Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

ALIGNING WILDFIRE MANAGEMENT RESOURCING DECISIONS WITH OPERATIONAL NEEDS

Ericson R. Davis
Christopher D. Johnson
David J. Levin
Rachel C. Morowitz
David K. Peterson
Michael R. Pouy
Vitali Volovoi

LMI
2000 Corporate Ridge
McLean, VA 22102, USA

ABSTRACT

A hierarchical modeling and simulation (M&S) framework can help federal agencies integrate the myriad business resourcing decisions they face as unmanned aerospace vehicle (UAV) systems are deployed within their federally authorized charters. An integrated M&S method offers a pragmatic approach to leveraging the power of analytical techniques and coping with the complex support requirements of modern macrosystems. In this paper, we demonstrate the benefits of incorporating several agent-based modeling (ABM) enhancements for UAV route planning into a hierarchical M&S structure.

1 INTRODUCTION

The level of resourcing available to an organization (be it civil or governmental) is determined in a complex web of interrelated decisions that span broad time horizons. Strategic resourcing plans consider decisions with a time horizon of more than 5 years; tactical resourcing plans consider requirements 1 to 5 years out; and operational resourcing plans drive decisions within the year. The outputs of one planning activity become the inputs for the next. Strategic resourcing decisions define multiyear, aggregate-level resource availability, which, in turn, bound the feasibility of tactical resource decisions. These tactical decisions disaggregate strategic-level resourcing to the working level and ultimately are translated into monthly, weekly, and daily operational resource allocations.

1.1 Federal Budget Guidance is Motivating Analytics

The complexity of the federal budget environment necessitates the use of sophisticated and integrated modeling and simulation (M&S) techniques, whereby managers can determine the most efficient and effective mix of resources required to sustain their systems and defend their agency budgets. This point was brought home in Office of Management and Budget (2014), which stated, “The Administration is committed to using taxpayer dollars effectively and efficiently.”

1.2 Two Agencies’ Analytical Reponses

Acknowledging the value that analytics can bring to helping an agency better manage its resources, many agencies are incorporating analytics into their resourcing decision process. For example, with the advent of the Space Launch System, the National Aeronautics and Space Administration (NASA) Administrator put forward "three principles for development of any future systems for exploration—namely that these systems must be affordable, sustainable, and realistic." (NASA 2011)

Similarly, with the drawdown from Iraq and Afghanistan, the U.S. Air Force is facing significant force restructuring and realignment decisions. At a recent Air Force Association event, Secretary of the Air Force Deborah Lee James noted that the Air Force needs to "deliver this value to taxpayers with programs that are on budget [and] on schedule…" (Mehta 2014)

As NASA and the Air Force have learned, keeping a program affordable, sustainable, realistic, on budget and on schedule requires analytics.

1.3 Federal Managers Still Face Analytics Challenges

This vision of efficiency and effectiveness also extends to the wildland fire community, as interview comments by Tom Harbour, Director of Fire and Aviation Management for the U.S. Forest Service, reveal: "[W]e don't have any problems, usually, activating assets; it's making sure we use them effectively and making sure that we've got these assets for tomorrow and the next day." (Lauren 2009)

Of course, bringing analytics to bear on federal resource management decisions is easier said than done. A 2011 Government Accountability Office (GAO) report found the Forest Service had persisting management challenges within "wildland fire management, data on program activities and costs, and financial and performance accountability." (GAO 2011)

1.4 Business Analytics—A Match for Federal Analytics Needs

For federal resource managers, the types of analytical tools they need are generally categorized as "business analytics." According to Evans (2012), business analytics is commonly viewed from three major perspectives: descriptive, predictive, and prescriptive. *Descriptive* analytics use data "to understand past and current business performance and make informed decisions." *Predictive* analytics consider "past performance in an effort to predict the future by examining historical data, detecting patterns or relationships in these data, and then extrapolating these relationships forward in time." *Prescriptive* analytics use "optimization to identify the best alternatives to minimize or maximize some objective."

A comment by Parlier (2014), although directed towards Department of Defense analytics, rings true for today's federal resource manager: "Transformational analytics can provide engines for innovation that generate and sustain continuous improvement in demanding, increasingly resource-challenged environments."

2 BACKGROUND

The resourcing environment facing federal agencies is a complex series of cascading decisions that span wide-ranging time horizons, where the outputs of one resourcing decision become the inputs for the next. For example, multi-year strategic resourcing decisions set aggregate-level budgetary and resource availability. Tactical decisions translate strategic resourcing decisions into working-level resource investments on a year-by-year basis. Finally, operational resource decisions deploy resource investment into actionable yearly activities.

2.1 The Need for Integrated Resourcing Decisions

By employing hierarchically integrated modeling and simulation techniques, federal agencies that deploy unmanned aerospace vehicles can ensure consistency in the resourcing of UAV programs across relevant budgetary time horizons. Further, an integrated approach is essential for ensuring effective macrosystem performance of such systems.

Even the best resourcing techniques will achieve only locally optimized solutions if a macrosystem's ultimate operational performance is not considered when making strategic-level resourcing decisions. As recently noted by the Subcommittee on Unmanned Systems (SUS 2013), "With the demand for such systems becoming higher, and resources becoming more limited, a more careful government-wide approach to the acquisition and utilization of unmanned systems is required."

2.2 Recent History of Integrative M&S Research

Modern engineering systems have become highly complex and interrelated macrosystems—sometimes referred to as systems-of-systems—that depend on the complementary performance of their components to achieve a larger common objective. The question for federal UAV operators and managers becomes—how to sustain a UAV in a fully operational state, especially when resources and budgets are constrained? Unfortunately, no single M&S technique completely fulfills the analytical role needed for achieving and sustaining operational capability at an affordable cost. This is where a hierarchically integrated set of M&S techniques can prove useful.

Our most recent research (Davis et al. 2013) differed from the previous integrative literature in two ways. First, our integration of network design (infrastructure), inventory optimization, and operational system performance had not been done for real-world problems related to UAV resourcing. Second, we integrated models whose performance could not be described with simple parameters or expected values. Rather, we optimized infrastructure resourcing based on the expected operational reward according to the historic wildfire risk elements related to the wildand-urban interface.

The current research implemented a limited-scale hierarchically integrated resourcing model. Our strategic-level mathematical program solved the infrastructure problem, with the goal of maximizing ultimate system performance at the operational level. Similarly, the tactical-level inventory optimization recommended an inventory investment suitable to the desired system availability.

While the implementations of strategic- and tactical-level optimizations were important first steps, their solutions needed to be examined further for overall operational (mission) effectiveness. To better assess the macro system's mission performance, we used a stochastic Petri net simulation (Volovoi 2006) to model the UAV-generated flying hours and an agent-based model (ABM) to estimate the UAVs' effectiveness in the timely detection of wildfires.

2.3 Literature Review

Published literature in the area of our research is almost exclusively confined to single aspects of our hierarchy of network optimization, readiness-based inventory optimization, agent-based modeling and optimal search algorithms. There is extensive research in the area of inventory optimization to meet equipment readiness objectives (see O'Malley and Peterson 2010 for a comprehensive review of the evolution of such models). Facility location optimization, such as for our network of UAV home station airports, has been approached in multiple ways, often as a set covering problem. Two relevant examples involve location optimization for search and rescue stations: Afshartous, Guan, and Mehrotra (2009) for the U.S. Coast Guard, and Başdemir (2004) for the Turkish Air Force. Agent-based modeling literature offers several relevant examples. Zhang and Brown (2013) use ABM to assign patrol districts for a police force, and Calvez and Hutzler (2006) present a method for tuning ABMs using genetic algorithms.

Most relevant to our immediate problem are those works pertaining to search path optimization. The area is well-studied, for the wildfire case specifically as well as more generalized target searching and threat avoidance problems. Several papers treat the UAVs as Durbin vehicles in a series of radius-constrained movements ending in specific locations and orientations. In such cases, the objective is to minimize paths to reach specific destinations (with assigned orientation). These are less relevant because, while UAVs do have a limited turning radius, our problem sees the paths not as a set of routes to be minimized, but as a way to accumulate the maximum reward. Schumacher et al. (2007) discuss a military scenario in which multiple UAVs are used (in sequence) to identify, destroy, and verify targets. They treat the problem as a scheduling problem that can be solved with mixed-integer linear programming (MILP);

each UAV is assigned a series of tasks in a way that minimizes the total time required to accomplish the total mission.

Most works specifically related to wildfires are oriented toward monitoring existing wildfires as opposed to searching broad swaths of terrain for previously undetected fires. For example, Merino et al. (2005) address the problem of uncertainty in fire detection by establishing a cooperative framework to process the information from multiple UAVs. Casbeer et al. (2005) developed an effective path planning algorithm for UAVs monitoring existing wildfires by identifying the leading edge of the fire and setting waypoints to follow that edge.

2.4 Summary

Given the current need within the federal UAV community to better quantify and document UAV program costs and resourcing, we suggest a hierarchical modeling and simulation framework can help federal agencies integrate the myriad business resourcing decisions they face as systems are deployed within their federally authorized charters. Our hierarchically integrated M&S methodology offers federal UAV operators and supportability managers a pragmatic and effective approach that leverages the power of complementary analytical techniques for coping with the complex support requirements of modern macrosystems.

In this paper, we demonstrate several ABM enhancements to increase the integrated M&S hierarchy's capability. The first is to fine tune the ABM's calibration in terms of event speed. Another improvement is in measuring the effectiveness of aerial surveillance; it would be preferable to deploy the mathematical program's reward (heat) map into the ABM and record a measure of relative rewards. We also wish to make the ABM sufficiently robust that it can serve as a platform for testing the relative effectiveness of alternative search patterns or algorithms while incorporating complex topographical and environmental factors.

Wildfire management agencies are highly skilled at developing and employing a variety of systems to fight wildfires. However, these same agencies must also quantify, document and project system costs and budgets. Hierarchically-integrated business analytics (linking strategic, tactical and operational decisions) can help agencies better address the many resourcing challenges involved with developing, deploying and sustaining the equipment needed to support their wildfire management missions.

3 METHODOLOGY

We consider an MQ-1 Predator UAV unit deployed to observe and report wildfire activity within a selected geographic region. The MQ-1s are operated from select bases servicing specified orbital areas located to maximize the MQ-1s' surveillance coverage over areas of high fire risk along a wildland-urban interface. The MQ-1 bases are resourced to be self-sufficient for 30 days of deployed operations, but they can also be supported from higher echelon logistics facilities (e.g., depots and manufacturers) if required (or desired).

3.1 Visualization

Visualization plays a key role in identifying, understanding, and communicating the behavior of the wildfire activity being modeled. Our modeling efforts are based on a visualization of the wildfire activity. Through the use of NetLogo, we can set parameters and add heat maps to determine a search path, and then calculate rewards associated with the generated path.

3.1.1 NetLogo

We selected NetLogo for our modeling environment because of its extensive visualization and experimentation capabilities. By running various experiments around flight characteristics (e.g., changing

UAV swath width or altitude) we can quickly determine optimal solutions. With NetLogo, we can set parameters for our experiments and also add a heat map to test the performance of the model.

3.1.2 Heat Map

An objective function based on a static reward structure, such as a heat map, can create a reasonably desirable set of outcomes. For this research, we developed heat maps by randomly generating complex reward structures. However, we can also create heat maps by assigning different weights to population density and forest coverage for the reward intensity calculation. For example, by dividing a region of interest into discrete grid squares of approximately 4 square miles, for the grid space at coordinate (i,j), we can quantify the value r_{ij} associated with monitoring that space in the following way:

$$r_{ij} = \alpha F(i,j) * (1-\alpha) D(i,j,\sigma).$$

Here, F(i,j) is the percentage of forest coverage of grid space at (i,j), D(i,j,σ) is the Gaussian smoothed population density (smoothing parameter σ), and $\alpha \in [0,1]$. The requisite population density and forest coverage information can be developed from vegetation and population images. (Davis et al. 2013)

3.2 Path Generation

To measure the effectiveness of MQ-1s in detecting and monitoring wildfires, we compare two types of models—one based on a fixed-path strategy and one based on an autonomous UAV strategy. In the first strategy, we determine fixed optimal paths in various scenarios by using a randomized search. In the second strategy, we determine autonomous actions using a neural network.

For wildfire detection, we need to develop models that compare different employment strategies with UAVs that look for fires where the potential for a large fire is high. This involves determining the optimal path using a fixed path strategy, and determining what are the important flight path variables to consider for autonomous UAVs.

For monitoring wildfires, we want to develop models that compare different employment strategies—the use of a single UAV following a fixed path or acting autonomously—to track the spread of a large forest fire under different scenarios. Of course, the value of monitoring one area for wildfires may not be the same as the value of monitoring other areas, even for equally sized areas. For example, an intense fire could spread quickly in a dense boreal forest, whereas in a grassland region, fuels for a wildfire may be less concentrated allowing the fire to be more readily contained; therefore, expending resources to monitor the forest may be considered of greater "value." Moreover, regions with higher population densities are intrinsically more valuable because of the higher likelihood of loss of life or property.

3.2.1 Evaluator

To compare the fixed path against the autonomous approach, an evaluator is defined that measures the effectiveness of a path. Given a heat map, the effectiveness of a path is defined by the formula:

$$100 * \frac{\sum v_{i,j}}{\sum r_{i,j}}$$

where $v_{i,j}$is 0 if the space at coordinate i,j has not been viewed by the UAV; otherwise the value is $r_{i,j}$. Thus the effectiveness or coverage of a path represents a percentage in the range [0, 100]; that is, a percentage of the area viewed by the UAV for fires.

3.2.2 Fixed Path: Randomized Search

Given a heat map, a fixed path is generated that optimizes the coverage using the evaluator. The randomized search model is run iteratively for a fixed number of steps. On each step a fixed path is generated and the coverage of the generated fixed path is calculated. If the coverage exceeds the coverage of a previously generated fixed path, the new fixed path is marked as preferred. After a specified number of steps, the best path is identified, but this is not necessarily the most optimal path. The higher the value of the number of steps evaluated, the more likely that is it the most optimal path, but it cannot be shown to be the most optimal path.

A path consists of a specified number of segments. In the NetLogo model this is identified as FLIGHT-TIME. At each segment the model determines the next heading on which to proceed. The UAV's speed is fixed. In the NetLogo model this is identified by UAV-SPEED.

To determine the heading, the model looks at possible locations in the cone determined by current heading and the view radius and view angle (these are specified in the NetLogo model by VIEW-RADIUS and VIEW-ANGLE). If the view angle is 0 degrees, the model looks only at possible locations directly in front of the UAV, but no further out than the view radius. If the view angle is 360 degrees, the model looks at all locations within a distance determined by the view radius.

Given possible locations, the model determines which locations have the highest $r_{i,j}$ value. The UAV will face that direction unless a random value is thrown that is less than a random number threshold indicated in the NetLogo model by RANDOM-PATCH. If that is the case, a random location is chosen from one of the possible locations. This is the randomizing component of the route selection process.

Figure 1 depicts a sample output of the randomized search model. (In the findings section, we discuss how to determine the optimal values of view radius, view angle, and random patch.)

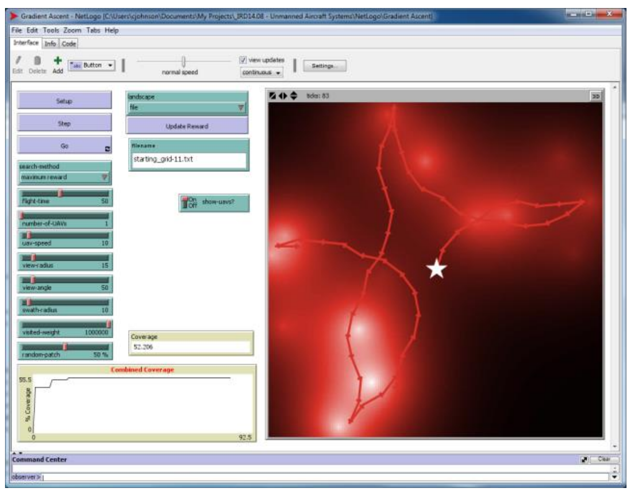

Figure 1: Randomized search sample output.

3.2.3 Autonomous Actions: Neural Network

This version of our UAV Optimization model can be used against a changing reward map, representing an existing wildfire which is spreading over time. The search path is determined by a neural network that updates the flight path periodically during flight time. The network is written in Java and uses a NetLogo Java extension to interface between NetLogo (randomized search pattern) and the Java Extension.

This model gives intelligence to the UAVs so they can respond to changing conditions. It also gives us a way to model areas with active fires that have potential for expanding. The model is based on inputs such as current direction, location of other UAVs, and fire hazards. The outputs are combined to determine a new heading. Important variables to consider with this model include distance to other UAVs (to avoid collisions and wasteful overlap), areas with a potential for large fires, fuel (to allow time to return to base), and tracking areas previously observed (to minimize time flying over duplicate paths).

Each time the application is asked for a new heading, it collects data for every grid in the search space. These data are passed into the neural network as inputs using the following aggregation:

$$Input_i = \sum_G \left(R(g_{xy}) e^{-d_i(\rho_i(g_{xy})-\mu_i)^2} - O_i(g_{xy}) e^{-h_i(\rho_i(g_{xy})-\mu_i)^2} \right) e^{-\sigma_i(g_{xy})/(v_i\rho(g_{xy})+1)}.$$

Inputs to the model:

- g_{xy} is the grid space at (x,y)
- $R(g_{xy})$ is the probability of fire for g_{xy}

Calculated values for each input node:

- $\rho_i(g_{xy})$ is the distance in the direction associated with input node i at which g_{xy} is normal to the curve
- $\sigma_i(g_{xy})$ is the minimum distance from g_{xy} to the direction associated with input node i

Values tuned to optimize UAV performance with respect to coverage:

- $O_i(g_{xy})$ is the penalty parameter for input node i that is applied if g_{xy} is occupied
- μ_i is the offset parameter for input node i
- d_i is the direct decline parameter for input node i
- v_i is the lateral decline parameters for input node i

The number of input nodes is the product of the two following analyst-provided settings:

- Number of directions to look in
- Sensors per direction

The neural network has two output nodes, both of which use a sigmoid activation function. After calculating the values for each output node, a new direction for the UAV is determined in the following way:

$$\Delta direction\ (degrees) = 180 * (0.5 - output_1/(output_1 + output_2)).$$

The analyst must also determine the number of hidden layers/nodes per layer to be used in the neural network. Once the neural network configuration is determined, we employ a genetic algorithm-based approach to tune the parameters given above, the activation function parameters for any hidden nodes, and the weights associated with the arcs connecting nodes of the neural network. Figure 2 depicts a sample output of the neural network model (for three UAV missions originating from a single base).

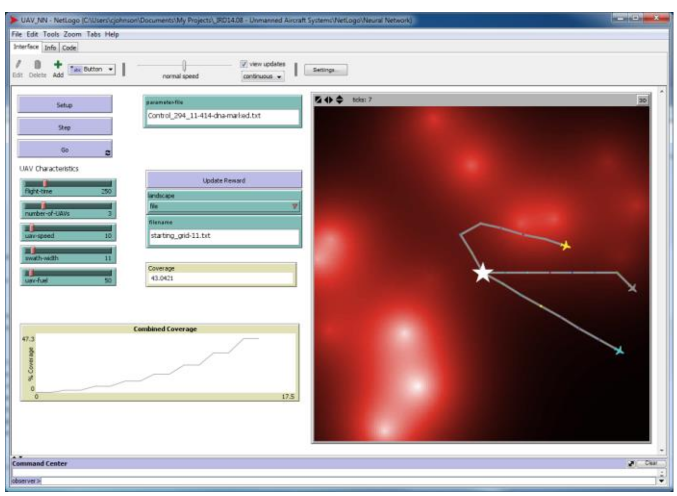

Figure 2: Neural network sample output.

4 DISCUSSION

After selecting an evaluator, we ran several experiments with a variety of heat maps. These results are presented in the following sections.

4.1 Fixed Path (Stationary Environment)

We performed 1,620 runs in which we changed the parameter settings for RANDOM-PATCH, VIEW-ANGLE, and VIEW-RADIUS and compared the coverage against the parameter settings. We varied RANDOM-PATCH from 10 to 50 by 10; the VIEW-RADIUS from 10 to 50 by 5; and the VIEW-ANGLE from 10 to 180 by 10. There was a weak inverse relationship between the RANDOM-PATCH and VIEW-RADIUS parameter settings and coverage, as shown in Table 1.

Table 1: Correlation between parameters and coverage.

Parameter	Linear correlation coefficient
RANDOM-PATCH	−0.15346
VIEW-ANGLE	0.09306
VIEW-RADIUS	−0.23397

The percentage of coverage is somewhat sensitive to the VIEW-ANGLE, as Figure 3 illustrates.

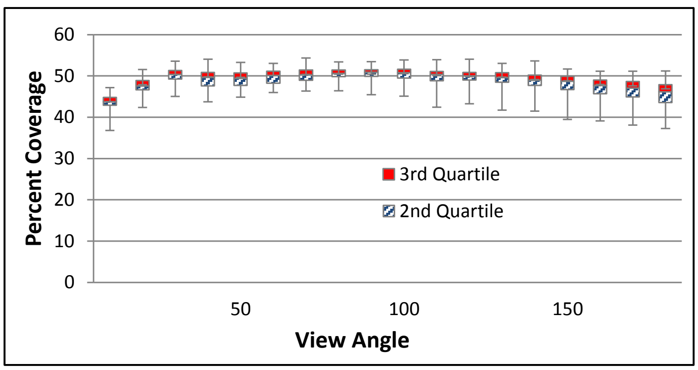

Figure 3: View angle vs. percent coverage.

While percentage of coverage is noticeably decreased when the VIEW-ANGLE is very small or very large, its variation in coverage is also noticeably more sensitive than when the RANDOM-PATCH or VIEW-RADIUS is changed, as shown in Figure 4.

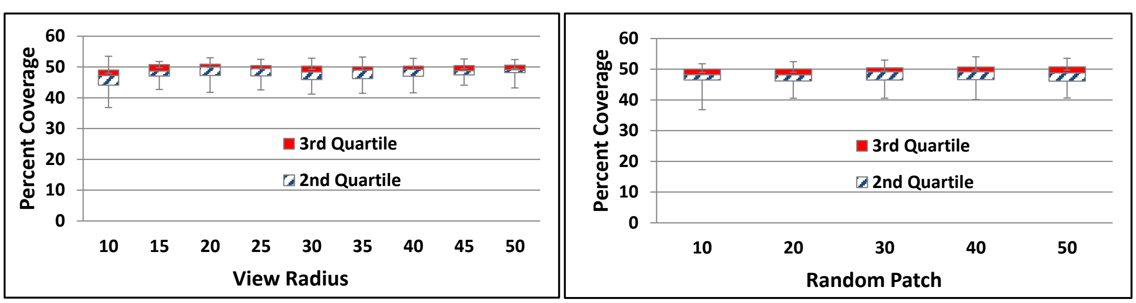

Figure 4: Percent coverage vs. settings (view radius and random patch).

4.2 Neural Network (Stationary Environment)

Three analyst-determined model settings are available for configuring the neural network: the number of directions from which to gather information, the number of sensor locations along each direction, and the number of hidden layers/nodes per layer to use in the neural network.

We have yet to perform an exhaustive sweep across all possible neural network parameter combinations; the genetic algorithm-based training process requires a significant amount of time to perform when computing resources are limited. However, early results indicate neural networks equipped with a hidden layer tend to perform more poorly than simpler models. For the comparison results below, we use a neural network with 12 directions of observation and three sensor locations per direction. We anticipate continued refinement of the neural network results will demonstrate that more complex models achieve better performance with further training.

4.3 Common Evaluation Framework

4.3.1 Using Different Heat Maps

We generated fixed paths against different heat maps and determined how the average percentage of coverage varied across different heat maps. Table 2 compares the average percentage covered using a fixed path and a neural network after 100 ticks. Of course, the percentage of coverage would increase the longer the UAV is flown. It appears that the percentage of coverage is better for heat maps (Figure 5) where the reward is more localized as in grid-13 and grid-16.

Table 2: Average percent covered using fixed path and neural network.

Heat Map	Percent coverage using a fixed path after 100 ticks	Percent coverage using a neural network after 100 ticks
grid-11	51.4	30.7
grid-12	48.7	28.6
grid-13	63.5	40.4
grid-14	52.0	42.8
grid-15	48.5	36.8
grid-16	57.3	40.9

4.3.2 Percent Reward

Although the fixed path consistently had a higher percent coverage than the neural network approach, as flight length increased, the difference between the two methods diminished. Table 3 summarizes the percent coverage for various flight times against the grid-11 heat map. One potential advantage of the neural networks is being able to respond to changing heat maps, which would outweigh the better percent coverage of the fixed path approach. Another advantage of the neural network approach is that it is repeatable (unless a fixed seed is used in the fixed path's randomization process).

Table 3: Percent coverage for various flight times, using grid-11 heat map.

Flight time	% coverage, fixed path	% coverage, neural network	% difference
50 min.	33.1	11.7	21.4
100 min.	53.8	30.7	23.1
150 min.	63.9	42.7	21.2
200 min.	69.6	56.4	13.2
250 min.	77.9	71.1	6.8

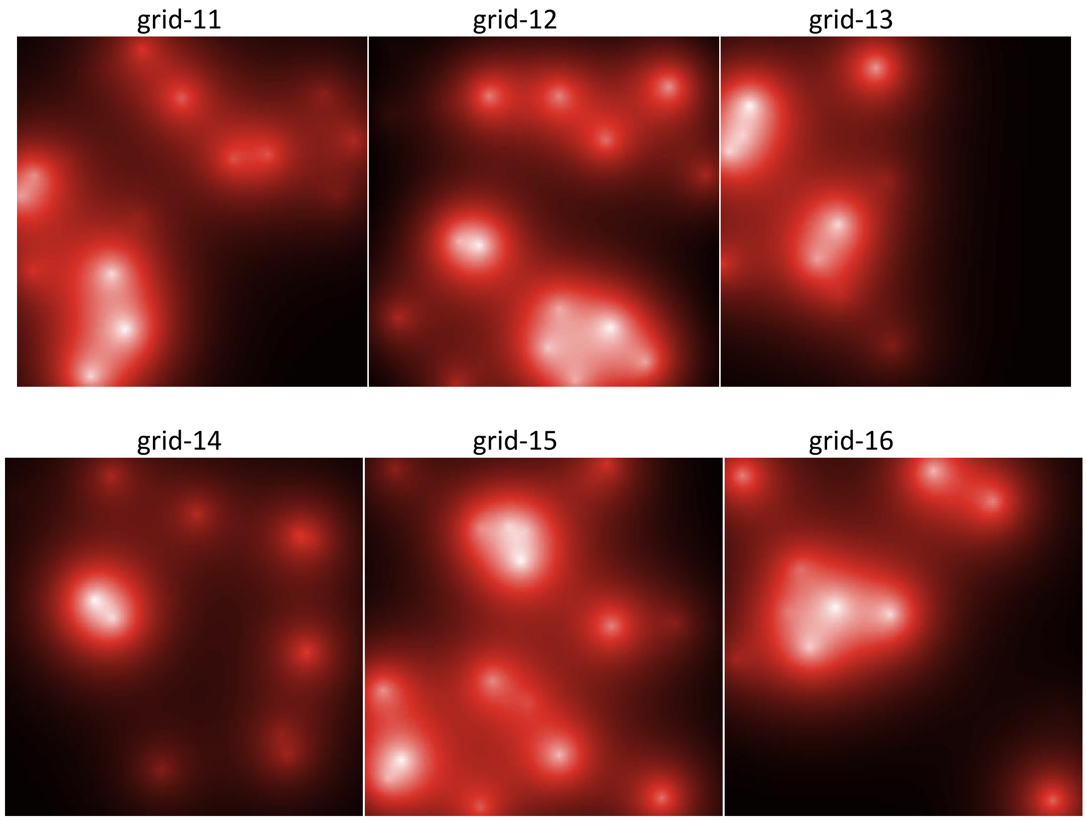

Figure 5: Sample heat maps.

4.3.3 Visualization

Figure 6 is a visual comparison between the fixed path and neural network against the grid-11 heat map for a flight time of 250 ticks. The green dashed line is the path followed by the neural network; the yellow solid line is the fixed path.

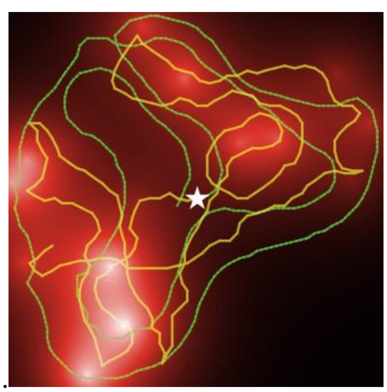

Figure 6: Visual comparison of fixed path (yellow) and neural network (green), grid-11 heat map.

5 SUMMARY

The proposed hierarchically integrated M&S methodology offers macrosystem designers, operators, and supportability managers a pragmatic approach to leverage the power of complementary analytical techniques for coping with the ever-more complex support requirements of modern macrosystems.

We implemented a hierarchically integrated resourcing model, albeit on a limited scale. While the implementation of a strategic-level optimization (which optimizes according to an approximation of the ultimate performance) is an important first step, that solution must be examined for its overall effectiveness.

To measure the potential of UAVs in detecting and monitoring wildfires, we explored two alternatives—a fixed path strategy and an autonomous UAV strategy. For wildfire detection we compared UAV flight path strategies to detect fires where the potential for a large fire is high. For monitoring wildfires we compared employment strategies of a single UAV following a fixed path versus acting autonomously to monitor the spread of an active forest fire under different scenarios. Based on coverage performance, the fixed path strategy is the preferred method when using a static heat map while an autonomous strategy is the preferred method when using a dynamic heat map.

Future research includes evaluating against a dynamic heat map (e.g., a forest fire spreading over time). Also, building composite heat maps derived from US Forest Service and US Geological Survey data systems to include possible criteria such as: terrain, forest coverage, fuel load, water/moisture, population, etc.

An integrated approach is essential to achieve "good," if not optimal, performance in a macrosystem hierarchical model. Even the best solution techniques will only achieve locally optimized solutions if the ultimate performance of the operational model is not addressed in the strategic-level decisions.

REFERENCES

Afshartous, D., Y. Guan and A. Mehrotra. 2009. "US Coast Guard Air Station Location With Respect To Distress Calls: A Spatial Statistics And Optimization Based Methodology." *European Journal of Operational Research* 196(3):1086-1096.

Basdemir, M. M. 2000. "Locating Search and Rescue Stations in the Aegean and western Mediterranean Regions of Turkey." MS Thesis. School of Engineering and Management, Air Force Institute of Technology, Wright-Patterson AFB.

Calvez, B. and G. Hutzler. 2005 "Automatic Tuning of Agent-Based Models Using Genetic Algorithms." In *Multi-Agent-Based Simulation VI*, edited by J. S. Sichman and L. Antunes, 41-57. Springer.

Casbeer, D. W., S. Li,, R. W. Beard, R. K. Mehra, and T. W. McClain. 2005. "Forest Fire Monitoring With Multiple Small UAVs." In *Proceedings of the American Control Conference*, 3530-3535.

Davis, E., J. Eckhause, D. Peterson, M. Pouy, S. Sigalas-Markham, and V. Volovoi. 2013. "Exploring How Hierarchical Modeling and Simulation Can Improve Organizational Resource Decisions", *Proceedings of the 2013 Winter Simulation Conference*, edited by R. Pasupathy, S.H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, 2496–2507. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Evans, James R. 2012. "Business Analytics: The Next Frontier for Decision Sciences." *Decision Line* 43(2): 4-6.

GAO. 2011. "Forest Service: Continued Work Needed to Address Persistent Management Challenges." GAO-11-423T. Government Accountability Office. Washington, DC.

Lauren, B. 2009. "Interview with Tom Harbour of the U.S. Forest Service." Fire Department Network News. Accessed February 11, 2014. http://www.fdnntv.com/Interview_with_Tom_Harbour_of_the_US_Forest_Service.

Mehta, Aaron. 2014. "USAF Secretary Sees Smaller Force in Future." Defense News. Accessed January 29. http://www.defensenews.com/article/20140129/DEFREG02/301290031/USAF-Secretary-Sees-Smaller-Force-Future.

Merino, L., F. Caballero, J. R. Martínez-de Dios , and A. Ollero. 2005. "Cooperative Fire Detection using Unmanned Aerial Vehicles," *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, 1896-1901.

NASA. 2011. "Preliminary Report Regarding NASA's Space Launch System and Multi-Purpose Crew Vehicle." National Aeronautics and Space Administration. Washington, DC.

Office of Management and Budget. 2014. "Analytical Perspectives: Budget of the U.S. Government Fiscal Year 2015 Budget." Washington, DC.

O'Malley, T. J. and D. K. Peterson. 2010. "The Evolution of Readiness-Based Sparing Models." *Logistics Spectrum*, 44: 17-21.

Parlier, Greg. 2014. "The State of U.S. Military O.R." *OR/MS Today* 41(1): 18-24.

Schumacher, C., P. R. Chandler, M. Pachter, and L. S. Pachter. 2007. "Optimization of Air Vehicles Operations Using Mixed-Integer Linear Programming." *Journal of the Operational Research Society*. 58(4): 516-527.

SUS. 2013. "Federal Unmanned Systems: Status, Issues, and Recommendations." Subcommittee on Unmanned Systems. Washington, DC.

Volovoi, V. 2006. "Stochastic Petri Nets Modeling using SPN@." In *Proceedings of the Reliability and Maintainability Symposium*, 75-81, Newport Beach, California.

Zhang, Y. and D. E. Brown, 2013. "Police patrol districting method and simulation evaluation using agent-based model & GIS." *Security Informatics* 2(1):1-13.

AUTHOR BIOGRAPHIES

ERICSON R. DAVIS received his undergraduate degree in mathematics from Washington and Lee University and is working to finish up his master's degree in mathematics from George Mason University. His email address is edavis@lmi.org.

CHRISTOPHER D. JOHNSON has extensive data processing experience in the areas of data base management systems and application development. He has an undergraduate and master's degree in mathematics from the University of Maryland. His email address is cjohnson@lmi.org.

DAVID J. LEVIN is a senior consultant with a focus on designing, administering, and analyzing surveys. He has a BA in political science from the University of Illinois, Urbana-Champaign, and a PhD in government from American University. His email address is dlevin@lmi.org.

RACHEL C. MOROWITZ has nearly 20 years of consulting experience in financial analysis, human resources, and information systems. She has a BA in mathematics from the University of Virginia and an MBA from Duke University's Fuqua School of Business. Her email address is rmorowitz@lmi.org.

DAVID K. PETERSON is a senior consultant specializing in readiness-based sparing inventory modeling. He earned his Ph.D. in Production and Operations Management from the University of North Carolina in 1987. He is a retired U. S. Air Force logistician. His email address is dapeterson@lmi.org.

MICHAEL R. POUY has over 40 years of experience in Operations Research. He holds a bachelor's degree in Mathematics from Villanova University and a master's degree in Operations Research from George Washington University. His email address is mpouy@lmi.org.

VITALI VOLOVOI is an independent contractor to LMI. He holds a Ph.D. in Aerospace Engineering from the Georgia Institute of Technology. His email address is vvolovoi@lmi.org.