Regular Papers

Model Driven Experimentation

Alexander H. Levis[1,*] and W.S. Vaughan[2]

[1]C3I Center, MSN 4D2, George Mason University, Fairfax, VA 22030

[2]Office of Naval Research, 800 N. Quincy Street, Arlington, VA 22217

Received February 5, 1999; revised May 21, 1999

ABSTRACT

Experiments with teams of human subjects in which they carry out realistic decision-making tasks are difficult to design and control. There are many variables, each one with a wide range of values. The use of detailed executable models in the design of experiments is perceived as one feasible approach to address these issues. A process for the use of modeling and simulation in the design of complex experiments that address command and control issues is described; the approach is then generalized to address series of experiments. The current theoretical and experimental research effort on Adaptive Architectures for Command and Control (A2C2) is used to illustrate the approach. © 1999 John Wiley & Sons, Inc. Syst Eng 2: 62–68, 1999

1. INTRODUCTION

Adaptation is one mechanism that organisms use to cope with change. The military establishment is undergoing drastic change in a way that is very similar to the changes that have been occurring during the last decade or so to industry. Globalization and information technology forced restructuring and changes in the operating procedures for many organizations; similarly, uncertainty in requirements, rapidly changing technology, and fundamental changes in the way forces are organized to execute diverse missions that fall short of conventional war, are the reasons for reexamining organizational structures and for focusing on architectures for command and control. Addressing the problems at the architectural level, a level of abstraction above the system design level, one suppresses the specific details of the changing technology and system implementation. Furthermore, interoperability issues are better solved first at the architectural level. Adaptive architectures are a level of abstraction higher than architectures, since an adaptive one subsumes many fixed architectures.

The objective in approaches that attempt to cope with change is to search for problem invariants—those aspects of the problem that do not change while other components do change. At the implementation level, the standards profiled in the technical architecture view

*Author to whom all correspondence should be addressed.
The work of the first author was sponsored by the Office of Naval Research; grant number N00014-93-1-0912

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **21 MAY 1999**	2. REPORT TYPE	3. DATES COVERED **00-00-1999 to 00-00-1999**

4. TITLE AND SUBTITLE **Model Driven Experimentation**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **George Mason University,System Architectures Laboratory,4400 University Drive,Fairfax,VA,22030**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
U.S. Government or Federal Purpose Rights

14. ABSTRACT
see report

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**7**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

[C4ISR Architecture Framework, 1997] provide the invariants: definitions of interfaces and message formats. At the architecture level, the operational architecture view provides the invariant: The systems architecture can evolve while supporting the given unchanged operational architecture. At the next level up, the operational architecture view may change, while still representing the same operational concept. The operational concept can be instantiated in terms of a task graph or several task graphs. An adaptive architecture is one that can accommodate multiple task graphs and multiple implementations of the same task graph. Thus, adaptive architectures represent an even higher level of abstraction.

The concept of the task graph is elaborated in the second paper in this issue [Levchuk, Pattipati, and Kleinman, 1999] and is exploited in the fourth paper [Handley, Zaidi, and Levis, 1999]. In some earlier work, Perdu and Levis [1998] considered one type of adaptation as a morphing process. An organization maintains its task graph, but reallocates the activities or functions in which the task has been decomposed to the different organization members in such a manner that, through a sequence of incremental function transfers, the organization morphs from one form to a different one while preserving functionality. Handley [1999] is considering adaptation as a change in the task graph, a change that preserves the operational concept but implements it in the form of a different task graph where the component functions may be different.

In conjunction with the development of a theory and a design procedure for organization design and adaptation, an experimental program has been undertaken at the Naval Postgraduate School under the sponsorship of the Office of Naval Research. The experimental program involves a number of teams carrying out a planning and execution task at the Joint Task Force level. The teams play the scenario using different organizational forms; they may start with one, and then they are given the opportunity to switch to another one. This is a complex experiment with multiple human subjects, a complex and demanding scenario, and many opportunities for decision-making. To handle the complexities of the experimental program, modeling and simulation have been used. The deliberate use of models has given rise to a procedure, called *model driven experimentation*, that has been refined over a series of five major experiments that build on each other. This procedure is described in this article; the other three articles in this issue address key technical aspects of the procedure.

The lessons learned from the development and application of model driven experimentation are believed to be relevant to the design of the Advanced Warfighting Experiments (AWEs) that are being undertaken by the Army, Navy, Air Force, and Marines, both at the service level and in Joint (multiservice) environments. The complexities of these experiments are immense. "The key challenge [in these experiments] is to develop tactics, techniques and procedures, and to evaluate advanced technologies that create or enhance future warfighting capabilities."[1] The implication of this statement that is applicable across the different AWEs is that in these experiments new operational concepts for new missions are being tested using essentially unchanged forces (the humans) in new organizational forms supplied with equipment with new capabilities. These large experiments that involve many thousands of humans are essentially live simulations (one run) within which focused hypotheses can be tested. At this time, a two-tiered approach has been used for a variety of reasons: short time line, limited resources. However, since a spiral development process is being used for the design and execution of these large scale experiment, it is possible to introduce a three tiered approach that uses model driven experimentation principles and procedures in the middle tier, as shown in Figure 1.

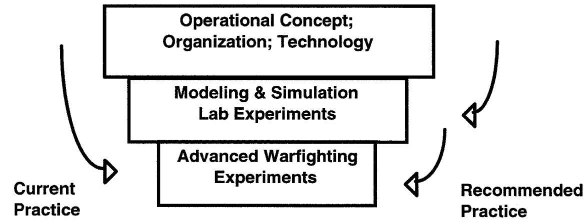

Figure 1 Two tiered versus three tiered process for the design of large-scale experiments.

Currently, an experiment is designed directly from an operational concept. While this may save time, it does reduce the probability that useful, reliable results will be obtained from the experiment. On the other hand, if the experiment is modeled first and then executed in simulation mode, it is possible to determine what data need to be collected and, more importantly, the values that the experimental parameters need to be set so that the desired phenomenon can be observed. This aspect is discussed further in Handley, Zaidi, and Levis [1999] in this issue.

In Section 2 of this article, the process for Model Driven Experimentation is presented. In Section 3, issues related to using the approach for large-scale experiments, such as the AWEs, are outlined, and a generalization of the approach is given.

[1]From a U.S. Marine Corps Warfighting Lab statement.

2. THE MODEL DRIVEN EXPERIMENTATION PROCESS

There exist several model taxonomies. One that is useful in this context is the categorization of models as predictive, explanatory, or prescriptive [Casti, 1997]. Predictive models are those that predict future behavior on the basis of system properties and current conditions. Models in physics such as Newton's laws or Maxwell's equations fall in this category. Explanatory models are those that provide a framework in which past observations can be understood as part of an overall process. Many economic models fall under this category. Finally, prescriptive models are those that offer an explicit way by which one can intervene to change the behavior of the system. Control theory models are typical examples.

In designing and conducting experiments, both predictive and prescriptive models are needed. Simulation models can be either predictive or prescriptive, depending on the manner in which they are used. The typical use of a simulation is in a predictive mode. A set of scenarios (a set of initial conditions and of inputs) is used to drive the model and the results are observed. To the extent that some of the inputs can be isolated and then manipulated in a controlled manner so that cause and effect can be identified, then the model is used in a prescriptive mode. In the model driven experimentation process, two types of model variables or parameters are varied in a controlled manner: those that are to be manipulated during the experiment, the independent variables, and those that set the conditions of the experiments, the operating point of the experiment.

The use of models in the experimental process brings with it all the usual concerns about model validity. Specifically, the models to be used must pass five tests: two of them technical tests and three that reflect the relationship of the user with the model [Levis and Levis, 1978]. In colloquial terms, the validation or coherence test addresses whether the model is a correct representation of reality, whether it captures the key relationships between variables, reflects correctly causes and effects. On the other hand, the test of verification or correspondence addresses whether the implementation of the model is correct. The test of clarity relates to the understandability of the model, to whether the reasons why results are the way they are appear transparent to the user. The fourth measure is a critical one: credibility. Does the user believe the results? Is he willing to act on them? Finally, the test of reliability can be thought of as credibility over time. Has the model produced credible results over a variety of scenarios and situations over time?

A second issue in using modeling and simulation for experiments involving humans is that one cannot predict the decisions the humans will make. On the basis of the operational concept and the constraints of the experimental context, it is possible to establish the set of alternative decisions. Consequently, one can run the models over the set of decisions. This becomes a problem when there are many decision-makers, each one with a wide choice of decisions. Fortunately, in the type of scripted experiments of military operations considered here, this problem of dimensionality of the decision space is manageable.

Given that it is possible to build credible models that represent the experimental situation, the question becomes how to use them effectively in the design and conduct of experiments. The Model Driven Experimentation process described in this section is one answer to this problem. It is an answer that has proven effective in the A2C2 program and shows promise for applicability to the large scale AWEs.

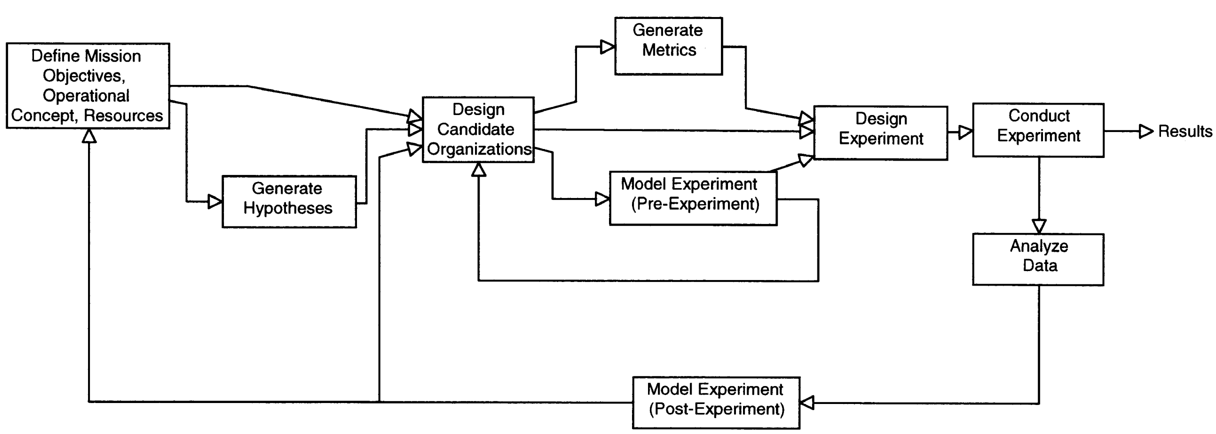

Figure 2 The detailed model driven experimentation process used in the A2C2 program.

A detailed block diagram of the process is shown in Figure 2. The first step is the establishment of the context for the experiment, whether a current context or a future one. In that context, a problem is posed in the form of a mission to be accomplished, and an operational concept for the execution of the mission is postulated. Mission objectives are established: For example, the context may be a joint operation for the capture of an airfield in a hostile country with the operational concept specifying an amphibious assault. Alternatively, the context may be a multinational humanitarian assistance/disaster relief operation in an island in the Pacific Ocean where heavy smoke from forest fires near the airport prevents the landing of large transport aircraft. The context is then expressed in the form of a scenario: a sequence of events (stimuli) that occur in time and trigger responses from the experimental subjects.

The second step is the formulation of hypotheses to be tested through the conduct of the experiment. Hypotheses can be formulated on the basis of theory, of prior findings, or can be derived from empirical evidence generated through computational procedures. The latter approach, applied to organizational architectures, is presented by Carley [1999] in this issue.

The third step is the design of the alternative organizational architectures for the given scenario. Given the scenario, a set of resources, and a set of objectives, optimal organizational architectures are derived for the given criteria. Alternative architectures are then derived by changing the problem constraints (e.g., different resources) or the objectives. The detailed algorithmic process for the design of organizational architectures is presented in Levchuk, Pattipati, and Kleinman [1999], also in this issue.

Note that the algorithmic design is based on a static formulation of the problem. The next step is then the development of a preexperimental simulation model of the experiment that can be executed using the given scenario. By considering the decision sets of each decision-maker and the given architecture, the experiment is simulated, and data are collected to determine whether the hypothesis holds true or not. Actually, the preexperimental simulations provide feedback to the designers in Step 3 regarding the dynamic behavior of the organizational architecture. They provide information regarding the timing of the various events and the tempo of operations that is needed, if the desired behaviors are to be observed. They also indicate whether the data collection scheme is adequate for testing the hypotheses. This information is given to the designers of the physical experiment to help them in fine tuning it. The details of the process in the context of the A2C2 program are presented in Handley, Zaidi, and Levis [1999] also in this issue.

The cycle of design, model and test, redesign, remodel and retest is repeated until sufficiently robust alternatives for testing the hypotheses are obtained that are also implementable in the laboratory experimental setup. This represents a case of spiral development using analytical and modeling and simulation tools.

The fifth step that actually occurs concurrently with the third and fourth ones is the design of the actual experiment using the available laboratory facilities and the "wargaming" software. A pilot experiment is then run to test the experimental setup. Data from that pilot experiment are used to rerun the preexperimental model, especially if the parameters used in the physical experiment (e.g., the tempo of operations) are outside the range used in the simulations. With this final fine-tuning, the experiment is then executed, and data are collected. The results are analyzed to determine whether the hypotheses have been validated.

The detailed experimental data, such as the actual times events occurred and the actual decisions made by the human subjects, are then used to run the simulation model again and to compare the predictions the model is now making with the actual results. This postexperimental modeling and simulation forms the basis of model validation and leads to model improvements. The improved model is then used in the next cycle of experiments.

These feedback loops that are inherent in model driven experimentation are shown schematically in Figure 3, where the detailed steps of Figure 2 have been suppressed. Loop 1 deals primarily with the use of simulation models to take into account the dynamic behavior in the design procedure for determining alternative architectures. The second loop corrects for the discrepancies between the actual experimental setup and conditions and the assumed one in the design phase. Loop 3, in turn, takes the results of the analysis of the experimental data and uses them to improve the design algorithms and the formulation of hypotheses.

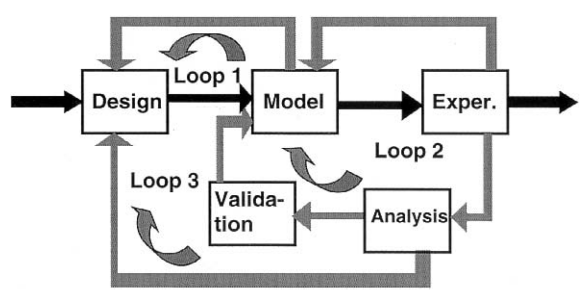

Figure 3 The feedback loops of the model driven experimentation process.

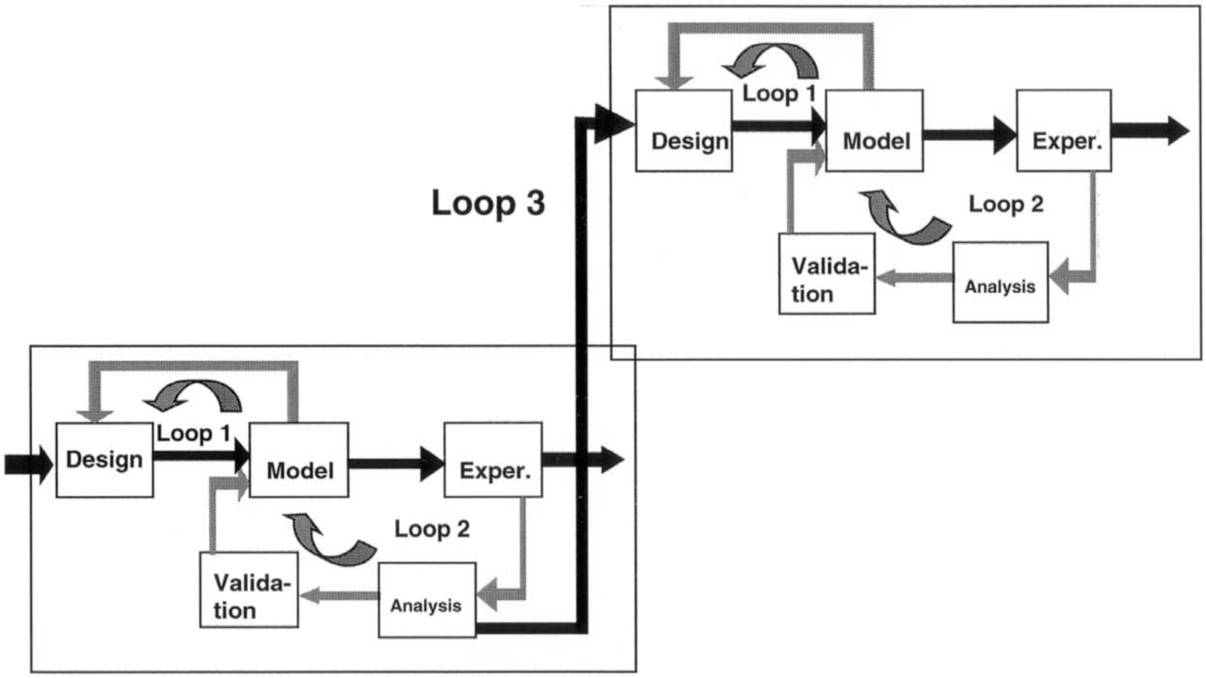

Figure 4 Model of evolutionary development of series of experiments.

This is a complex process in which a diverse set of scientists and engineers are involved. For its proper execution, a technical manager is required that can coordinate the set of activities and maintain the proper balance among the various steps. Usually, experiments, especially those involving human subjects, are resource-constrained and time-constrained. The availability of human subjects imposes tight constraints on the execution. Consequently, the model driven experimentation process must be managed carefully to ensure

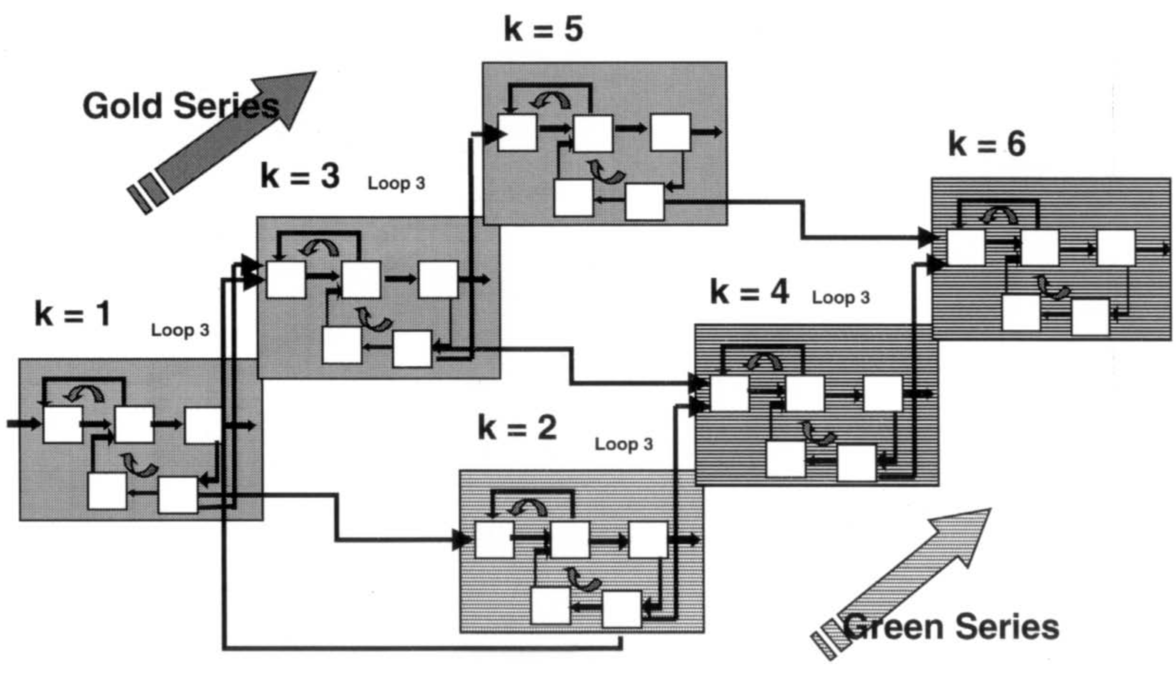

Figure 5 The double helix model of model driven experimentation for large-scale experiments.

that Loop 1 is executed a sufficient number of times to produce a well-tuned experiment that has a high probability of generating useful data. Similarly, Loop 2 is essential, if a sequence of experiments is planned. It establishes the credibility of the model and allows the consideration of more realistic contexts. The latter improves the linkage between the experimental setup and the operational environment, always a source of difficulty in trying to extrapolate from laboratory findings to operational environments.

3. GENERALIZATION

One approach to increasing the credibility of the experimental results is to employ a time-phased approach to the conduct of the experiments. This may be considered as an evolutionary experimental approach in which a set of experiments is built on the results of the previous set. As shown in Figure 4, the feedback Loop 3 does not go back to the original experiment, but goes forward as an input to the next set of experiments. While Loops 1 and 2 constitute a spiral development process, Loop 3 generates a helix—the spiraling is done over time and over a series of sets of experiments. However, the notion of the helix, while conceptually attractive, does not address a very real problem in the context of the large AWEs. Because the AWEs involve immense logistics problems on the one hand and they have to satisfy some funding cycle constraints on the other, it appears that there is inadequate time to carry out the model–test–model cycle while at the same time having as input the results of the previous experiment. To address this problem, a double helix is proposed, as shown in Figure 5. The concept is simple: There are two interleaved series of experiments with the odd series constituting one sequence and the even series another. This doubles the amount of time available to carry out the model driven experimentation process described in Figure 2. This does not imply that there is no interaction between the two series; on the contrary, results from small focused experiments embedded in an even (odd) AWE can affect the next odd (even) one. The two helices are coupled—hence the term double helix.

4. CONCLUSION

Model Driven Experimentation, as it evolving, appears to be a very promising approach for designing experiments involving human decision-making in a structured environment. It also seems appropriate for facilitating the design of series of large scale experiments.

REFERENCES

K.M. Carley, On generating hypotheses using computer simulations, Syst Eng 2 (1999), this issue.

J. L. Casti, Would-be worlds, Wiley, New York, 1997.

C4ISR Architecture Framework, Version 2, OASD(C3I), December 1997.

H.A.H. Handley, Effecting and evaluating organizational adaptation via dynamic process selection, Ph.D. Thesis, School of Information Technology and Engineering, George Mason University, Fairfax, VA, 1999.

H.A.H. Handley, Z.R. Zaidi, and A.H. Levis, The use of simulation models in model driven experimentation, Syst Eng 2 (1999), this issue.

Y.N. Levchuk, K.P. Pattipati, and D.L. Kleinman, Analytic model driven organizational design and experimentation in adaptive commend and control, Syst Eng 2 (1999), this issue.

A.H. Levis and I.S. Levis, "Toward a conceptual framework for policy analysis modeling," System theory applications to agricultural modeling, A.H. Levis and L. Quance (Editors), ESCS-07, USDA, Washington, DC, 1978, 9–14.

D.M. Perdu and A.H. Levis, Adaptation as a morphing process: A methodology for the design and evaluation of adaptive organizational structures, Comput Math Org Theory 4(1) (1998), 5–41.

Alexander H. Levis is University Professor of Electrical, Computer, and Systems Engineering. He is associated with the C3I Center, where he heads the System Architectures Laboratory. He served as Chair of the Systems Engineering Department in 1992–1994, and then again in 1996–1997. He was educated at MIT where he received the B.S. (1965), M.S. (1965), M.E. (1967), and Sc.D. (1968) degrees in Mechanical Engineering with control systems as his area of specialization. He also attended Ripon College where he received the A.B. degree (1963) in Mathematics and Physics. He taught systems and control theory at the Polytechnic Institute of Brooklyn from 1968 to 1973 and, for the following six years, he was with Systems Control, Inc. of Palo Alto, CA, where he was manager of the systems research department. From 1979 to 1990 he was a Senior Research Scientist at the MIT Laboratory for Information and Decision Systems. He joined George Mason University and the C3I Center in 1990. In 1992, he received the Distinguished Faculty award. Dr. Levis is a Fellow of the Institute of Electrical and Electronic Engineers (IEEE) and past president of the IEEE Control Systems Society from which he received in 1987 the Distinguished Member award. He is also a Fellow of the American Association for the Advancement of

Science (AAAS), a member of AFCEA, and a senior member of AIAA. Dr. Levis' research interests for the last fifteen years include architectures for command and control, organization theory and design, human decision making, and distributed intelligence systems. He has published over 130 papers and many book chapters and has co-edited three volumes on The Science of Command and Control published by AFCEA.

W.S. Vaughan is Director, Cognitive & Neural Science & Technology Division, Office of Naval Research. His Division has supported a continuous series of basic and applied research programs in distributed team decision making since 1982: Distributed Tactical Decision Making, Decision Making in Hierarchical Teams, and Tactical Decision Making Under Stress. In 1995 he began a new initiative, Adaptive Architectures for Command and Control, with a mix of academic, industrial, and Navy performers. The articles in this issue are representative of the research being conducted with support from this program. Dr. Vaughan has a Ph.D. in experimental psychology. He is a Fellow of both the American Psychological Association and the American Psychological Society. He is a frequent contributor to the annual technical program of the Command & Control Research and Technology Symposium.