelly

Validating the N2C2M2 C2 Approaches using Elicit – Marco Manso

Application of Data Farming to DoN MPT&E Models – Chad Seagren

Wednesday

SEED Center Update and Design of Experiments – Susan Sanchez and Tom Lucas

Data Farming Tools – Steve Upton and Ted Meyer

Thursday

Modeling the effects of Human Intangibles: A Final Update and Exploiting Simple Robots using a Concept Development and Analysis Environment – Choo Chwee Seng

Data Farming Collaborative Processes – Gary Horne and Johan Schubert

Team 6: Integrating Social Network Analysis to Data Farming

TEAM 6 MEMBERS

Meyer, Ted
McDonald, Mary
Upton, Steve
Roeder, Paul
Seagren, Chad
Nannini, Chris
Naval Postgraduate School, US

Middleton, Donna
Northrop Grumman, US

Fernando Freire
Portugal National Military Academy

Christina Bouwens
SAIC, US

INTRODUCTION

Team 6 is undertaking an ongoing study and effort to integrate Social Network Analysis (SNA) techniques into data farming processes and analysis. Our initial context for this activity has been insurgent warfare and Counter-Improvised Explosive Devise (C-IED) efforts. We continue to explore methods of extracting, analyzing, and visualizing dynamic social networks that are inherent in agent-based models in order to build tools to examine and better understand insurgencies. We have begun our effort with the emergence and evolution of cliques and are examining the types of network statistics that can be used as MOE and pointers to unique and emergent behaviors of interest.

Background

During IDFW 19 Team 6 demonstrated the ability to identify, extract, and visualize emergent complex networks from relatively simple agent-based scenarios. In IDFW 20 we began examining the usage of SNA statistics extracted from the emergent networks in illustrative scenarios as a basis for data farming. These statistics were explored in detail to determine which MOEs would be most beneficial for analyzing the types of networks produced by our agent based model. At the conclusion of IDFW 20 it was concluded that Team 6 would focus on specific counter-insurgency (COIN) questions in subsequent efforts to provide context for further development of capabilities.

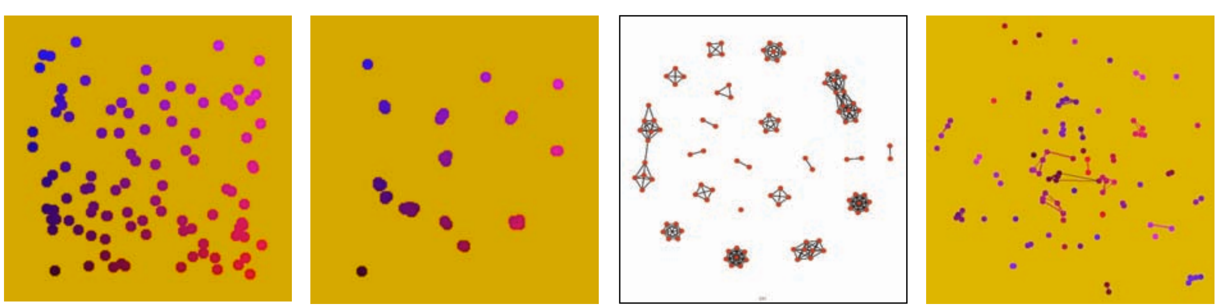
Within insurgent, IED-using networks there are two of interest: IED Emplacement Networks (consisting of personnel that is directly involved with IED usage) and IED Enabling Networks (consisting of communities that indirectly support the IED Emplacement networks). Team 6 indicated that they were interested in focusing on questions focused on the latter.

IDFW 21 Goals

Team 6 had several high-level goals for IDFW 21:

- Continued improvement and expansion of SNA Data Farming capabilities;
- Analysis of CliqueCreator Data Farming Runs—The CliqueCreator scenario is a simple agent-based model that produces evolving cliques; and
- Begin defining a focus question and building an illustrative model to provide COIN/C-IED context for the ongoing study of SNA data farming capabilities.

The CliqueCreator scenario provided the initial context for the weeks continued capability development efforts. CliqueCreator, developed using the Pythagoras modeling environment, uses agent interactions to affect agent "Persona" attributes. Agent interaction results in agents becoming more similar in "Persona." Agents tend to move toward similar agents and away from dissimilar. As "cliques" emerge and evolve, their movement may result in interactions with other cliques, resulting in "theft" of members and large scale movement in "Persona" attributes. Figure 1 shows "snap-shots" from three different views of this model using different attributes and methods to show



A - Persona Space Step 0 **B - Persona Space Step 170** **C - Network View Step 170** **D - Spatial View Step 115**

Figure 1 - CliqueCreator Scenario - Three Views

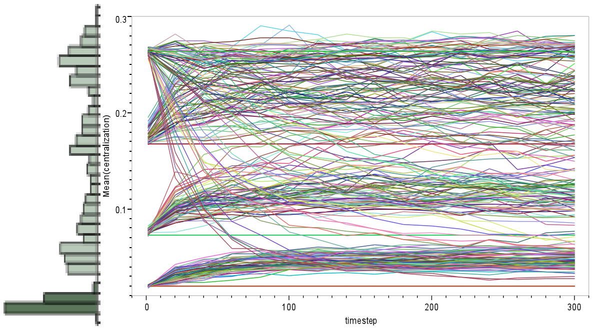


Figure 2: Different Starting Populations (Random Seed)

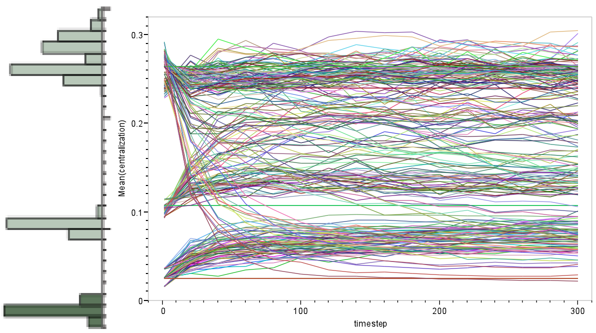


Figure 3: Same Starting Populations (Fixed Seed)

changes in agents and their relationships. Figure 1A and B show the movement of agents in the color-based "Persona"-space. Figure 1C shows a traditional network view of the agents in a homophilic sense using the Persona. Figure 1D shows the more traditional spatial view with interaction shown with lines.

An illustrative set of data farming runs was executed and Team 6 began analysis to address the following questions:

- "How important is the exact layout and specific agent attributes of the initial population to the statistical outcomes of the scenario?"
- Do specific agents consistently establish the same network roles?
- Are specific groups of agents "destined" to be in the same cliques?

Table 1 provides the specific variations that were made to scenario parameters. Not shown in the table is that this matrix was executed for two separate runs: one in which the random seed that established the initial population and layout was allowed to vary for each run, and another where the same random seed was used for all runs. In both cases, the populations had the same statistical makeup, but in the former case each starting population was different.

Full Factorial	
Parameter	Design Values
colVulTol	0.0, 0.5, 1.0
colVul	0.0, 0.5
relativeChg	10, 20, 30, 40
influenceRange	10, 100, 250
friendThresh / enemyThresh	50/105, 90/145, 130/185

colVul - Color Vulnerability (Level of effect of "chat" for agent)
colVulTol - Color Vulnerability Tolerance (Variability of colVul)
relativeChg - Percentage relative change of color when "chatted"
influenceRng - Maximum distance of interaction (chat)
friendThresh/enemyThresh - Range where agents are "linked"

Table 1 - CliqueCreator Data Farming Design Matrix

Figures 2 and 3 are a comparative analysis plots using the JMP software that represent the difference of these two cases across a set of the design parameters. Initial examination indicated significant difference in variability, but more analysis is required.

Focus Question: Village Scenario

Figure 4 represents the set of networks, hierarchies and relationships that are the target make up of an "Afghan Village" scenario. The purpose of this scenario is to provide and illustrative forum to begin to address the following questions:

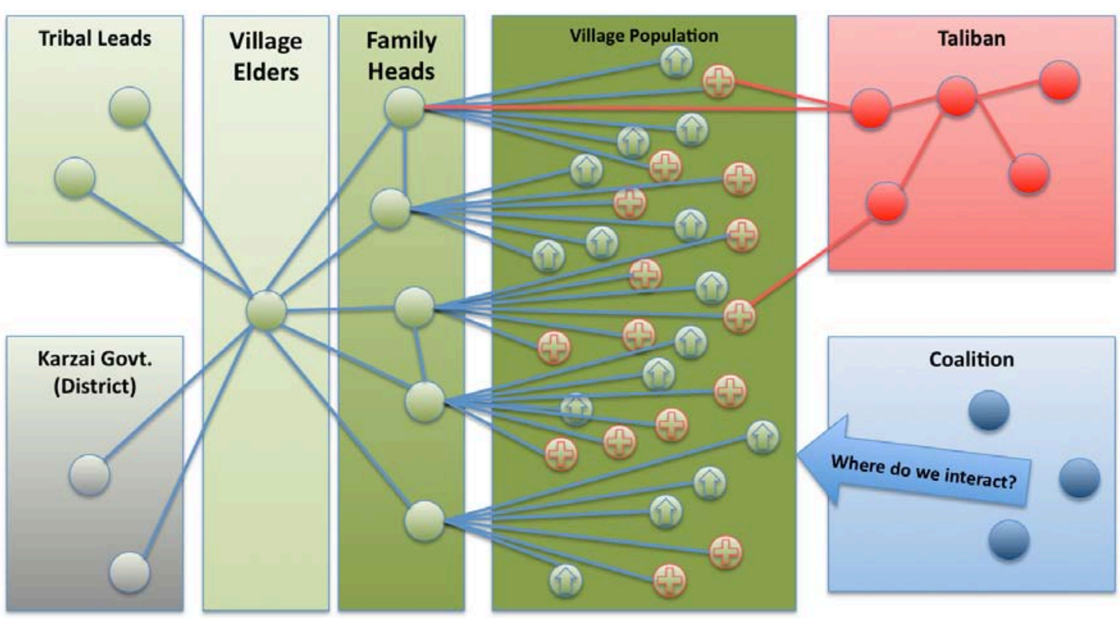


Figure 4 - Evolvable Networks and Relationships for Village Scenario

- What actions should blue take to eliminate the employment of IEDs?
- Are social networks important factors in the tendency for individuals to employ IEDs?
- Given the importance of social networks what actions blue should take in order to eliminate their effectiveness in terms of IED employment? Figure 5 offers "Law Enforcement" and "Female Engagement" as two potential actions to be tested.

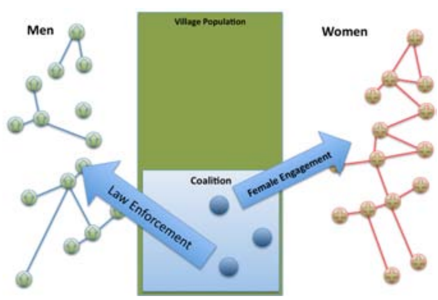


Figure 5 - Question: What actions should blue take to eliminate insurgent recruitment and the enabling of IED emplacement?

Part of the focus into these questions is intended to support the identification of SNA metrics that will assist in the evaluation blue actions.

An existing Afghani village, Kace Satar, was examined and will be used as a basis for scenario development. This village is at the intersection of the Helmand, Farah, and Nimroz provinces in Southern Afghanistan. The population within a 7 km range is about 298. The specific distribution of population classes is currently uncertain, but discussion with subject-matter experts (SMEs) indicates that the social interactions and hierarchies shown in Figure 4 are of significance and have real impact on potential recruitment. These networks include:

Village Family Leadership and hierarchy – Although the family leadership and relationships are primary, they can be subordinate to broader and external Tribal leadership. These "command" structures can be hierarchical or matrix... but can also be considered somewhat stable. Removal of some central figures can cause significant change to the overall network structure.

Taliban – The insurgents can be completely independent of the other hierarchies and maybe working in opposition to tribal and family goals.

District – The Karzai leadership and judicial structure is also independent of the tribal and family structure and also may be in opposition to tribal intent.

Young males (recruitment age) - Some research has indicated that there are specific personality attributes that can affect the likeliness of recruitment into insurgent behaviors. We will consider using these as potential "Persona" attributes for young male villagers. Some of these attributes include: Status (degree of recognition desired); Thrill (desire for adventure); Revenge (outlet for frustration); Identity (need for belonging); and Money (Survival).

Village Women/Village Men - Women have influence in Afghani society. This influence is not generally exercised in public, however, but through interaction with family.

Scenario Status

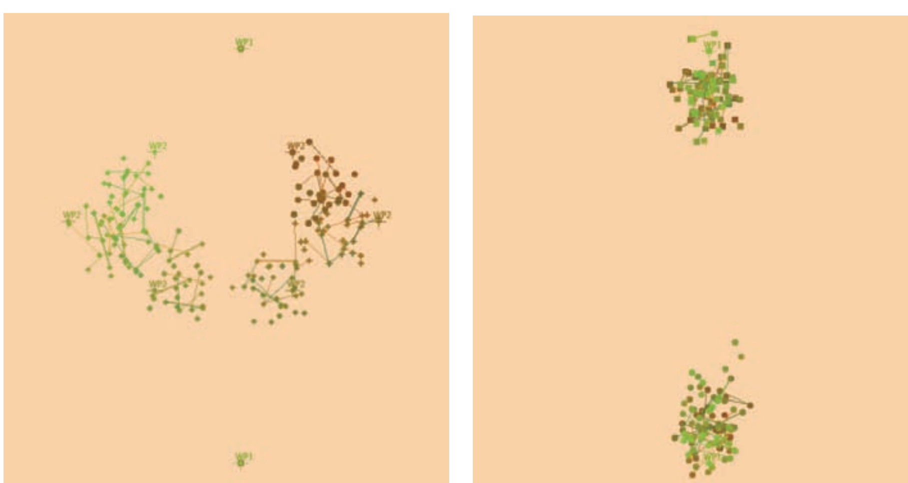
Team 6 focused on developed an initial representation of the day-to-day periodic relationships of men, women, and families in the Afghan Village. We have built a six family (180 agents) scenario that establishes a "daily" period of home to work (100 time steps per cycle; 8 "days"), where work is segregated by sex. Each family is represented by an attribute range and "FamilyTalk" and "WorkTalk" can change a "persona" attribute relative to color of two agents interacting. Figure 6 shows provides snapshots of this effort.

Accomplishments and Way Ahead

The initial data farming and results examined pertaining to the importance of specific initial populations demonstrated differences in variability, but was not conclusive and led to a set of interesting questions that need to be examined.

The initial implementation of the village families with family and independent male and female interaction has been accomplished, but Team 6 believes that even this basic interaction should be data farmed and analyzed before proceeding to a more complex scenario with interacting networks.

So far, Team 6 has developed tools that focus on homiphily networks based on Pythagoras color. EWe intend to expand data farming methods for other network layers to include interactions (chat, weapon, attribute change, etc) and spatial (proximity networks).



A B

Figure 6 -Pythagoras Village Scenario's Two Modes for Family Agents. Figure 1A represents "Family Time" when households gather as families such as for evening meals. Figure 1B, "Work Time," represents the daily period in which villagers congregate, predominately by sex, to undertake work chores.

Team 7: The Application of Agent Based Modeling to Determine the Placement of Resources during Humanitarian Relief Missions

TEAM 7 MEMBERS

Mr. Andrew Turner
Georgia Institute of Technology, US

Dr. Santiago Balestrini-Robinson
Georgia Institute of Technology, US

Dr. Gary Horne
Naval Postgraduate School, US

INTRODUCTION

Team 7 developed an Agent Based Model in NetLogo 4.1 to study the impacts of the placement and size of resource dispensaries and processing centers on the successfulness of a Humanitarian Relief Mission. The model tracks the number of people in need of resources, time to receive resources, crime incidents, and population migration. The model incorporates social attributes, ethnicity, and people's resource desires.

MotIvation

As evidenced by the humanitarian disasters in Africa, Haiti, Pakistan, and Turkey, humanitarian assistance and disaster relief (HA/DR) missions continue to be in major demand. As evidenced by the examples presented above, these oftentimes lead to sociopolitical instability, and in some extreme cases, war and genocide.[9] It is well understood that a country's situation can quickly deteriorate when struck by a natural disaster of a sufficiently large magnitude. What is more difficult to prove, but has in fact happened on a number of occasions, is that humanitarian assistance missions produce unexpected effects that could have been avoided if the missions would have been planned differently. Somalia in 1990, Rwanda in 1993, East Timor in 1998, New Orleans in 2005, and Haiti in 2010 are all cases where the humanitarian assistance was either insufficient, lacked a comprehensive spectrum of operations, and eventually fueled blowbacks[1].

The majority of the work in this field focuses on optimizing the logistics to bring maximum amount of resources in the minimum amount of time to the region in question. This, however, is not always sufficient. In the aftermath of the 7.0 Richter Scale magnitude earthquake that struck Haiti in 2010 there were many accounts of looting, gun-fights, and riots due to the lack of security enforcement and resource shortages.[1,2] It is not enough to just get relief to the region it must also be distributed throughout the population in a safe and secure manner. The most common approach is to setup centers in order to provide the population with the required resources and services. The questions we ask are how should these centers be set up to best meet the needs of the people? Should there be fewer centers with greater capacity or should there be more low capacity centers? Should the centers' locations account for the characteristics of the population, e.g., can resource distribution incite ethnic violence? How does the total daily operation time affect the distribution of resources and services? And finally, how do these produce different levels of insecurity and population migration? In order to study these effects, Team 7 developed an agent-based model that attempts to capture the most pertinent elements of the problem.

Modeling

In order to develop the proper model of a HA/DR mission, one must consider the following aspects of the community in distress: population density, ethnic makeup and tensions, social attributes, resources availability and desire, crime rates, and the location and makeup of processing and dispensary centers. The model was developed in NetLogo 4.1, a free agent-based modeling and system dynamics modeling framework developed by The Center for Connected Learning and Computer-Based Modeling at Northwestern University.[10]

Population Density

Modeling every individual in the population as an agent would be infeasible from a computational standpoint, so a method for simplifying the pertinent characteristics of the population had to be devised. To confront this issue a combination of Cellular Automata and Agent Based Models were used. The environment that the model operated on was split up into 32x32 patches. These patches represented a geographical area of a given physical dimension represented in meters. Each patch contained information on the number of individuals living in this area in addition other information discussed in the following sections. The total number of people in the model is predefined and then is random distributed throughout the map. The model can be easily modified to have higher resolution—i.e., higher discretization —of the environment.

Ethnic Considerations

Not all HA/DR scenarios have a major focus on ethnic conflict. On the other hand, some HA/DR missions are a

---

[1] Blowback is a term used to refer to situations where unexpected and undesirable consequences occur from seemingly benign actions

direct result of, or can be affected by, ethnic tensions. For this reason the ethnic makeup and corresponding tensions of a region must be considered in order to study how conflict arises. Of particular interest to this study is: how does the placement and distribution of the centers impact ethnic tension?

A simple example of how resource placement can induce violence can be explained by Figure 1. Let's assume we have two ethnic groups (A and B). In addition assume these two groups have a history of violence , then by the placement of a resource center (denoted as a blue star) can lead to increased violence by forcing ethnic group A to travel through a region dominated by group B.

The model includes the ethnic group breakdown by percentage for each patch. In addition the model includes an inter-relationship matrix that determines how well the different ethnic groups interact. This will have an important impact when studying the crime.

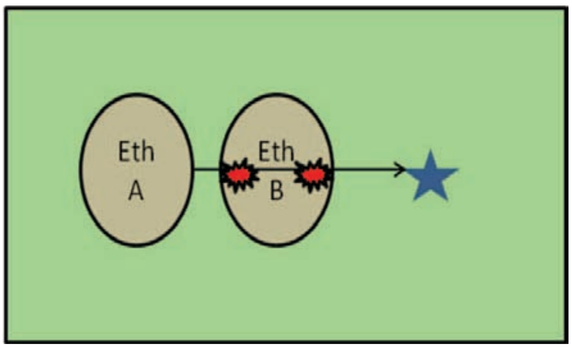


Figure 1: Example of violence induced by resource placement

Social Attributes

Social attributes help to better define the makeup of the population. This data is stored in the patch. Some examples of these attributes are: poverty rates, education rates, and employment. These metrics will play a major role in calculating crime. The social attribute data can be attained from census data.

Resource Availability vs. Desire

Every patch will contain information on the amount of resources that exist on that patch. Examples of this could be liters of water and calories of food. The patch will consume the resources at a specified rate. This will continue to change until the patch reaches the desire threshold. Every patch has a slightly different desire. If the patch reaches the desire threshold then those on the patch deem their state of resources to be insufficient and will create a gathering agent. This gathering agent will consist of a percentage of the people on the patch. The percentage is predetermined. This gathering agent will then travel to the nearest resource dispensary to acquire the desired resources and bring it back to its home patch.

Processing and Dispensing Centers

An important distinction needs to be made between a processing center and a dispensing center. A processing center is a center that the people visit to have some service done for them or to them. There is nothing physical that the people leave the center with. The people must report here to receive what is needed. Examples of this include hospitals or vaccination clinics. The demand for processing is created randomly in the model. In contrast, a dispensing center is one that gives the people a material good that can be carried back to their home. The people could either report to the center personally to receive the good or have someone retrieve the good for them. Examples of this are food, water, and tents.

Every center has a maximum throughput capacity and a limited supply. The throughput capacity is determined by the number of people that can be processed at once and the time it takes to process an individual. The throughput capacity of the resource and processing centers can, and probably will, differ greatly. For example, more time is required to treat medical needs than to hand out food. In addition, medical experts are in shorter supply than people who can hand out food. The agent will arrive at the center and get into a line. They will wait until they are processed, the center runs out of resources, or the center closes. Once this occurs the agent returns home.

Crime

Crime is an important and complicated aspect of this model. As referenced earlier, crime ran rampant in a wide variety of HA/DR missions, especially in Haiti after the 2010 earthquake. This was a result of insufficient security forces and lack of vital resources. Understanding how the placement of centers impacts the crime of the affected area is essential to produce a comprehensive and satisfactory plan for HA/DR missions.

The occurrence of crime is a result of a vast number of different factors.[3] These factors range from socioeconomic status and education to criminal punishment and reinforcing nature of crime.[3,4,5,6,7] In addition, crime rates and the sources of crime vary across different societies.[3] For a measure of impact on crime rates the reader is referred to references 3 through 7.

Due to the wide range of factors contributing to crime and the varying impacts across different societies an expandable and adaptable crime model was developed. This model is composed of two phases. The first phase is the probability of a patch to create a crime agent. The second phase takes place when the crime agent travels in a random walk until it commits a crime. A crime agent will commit a crime based on a separate probability, based on the characteristics of that agent and the patch where that agent currently is. The probability of a patch to create a crime agent is presented in Equation 1. The probability of a crime agent to commit a crime is presented in Equation 2.

Equation 1 is composed of six elements. The first is the dominating coefficient multiplying the whole equation, DN. This coefficient allows the probably to distinguish between day and night. The second part is a summation of the impact of social attributes on crime with their corresponding weightings. The third part is a measure of the desire level of the patch. If the people are without critical resources they are more likely to engage in criminal acts out of desperation. The fourth is a measure of an ethnic group's tendency towards crime. The hypothesis is that one ethnic group may be quicker to resort to crime than another. This ethnic consideration may not always be present and can be zeroed if deemed irrelevant. The fifth part is the factor that describes the reinforcing nature of crime.[4,5] The sixth, and final part is a measure of the impact on the presence of security forces.

Equation 1

$$P = DN\left[\begin{array}{l} \sum_{i=1}^{n} a_i \frac{(100 - SA_i)}{100} \\ + \sum_{j=1}^{m} a_{n+j} \max\left[0, 1 - \frac{RL_j}{RD_j}\right] \\ + \sum_{k=1}^{o} a_{n+m+k} Eth_k \\ + c * CC \\ - \sum_{l=1}^{e} E \frac{1}{\max\left[1, R_l^2\right]} \end{array}\right]$$

Equation 2 is the probability a crime agent will commit a crime, and it is similar in form to Equation 1. The first significant change is the second summation term. This is a measure of the crime agents' desire for resources and the potential victims' desire for resources. The potential victim is the current patch that the crime agent is on. The next difference is in the next term. Here the ethnicity of the crime agent and the potential victim plays a role. Depending on the ethnic relationship this could increase or decrease the probability of a crime being committed. The final difference is that there is no self reinforcing nature of crime once the crime agent is produced.

Equation 2

$$P = DN\left[\begin{array}{l} \sum_{i=1}^{n} a_i \frac{(100 - SA_i)}{100} \\ + \sum_{j=1}^{m} a_{n+j} \left(1 - \min\left[1, \frac{RL_j}{RD_j}\right]\right) \frac{RL_v}{RD_v} \\ + E_{Et,Et} Eth_v \\ - \sum_{l=1}^{e} E \frac{1}{\max\left[1, R_l^2\right]} \end{array}\right]$$

Migration

The final element to be modeled is migration. The premise of this portion of the model is that if people are suffering—e.g., due to crime, lack of resources or services, ethnic tensions—and there are areas with better conditions, or a promise for better conditions, they are likely to leave and move to the more promising area.

Equation 3 describes the elements that compose the calculation that determines the goodness of a given patch, Pgood. The a, b, c and d terms are multipliers for each of the terms. The term rp is a relaxation constant, if it is zero the goodness of the patches does not change from one time step to the next, if it is set to one, it will have no memory of the goodness from the prior step. The first term is the summation over the m Social Attributes of patch, e.g., education, employment, etc. The parameters CT, CGM and CM, are the counters for the number of crimes committed by crime agents from other patches on the patch, how many successful crimes crime agents from that patch have conducted in other patches, and the number of gatherers that have been mugged on that patch respectively. The parameter t is time. Pop and PopAreaRatio are the number of people residing on that patch and the ratio between total area and total population respectively. This term helps quantify overcrowding in relative terms. The final term is a measure of how many resources that patch is lacking, where (RD)i is the ith resource desired and (RP)i is the amount of that resource present. The coefficient ei is a measure of the weighing given to that resource by the population on that patch.

Equation 3

$$P_{good} = (1 - r_p) P_{good} + r_p \left[\begin{array}{l} \frac{a}{m} \sum_{i=1}^{m} SA_i \\ - b \frac{(CT - 4CGM - CM)}{t} \\ - c(Pop \times PopAreaRatio) \\ - d \sum_{i=1}^{n} e_i \frac{(R_D)_i - (R_P)_i}{(R_D)_i} \end{array}\right]$$

The goodness of all the patches is calculated at every time step, and it is compared to a parameter that represents the value of the property in that patch. This parameter accounts for the fact that if people have a highly valuable property, they are more likely to remain there rather than if they have no material reason to stay.

Once a group of people in a patch decides to migrate, they look for a patch that is at least a certain amount better than their patch and has their ethnicity. Then a migration agent is created and that agent traverses to the new location.

ANALYSIS

Once the model was created, a Design of Experiments (DOE) could be executed to determine how the centers should be set up to best meet the need of the people. The first step of this process is to define the control variables of the model and the subsequent ranges.

Design Ranges

Design ranges for the center control variables can be developed from the operations used by the US Army Corps of Engineers (USACE).[8] USACE uses three different types of resource centers. They operate by loading resources into cars that pass through 4, 2, and 1 lanes of cars, respectively. This case is amenable to a domestic HA/DR operation, e.g., Hurricane Katrina. They make the assumption that each lane can process 5,000 people every 12 hours. Each car is assumed to represent 3 people and is given 1 day of supplies for each person. The centers operate for a total of 12 hours a day. With this information in addition to basic approximations, design ranges for the 10 input variables were defined and are shown in Table 1.

Variable	Lower Bound	Upper Bound
Population	50,000	200,000
Center Operation Time	8 Hr	18 Hr
Resource Limit	2,000 ppl	20,000 ppl
Dispensary Lines	1	6
Time to Dispense	20 sec	30 sec
Number Resource Centers	1	20
Supplies Dispensed	1 Day	10 Days
Number Process Centers	1	8
Processing Lines	2	10
Time to Process	5 minutes	60 minutes

Table 1: DOE Variable Ranges

Design of Experiments

The DOE selected for the analysis of the model utilized a 128 case Nested Latin Hypercube Design (NLHD) developed by Prof. Peter Qian from the University of Wisconsin plus three different variations of a 20 case Robust Screening Design (RSD). These 20 cases were scaled to span 50%, 75% and 100% of the design space, for a total of 60 cases. Each of the 188 cases was executed 20 times to obtain statistical significance.

The 128 NLHD cases allow the designer to run increasingly larger blocks which remain orthogonal, i.e., the first block has 16 cases which are orthogonal, and when the additional blocks of 16, 32, and 64 cases are included, the correlation of the aggregated design remains at a minimum value. This allowed the team to obtain results at the workshop, whereas it would not have been possible from a computational standpoint to execute the 128 cases with their 20 repetitions during the workshop. Including the RSD and NLHD cases and their 20 repetitions, Team 7 executed a total of 3,760 cases.

The RSD cases are used to validate the goodness of the regressions based on the NLHD cases. The sequentially increasing span of the RSD allows for the testing of how well the model interpolates and extrapolates to the corners of the design space. The authors extend their thanks to Tom Donnelly from JMP for providing the knowledge and the designs.

Results

The data collected from the model included resource needs, processing needs, crime rates, and migration at 6 points over three days (every 12 hours of simulation). The data was analyzed using JMP. The analysis shed light onto the question of how the centers should be set up. It was found that the number of centers was a more critical factor than their number of lines. This tells us that during HA/DR missions it is better to set up several small centers with low capacity throughout a region as opposed to few large centers with high capacity. This result is in agreement to what is to be expected, since the economies of scale of having fewer larger centers and their increased logistic efficiency cannot be currently computed by the model. Total time of operation of the centers did have an impact, however it did not have nearly as large an impact as the number of centers or total capacity did.

Future Work

Future work will focus on improving the behavior of the agents and the models for crime and migration. In addition, the team plans to develop a more intelligent method for placing the centers, allowing greater granularity in the study of the planning of HA/DR missions.

REFERENCES

[1] "Haiti Earthquake: Looting and Violence Break out - Telegraph." Telegraph.co.uk - Telegraph Online, Daily Telegraph and Sunday Telegraph - Telegraph. Daily Telegraph, 15 Jan. 2010. Web. 29 Nov. 2010. <http://www.telegraph.co.uk/news/newsvideo/6996287/Haiti-earthquake-looting-and-violence-break-out.html>.

[2] Sherwell, Philip, and Patrick Sawer. "Haiti Earthquake: Looting and Gun-fights Break out - Telegraph." Telegraph.co.uk - Telegraph Online, Daily Telegraph and Sunday Telegraph - Telegraph. Daily Telegraph, 16 Jan. 2010. Web. 29 Nov. 2010. <http://www.telegraph.co.uk/news/worldnews/centralamericaandthecaribbean/haiti/7005554/Haiti-earthquake-looting-and-gun-fights-break-out.html>.

[3] Malleson, Nick, Andrew Evans, and Tony Jenkins. "An Agent-based Model of Burglary." Environment and Planning B: Planning and Design 36 (2009): 1103-123. Print.

[4] Schrag, Joel, and Suzanne Scotchmer. "The Self-reinforcing Nature of Crime." International Review of Law and Economics 17.3 (1997): 325-35. Print.

[5] Buonanno, Paolo, and Daniel Montolio. "Identifying the Socio-economic and Demographic Determinants of Crime across Spanish Provinces." International Review of Law and Economics 28.2 (2008): 89-97. Print.

[6] Scorzafave, Luiz Guilherme, and Milena Karla Soares. "Income Inequality and Pecuniary Crimes." Economics Letters 104.1 (2009): 40-42. Print.

[7] Pablo, Fajnzylber, Daniel Lederman, and Norman Loayza. "What Causes Violent Crime?" European Economic Review 46 (2002): 1323-357. Print.

[8] "LEOP Planning – Appendix 4 to Annex O" State of Missouri - State Emergency Management Agency. Web. 04 June 2010. <http://sema.dps.mo.gov/Planning / LEOPPlanning.htm>.

[9] Diamond, Jared. "Collapse: Why Societies Choose to Fail or Succeed." New York, NY: Viking Press. 2005.

[10] Wilensky, Uri. "NetLogo," Center for Connected Learning and Computer-Based Modeling, Northwestern University. Evanston, IL. 1999. <http://ccl.northwestern.edu/netlogo/>.

Team 8: Investigation of the Impact of Ship Loading Strategies on USMC MPF Arrival and Assembly

TEAM 8 MEMBERS

Jonathan Derosier, Captain
Aaron Burciaga, Captain
Michael Harvey
U.S. Marine Corps

Joseph Dumar, Captain
U.S. Marine Corps, Naval Postgraduate School

Laura Whitney
Dr. Daniel Nussbaum
Naval Postgraduate School, United States

Dr. Preston White
University of Virginia, United States

Callie Beagley
Systems Planning and Analysis, United States

Britt McNeill
Systems Planning and Analysis, United States

Dr. Bernd Heinen
JMP, Germany

INTRODUCTION

The U.S. Marine Corps' Maritime Prepositioning Force (MPF) enables the rapid deployment of Marine forces to permissive areas of operations. The MPF consists of more then a dozen ships divided between three squadrons. Each squadron supports a notional Marine Expeditionary Brigade (MEB) and is based in one of three locations: the Pacific Ocean, the Indian Ocean, or the Mediterranean.

MPF Operation

During an MPF operation, a Maritime Prepositioning Ship Squadron (MPSRON) or some portion or combination thereof, is deployed to a permissive area of operations where its equipment and supplies are offloaded. A fly-in echelon (FIE) compromising the bulk of personnel and additional equipment is flown into a nearby airport. The equipment and personnel are then integrated to form a functioning Marine Air Ground Task Force (MAGTF). This process is called Arrival and Assembly.

Motivation

The MPF concept of operations has historically been focused on the employment of a MEB. The equipment that a MEB requires (its table of equipment (TE)) exceeds the equipment that a MPSRON can provide. Therefore, a MPSRON's entire set of equipment is allocated to a MEB with the remainder of the MEB's TE being designated for the FIE. This operation employment concept results in ships being densely packed to maximize the amount of equipment that can be prepositioned, reducing the FIE.

Embark constraints to some degree determine how the prepositioning objective (portion of the MEB TE that is prepositioned on a MPSRON) is distributed across the ships in a MPSRON and where within a ship the items are placed. For example, tanks are spread across the ships due to weight and some items are placed in specific holds or decks due to height restrictions. With one exception, equipment is generally loaded by these constraints with little regard for operational employment since the entire set of equipment is needed to support the MEB and equipment is only designated down to the MAGTF element level (Command Element (CE), Ground Combat Element (GCE), Air Combat Element (ACE), and Logistics Combat Element (LCE)).

A subset of each MPSRON's equipment is designated for the Marine Expeditionary Unit (MEU). The "MEU slice" is loaded on two ships and in locations that enable the equipment to be offloaded with out having to offload much non-MEU equipment.

The MPF concept of employment may head towards supporting less than MEB sized units or capability sets (LTMUs). Currently, the equipment to support a LTMU may be spread across multiple ships within a squadron and may be embarked in inaccessible locations.

Workshop Goals

The goal of this work at IDFW 21 is to use data farming techniques and the MPF Arrival and Assembly model to explore the trade off between the size of an LTMU equipment set, the access of equipment on the MPSRON and the number of ships that the equipment is drawn from. Access is a combination of two factors; how much equipment that is not required must be offloaded to allow the offload of the required equipment and the relative ordering of the required and not required equipment.

ARRIVAL AND ASSEMBLY MODEL

The MPF Arrival and Assembly Model is a discrete event simulation implemented in ExtendSim7. The model has two main processes: the offload of equipment from a ship to a pier and the throughput of equipment from the pier to its using unit located some distance from the pier.

Offload

The offload process models the interaction between ships and docks, where a dock is required to conduct an offload. Multiple docks allow for the simultaneous offload of ships. There are two methods for offloading equipment from a ship:

1. Roll On Roll Off (RORO) is used for vehicles that can be driven off the ship via its stern ramp. RORO requires both a ramp (ship asset) and offload drivers.
2. Lift On Lift Off (LOLO) is used for offloading containers (and possible vehicles) by lifting them with either a ship crane (ship asset) or a gantry crane (dock asset).

Equipment is offloaded in a random order.

Throughput

The throughput process models the physical movement of equipment from the pier to the using unit and any maintenance or setup actions that must be completed to make equipment operational. The equipment is classified into four types; ammo containers (AMMO), non-ammo containers (ISO), vehicles that require a heavy equipment transporter (HET), and vehicles that can move themselves (RS).

Scenario

In this scenario, the throughput parameters are fixed. The quantity of equipment (both required and not required), the offload ordering, the number of ships, and the number of docks are explored using a full factorial design.

Metrics

Figure 1 is a screen shot of the model outputs. The blue, green and red lines represent the counts of equipment over time at the pier, at the final destination, and in the throughput process respectively. We use days to complete throughput of the required equipment as our primary metric.

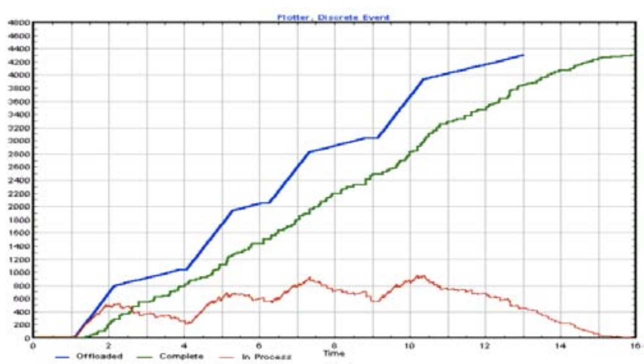


Figure 1. Simulation Output. The blue line identifies the count of equipment as it is offloaded at the pier. The green line is the count of equipment as it arrives at the final destination. The red line is the count of equipment in the throughput process.

DESIGN OF EXPERIMENTS

The equipment on the MPSRON is partitioned into three sets: offloaded required, offloaded not required, and not offloaded. The total amount of equipment is always fixed at 5000. The quantity of offloaded required equipment is a factor and varies from 100 to 2500 in increments of 200. The quantity of offloaded not required is a proportion of the not required equipment. The proportion is a factor and varies from 0.0 to 1.0 in increments of 0.1.

The number of ships varies from 1 to 4. The amount of required and not required equipment is equally distributed across the number of ships and the four equipment types in the scenario.

The number of docks in the scenario is either 1 or 4 representing the extremes of one ship offloaded at a time and all ships offloaded at the same time.

The offload ordering is determined by assigning each piece of offloaded equipment a random number between 0 and 1. The distribution that this number is drawn from varies for the required and not required equipment as depicted in Figure 2.

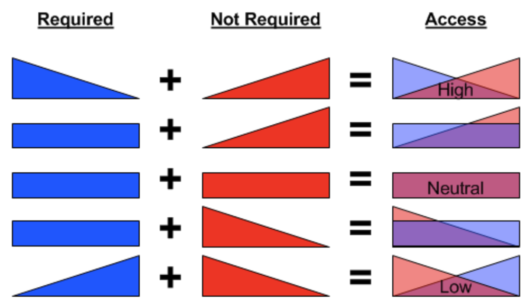


Figure 2. Offload ordering distributions. Each equipment item is assigned an ordering priority drawn from a random variable. The distributions used determine the relative access of the required equipment.

RESULTS

For each level of required equipment, a linear model with the time to throughput all required equipment to its destination versus the number of docks, the number of ships, the amount of equipment not required and the access ordering of the equipment and all two way interactions as factors, was fit and the significance of each factor calculated. The results are in Table 1. A plot of the effects of the most significant factors is shown in Figure 3.

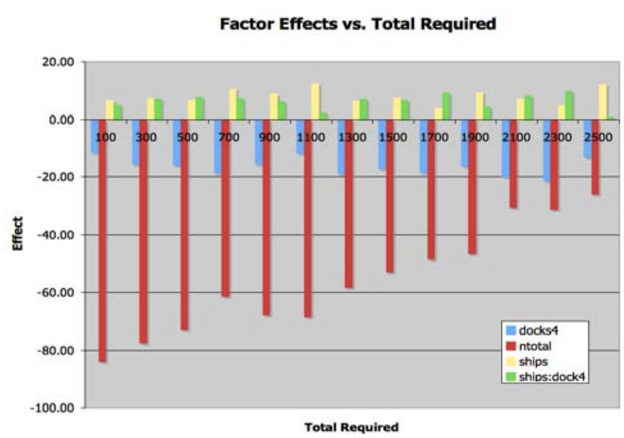


Figure 3. Factor effects. The amount of equipment not required has the largest effect on the response. However, its magnitude is decreasing as the size of the required equipment increases. The other factors have a relatively constant effect on the response.

The total amount of not required equipment that must be offloaded plays a significant role across all of the levels of required items. The number of docks and ships are significant in some levels of required items. The relative ordering of equipment does not play a significant role in all but one level of required items.

The effects plot shows that the not required equipment has the largest effect. However, its effect decreases as the amount of required equipment increases. The other factors have a relatively constant effect on the response.

Figure 4 is a plot of the design points where the average day to complete the throughput all of the required equipment was day five. The plot is faceted by the total required equipment versus the total not required equipment with number of ships on the x-axis and access ordering on the y-axis. The number of docks is indicated by the color of the points. This plot reveals that having multiple docks enables the offload of much more equipment in a particular time frame. It also reveals that there is little correlation between the number of ships and the access order.

Inspection of these plots across the set of days required to complete the throughput of required equipment (2 days to 23 days) shows that the time required is highly dependent upon the size of the equipment sets.

The access of LTMU sized equipment sets will be an important consideration in the load planning of the MPF ships in the future. The ships have limited high access locations and there are many different LTMUs that could be sourced from a MPSRON (e.g., Humanitarian Assistance, Disaster Relief, Security Cooperation MAGTF, fuel, water or life support equipment sets).

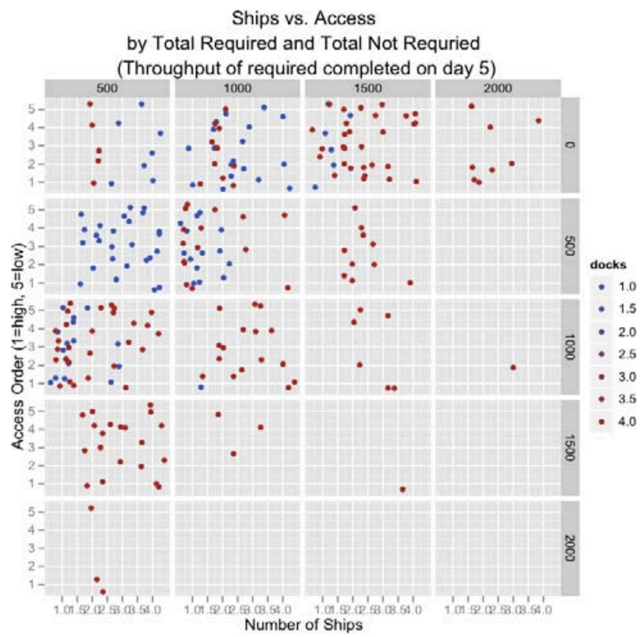


Figure 4. Plot of the design points where the mean days to complete throughput of the required equipment was on day five. The plot is faceted by the total required and not required equipment with the number of ships on the x-axis and the access ordering on the y-access. The number of docks is indicated by the color of the points.

The next step will be to explore specific scenario offloads. This will require the specification of the required equipment set and an offload plan derived from the actual load plans to

Team 8

include the deterministic offload order vice a random order and the not required equipment set to be offloaded.

SUMMARY AND WAY AHEAD

The access of equipment plays a significant role when offloading a LTMU equipment set during an MPF supported operation. The access of the equipment has two components, the size of the equipment set that is not required but must be offloaded and the relative ordering of the not required and required sets. We found that the size of the not required equipment set is the most significant factor and that it has the most effect on the time to throughput the required equipment. However, this effect decreases as the size of the required set of equipment increases. The two are related because the total amount of equipment on a MPSRON is finite and fixed.

The relative ordering of the equipment sets is not significant and has a relatively small effect on the time to throughput the required equipment. However, the true effect may be masked by the choice of metric. The time to throughput all of the required equipment to its final destination is tied to the last piece of equipment. The shape of the accumulation curve at the final destination (green line in Figure 1) is not considered. The majority of equipment could arrive relatively quickly while a few items are delayed at the end thus skewing the final time to complete the throughput. The impact of this choice of metric must be further explored.

International Data Farming Workshop 22

When: 20 - 25 March 2011

Where: Naval Postgraduate School, Monterey, California

Data farming is a capability that makes use of high performance computing to run models many times. This capability gives modelers and analysts an enhanced ability to discover trends and outliers in results, do sensitivity studies, verify and validate over extended ranges of input parameters, and consider modeling and analyzing non-linear phenomena with characteristics that cannot be precisely defined. The International Data Farming Workshops have been a forum for the exploration of important questions for many years. The cores of the workshops are teams that are formed around these questions. These multi-disciplinary teams use data farming practices including simulations, such as agent based models, rapid model prototyping, high performance computing, and data analysis, state-of-the-art design of experiments, parameter space exploration, and collaborative environments. The first workshop took place in Maui in 1999 and the workshop coming up in Monterey next month is number 22. We now have 12 teams lined up for IDFW 22 and whether you are a newcomer to the workshops or have participated in the past, we welcome you to participate!

IDFW 22 Tentative Agenda

- **Sunday, March 20:** Optional technical sessions; Opening reception and dinner
- **Monday, March 22:** Opening briefs and team poster sessions in the morning, then begin work in teams
- **Tuesday - Wednesday, March 23 - 24:** Work in teams
- **Friday, March 26:** Outbriefs and Closing Ceremony in the afternoon

More Info : http://harvest.nps.edu

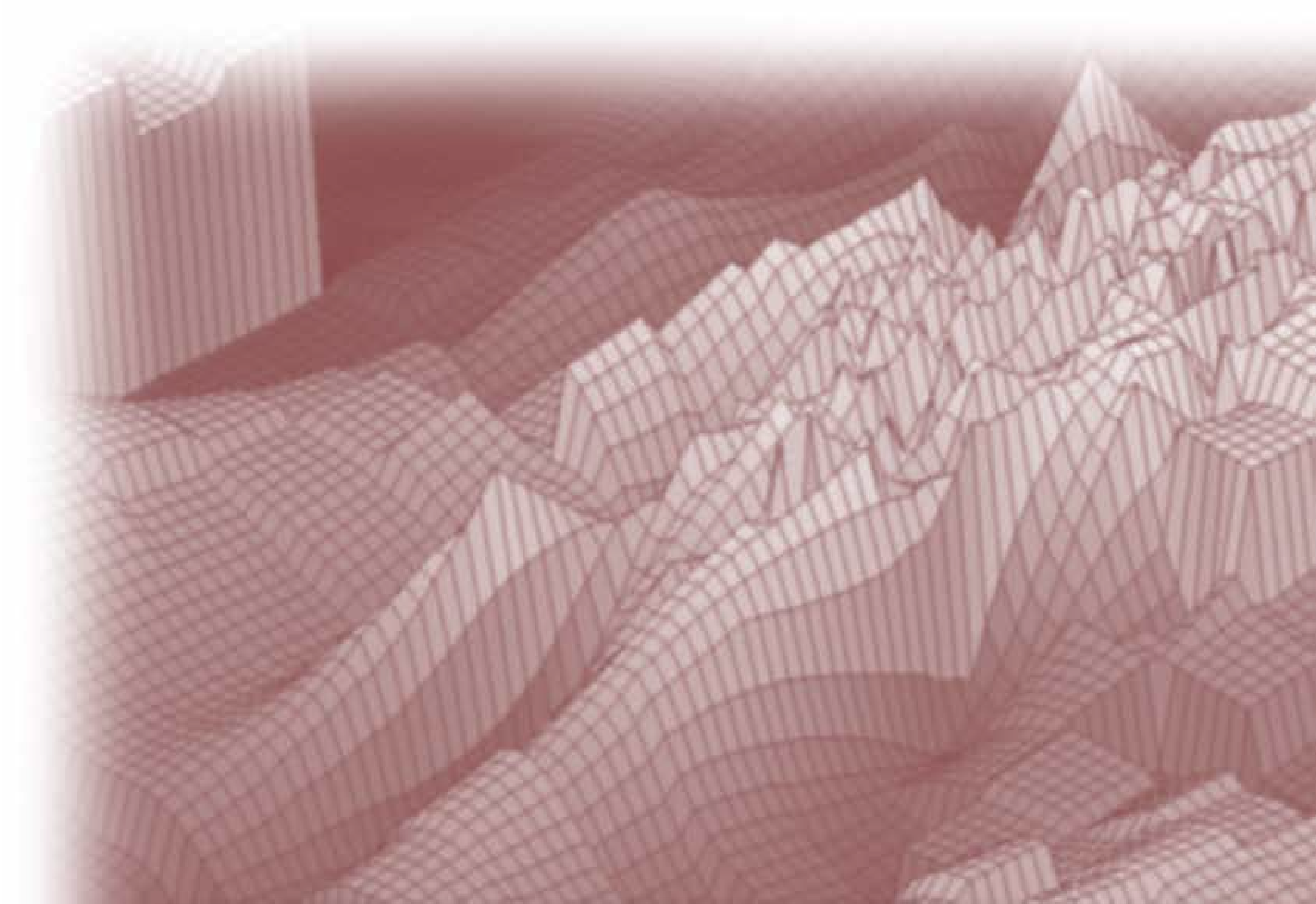
Call for Team Leaders : Please email gehorne@nps.edu if you want to lead a team.

Theme: Enrichment II

International Data Farming Workshop 22

March 20-25, 2011

Monterey, California



Scythe - Proceedings and Bulletin of the International Data Farming Community
Seed Center for Data Farming
273 Glasgow Hall ~ Naval Postgraduate School ~ Monterey, CA 93950

Issue 9 - Workshop 21