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Agent-based simulation for computational experimentation: Developing an artificial labor market

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Abstract

This paper discusses the creation of an artificial labor market (ALM) as an agent-based simulation model. We trace the development of the ALM by adapting the traditional simulation life cycle into two main parts: the model phase and the simulation phase. In the modeling phase of the life cycle, we focus upon agent representation and specification within the virtual world. In the simulation phase, we discuss the use of scenario planning as the experimentation vehicle. Throughout, we use military recruit market as an example to illustrate the methodology. The benefits of the ALM are (1) it provides a virtual world for continuous computational experimentation, (2) it supports market segmentation by allowing "drilldowns" to finer and finer levels of granularity, and (3) when connected via a common OLAP interface to a "real world" counterpart, it facilitates a tightly integrated, persistent, "sense and respond" decision support functionality.

Keywords: Artificial intelligence; Decision support systems; Simulation; Modelling systems and languages; Economics

1. Introduction

Agent-based simulation is now widely used in a dizzying array of applications ranging from simple auctions to traffic models to complex 3-dimensional combat simulations. One robust area within the agent-based simulation arena has been the development of synthetic economies and societies, fueled in large part by the seminal work of Epstein and Axtell [12], and the electronic marketplaces which have emerged from the Internet [24]. Much of the effort in this line of research has been involved at the microeconomics level, e.g. constructing various auction mechanisms and studying the equilibria, if any, which result [22]. Although this is certainly useful research, our interests in this

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paper are focused on macroeconomic phenomena, which require modeling of a broader range of phenomena and events than is typically undertaken with micro-based synthetic economies.

In this spirit, we note that within the synthetic economies landscape there has been very little attention focused upon labor economics and labor markets. In this paper, we discuss agent-based simulation (ABS) as a vehicle for studying critical problems that arise in labor markets. Specifically, we look at ABS as a platform for building a large-scale artificial labor market (ALM) [1] that can, in turn, be used as a basis of analysis for generating and testing various decision policies with regard to recruiting from a specific segment of the workforce. Our objectives in this research are to model an existing labor economy using agent-based technology by programming micro-level agent behavior, observing the macro-level behavior that emerges, and calibrating the system so that the ALM emulates the "real" economy in pre-specified ways. By "large-scale", we include two different aspects: (1) agents will be more behaviorally complex than the simple rule-driven 2-dimensional cellular automata used in many virtual market environments, and (2) the numbers of concurrently running agents will correspond roughly to the number of individuals in the labor market (e.g., on the order of 10 ** 5–10 ** 7), which can subsequently be grouped and disaggregated in ways analogous to conventional market segmentation.

We are interested in the process of building a large-scale, agent-based model, conducting experiments with the model, and identifying the benefits to be derived from such a model in the form of integrated decision support. We use the ALM as an application for surfacing these issues. We approach the construction of the ALM by adapting the traditional simulation life cycle methodology to an agent-based simulation life cycle, consisting of two major segments: the model and the simulation. The model segment is primarily focused upon agent representation and specification, with special attention given to the data mining requirements for determining agent behavior. Once we have elaborated the agent representation methodology for building the ALM, the simulation segment demonstrates its use through a particular form of experimentation, involving "human in the loop" simulation. The ALM, whose emergent behavior defines the marketplace, can be used as an environment in which human players can engage in strategic decision-making simulations. We use throughout the methodology an example case study with 100,000 agents to represent a labor market of 1.4 million individuals. Our application domain is the military recruiting of the available population of 18–24 year olds in the United States, and our goal is provide a virtual market test bed in which to experiment with different recruiting strategies. The ALM used in this way is a hybrid of microeconomic analysis combined with the OR/MS discipline of simulation.

We take experimentation one step further to the notion of continuous, computational experimentation, and suggest how the ALM can serve in a larger context as an integrated decision support environment by linking it to an existing "real time" data warehouse. Using an identical data visualization user interface for accessing the warehouse and the ALM simulation allows users to switch between the real and virtual environments easily. We call this *parallel worlds* wherein a sensor-based real world environment complements a virtual decision test bed environment. This marriage offers true leverage for the effective deployment and integration of operations research and management science models.

Our contribution from this work is a large-scale, macro-level artificial labor market that includes:

- A methodology for building a large-scale, macro-level synthetic economy, which works from traditional simulation life cycle principles.
- An effective agent representation technique for synthetic economies, which supports market segmentation.
- An experimentation process of "human in the loop" strategic war gaming.

[1] We adopt the term "artificial labor market" in the spirit of Epstein and Axtell, but use the terms "synthetic economy", and "virtual market" synonymously.

- An integrated decision support loop based upon uniform data visualization for combining "real world" operational data with "virtual world" simulation model data.

We believe the ALM we have developed is substantially larger in scope than the majority of previously developed synthetic economy environments, and subsequently provides a robust platform for integrating other modeling paradigms.

The remainder of the paper flows as follows. The next section provides a theoretical and conceptual motivation for developing a synthetic economy for labor markets, using agent-based technology. Sections 3 and 4 enumerate the model and simulation segments of the ALM development methodology respectively. Section 3 describes the agent representation dimension of the ALM, including the data mining requirements for specifying agent representation, whereas Section 4 enumerates the scenario planning experimentation approach to exercising the agent-based model. Section 5 extends these notions to one of continuous computational experimentation earmarked by linked virtual and real worlds operating in parallel. Limitations to our approach are also discussed. Section 6 summarizes our results.

2. Agent-based simulation and synthetic economies

Agent-based techniques have gained prominence in management and economics [15,16] and show much promise in terms of addressing the three major challenges to standard neoclassical economics, which have arisen from experimental economics, behavioral economics, and learning theory. Experimental economics shows that while some parts of economic theory hold up reasonably well (such as static markets with bids and asks) others such as individual decision-making do not, and are subject to biases, errors and misperceptions [20]. Behavioral economics complements experimental economics quite nicely by looking for field data as opposed to experimental data and showing that many of the same biases are found in real life [26]. Similarly, learning theory assumes that rational behavior does not emerge fully formed but through a great deal of trial and error [13].

The motivation for agent-based economies becomes more forceful then. Rust [31] argues that researchers are forced to build models which are either stylized enough to be solved analytically or small enough to be solved computationally. Each of these kinds of models is, in Rust's words, a "toy model". Moreover, such models are not modular and cannot be built up cumulatively by large teams of researchers working together, each developing a separate piece of the puzzle. Therefore, Rust suggests that we mimic the intelligence demonstrated in the organization of the market and use decentralized computing along with agents, to study these models. Rust's suggestion is quite appealing. He mentions a number of desiderata for such an agent-based environment. Among them is the ability to seamlessly integrate human and artificial agents in the same environment, which would allow experiments of greater complexity and scale than those possible with existing software such as the pioneering *MUDA* program developed by [28] at California Institute of Technology. This would enable true multi-disciplinary research. Computer-based information systems can then be integrated with economics to create synthetic economies to be used as a common meeting ground for techniques from operations research, management science, psychology, and computer science.

2.1. Artificial labor markets

In the spirit of research suggested above, we seek to build a large scale, synthetic economy to study the labor market for military recruiting. The modeling approach adopted in this experiment is motivated by Rosen's classic statement of pecuniary and non-pecuniary benefits in various jobs [30]. Jobs in sector A provide a wage W_A and jobs in sector B provide wage W_B. Sector A may be thought of as the military sector and sector B as the civilian sector. In addition there are non-pecuniary benefits b_A and b_B. Therefore a potential recruit weighs the sum of pecuniary and non-pecuniary benefits in the two sectors and joins sector A if $U_A = W_A + b_A > U_B = W_B + b_B$ where U_A is the utility in sector A and U_B is the utility in sector B. Of course, the distribution of b_A and b_B varies across the population. This distribution of utilities, as estimated may be used to derive the labor supply to the military in relation to the military wage rate. This is the method adopted in this paper.

We draw upon the first generation of labor supply models created by Goldberg [17], Ash et al. [1], Dale and Gilroy [8], Brown [6], and Nelson [27], which focused upon the behavior of recruits. Quality of recruits is also considered. For example, the empirical literature, as summarized by [34,5, 29,18,9,21] finds that the high-quality enlistments are influenced by pay relative to civilian sector (elasticity in the 0.15–1.89 range), by the unemployment rate (elasticity in the 0.49–1.36) and by advertising (elasticity in the 0.05–0.10 range). However, these figures are misleading since the attractiveness of the strategies is actually in reverse order. This is on account of the interesting phenomenon that raising the pay for the marginal recruit requires raising it also for the recruit who would join anyway. For this reason, as indicated in [34], marginal costs for attracting an additional recruit vary by instrument. For entry basic pay it is \$34,800, for enlistment bonus it is \$18,600, for national advertising it is \$8100, for adding recruiters it is \$7300, and for educational benefits it is \$6900 (all in 1990 dollars). In addition, high-quality recruits are 4–8 times more difficult to recruit than low quality ones [29,9].

The treatment of bonuses is very much in the spirit of [29] who describe the experiment mandated by Congress conducted during 1982–1984 when bonuses were varied across the United States and compared with controls. This experiment does not model recruiter behavior as is done in the second generation of models [10,9,29,5]. For example research indicates a ratchet effect in that recruiters who do well are given higher quotas [5]. This may have complicated effects on behavior and will be incorporated in future work.

Although we are examining a specific labor market in our experiment, we believe that the methodology for constructing ALMs is generalizable to a wider context than military recruiting. Therefore, before delving further into the details of our specific ALM, we step back and look at a general methodology for constructing an ALM.

2.2. Computational models of human behavior

For the ALM approach to work effectively, viable virtual economies must be constructed. This requires careful attention to the design and specification of the agents who will populate the economy. In the large, this demands that we be able to access reliable, accurate computational models of human behavior that we can then bestow appropriately upon our population of agents to achieve a marketplace behavior with acceptable verisimilitude. There is a vast literature of such models from disciplines such as experimental economics, artificial intelligence, cognitive science, psychology, and decision theory.

Traditionally, economics, and by extension, large sections of management, have largely been insulated from the rest of the social sciences. However, if the assumptions of the standard model are modified, then the door is opened for importing significant insights from the sister disciplines such as psychology, that have had a long history of studying behavior as observed, as opposed to behavior as deduced, from a set of axioms. Clearly then, there is significant motivation for building agents that engage in specific behaviors as opposed to optimization. One can then put them together in increasingly complex environments to see what sort of emergent behavior results [12]. However, much more sophisticated agents are required. At least four classes of capabilities have to be modeled in detail, including information gathering, information processing, responsiveness and interaction.

It is important to analyze and classify these behaviors with a view to applying them in a broad range of social disciplines in a collaborative, modular fashion. We describe in the next section a methodology for building an artificial labor market and a representation schema for the agents who will populate it.

2.3. Developing an ALM: Methodology and example

An objective of this paper is to enumerate one way to build an ALM, and to illustrate this methodology through a case study that employs it. We anchor our treatment to the traditional simulation life cycle for discrete event simulations, however we take pains to differentiate agent-based from discrete event simulations. Agent-based models are intended to be emergent, bottom up simulations whose aggregate behaviors arise from large numbers of non-linear interactions among individual agents with specified rules of engagement. Discrete event simulations on the other hand, are designed more from the top down with pre-programmed behaviors and interactions, oftentimes guided by underlying probability distributions for exogenous variables. Nevertheless, the life cycle provides a plausible launching point for describing the development of an agent-based ALM. Although the results of agent-based models are intended to display emergent behavior, the construction of agent-based models is not itself, nor should it necessarily be, an emergent process.

We use the basic simulation life cycle as our departure point as shown in Fig. 1 [3]. The life cycle proceeds through phases represented as shaded boxes from the upper right, System and Objectives Definition in Fig. 1 clockwise to Simulation Results. As in any model building enterprise, the process is iterative and cyclical. There are two major pathways through the cycle: the dotted lines which indicate the processes which link each of the phases, and the solid lines which refer to the credibility assessment (or verification, validation and testing (VVT) stages.

For ease of discussion, we divide the life cycle into two major segments: the model and the simulation, which correspond to the right hand and left hand sides of Fig. 1 respectively. The first segment has as its focus the conceptual and pro-

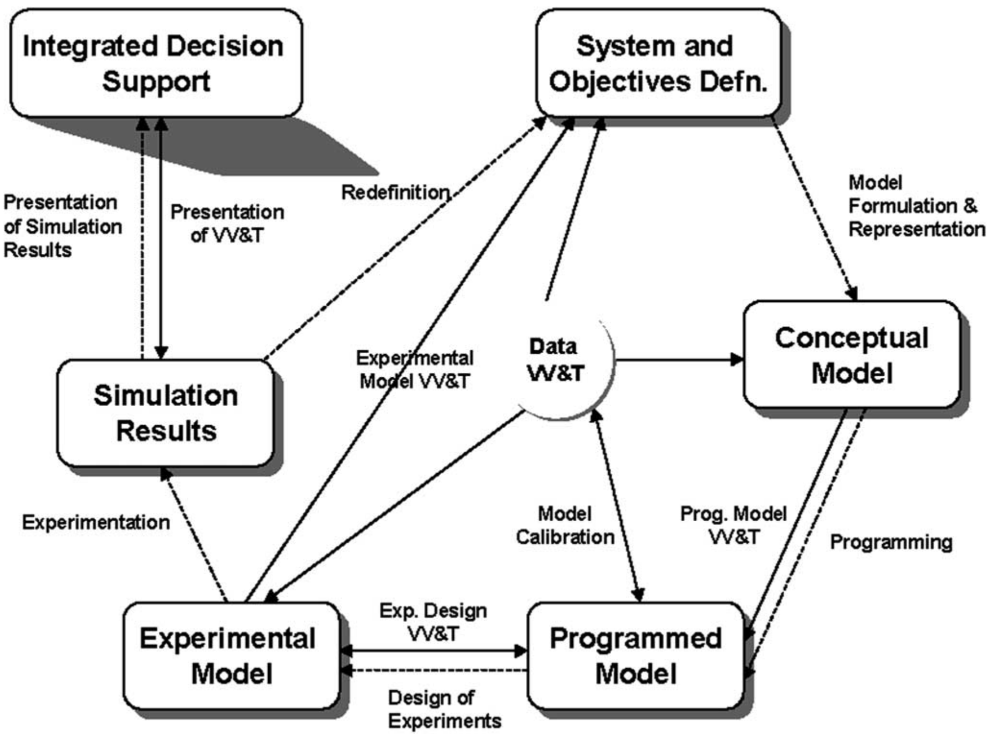

Fig. 1. Conventional simulation life cycle (adapted from [3]).

grammed phases of the model, which largely involve the seminal issues of agent representation and specification of agent behaviors using data mining. This is discussed in the next section. The second segment deals primarily with issues of simulation experimentation in which we discuss the mode of experimentation known as scenario planning, or strategic war gaming. This is discussed in Section 4.

In order to illustrate the methodology effectively, it is useful to have an example to demonstrate each of the stages of the life cycle. The artificial labor market we use as an example is the enlisted military recruit market for the US Army, typically consisting of youths between 18 and 24 years of age. The agency responsible for recruiting these individuals is the United States Army Recruiting Command (USAREC), which is typically tasked with contracting approximately 70,000–80,000 recruits annually.

3. Agent-based modeling life cycle, Part 1: The model—agent representation and specification

We will discuss each phase and process in turn from a generalized perspective applied to agent-based simulation, using specific examples from the Army recruiting environment to illustrate the concepts.

3.1. System and objectives definition

We begin the modeling life cycle after a process of requirements gathering and analysis which results in a definition of the system and its objectives. Our objectives are to build an artificial labor market that can be segmented by demographic dimensions on the labor supply side and by organizational attributes (e.g., military, educational, professional, vocational) on the labor demand side. The ALM must support the following experimentation modes including "human in the loop" capabilities so that human agents can interact with the artificial agents in a gaming situation:

1. Multiple interactive human players, synchronous mode: Sometimes called business war gaming, teams of human players convene in a single location to compete and/or cooperate with one another to meet specified performance measures within specified scenarios.
2. Multiple interactive human players, asynchronous mode: Similar to synchronous except human players are geographically distributed and the game is played remotely via the Web, often over extended time periods compared to synchronous mode.
3. Single interactive human player, standalone mode: This is similar to the various computer games such as SimCity and its descendants wherein there is only one human player. Roles that would be played by other human players in either of the above modes must also be simulated in addition to the artificial agents.
4. No interactive human players: Organizations and recruits are seeded with initial values and the simulation runs without human intervention.

The simulation must be "bottom up", that is we want market behavior to emerge from the interactions of agents who are programmed with rules of engagement to respond to the labor market under varying economic conditions and stimuli.

USAREC Example

The United States Army Recruiting Command (USAREC) has one overriding mission, which is to recruit on an annual basis the manpower required to keep the force at the desired end strength to maintain military readiness for the country. Congress mandates the number of new people who must be recruited every year, and USAREC must fill that number. By law, they cannot recruit more than that number, and recruiting less than that number generally has dire consequences for everyone affected. Recruiters therefore are under very heavy pressure to meet their missions; it is perhaps the most stressful of any non-combatant job in the Army. USAREC's objective is to develop a suite of simulations that assist leadership in making strategy, policy, and resource decisions with the necessary facts to support long-term recruiting success. These models and simulations will allow commanders and staff to better understand the recruiting process, test and evaluate new recruiting products and strategies, and determine current and future programs' effects on recruiting success. Currently, there is no single model or set of models that are accepted as being able to credibly support decision-making, measure the effects of various resources, train commanders and staff, or explain the impact of marketing phenomena.

3.2. Model formulation and representation: Agent DNA

The model formulation and representation process, also known as model design, converts the requirements specification into a conceptual model, the representation of which should be intelligible to both end users and analysts. Conceptual models for conventional operations research/management science models exist in many forms including structured modeling [14], meta-models [4], influence diagrams, and graph grammars [19]. Although these techniques are powerful for depicting the structure of mathematical models in terms of entities, attributes and relationships, they are less effective in capturing the semantics of agents which tend to be rule-based and event-based rather than mathematically driven.

As a result, we adopt a conceptual agent model in the ALM based upon the well-known double helix DNA (Fig. 2). In this model, one strand contains agent *behavior* and the other agent *intelligence*. The *behavior* strand of the helix contains the various genes, which are of interest for each agent. These genes are relevant attributes such as age, gender, race, education level, and geographical location, which motivate the behavior each agent will manifest in response to the economic

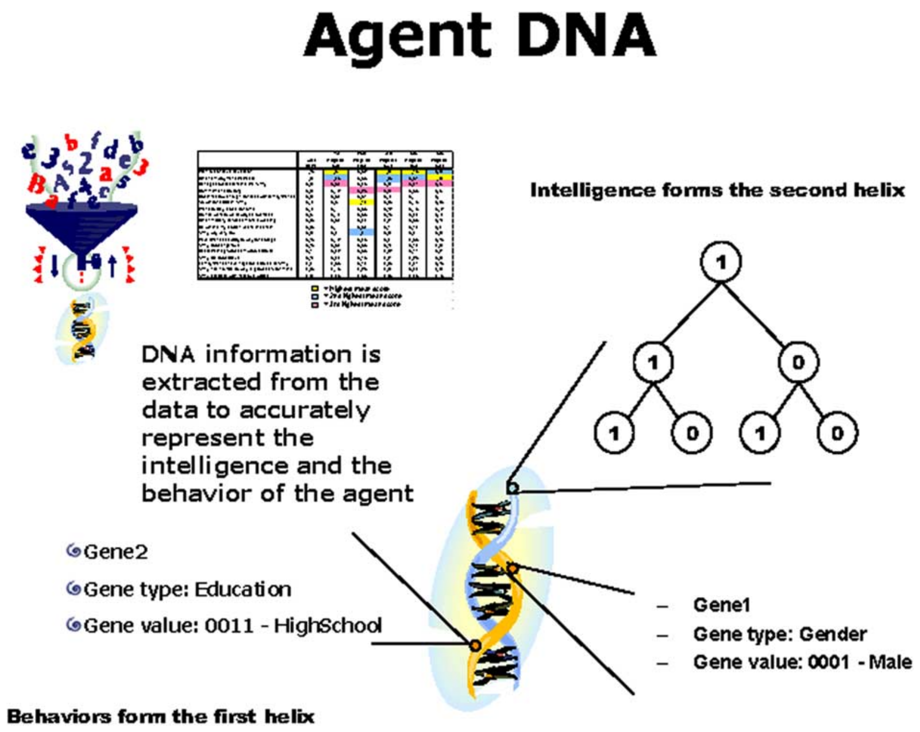

Fig. 2. Agent DNA structure.

environment. The *intelligence* strand of the DNA contains the rules of engagement by which that agent abides during the course of the simulation. The rules of engagement are a mapping between the portfolio of gene values that a specific agent possesses and the exogenous variables, which the artificial economy supports. A typical rule might be of the form, working from the simplified gene pool above, "if agent is 18 years old, male, Hispanic, high school graduate from San Antonio, then response to Hispanic-targeted advertising campaign is high." Exogenous variables may be decision parameters specified by human players in the environment (e.g., to target advertising to the Hispanic market), or general market conditions such as the unemployment rate.

In addition to the elemental agent structure, it is necessary to provide a conceptual model for agents to communicate and collaborate in the environment. Since emergent behavior culminates from the non-linear interactions of agents with the environment and with each other, there must be primitives supplied for facilitating communication. Fig. 3 lists the eight basic behavior primitives which our artificial agents may exhibit. Especially critical are the functions of communication and collaboration. The conceptual model for this aspect of agent structure is based upon conceptual *ports* and *channels* (Fig. 3). A *port* is a place where an entity submits its outgoing messages to the environment. A *port* allows its owner to configure its own communication rules. A *channel* on the other hand is a place where an owner can query messages from the environment discriminately. Entities that are interested in messages will create *channels* to query the *ports* for messages. This allows the system to define communication rules prior to runtime. Using the example above, if a human player desires to target Hispanic agents for a marketing campaign, then this would be done by sending a message on his/her port; the Hispanic agents in turn would poll messages on this port to see what, if any, messages currently exist that they should be aware of.

Another critical aspect of the model formulation process is input data analysis and modeling, which involves in the large preparing the data upon which the model depends for its solution. This is often the most time-consuming task in the model life cycle. Simulation data analysis can be *self-driven* or *trace-driven* by which is meant respectively, deriving input values by sampling randomly from probability distributions, or deriving

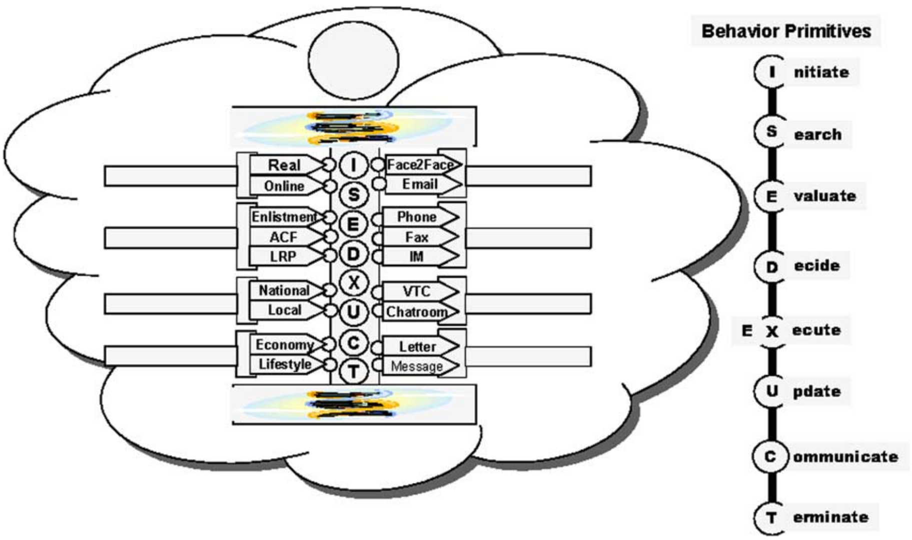

Fig. 3. Combination and collaboration structure for agents.

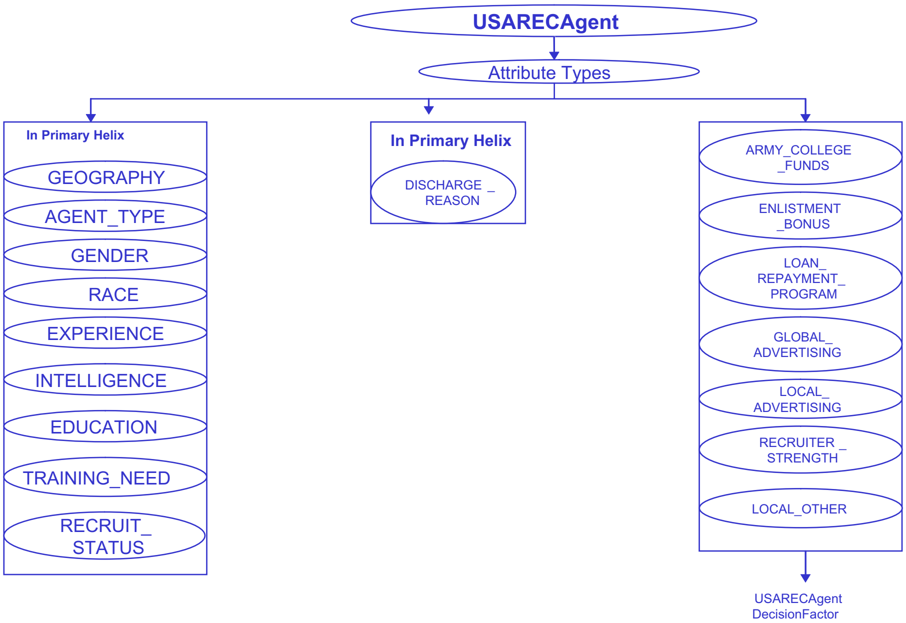

Fig. 4. Primary helix of agent demographics and characteristics.

Table 1
Recruit agent genes and categories

Gene	Categories
AGE	18–24
Experience	Non-prior service/prior service
Race	African-American/Caucasian/Hispanic/Asian/Native
Gender	Male/Female
Education/intelligence	HSl Graduate Alpha/HS Grad Bravo/HS Senior Alpha/HS Senior Bravo/GCA
Type	Active/reserve
Geography	41 different regions, each covered by a battalion
Training need	Trainer/non-trainer

data from measurement of the real system. In the ALM, agent rules of engagement within the labor market are trace-driven in that they are generated from various data mining procedures which are discussed below.

In summary, the basic steps relevant to model formulation of the ALM are as follows:

- Identify the artificial agents and the human agents who will participate, or "play", in the ALM.
- Specify the artificial agent genes (attributes).
- Specify the decision parameters which each human agent can control.
- Identify market exogenous factors.
- Identify performance measures for human players.
- Specify the artificial agent behavior, or rules of engagement, with respect to each decision parameter and market exogenous variable. (This often requires substantial data mining analysis.).

We discuss each of the model formulation steps in more detail for the USAREC environment.

USAREC Example

Identify agent classes. For the USAREC ALM, we have only one overall class of artificial agent, namely, the 18–24 year old potential military recruit. Although the simulation environment (to be discussed below) can support multiple classes of agents simultaneously, the initial version will have little breadth but significant depth. The intent is to scale the system to support as many instances of this agent class as possible, up to the 1.4 million recruit pool that the Army contacts every year.

The human agents reflect the USAREC environment and consist of three classes of players: US Army Group, USAREC Headquarters, and the Recruit Brigade Commander. The US Army Group is primarily concerned with the strategic, long term view of the Army, particularly with respect to the eventual force strength, or end strength, and whether this will be sufficient to meet the missions the Army will be required to perform. Army Group dictates budget resources and constraints that are mandated by Congress and passed down to USAREC. USAREC is the operational activity that distributes the resources received from the Army Group to the various recruiting brigades. There are five brigades in the US, each of which is broken down in to various Battalions, of which there are 43 in all. The Recruiting Brigade Commanders are the tactical players and must do the hard work of actually recruiting people into the Army. A typical annual mission is between 70,000 and 80,000 new recruits per year.

Specify artificial agent genes. An agent's demographics and characteristics are encoded as genes on a helix. The first helix is the primary helix and the information encoded there is pretty much static. Decision factors and non-permanent information are encoded on the secondary helix. Each agent may have a large combination of potentially different genetic makeup depending upon the number of genes and the associated subclasses within those genes. The recruit agent, for example, has eight major genes: race, gender, education level, intelligence, recruit type (active or reserve), prior military experience, training need, and geographic location (Fig. 4). Each of these genes has distinct categories that may be of interest in post simulation analysis. Table 1 shows the various genes and categories which have been identified by USAREC as important during the requirements analysis. Notice that there is a total combination of $2 \times 5 \times 2 \times 5 \times 2 \times 41 \times 2 = 16{,}400$ possible individual genotypes given this basic genetic structure. This combinatorial explosion poses a significant challenge in the data mining process for each of these combinations may have a different response function to the exogenous and decision factors present in the ALM.

Specify human agent decision factors. The recruit agents constitute the labor supply pool. The demand side of our market consists of the US Army and everybody else including corporations, other military services, colleges and universities. We are interested in measuring the propensity to enlist for each of the recruit agents given the availability of the options in the labor demand market. This propensity to enlist may be affected directly or indirectly by any or all of the decision parameters, which the human players have the ability to specify. Table 2 shows the decision factors, again determined in the modeling requirements phase, which each class of human player can change. The decision factors will define how agents evaluate the actions taken by the Army and match them to their own preferences (Fig. 5).

Specify market variables. Table 2 shows the market parameters used in our SSLE simulation, which are the unemployment rate and the growth rate of the economy. This is an assumption which simplifies the model somewhat; other factors such as pay rate and comparable pay rates could justifiably be argued as important factors here as well. For initial entry recruits, however, pay rate is less a factor than incentives such as college bonuses.

Specify performance measures. The critical performance measure for USAREC is how well the mission is being met. The overall annual mission is dictated by Congress and decomposed and allocated by USAREC Headquarters to each of the recruiting brigades and their associated battalions. Therefore, the main measure independent of whether we run single year or multiple year scenarios is *%_Mission_Accomplished*. Another critical

Table 2
Human player decision parameters and market exogenous variables

Human player/team	Decision parameter
Army group	Overall budget Annual mission Recruiter strength (# Recruiters Available) Budget for recruiting incentives and bonuses (Army College Fund; Enlistment Bonuses; Loan Repayments) Global advertising budget Local advertising budget
USAREC	Allocation of recruiters to brigades Allocation of bonus incentives to brigades Allocation of local advertising budget to brigades
Brigade commanders	Allocation of recruiters to battalions
Market	Unemployment rate Economy growth rate

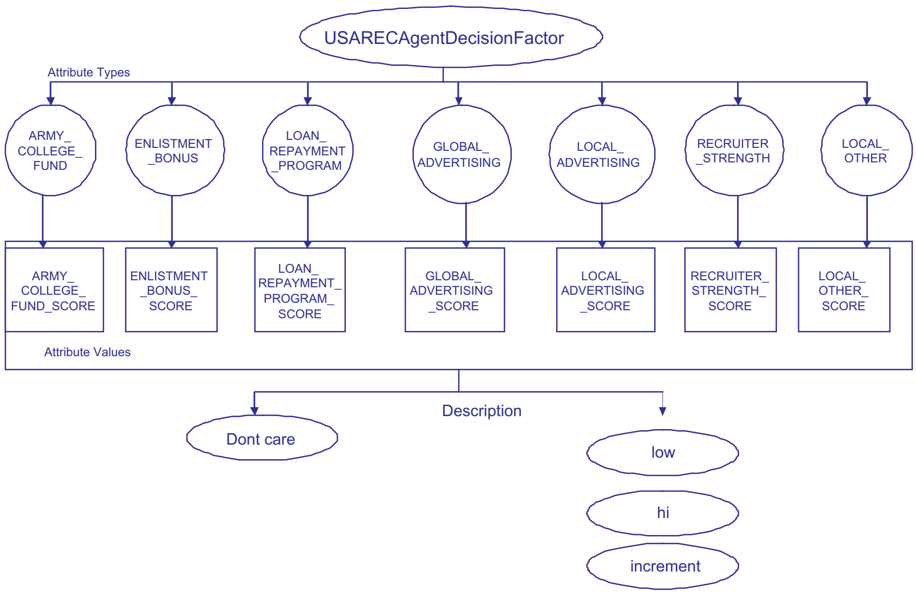

Fig. 5. Secondary helix of agent decision factors.

consideration in the Army recruiting process is management of the inventory of recruits, known as delayed entry program (DEP). When a contract is signed with a new recruit, it is not always possible to assign that individual to initial entry training (IET) right away. The recruit may want to finish high school, for example, or there may not be room in the IET classes right away. As a result, many new recruits go into the delayed entry program to await assignment; this waiting period may extend from a few weeks up to nine months. The DEP is effectively an inventory of contracted recruits and is a closely watched parameter. During this period there is a certain amount of attrition from people who change their minds and subsequently decide not to join the Army after all. This *DEP_Loss* is another key performance measure used in the simulation.

Specify agent behavior: Data mining and analyses. The major challenge in building an ALM is specification of the various agent response functions for each of the exogenous variables and decision parameters. Table 3 provides an overview of the methodology we use to define appropriate agent response behaviors. What we are interested in measuring is each agent's propensity to enlist in the Army, and this may be affected by two types of decision factors: horizontal factors which are individual specific factors and vertical factors which exogenous market variables. Horizontal factors may be global which include various incentives such as the Army College Fund, enlistment bonuses, loan repayment programs and national advertising, or local, which are comprised of local advertisement and the number of recruiters assigned to a geographic area. Take the case of national advertising budget. Intuitively, we would expect that if the Army increases its national advertising, more military eligible youth would become aware of the Army as a viable alternative, and therefore we would expect a higher propensity to enlist as a result. But how high? And how would this propensity differ between men and women, between different education levels and across different races? This is quite a large space since each of the 16,400 genetic blueprints must respond in a realistic way in order to reflect the real world demographic behavior. In general, if there are n agent individuals and m exogenous variables, then there is a possible space of $m * n$ response functions which must be considered. This space will be reduced in general because not all exogenous variables will affect all individuals; further, some genetic individuals may have similar, if not identical, response functions. Nevertheless, it is a daunting task to determine which cells in the matrix must be populated and what data mining is necessary to determine reasonable demand response functions.

We only describe the data mining procedure in general terms. An agent's demographics and characteristics (Fig. 4) are matched against the decision factors (Fig. 5) by inducing rules from real data, and encoding these rules into the decision factor genes of the agents (Fig. 6). For each (agent, decision factor) pair, a threshold value is

Table 3
Process for defining agent decision-making behavior

Gather user inputs from GUI	Map user inputs to external performance moderators	Adjust strengths of external performance moderators	Agents respond on external performance moderators	Agents take action
Description				
• Gather inputs by human decision makers	• Organize and store user inputs according to the external performance moderator maps	• Calculate resulting strengths of external performance moderators which are tied to user inputs • External moderators not tied to user inputs are adjusted based on other environmental variables such as season changes	• Each agent looks up for the set of interested external moderators • Strength of the interested external moderators are compared with each agent's personal preferences	• AS a combined result of the agent's personality traits and the external performance moderators, each agent selects an action from the set of defined behaviors/actions

computed from a Gaussian function derived from the data. The mean and standard deviation of the distribution are adjusted in accordance with the data to give higher or lower probabilities for a threshold value being selected. Table 4 shows the data sources for mining agent behaviors for the simulation. The major problems encountered in data mining have to do with the lack of data for determining some response functions. For example, precise data on effectiveness of advertising at both the national and local levels is typically elusive at best. In those instances, we have had to

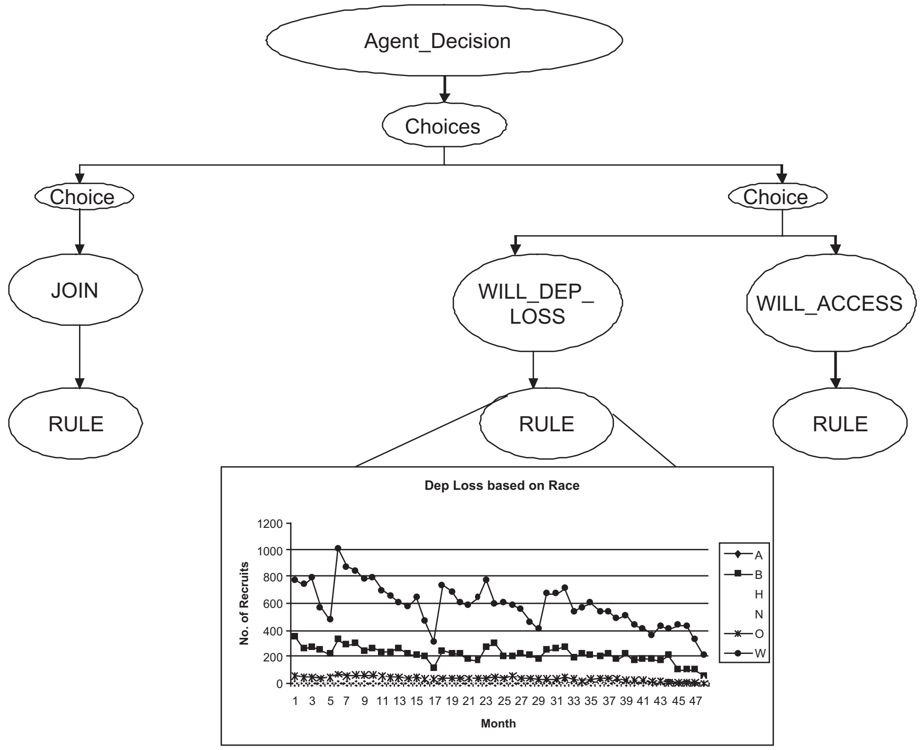

Fig. 6. Rule induction for agent behavior from data mining.

Table 4
USAREC data sources for data mining (bold face indicates those files actually used in the study)

ENLISTMENT EARLY WARNING SYSTEM	PRIME MARKET STUDY
YOUTH ATTITUDE TRACKING STUDY (YATS)	COLLEGE/WORKFORCE POTENTIAL
ENHANCED APPLICANT FILE	COLLEGE MARKET DATABASE
MARKET SHARE/COMPETITIVE ANALYSIS	RECRUITS WITH COLLEGE SURVEY
SAMPLE SURVEY OF MILITARY PERSONNEL	NEW (COLLEGE) INCENTIVE ANALYSIS
NEW RECRUIT SURVEY (NRS)	SURVEY OF ELITE COLLEGE STUDENTS
PARENTS OF NEW RECRUITS SURVEY	LEADS DISTRIBUTION SYSTEM ANALYSIS
TEENAGE RESEARCH UNLIMITED (TRU)	YOUTH DECISION MAKING PROCESS
MONITORING THE FUTURE	BARRIERS TO ARMY ENLISTMENT STUDY
YANKELOVICH MONITOR	PRIOR SERVICE FOCUS GROUP (USAR)
LIFESTYLE SEGMENTATION SYSTEM	RECRUITER SELECTION STUDY

guess at the agent response threshold values and rely upon the agent calibration process to refine these values.

3.3. Programming, model solution, and calibration: SEAS

The third major phase in the life cycle is the Programmed Model, which addresses the software implementation of the model and the associated processes of model solution and model calibration. ALM is developed and programmed within an overarching agent-based simulation environment called the Synthetic Environment for Analysis and Simulation (SEAS). SEAS is an agent-based simulation engine which provides the capability to construct artificial agents having the characteristics defined in the previous sections, and which provides for "human in the loop" simulation allowing human players to interact with the artificial economy. SEAS has been developed specifically to scale easily to support multiple classes of agents with large numbers of each (typically a million or more) in a Web-based, ASP environment. We provide only a very high level overview of SEAS here; the reader is referred to [2,7] for more detailed discussions of the SEAS architecture.

SEAS is an interactive synthetic economy that models the critical relationships between economies, markets, product and process innovations, price, and business rules using human and artificial agents. It allows participants to view the economy from different perspectives such as the government, universities, commercial sectors, and the households/consumers/tax payers.

An internet-based SEAS virtual execution environment (VEE) is depicted in Fig. 7. In the SEAS VEE, participants can take part in an exercise from any distributed locations. VEE consists of three classes of servers: the proxy server, application servers, and distributed database servers. Proxy servers ensure restricted access for the subscribers. There are three different classes of application servers:

(1) Agent Processing Servers capable of running hundreds of thousand of different kinds of agents.
(2) Economic Processing Servers capable of representing different types of markets.
(3) Visualization Servers that generate advanced 3-D displays of the data generated during the exercise.

There are individual database servers that support each of these application servers. These database servers may run at one or more locations. Thus, the distributed design enables any number of participants to take part in an exercise from any number of locations, and any number of exercises may be available at any given time.

Once the agents have been implemented and interfaces have been designed for the human agents to input decision parameters, the model must be solved and calibrated. Solving the model generally occurs in single cycles. Once human

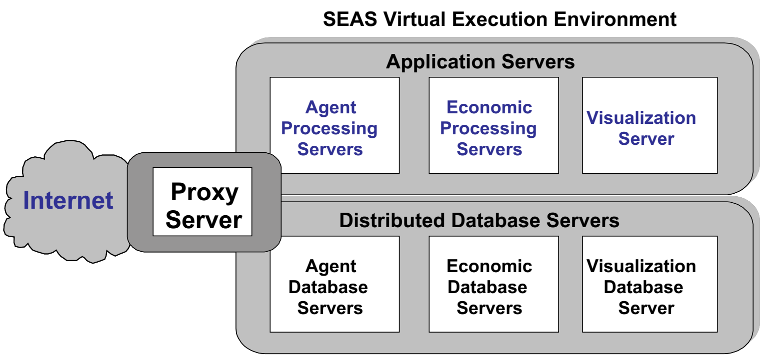

Fig. 7. SEAS virtual execution environment.

players have set decision parameter values for a particular slice of time, a solution cycle involves evaluating each agent to see whether it changes its state. A weighted average of each agent's threshold factors is compared against the decision factor values input by the human players. If the weighted average falls below the decision factor values, then the agent does not join the Army; if it exceeds this value, then the weighted average is compared to a random number from a Gaussian distribution in the interval $[0, 2]$. If it exceeds this number, then the agent joins the Army. This evaluation process can be a time-consuming task when hundreds of thousands, or millions of agents are involved. In very large-scale applications including an ALM with one-to-one granularity, grid computing-based model solution may become necessary to reduce single cycle computation times to manageable durations. Techniques for calibrating the model include retrofitting the model to historical data; this is an integral part of the model VVT process.

USAREC Example

Agent calibration. Agents were calibrated by comparing the numbers of simulated recruits with actual recruits for the years 1998–2001. This was

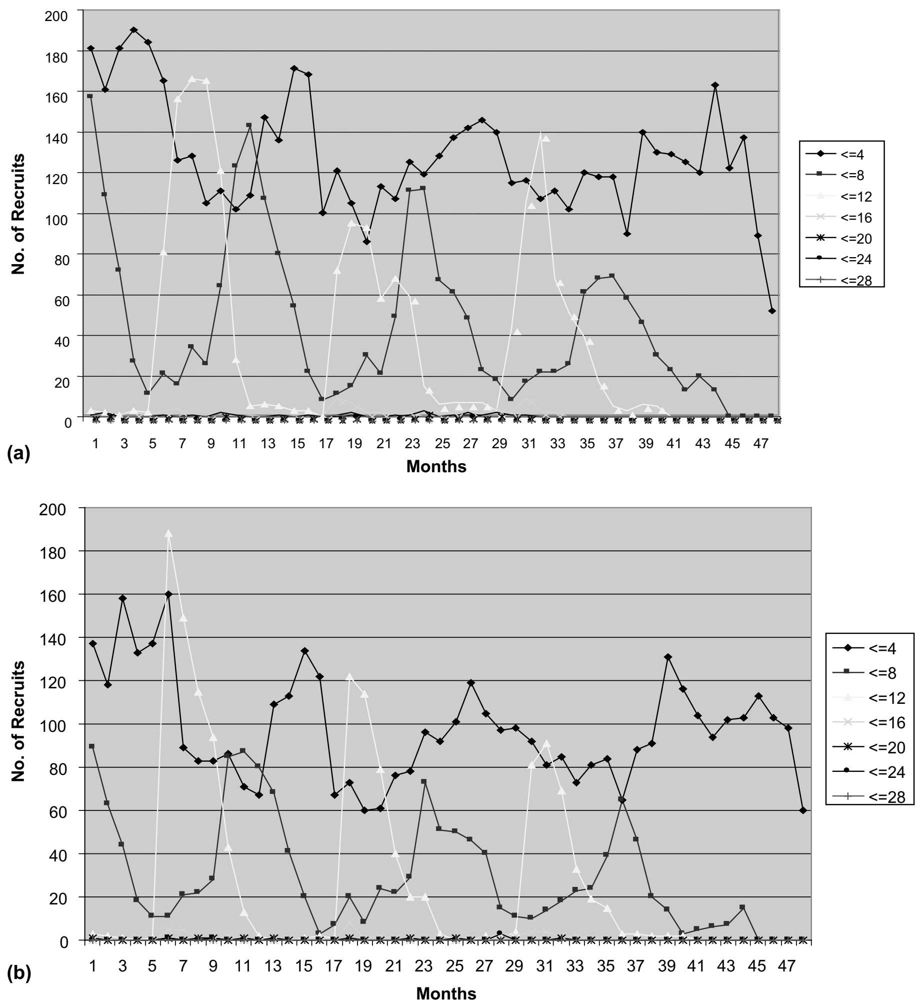

Fig. 8. (a) Actual DEP loss for brigade 1 during 1998–2001. (b) Simulated DEP loss for brigade 1 during 1998–2001.

done at the battalion level and aggregated to the brigade level as shown in Fig. 8a and b for the DEP Loss performance measure. However, this works only as a rough approximation, and may miss local or current phenomena which affect market behavior in the short term, e.g., the impact of 9–11 on the patriotic pulse of the country. We need finer and finer ''drill down'' calibration techniques with much more recent market data complementing the approach we've taken so far. We address this issue in Section 5 in our discussion of computational experimentation.

Human player interfaces. Each human player/team must be provided with customized input screens so they can supply values for the decision parameters which they control. Fig. 9 shows an example of an input screen for the Army Group to set the recruiting mission for the current year. These human player interfaces are the biggest obstacles to simulation reusability, since they must be tailored for every application, and each screen must feed the appropriate database tables.

The focal point of the first segment of the life cycle is on agents and how they are represented and constructed. The other major component of the life cycle is the experimentation segment, so we can characterize the two segments as the model and the simulation. The model involves the representation aspects and the simulation represents how the model is going to be used for analysis and decision-making. We now move to discussion of the experimentation phase of the life cycle.

4. Agent-based modeling life cycle, Part 2: The simulation—experimentation using scenario planning

Whereas the first segment of the life cycle is model-focused, that is, determining model representation and structure, the second segment of the life cycle is oriented towards the simulation dimension, that is, how we execute the model, and interpret and analyze the results.

4.1. Design of experiments: Scenario-based strategic war gaming

This phase of the life cycle is perhaps where conventional discrete event simulation and the agent-based ALM simulation depart the most radically. In the former context, design of experiments involves generating a model solution plan to gauge the effects of input variables on one or more response variables. This may include any or all techniques of goal seeking, optimization and factorial design.

In the ALM environment, we seek to support ''human in the loop'' transactions in conjunction with artificial agents. In particular, we employ humans to play various employer organizations while the artificial agents represent the employees whose services are being sought. Thus, the input variables are being set by the various human players in the game who in general are trying to attain one or more performance objectives by their actions. Human players may compete as in combat simulation and/or cooperate with one another depending

Set Mission										
	NPS Trainers			NPS Non - Trainers			Prior Service			Total
	NPSM	NPSF	Total	NPSM	NPSF	Total	PS T	PS NT	Total	78,950
Quarter 1	7,762	2,838	10,600	546	154	700	414	986	1,400	12,700
Quarter 2	14,947	4,453	19,400	702	198	900	630	970	1,600	21,900
Quarter 3	13,720	2,980	16,700	624	176	800	615	885	1,500	19,000
Quarter 4	18,550	4,700	23,250	468	132	600	290	1,210	1,500	25,350
Total	54,979	14,971	69,950	2,340	660	3,000	1,949	4,051	6,000	78,950

Fig. 9. Sample-based input screen for army group team to set active army recruiting mission.

upon the circumstances, or scenarios, of the "game". This approach is called scenario planning [32,33], and in this version of simulation, experimental design involves determining what the values of the market exogenous factors will be (i.e., what scenarios will be played) in conjunction with key decision parameters each human player is allowed to affect.

4.2. Experimentation

This phase involves experimenting with the model for specific purposes which may include evaluation of decision policy tradeoffs, insight into the overall system, team building, and training. We should point out that one of the common purposes for building simulation models, namely forecasting, does not apply to the strategy-oriented, scenario-based ALM. The strategic war game environment is intended as a test bed to try different policies and examine *possible* outcomes, then use these outcomes to examine the decision-making processes themselves. Insight into the dynamics of the decision-making processes is desired as opposed to providing an accurate and reliable forecast of what will happen when certain decisions are made. We also note that in the ALM context, the experimentation process should actually precede, or be integrated with, the experimental design activity since determining the purpose will directly affect the solution plan. For example, a scenario in which the human players are required to meet certain performance goals will exercise the model in different ways than one in which players are encouraged to try different decisions and examine the resultant outcomes. The latter may require the simulation to be rolled back periodically whereas the former may be played straight through from beginning to end.

USAREC Example

The Strategic Simulation Leadership Exercise (SSLE) is an annual synchronous business war game conducted by USAREC to stimulate strategic thinking, leadership, and team building across all echelons of decision-making. The exercise lasts for two days and includes a series of workshops, simulation moves, and after action reviews. The scenarios that drive the exercise are based on combinations of the economy and projected force end strength. In general, recruiting is more difficult when there is a strong economy and somewhat easier when the economy is weak. End strength directly affects the recruiting mission since a larger force will usually require more recruiting. Reductions in force, on the other hand, generally lower the recruiting mission. Thus, the easiest scenario is a weak economy with a reduction in force, whereas the most challenging is a strong economy concurrent with an increase in end strength.

4.3. Presentation of simulation results

Once the model has been "solved" or executed according to the experimental design, the critical step of displaying the results occurs. The results must be presented to the end users (the human players in the ALM case) in a timely and comprehensible fashion. Our approach for this phase has been to develop a map-based, drill down interface which is very similar to existing on-line analytical processing (OLAP) tools. Users are presented with a menu of performance measures, any one(s) of which they can view at different levels of map granularity. The primary advantage of this interface is that it can be used not only for viewing simulation results but also for viewing "real" data from an appropriate data warehouse. This provides the capability of comparing real versus simulated data "on the fly". We show the interface in the next section and also indicate how it contributes to our notion of computational experimentation and integrated decision support, which in turn will be instrumental in our verification and validation process. We also note that this phase provides an important step in our model VVT. Although, our intent in model calibration is to have provided sufficient model verisimilitude to achieve the goals of the experimentation, this is nevertheless a point where participant feedback may surface additional shortcomings in the model validation.

USAREC Example

One of the critical success factors in the first SSLE was the output display format. We note that much of the process that we have described so far in constructing the ALM is very similar to what is done in building a data warehouse [11]. The agent's genes effectively describe what would be used as drilldown dimensions in a data warehouse OLAP application, i.e. age, education level, etc serve as drilldown pathways. This is not surprising since it is reasonable to expect that simulation users would want to view the same factors and dimensions that they do in "real life" situations. As a result, we developed a map-based, OLAP-based environment for viewing the overall results of the simulation (Fig. 10). The map at the top level is segmented by brigade and battalion with color coding used for cueing the user about performance (%_Mission_Accomplished). Results can then be viewed along any of the genetic axes, for example, show recruiting by educational level for all battalions in the 6th brigade, and as with standard OLAP tools, data can be organized into tables and charts. Another display allows users to specify any from up to 18,000 parameters for display and graphing. This ability to explore the solution space along any of the agent attributes mimics what is done in the tactical day-to-day process of gauging and analyzing recruiting success. We will leverage this display in the next section to facilitate a parallel worlds environment, which allows users to access real data and simulated data simultaneously.

4.4. Market verification: Strategic war game

The results from the war game are qualitative in nature. Since the model is not intended to be predictive at this stage of development, we sought to achieve an initial level of verification for the reasonableness and verisimilitude of the agents' behaviors, and the resultant emergent market behavior. The players, particularly the Recruit Brigade commanders, are very familiar with the markets in their respective regions, and any major discrepancies between the simulation and their perceptions would immediately have been identified. The war game numbers met with acceptance from players. It allowed them to try different ideas, all of which resulted in outcomes they could believe. For example, one commander switched

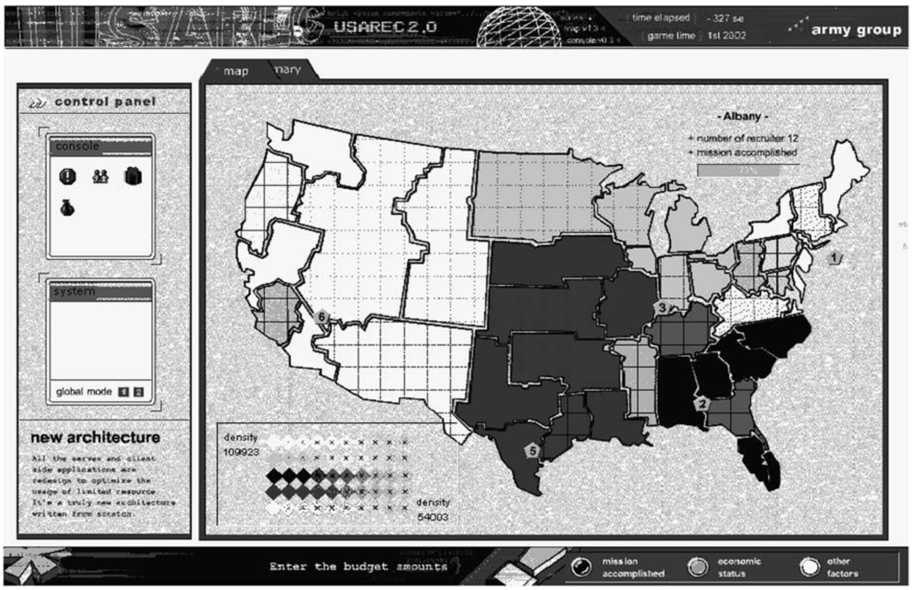

Fig. 10. Map-based, OLAP-based simulation user interface for output analysis.

50% of his recruiters from a major Western city with an historically bad track record of success to a different area within his region, in the process realizing an increase in recruiting mission achievement according to the simulation. This led, in turn, to a discussion of the viability of mobile recruiting stations as a mechanism for mitigating the effects of "slow" markets, and being able to respond quickly to shortfalls in mission. This ability to try different ideas, analyze the tradeoffs, and brainstorm new approaches to old problems is the main benefit of strategic war gaming, and by these objectives our simulation exercise was a success.

4.5. Redefinition

This phase captures the iterative nature of all modeling wherein modifications and enhancements are required to either "fine tune" the model, or to apply it to different situations.

USAREC Example

One of the by-products of a successful simulation is that it breeds a demand for decision support tools that are consistent with the strategic results, but provide additional support at the operational and tactical levels. In the USAREC case, this manifested in several forms: the desire for a version of the simulation available in asynchronous form, and the desire for a user interface that interacts with near real time data from a warehouse as well as with the simulation. The real world version characterized by the data warehouse is discussed in the next section. The asynchronous version has two dimensions: one which allows the war game to be played remotely with all players participating otherwise as in the war room, and another which allows players to use the simulation in stand alone mode as a decision support vehicle. In this latter situation, the behaviors of the other human players in the game representing agencies would have to be simulated in addition to the agent-based market.

One of the critical success factors in recruiting success is the quality and leadership of the recruiters themselves. One of the additional requirements, which surfaced quickly during the exercise, was the desire to have some player control over the recruiters, not only in the quantity of same, which this game supported, but also the quality. Thus, a desirable enhancement emerged for building another class of agents representing recruiters, and constructing appropriately realistic recruiter behaviors.

Other domain-specific enhancements have naturally arisen, but the major thrust is to increase the verisimilitude of the model so that its value increases at all levels of the decision support chain. One of the impediments we currently face is that the model verification process which worked well for the initial war game held in August 2001 is too coarse-grained to capture current events which affect recruiting. For example, the patriotic upsurge which followed the events of the 9–11 terrorist attack, may very well have increased the propensity to enlist in the marketplace, at least in the short term. This made it easier to reach mission this past year, and may continue to do so for the next year or so. Our model needs to be able to reflect these short-term phenomena in the marketplace, which, in turn, requires a much stronger coupling with current market data than we currently have implemented. In effect, this requires moving from model verification to model validation, which is a non-trivial leap for a model of this kind. The next section discusses our approach to this challenge, which leverages the scalability of the model and the integration of data warehouse with agent-based modeling to provide a lens into the real and virtual worlds simultaneously.

5. Integrated decision support: Continuous computational experimentation

From the discussion of the previous two sections, we can now present the agent-based life cycle which reflects the exigencies of constructing an artificial labor market (Fig. 11), and which incorporates the tools and methodologies we have developed and adapted in support of this objective.

The ALM provides a virtual world for the Army to test recruiting policies and continuously

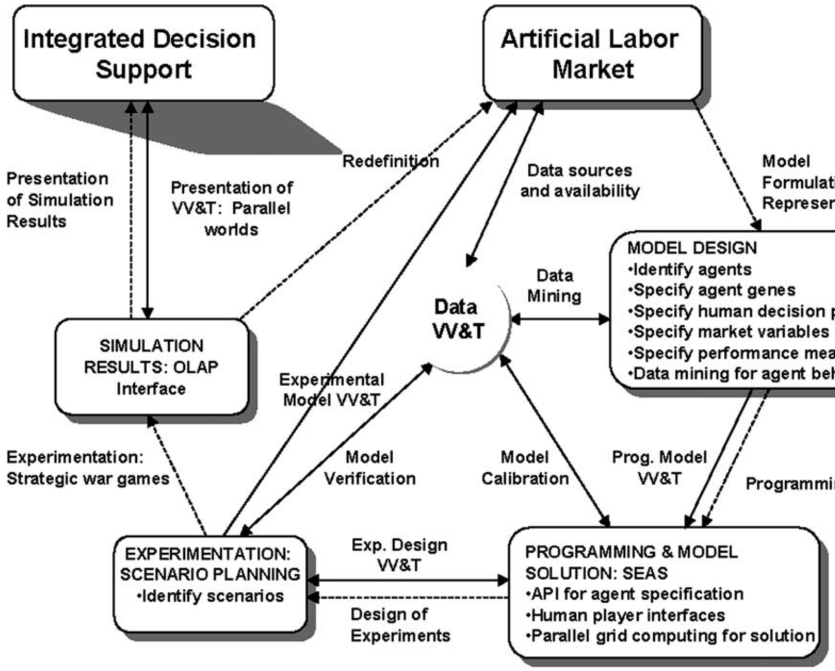

Fig. 11. ALM agent-based simulation life cycle.

explore its marketplace, just as it does in the "real world". Because the virtual world is a persistent process in the software sense, that is, it is always running, we refer to the overall process as *continuous computational experimentation*. Continuous computational experimentation via agent-based simulation provides integrated decision support beyond the reach of a traditional single-purpose, low reuse simulation model, particularly when it is linked with its "real world" counterpart as we indicate below.

5.1. The "real world": Data integration

As alluded to earlier, we consciously designed the user interface for the simulation to be consistent with prevailing approaches used in data warehouse OLAP technology. This was done intentionally so we could use the same interface to access the USAREC data warehouse containing the actual, or "real world", operational data. It is important to realize that each artificial agent has a history just as each "real world" individual does. Each agent not only possesses personal characteristics but also completes various transactions throughout the course of a simulation. For example, an agent, just like an individual, may decide to join the Army, undergo initial entry training, be assigned a military occupational specialty (MOS) and so on. These events are recorded in the simulation database that is the virtual counterpart of the data warehouse used to track real world enlistees. It is therefore possible to do the same kinds of queries and reports in the virtual world as we do in the real world warehouse. For example, we can use on line analytical processing (OLAP) tools to investigate the major reasons why virtual agents chose not to enlist in Texas, or which regions made mission the soonest with respect to female recruits.

5.2. Model validation: "Near real time" feedback loop

By maintaining a virtual warehouse and developing a user interface that can be connected to it as well as to the "real world" data warehouse,

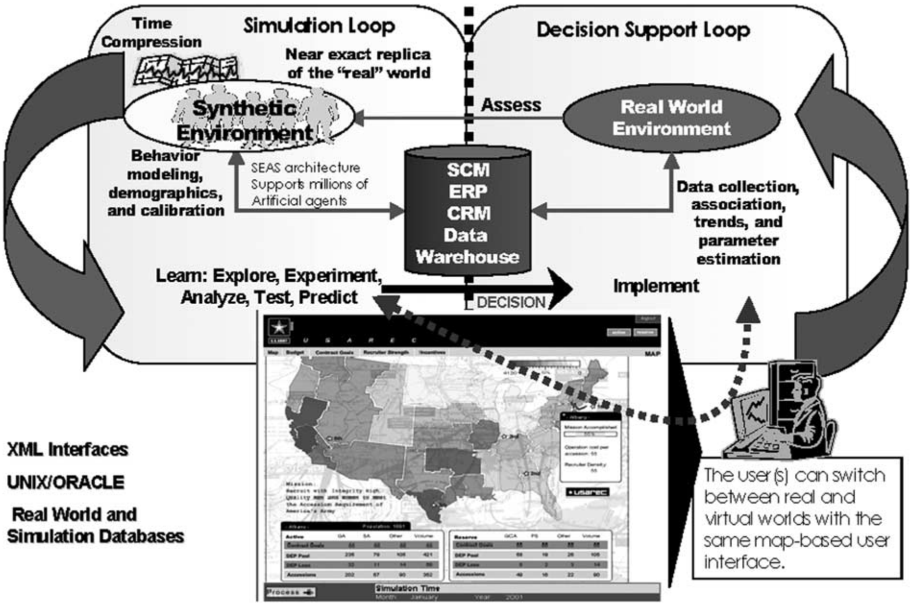

Fig. 12. Parallel worlds.

we have created "parallel worlds", one that tracks the real labor market and one that maintains the ALM (Fig. 12). In this environment, we can now begin to address the difficult problem of validating the ALM model. The challenges of validating emergent models are well-known [25]; the existence of parallel worlds allows us to conceive of "near real time" feedback mechanisms, perhaps consisting of layers of artificial neural networks (ANNs), which keep the ALM synchronized with the actual market. This scenario allows a very tight decision support loop wherein the "real" world serves a performance tracking, problem search function while the virtual world provides a decision test bed for trying new policies and decisions to illuminate alternatives to address these problems. USAREC intends to use this environment exactly in this "sense and respond" way as they proceed through a recruiting year. As shortfalls in mission appear around the country, they will be quickly identified and addressed using the data warehouse. Alternative courses of action can then be evaluated in the virtual world to see if they correct the shortfall within budgetary and resource constraints. The real world can then be monitored to assess the impacts of any choices that have been implemented.

5.3. Limitations of the ALM

Agent-based models have inherent limitations some of which are reflected in our ALM. For example, because agent-based models are emergent, it is often very difficult to identify and understand the mechanisms which are responsible for observed systems behavior. This is particularly true for macro-level models such as we envision here. In many cases, reliable knowledge about such mechanisms is essential for decision-making [23]. When USAREC does not meet mission in a simulation run, for example, it is important to know whether this came as a result of DEP Loss, too low a number of recruiters, or other phenomena. To combat this "black box" aspect of agent-based models, our OLAP visualization tool allows users to drill down through the simulation results and conduct "casual" data mining analysis. Application of more formal data mining techniques to the simulation results is a promising area for future research.

A second limitation of our model is that it is not a forecasting model. When people make a decision and observe the results of their decisions in the gaming environment, we cannot say with any degree of certainty that that same decision will lead to the same outcome in the real world. The strategic war-gaming process is more focused upon the *process* of decision-making and the interaction and coordination of the human players than it is on predicting the future. In fact, agent-based models and virtual worlds are often used for training purposes. We would like to overcome this limitation for the ALM in the following way:

- Increase the scale of our ALM so that there is effectively a one-to-one mapping between artificial agents and their ''real world'' counterparts (vis-à-vis our current 14-to-1 ratio).
- Apply some form of the ''near real time'' feedback loop described above to link the data warehouse and the simulation.
- Use drilldown calibration so that all segments of the market are continuously calibrated as well as the macro-level market.

If we can maintain this degree of verisimilitude between the two worlds, then we can use the agent-based model as an analytical tool in addition to a decision-making tool.

6. Conclusions

Developing an agent-based ALM in the broader context of computational experimentation provides a much more resilient and enduring decision support platform than traditional simulation models have typically yielded. Simulations have notoriously long development times and notoriously short half-lives. Further, their reusability index is low because they tend to be so application-specific and programming-oriented. A virtual market, once built, verified and validated, can be used over and over for many different applications.

We have described an ALM that is different in concept from most other synthetic economies. The ALM serves as a simulacrum of a real world labor market, i.e., it is a complex, detailed model of a labor market, which is available electronically for decision-makers to test new policies. We have described our methodology for building this marketplace using the conventional simulation life cycle as our starting point. The SEAS environment coupled with scenario planning simulations affords a rich ''human in the loop'' strategy oriented decision support vehicle. Leveraging this with familiar, yet powerful, map-based, OLAP-based user interfaces, provides market segmentation analysis at multiple levels of granularity, and allows the environment to be used at lower levels of tactical and operational processes as well. The use of OLAP-based simulation visualization capabilities opens the vista for joint real and virtual world exploration, and near real time synchronization. We believe our large-scale labor market experiment shows the power of agent-based modeling, and affirms its legitimacy as a new simulation technology in the arsenal of operations research and management science modeling.

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