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Using Complexity for Manpower Modeling: A Feasibility Study

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Executive Summary

We examined whether the class of complexity-based model(s) known as Agent-Based Models (ABMs) could be a useful decision-support tool for use in personnel planning and management.

In using ABM, a system is modeled as a collection of autonomous, decision-making agents. ABMs are built using an object-oriented programming language. Each agent, the agent's environment, and the schedule that controls the model run are independent objects that can be matched in a variety of ways.

A major strength of ABM is its ability to simulate real interactions between individuals and groups allowing for a wide variety of feedback, adaptation, and negotiation behaviors. However, ABM's results are sensitive to initial conditions, and the reliability of such results is limited to ranges of outcomes linked to ranges of input parameters.

In examining a variety of ABM applications—including biological, behavioral, and organizational—we determined that ABMs have dealt with the kinds of issues important to the Navy and that, while not a perfect analogy, an ABM supply chain type of model would meet many of the Navy's personnel modeling requirements.

Given the possible benefits of using an ABM, we feel that there would be value in building a prototype "proof-of-concept" ABM to test its utility.

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In this study, we examined whether a complexity-based model(s) could be a useful decision-support tool for use by the Navy for personnel planning and management. Might a complexity-based model do a better job in dealing with problems of feedback and changes in the environment than a linear model?

We examined the class of complexity-based models known as Agent-Based Models (ABMs). In an ABM, a system is modeled as a collection of autonomous, decision-making agents, each of which autonomously assesses its situation and makes decisions on the basis of a set of internal rules. ABMs are commonly built using an object-oriented programming language and are modular. Each agent, the agent's environment, and the schedule that controls the model run are independent objects that can be matched in a variety of ways.

A major strength of an ABM is its ability to simulate real interactions between individuals and groups. Basing these interactions on formal, informal, and spatial links allows for a wide variety of feedback, adaptation, and negotiation behaviors. This combination of interaction and adaptation with built-in flexibility gives an ABM its superiority to linear programming techniques relative to the problems identified above. However, because ABM's depend on micro-level behaviors, their results are quite sensitive to initial conditions. Also, though ABM outcomes may be mathematical estimations, the reliability of such results is limited to ranges of outcomes linked to ranges of input parameters.

We examined a wide variety of ABM applications—including biological, behavioral, and organizational—to determine whether ABMs have dealt with the kinds of issues important to the Navy and whether model outputs would be useful for the Navy. In our judgment, an ABM supply chain type of model, while certainly not a perfect analogy, would meet many of the Navy's modeling requirements. Such supply chain elements as obtaining raw materials, product manufacture and distribution, and the management of a multi-production site, multi-product organization have many analogies to Navy recruiting, training, billeting, and retention.

Given the possible benefits of ABMs and the state of their development, we feel that there would be value in building a prototype "proof-of-concept" ABM to test its utility.

Concerns About Existing Navy Personnel Modeling Tools

- Difficult to integrate policy to achieve maximum overall performance
  - Negotiations between local decision-makers
  - Local versus overall performance goals
- Poor accounting for feedback effects
- Difficult to foresee and manage unintended effects
- Inadequate response to unforeseen events because basis is extrapolation from historical data

Because the current models for recruiting, training, and retention are linear based and not linked, they do not account for how changes in one community or service affect the other communities. It is possible for the separate models to reach local optima for their respective subsystems, while in the aggregate, not to arrive at the best solution for the entire organization. These models also fail to allow for negotiations between local decision-makers. Further, because they are based on extrapolations of historical data, the present models cannot capture unforeseen, emergent behavior(s) that can result from the interaction of the large number of individual actors and organizations that make up the whole. Lastly, the models do not respond well to rapid changes in the environment.

Scope of Study: Questions

- Have Agent-Based Models (ABMs) been developed in areas similar to those required to meet the Navy's manpower modeling needs?
- Does the output from such ABMs have the precision required by Navy decision-makers?
- Can a useful ABM be developed in a reasonable amount of time?

The quick answer to the first question is yes. We have identified ABMs in which agents negotiate and cooperate with each other for the optimum use of resources for the group and ABMs of both supply chains and manufacturing. Several models of cooperation between agents identified the counterintuitive result that simple reciprocity between cooperating agents does not necessarily result in an optimal result for all agents. The supply chain model also demonstrated (see later slide) that received wisdom does not lead to optimal results. In one particular case, the sacrifice of efficiency in a portion of the chain enhances the total behavior of the chain. These types of ABMs have strong analogies to the requirements of a Navy model.

The answer to the second question obviously depends on the precision that various decision-makers feel is required. ABMs can generate two sorts of outputs. By producing multiple runs of the model while varying the behavior rules of the agents, a decision-maker can expect to obtain a "spectrum" of outcomes that should encompass how the system will behave over time. This spectrum can be used as a guide to develop a flexible policy set that should respond to the likely behavior of the system. By varying the exogenous inputs to the model, it should also be possible to develop a set of "what if" contingency responses to unforeseen and/or changing needs.

A second type of output from ABMs does produce numerical estimates of the type required for personnel management. That is, one can ask such questions as, “What is the impact of changes in base pay or bonuses on recruiting or retention?” and obtain numerical answers of the type obtained from other models. It is not clear, however, that the answers to these questions are better obtained through ABMs or through the more traditional models.

Finally, after meeting with several experts on the design and building of ABMs, we conclude that a prototype “proof-of-concept” ABM could be developed within six months.

Scope of Study: Approach

- Survey literature for existing ABMs and current developments in ABMs
- Consult experts about most useful features of ABMs and their ability to meet the Navy's specific requirements

In surveying the literature, we determined that it is important to include commercial communications and periodicals as well as the proceedings of ABM meetings because of the tight link between research and application. These are likely to be a rich source of information to meet the Navy's needs. Examples of the literature we examined include:

- *Cap Gemini Ernst & Young's Focus E-zine*
- *Capturing Business Complexity with Agent-Based Simulation*
- *Computer-Aided Civil and Infrastructure Engineering*
- *Computerworld*
- *Journal of Artificial Societies and Social Simulation*
- *Proceedings of the 2002 Agent Conference*
- *RAND Research Publications*
- *Social Science Computer Review.*

We consulted a variety of experts in the ABM field (a listing of these experts is detailed in a separate slide). Because ABM development is a relatively new field, we found a wide diversity of opinion on the strengths, weaknesses, and utility of the use of ABMs in our discussions with experts. This is understandable given the lack of an existing large body of work and the different backgrounds (both philosophical and research area) with which people enter the field.

Agent-Based Modeling: What is it?

- Produced using object-oriented programming
- Generally have three classes of objects
  - Agents: individuals, groups, mega-groups (such as organizations)
  - Environment: 2- or 3- dimensional grid, formal or informal network
  - Schedule: time, random or controlled ordering, or decision propagation
- Establish behavior rules for objects
- Produce multiple runs using varying initial conditions and/or rule sets

In ABMs, a system is modeled as a collection of autonomous, decision-making agents. Each agent autonomously assesses its situation and makes decisions on the basis of a set of rules. Agents may execute various behaviors appropriate for the system they represent. The rule set by which the agents operate and make decisions is often quite small, no more than seven or eight rules, but it is critical that these rules reflect the actual way in which an agent would act if the model output is to have validity.

An ABM differs from a Cellular Automata model in that the agents can respond asynchronously depending on their specific behavior rules. Repetitive, competitive interactions ensue that explore dynamics that are out of the reach of pure mathematical models. Sophisticated ABMs may also incorporate neural networks, evolutionary algorithms, or other learning techniques to realistic learning and adaptation to new situations.

In implementing an ABM, one generally uses an object-oriented programming language such as C++, Java, or Small Talk as the most natural way in which to establish self-contained objects. It is important to understand that in ABMs both the environment in which the agents act and the schedule of their actions can be self-contained objects. By structuring the model in this way, both the environment and schedule of operations, individually or simultaneously, can be changed without redoing the model.

The environment may have a physical representation (such as a roadway or terrain); in the modeling of social processes, the environment may represent a network of formal or informal relationships (such as an organizational structure or a network of friends).

The schedule may represent time, may trigger changes in state of some or all of the agents on a random basis, or may trigger changes in state in an agent(s) dependent on the change of another agent.

The behavior of the model is examined by producing multiple runs that vary in initial conditions and/or agent rule sets. In this way, one attempts to determine the sensitivity of the outcomes to initial conditions. If they vary widely, it could be that the model is misspecified or that one has identified a behavior of interest. The judgment of experts on the system is required to make this determination.

An interesting concept called "docking" has been used to examine the validity of some ABMs. Using this approach, a second model, dissimilar to the first, is built to address the same problem and one asks: Do the two models give similar results? Are there new insights from the second model? Is one a special case of the other? Is a third model called for?

Ultimately, a well-developed ABM should have three characteristics: validity, usability, and extendibility. **Validity**: the program must correctly implement the model so that one knows whether an unexpected result is a reflection of a mistake in programming, or a surprising consequence of the model itself. **Usability**: allows one to run program, interpret output, and understand how it works. **Extendibility**: allows a future user to adapt the program for new uses.

Use of ABMs: Strengths

- Why is ABM a reasonable approach?
  - Reality based
  - Good at managing feedback, negotiation among stakeholders
  - Can consider phenomena that are multi-level and multi-theoretic
  - Considers human behavior credibly (attributes and relationships, as well as macroscopic outcomes)
  - Can adapt to unexpected events and unintended consequences
  - Can identify emergent behavior of the system that could not be predicted from its individual components

A major strength of ABM is its ability to simulate real interactions between individuals and groups. Further, the ability to base these interactions on formal, spatial, and informal links allows for a wide variety of feedback, adaptation, and negotiation behaviors to occur. This combination of interaction and adaptation, with built-in variation of flexibility, gives ABM its superiority to linear programming techniques.

Based on this power, ABMs can be used to simulate phenomena that are multi-level. That is, agents can represent individuals, groups, and large pieces of organizational structure, depending on how the interaction is constructed. For example, an individual taxpayer's or family's payment of federal taxes can be modeled as an interaction between an individual or group agent and a large structure, the Internal Revenue Service. If a family is audited, an individual adult member may interact with an individual member of the IRS organization, characterized by different behavior rules.

Different individuals, depending on their personal expertise and experiences with the IRS, may behave based on different theories about how the IRS operates. A tax accountant with vast experience defending clients during IRS audits may be far more confident and knowledgeable about applicable laws than a novice. Such an individual may even have good working relationships with IRS agents and, combined with his/her knowledge, may therefore be able to achieve a far different outcome than the novice. In this way, interactions can be modeled as multi-theoretic, and, by extension, different theories lead to different behaviors, and thus different outcomes.

These kinds of complexities can more credibly consider human behavior, producing more accurate and relevant results. Adaptation and negotiation abilities then allow for quick responsiveness to unexpected events and emergent and unintended consequences of previous decisions. The resultant system-level outcomes are then based on very complicated sets of interactions and may not be traceable back to single initial components. In this way, ABM provides insights inaccessible with modeling systems that depend on a priori knowledge of all possible developments.

Use of ABMs: Limitations

- Dependent on the understanding of the system by its participants
- Can be very sensitive to initial conditions
- Not a predictor of individual decision-maker behavior
- Will not yield precise mathematical estimates

The greatest limitation of ABM is common to most modeling systems: the model and its results are only as good as the theory and information on which they are built. ABM greatly depends on deep understanding of the phenomena being modeled. This means that ABMs cannot be created by highly competent programmers with little input from content experts. ABMs are built on an understanding of a complex system or process from the perspectives of *all* participants and stakeholders.

Because of ABM's dependence on micro-level behaviors, results are also very sensitive to initial conditions. This means that the results and insights gained from ABM are not predictive of individual behaviors and outcomes. While ABM outcomes may take the form of mathematical estimations, the reliability of such results are limited to ranges of outcomes linked to ranges of input parameters.

Features of Useful ABM Development Systems

- Use a simple programming language and the modularity of object-oriented programming
- Have an extensive library of agents available
- Can use genetic algorithms and neural nets
- Allow "rapid" prototyping
- Allow use of existing powerful analytic tools to examine results

The essence of an ABM is that it is composed of self-contained objects. It is this feature that allows one to examine behavior of a system by simply changing some characteristic of the object rather than rewriting the entire model. Clearly this requires using an object-oriented language to produce the model. While ABM development does not require use of a simple language, a simple language would greatly increase the ease of development and maintenance of the model. Having an extensive library of agents available again takes advantage of the object-orientation of ABMs by allowing one to rapidly develop new models by adding new agents and/or mixing and matching components with a minimum of new code development. The class of ABMs that is likely to be of utility to the Navy is called a Complex Adaptive Systems (CAS). This name implies that the agents in the system can learn and adapt to changes in the system. Genetic algorithms drive the production of new behavior rule sets among the agents (analogous to chromosomal recombination in organisms) and allow for selection of those rule sets best adapted to the system. Neural nets are a programming device that allow agents to "learn" as they select from a set of behaviors by strengthening the likelihood that an agent will chose the most effective behavior.

All of these features allow for rapid prototyping of basic models. As discussed later, such programming speed depends on careful model specification. Given proper design consideration, ABM allows modelers and programmers to quickly implement and use powerful internal and external analytic tools. A useful ABM development system should have very good capacity to input and output parameters, offer data storage in many common analytic formats, and work well with many existing analytic tools and software packages.

Examples of Existing ABM Programming Systems

- Swarm: Swarm Development Organization
- RePast: University of Chicago
- Ascape: Brookings Institution
- Einstein: CNAC*

* Included as an example of an ABM designed for a specific purpose.

Swarm – developed at the Santa Fe Institute. Swarm is a set of portable protocols (libraries) written in either Objective C or Java for describing objects that have behaviors and an experience of time and space. Its key feature is its function as a virtual machine, controlled by a schedule (also an object) for running numerous instances of these agents in a measurable, scalable, and reproducible manner. Agents have a series of values associated with them (location in environment, previous interactions, skill level at particular tasks, etc.) that define their state and that may change over time. Agents or hierarchies of agents respond to messages in a way they deem appropriate, often as a function of their present state.

RePast – developed at the University of Chicago. It is a software framework for creating Java-based ABMs. It provides a library of classes for creating agents, running simulations, and displaying and collecting data. Changes in state of any of the components occur through a scheduler. A particularly attractive feature of RePast is that the space in which the agent(s) operate can be either a grid (2- or 3-dimensional) or a network (formal or informal).

Ascape: developed at The Brookings Institution. Ascape is a Java-based ABM environment with many similarities to Swarm and RePast. The key difference is the degree of abstraction used in defining its components. A model in Ascape is an agent itself built from hierarchies of agents. This design greatly simplifies the coding but gives up some control of the agents' behavior.

Einstein: developed at CNAC. EINSTein is an adaptive, multiagent-based, artificial-life "laboratory" for exploring self-organized emergent behavior in land combat. EINSTein was developed for the U.S. Marine Corps to simulate combat—on a small to medium scale—by using autonomous agents to model individual behaviors and personalities rather than specific weapons.

Current Applications

- Self Organization
  - Termite colony, bird flocks, fish schools
  - Traffic
- Social Interactions
  - Flow management
  - Housing segregation (The Schelling Model)
- Manufacturing and Distribution
  - Proctor and Gamble (supply network)
  - Southwest Airlines (cargo routing)
  - Eli Lilly (drug development)

Self Organization

ABM allows one to examine whether very complex behavior can arise from the interaction of independent agents following simple behavior rules. Many of the initial uses of ABMs involved studying the behavior of biological systems. Thus, ABMs have been used to demonstrate that the immensely complex building, food gathering, and reproductive behavior of a termite colony that may be 60 feet tall and contain millions of inhabitants is the result of the interaction of individuals following a few (less than 10) simple rules. The termite queen does not have an administrative hierarchy passing on commands to the workers and is no more or less independent than the other classes of individuals in the colony. In much the same way, ABMs have demonstrated that flocking behavior in birds and schooling behavior in fish are the result of the interaction of individuals rather than a leader and social structure. ABMs have also shown that traffic can be accurately modeled as a self-organized (though frustrating) system in which individual drivers follow three rules: speed up if you are far from the car ahead of you, slow down if you are close to the car ahead, and, sometimes, randomly change your speed. Using these three rules, all of the salient features of traffic can be demonstrated.

Social Interactions

Theme Park: An interesting application of ABM to flow management is the simulation of customer behavior in a theme park. The collective patterns generated by thousands of customers can be extremely complex as customers interact with one another: for example, how long you wait at an attraction in a theme park depends on other people's choices. An ABM of the park was built that provided an integrated picture of the environment and all of the interacting elements. The model provided a fast, *in silico* way for managers to identify, adjust, and watch the impact of any number of management levers, such as:

- When or if to turn off a particular ride
- How to distribute rides per capita throughout the park space
- What the tolerance level is for wait times
- When to extend operating hours.

Agents were built that represented a realistic and changeable mix of both supply (attractions, shops, food concessions) and demand (visitors with different preferences) elements of a day at the park. Using such data as customer surveys, segmentation studies, queue timers, people counters, attendance estimates, and capacity figures, the model generates information about guest flow. A large number of scenarios (interaction among agents and environment, ride utilization, traffic flow and mobility, visitor preferences and behavior), were run to test the effectiveness of various management decisions and to track visitor satisfaction throughout the day.

Agent-based simulation works well in this context because the mapping between the agents' preferences and behaviors on one hand, and the park's performance (in terms of average waiting times, number of attractions visited, total distance walked, etc) on the other hand, is too complex to be dealt with using mathematical techniques and purely statistical analysis of the data. Why is the mapping too complex? Because, for example, the time a given customer has to wait at a given attraction depends on what other customers are doing, how they respond to different park conditions, what their wish list is, and so on. The flows of customers in the park, and the money they spend, are an "emergent" property of interactions among customers and between customers and the spatial layout of the park.

Housing segregation: In 1971, Thomas Schelling developed a model of racial segregation in housing, based on a simple preference for living near a certain percentage of people of the same race. The behavior rules are (1) look at your four nearest neighbors (north, south, east, and west on a square grid); and (2) if more that 33% of your neighbors are of a different race than you, move. From this simple model containing four families living in a two-dimensional grid world, Schelling was able to recreate observed racial segregation with a relatively small preference for same-race neighbors. This model has proven quite powerful, and has now been matched to actual housing patterns in the area surrounding San Diego, California.

Manufacturing and Distribution

An interesting example in which ABM was used to analyze a supply chain done using ABM was performed by the BiosGroup (now defunct) for Proctor and Gamble (P&G). P&G's problem was that, although the company had a multi-billion-dollar inventory in its supply system, many retail stores that sold P&G products either were out of stock or didn't know they had the products in their storerooms. The company contracted with BiosGroup to develop a complex adaptive ABM that would help P&G reach its goal of reducing inventory by $1 billion while not increasing its out-of-stock problem. BiosGroup first built an ABM with various agents representing manufacturing lines, trucks, warehouses, customers, and consumers to model the transportation and logistics of one particular product under ideal conditions (constant demand, constant price, constant production, etc.). Volatility was then added to the model using probability distributions of customers' response to sales as well as buying competitors' products in an out-of-stock situation. This "real world" model was then used to test the impact of modifying various components of the supply chain.

Several important findings were derived from this analysis. P&G's policy of offering price breaks only to customers that ordered full trucks caused customers too carry to much inventory, which often meant they could not find product even when they had it on hand, thus causing an out-of-stock situation. By ordering quantities to fill a truck, P&G did not obtain a true measure of demand.

It also increased the effect of product obsolescence, since the excess product in the pipeline needed to be reclaimed at the end of a marketing cycle. Analysis showed that the built-in delay in responding to orders could be ameliorated if delivery trucks shifted product between stores daily on an as-needed basis. The end result of this ABM analysis is that the company dramatically shifted its policies concerning shipping and has seen a $600-million drop in inventory, and expects to reach its $1-billion goal by the end of 2003.

Southwest Airlines uses ABM to revamp its rules for handling cargo. Using ABM to examine how it managed cargo delivery, the airline came to the counterintuitive understanding that, rather than switching cargo to planes that followed the most direct route to the cargo's final destination, allowing the cargo to remain on one plane was the most cost-effective and efficient process. This ABM analysis has saved the company $2 million per year in labor costs.

Eli Lilly Pharmaceutical Company has used the results of an ABM model to reorganize its early phase development process, which resulted in more productivity and enhanced speed in drug development.

Development of ABM: Model Specification

- Most crucial and time-consuming part of the modeling process
- Requires specificity of grain sizes, attributes, behaviors, and interactions
- Requires the participation of all stakeholders and decision-makers

Model component and structure specification is the most crucial and time-consuming part of any modeling process. First, this process *requires* input from all decision-making constituents (formal and informal). Just as social practices, personal relationships, shared histories, trends, and behavioral norms affect the decision-making and behavior of individuals in a society, such informal and evolving phenomena affect the behavior of individuals and groups within a formal structure. Therefore, model specification must take into account formal structures, decision chains, and behavior policies, as well as informal relationships, political alliances, and stylistic preferences.

Model specification must also include attention to grain sizes of agents and environmental objects. For example, in the Schelling model, the agents making moving decisions represent families making decisions based on a set static preference for racial difference. A more complex version of the Schelling model might be based on a group decision constructed from the interaction of family members with varying individual preferences. Another version might also consider such issues as financial resources, school quality, and transportation constraints. Still another version might be based on a more complex definition of neighborhoods, which include social groups, shared resources, and physical space allocations. From these examples, we can imagine very different outcomes based on the issues considered and the complexity of the design.

Further, model specification relies on good knowledge of the programming capabilities. As discussed earlier, the schedule of program execution can be treated as a programmable object. With this knowledge, designers can engage stakeholders in discussions about how the timing of actual decisions affects the overall system. Thus, events can be scheduled based on absolute time, relative to or contingent on other events, and/or with some degree of randomness, as would simulate the real phenomena being modeled.

As has been illustrated, the process of model specification can be quite time consuming and complicated. However, this time and effort are well spent. Since the results, insights, and policy implications that come out of the modeling process depend greatly on the care with which the model is designed, it is crucial to make this investment upfront.

Conceiving the Navy Manpower System as a Supply Chain: ABM Requirements

- ABM Components
  - Supply Chain Components
    - Recruits are raw materials
    - Training is the parts manufacturing process
    - Detailing is distribution against a needs (mission) blueprint
    - Post-detail personnel reenter supply chain at training or detailing level
- Management and Policy Requirements
  - Need to schedule production of multiple parts (skill sets) and schedule for multiple billeting and mission requirements

While not a perfect analogy, one can make a reasonable argument that a useful conception of the Navy personnel system on which to base an ABM is that of a multi-product supply chain. It could start with the combination of financial and personnel resources available to the Navy as inputs and its variety of readiness needs as product outputs. There is, then, a clear correspondence between recruiting, training, detailing, and retention in either the same or new duties and the basic components of a supply chain. Influences of service communities and structural divisions can be seen as a problem faced by any large organization in managing the chain in such a way as to respond to the market and to the needs of each of the chain components.

As we indicated, however, conceiving the personnel system as a supply chain is not a perfect analogy. One of the key differences is that while the materials in a supply chain don't "care" what they are made into and the products don't "care" how they are distributed, recruits and sailors do care. Actually, accommodating this difference between a supply chain and the Navy personnel system speaks to one of the strengths of ABM. In an ABM, one can build in the impact of the wishes of the materials and products through agent behavior rules. This cannot be done in linear programming models.

Conceiving the Navy Manpower System as a Supply Chain: ABM Requirements (cont.)

- Management and Policy Requirements (continued)
  - Need to capture feedback effects from interaction between Navy personnel divisions, from other service communities, and from the broader environment
  - Need to identify unintended consequences of management policies
  - Need to manage (guide policy) toward maximizing overall rather than individual or subgroup performance
- Serve as a "management flight simulator" for training personnel management and running "what if" experiments

Influences of service communities and structural divisions can be seen as a problem faced by any large organization in managing the chain in such a way as to respond to the market and to the needs of each of the chain components.

Our second bullet—Management and Policy Requirements—represents what we see as the major strength of an ABM model. Several existing ABMs demonstrate the ability to manage the assignment of raw materials to production facilities followed by scheduling of the production run and the distribution of the various products. Using an ABM the company can maximize the effectiveness of its entire operation even if it does not produce the optimal function of any individual production and/or distribution components. For the Navy personnel arm, this would mean optimizing its ability to carry out its mission(s) even if the function of any of its components (recruiting, training, retention, retirement) was not optimal.

The structure of an ABM is such that the feedback and possibly unintended consequences resulting from the interaction of the components of the personnel arm, the rest of the Navy, other services, and the broader environment (economic conditions, national and world events) could be captured.

Other modeling techniques simply cannot account for the impact of a large number of autonomous agents interacting with each other. Clearly, understanding these feedback effects and recognizing possible unintended consequences of policies and procedures would be of great value in deriving policies that maximize organizational performance.

A great strength of ABMs is their flexibility for change and the ease with which one can run "what if" experiments. This makes them a valuable laboratory for examining the consequence of policy changes. Finally, since an ABM is based on the behavior of individual agents and can be examined one step at a time as its behavior unwinds, it is an ideal tool for learning. Personnel officers can see and understand exactly the consequence of any action.

Summary of Recommendations

- Contract for the development and test of a prototype high-level model
  - Model should treat specific features that are weaknesses in current tools
  - Must establish appropriate metrics to determine whether model outperforms existing models or produces insights that do not come from existing models.
- Establish an advisory committee to make recommendations concerning requirements for full-scale development concurrent with prototype development.

Based on our review of the ABMs that have been developed as commercial decision-support tools, we feel that development of a prototype model to examine its utility for modeling Navy personnel issues is merited.

We would begin with an in-depth discussion between representatives of the various divisions to begin to develop a detailed integrated conceptual model of the entire personnel system. This discussion can be the basis of the development of an RFP for the development of a model that investigates whether one can effectively simulate negotiations between agents representing the various components of the personnel system, recruiting, training, community managers, and retention since this is the greatest shortcoming in the present group of support tools. Such a prototype ABM should specifically examine whether one can input a yearly resource allocation, manpower goals, and mission requirements and simulate negotiation between the agents resulting in an effective split of the resources related to the mission goals. Clearly, to understand whether the prototype ABM is of value, a series of metrics must be established by which to determine if the ABM represents an improvement over existing tools. Such metrics should address the following: Is the resource split reasonable? Does the model demonstrate the effect of feedback between agents? How sensitive are the results to unforeseen change in the environment? In the last case, does the model still yield reasonable results?

Independent of its performance on the above metrics, it is possible that an ABM would be of value because it might provide insights not now obtainable as to how the system functions as a whole.

In contracting for the model, the Navy should consider whether it would also be valuable to fund a docking study, the development of a second ABM dissimilar to the first but dealing with the same issues. If the results from these dissimilar models were comparable, one would have greater confidence in the validity of the ABM approach.

Full-scale development of a model will, among other things, require the Navy to produce a management plan to integrate the development of ABM subsystem models, develop methods for the importation and utilization of existing data, determine the format and type of outputs required to best serve the Navy's needs, and understand how to integrate this new tool into the Navy's policy environment. Therefore, we suggest that an Advisory Committee be established concurrently with the development and test of the prototype ABM to deal with these issues so that, if warranted by a successful test, development of a full-scale model can begin quickly and efficiently.

Bottom line:

It's feasible, but a prototype will help determine its utility

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Examples of Commercial ABM Developers

- Altarum: 4401 Ford Avenue, Suite 800, Alexandria, VA 22302, (703) 315-1200
- Icosystem Corporation: 10 Fawcett Street, Cambridge, MA 02138 (240) 401-6574
- Industrial Science, LLC: 6700 Woodlands Parkway, Suite 230-202, The Woodlands, TX 77382 (281) 363-3861
- Least Squares Inc.: 2400 Louisiana Boulevard NE Bldg.3, Suite 210 Albuquerque, NM 87110 (505) 266-6199

Altarum: has produced ABM for manufacturing systems, for analysis of supply chains, for product-process integrated design, and for task scheduling.

Industrial Science: has produced ABM for competitive pricing analysis and oil field exploration strategy.

Icos: has produced ABM for theme park flow management, stock portfolio management, drug development, and optimal operation in the oil and gas industry.

Least Squares: have produced the “Archimedes Military Operations Modeling Platform.

Experts Consulted

Dr. David Dixon, President, LeastSquares, Inc., Albuquerque, NM.

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