Yugoslav Journal of Operations Research
12 (2002), Number 2, 141-156

APPLICABILITY OF AN AGENT-BASED MODELING CONCEPT TO MODELING OF TRANSPORTATION PHENOMENA

Shinya KIKUCHI

Department of Civil and Environmental Engineering
University of Delaware, Newark, Delawere
kikuchi@ce.udel.edu

Jongho RHEE

Department of Urban & Transportation Engineering
Kyonggi University
Yiui-Dong, Paldal-Gu
Suwon, South Korea
jhrhee@kuic.kyonggi.ac.kr

Dušan TEODOROVIĆ

Department of Civil and Environmental Engineering
Virginia Polytechnic Institute and State University
Northern Virginia Center, Falls Church, Virginia
duteodor@vt.edu

Abstract: Today's transportation problems are found in the complex interactions of social, financial, economic, political, and engineering issues. The traditional approach to analyzing transportation problems has been the top-down approach, in which a set of overall objectives is defined and specific parts are fitted in the overall scheme. The effectiveness of this analysis process has been challenged when many issues need to be addressed at once and the individual parts [participants to decisions] have greater autonomy. A factor contributing to this phenomenon is the greater opportunity and power for individual parts to communicate and to interact with one another. As a result, it has become increasingly difficult to predict or control the overall performance of a large system, or to diagnose particular phenomena. In the past decade, the concept of agent-based modeling has been developed and applied to problems that exhibit a complex behavioral pattern. This modeling approach considers that each part acts on the basis of its local knowledge and cooperates and/or competes with other parts.

Through the aggregation of the individual interactions, the overall image of the system emerges. This approach is called the bottom-up approach. This paper examines the link between today's transportation problems and agent-based modeling, presents the framework of agent based modeling, notes recently used examples applied to transportation, and discusses limitations. The intent of this paper is to explore a new avenue for the direction of modeling and analysis of increasingly complex transportation systems.

Keywords: Multi-agent systems, transportation, swarm intelligence.

1. INTRODUCTION

The way we deal with transportation problems has changed over the years. Today, we consider transportation services and facilities as part of a complex physical, social, and institutional infrastructure. Most analysts view transportation activities as a systems phenomenon and suggest a systems approach, whatever it may mean, to solve the problems. Under this setting, transportation is considered to be a large-scale system in which many elements interact in a complex manner to achieve a set of objectives.

Solutions to a transportation problem are found in the confluence of a set of objectives and constraints. In most cases, both the objectives and the constraints are not well understood or defined. Additionally, the priorities among the objectives are not known also. Further, perception of the problem is different among the population groups. As a result, we rarely find solutions which everyone considers to be optimal. The domains of the problems include prediction of the system performance in terms of some social and economic measures, diagnosis of a particular phenomenon, and determination of values for a set of decision variables.

In the past decade, a series of new concepts and approaches has emerged in the field of systems science. Transportation researchers began to exploit some of the new approaches. Among them, the agent-based approach has interesting characteristics both philosophically and analytically. It is an approach based on the idea that decentralized individual "agents" make up a system and each "agent" interacts with other agents within rather small confines according to the localized knowledge. The interacting agents might be individual travelers, drivers, economic or institutional entities, which have some objectives and decision power. Transportation activities take place at the intersection between supply and demand in a complex physical, economic, social and political setting. The overall performance of the system reflects the outcome of complex interactions of the individual agents. We feel that agent-based modeling holds a promise in application to transportation analysis, because this approach is not just a specific computational tool, but a concept and a pattern of thinking.

In this paper, we ask, what is agent-based modeling?, how can we use it?, where are the potential applications to transportation?, and what are its limitations? This paper is divided into six main sections. After this introduction, we examine the nature of the transportation problem and the trends that necessitate new approaches. Thirdly, we introduce the agent-based systems approach and its internal workings. Fourthly, we introduce examples of application of agent-based modeling to the transportation field. Fifthly, we discuss limitations of the agent-based system approach when applying it to transportation planning and engineering. Finally, we summarize the conclusions of the paper.

2. BACKGROUND: THE CHANGING NATURE OF TRANSPORTATION ANALYSIS

Traditionally, the approach to analysis of transportation follows the classical science model, in which there is a set of general rules that govern the overall behavior of the system. The rules are supposed to be universal, rational, and logical. They may be rooted in economic, physical, engineering, mathematical, and sociological principles. Normative macroscopic transportation research has employed the following: make hypotheses about the rules, prove them through experiments and surveys, and apply them to construct models for a particular situation. In general, the models are used to predict, diagnose, and control (or regulate) a particular transportation setting for various decisions. This scheme is generally called the top-down approach.

2.1. The Nature of Transportation and an Emerging View on Modeling Transportation

In the past three decades, the scope of the analysis of transportation has become larger and larger both in spatial and temporal dimensions as well as the coverage of topics, e.g., environment, energy, quality of life, and land use. The problem is generally characterized as complex and multidimensional. The nature of the problem has the following characteristics:

> Many players exist and they interact with one another to produce a set of outcomes. The players are found in the users of the system, non-users, or the suppliers of transportation service, and also in private and public sectors.
>
> The solutions being sought are multi-objective. The objectives are often conflicting, and each participant to a decision-making process does not have a clear idea about the priorities among them.
>
> Uncertainty is prevalent not only in the knowledge base of the behavior of the system but also in the data, objectives, and constraints.
>
> Information, computer and communications technology plays an important role. Each participant has access to a significant amount of information processing capability.
>
> The structure of the system changes dynamically. The components of the system are not known in advance; they can change their nature and in numbers over time, and may be highly heterogeneous. Such a system is called

an open system. A typical example is the structure of an ITS communication and information system, which is fluid.

The traditional approach has limitations in its ability to capture the behavior of the entire system described above. The entirety is not only changing [expanding] but is also not known. Firstly, the connection between transportation and other aspects, say, environment or energy, is not well established, not to mention, the lack of data to back up the connections. Secondly, the system is so complex that feedback loops of chain reactions cannot be captured as a controlled process. Further, a new view that casts some doubts on the traditional thinking has emerged; in that, the behavior of the whole is the aggregation of individual behaviors, which are based on a set of rather simple rules.

Given this environment, transportation researchers have been searching for new approaches to deal with the changing nature of the problem. An approach that focuses on interactions of individual elements of the system, rather than on system-wide universal rules, has been receiving attention among transportation engineers as well as many other areas of sciences that are encountering similar limits in the traditional approach. We call this approach the bottom-up approach, as opposed to the top-down approach mentioned before.

This new view is supported by various observations in behavioral science and biological systems. Testing such a theory has become possible with the use of massive computing capability. A frequently cited example is traffic flow behavior. Each individual driver follows a simple set of rules, like accelerate when the vehicle in front accelerates, decelerate when the front vehicle decelerates, otherwise just follow the vehicle in front. Aggregating individuals who behave on the basis of these simple rules, one can see the overall traffic pattern emerging and the propagation of shock-waves and bottlenecks in the flow. In other words, the mutual interactions of individual elements breed to produce the whole picture that has certain patterns and organizations. In the words of Resnik [37] in his well-known book, *Turtles, Termites and Traffic Jams*, "it deals with a behavior in which simple parts organize themselves into complex and sophisticated wholes."

2.2. Developments Found Outside Transportation

If we consider humans' activities and behaviors as part of a biological system, we find a number of references relating to the behavior of insects and animals whose survival depends on social interaction and transportation. Let us look at some of the studies that might shed light on our quest for finding a way to look at complex transportation related problems.

Social insects (bees, wasps, ants, and termites) have lived on earth for millions of years. It is well known that they are very successful in building nests and more complex dwellings in a societal context. They are also capable of organizing production. Social insects move around, have a communication and warning system, wage wars, and divide labor. The colonies of social insects are very flexible and can adapt well to the changing environment. This flexibility allows the colony of social insects to be robust and maintain its life in an organized manner in spite of considerable disturbances.

Interaction between individual insects in the colony of social insects has been well documented. The examples of such interactive behavior are bee dancing during food procuring, ants' pheromone secretion, and performance of specific acts which signal the other insects to start performing the same actions. These communication systems between individual insects contribute to the formation of the "collective intelligence" of social insect colonies.

Recently, the term "swarm intelligence", denoting this "collective intelligence", has come into use [3, 4, 5, 6]. We present two cases of social behavior of ants and bees as an introduction to the social behavior we may want to adopt for analysis of transportation.

Self-organization of ants is also based on relatively simple rules of an individual insect's behavior [16]. In the majority of ant species, a number of "scouts" leave the nest foraging for food [17]. The ants that are successful in finding food leave behind a pheromone trail that the other ants follow in order to reach the food. The appearance of the new ants at the pheromone trail reinforces the pheromone signal. This comprises typical autocatalytic behavior, i.e. the process that reinforces itself and thus converges fast. The "explosion" in such a process is regulated by a certain limitation mechanism. In the ant case, the pheromone trail evaporates with time. In this behavioral pattern, the decision of an ant to follow a certain path to the food depends on the behavior of his nestmates. At the same time, the ant in question will also increase the chance of the nest-mates leaving the nest after him to follow the same path. In other words, one ant's movement is highly determined by the movement of previous ants.

Self-organization of bees is based on a few relatively simple rules of an individual insect's behavior [13]. Each bee decides to reach the nectar source by following a nest-mate who has already discovered a patch of flowers. Each hive has a so-called dance floor area in which the bees that have discovered nectar sources dance, thus trying to convince their nest-mates to follow them. If a bee decides to leave the hive to get nectar, she follows one of the bee dancers to one of the nectar areas. The mechanisms by which the bee decides to follow a specific dancer are not well understood, but it is considered that "the recruitment among bees is always a function of the quality of the food source" [13]. It is also noted that not all bees start foraging simultaneously. Experiments have confirmed that "new bees begin foraging at a rate proportional to the difference between the eventual total and the number presently foraging".

As exemplified above, study of individual behavior in the context of a decentralized mutual interaction behavior is collectively called the agent-based system approach. In the next section we examine the agent-based approach for its specific modeling mechanism before discussing its transportation applications.

3. AGENT-BASED MODELING

A phrase "agent-based" has been used often to characterize the type of modeling approach that focuses on the behavior of individuals and builds the image of the entire system based on the mutual interactions of the individuals. Agent-based modeling is a term that is not associated with a specific mathematical computational algorithm. It is a modeling concept, in which many "agents" exist, and each behaves in a certain manner (e.g., rules, that Resnik [37] says, "wander," "avoid," and "explore.") according to the given environment. In general, a multi-agent system can be described as a system composed of physical individuals (robots for example) or "virtual" (artificial) ones that communicate among themselves, cooperate, collaborate, exchange information and knowledge, and perform some tasks in their environment.

3.1. What is an Agent?

An agent is defined in different ways by many. Hewitt [25] states that it is a concept of a self-contained, interactive, and concurrently executing object, an "actor." This object can respond to messages from other similar objects.

Jeenings and Wooldridge [26] define an agent that is capable of autonomous action in order to meet its designed objectives. Autonomy means that the agent should be able to act without a direct intervention by other agents and should have control over its own actions and internal state. An agent should perceive its environment and respond in timely fashion to the changes that occur in it. An agent should be able to exhibit opportunistic, goal-directed behavior, and take the initiative where appropriate. An agent should also be able to interact with other artificial agents and humans in order to complete their own problem solving and to help others with their activities.

Nwana [33] and Moulin et al.[32] view an agent in three layers: a definition layer, an organization layer, and a cooperation/coordination layer. At the definition layer, the agent is defined as an autonomous rational entity in terms of its reasoning and learning mechanisms in defining goals, resources, skills, beliefs or preferences. At the organization layer, it is defined in terms of its relationships with other agents, e.g. organizational relationship, roles, and abilities. At the coordination layer, the social abilities of the agent are specified.

Nwana [33] also defines an agent as a component of software or hardware which is capable of accomplishing tasks on behalf of its user. In this case, it is defined more like a real human agent.

Summarizing the references, we find the following five attributes or abilities of "agenthood" identified by most researchers, and relevant to transportation modeling.

- autonomy: the ability to function independently of human intervention,
- social ability: the ability to interact intelligently and constructively with other agents and /or humans,
- responsiveness: the ability to perceive the environment and respond in a timely fashion to events occurring in it,
- pro-activeness: the ability to take the initiative whenever the situation demands,
- learning ability: the ability to improve performance over time.

An agent has the goal-oriented behavior, the knowledge of the problem-solving techniques on behalf of the analyst, and the ability to learn from experience. In transportation application, an agent can be an individual or institutional entity. For example, a vehicle, a driver, a traveler, a traffic signal, an air traffic controller, a transportation service provider (e.g., transit agency, taxi, shipping company), planning agency, citizens' group, etc., if each such entity has all the characteristics listed above. A multi-agent system is designed and implemented as several interacting agents. It is more general and complex than a single-agent case.

3.2. Nature of Interactions among the Agents and the Environment

If the scope of a problem is large and unpredictable, then the only way that a problem domain can be represented may be by a number of modular components and by focusing on how they interact. In broader terms, such an approach is also referred to as agent based modeling. The interactions between individual agents may be categorized as the following: Collaborative, Interface and learning, Cognitive, and Reactive.

Collaborative refers to autonomy and cooperation with other agents in order to perform tasks. This character allows for interconnection among the agents and provides for solutions to an inherently distributed problem. Consider air traffic controllers. Each controller guides specific aircraft, yet each cooperates one another in order to achieve overall efficiency and safety. A similar description may be made if we consider individual traffic signals on a corridor as agents where each tries to maximize its capacity and, at the same time, each coordinates with one another to maximize the overall throughput on the corridor.

Interface and learning refers to the constantly changing behavior of interaction. Each agent learns from past experience of interaction and changes its behavior constantly. This may be the case of human choice behavior under the information that is constantly updated, a scenario that takes place under ITS. This may also be true in the case of a transportation planning agency's behavior that change its position [in a good sense] according to the results of many public meetings.

Cognitive refers to intention to reach explicit goals. Individual agents control their behaviors and choose between possible actions. An individual agent of a system may have a specific intention. This may be the case of a vehicle traveling on a freeway when only few other vehicles are around and the vehicle can choose its own speed.

Reactive refers to not being able to choose between possible actions. It does not need any memory of its experience. It acts according to a stimulus-response process. It cannot be used for a complex communication mechanism. This may be the situation of a vehicle traveling under a very congested bumper-to-bumper situation, so that the movement of the vehicle is simply the stimulus-response pattern affected by the movement of the vehicle in front only.

Many problems and issues of transportation can fall into one of these categories. For example, the traffic flow is a complex situation in which the drivers search for the best outcome during weaving, lane changing, merging, and diverging. This type of behavior is also found when an individual searches for the best paths in the network under a congested situation. Use of information is another example: given information, each tries to "beat" the others rather than cooperating with the others. The whole game of choice under dynamic conditions perhaps belongs to this category.

An optimization problem in complex interactions of different parties with each other is having objectives and constraints (or limitations).

In infrastructure planning, compromises emerge as a result of individuals acting to pursue their own interests, and, at the same time, the individuals recognize that the others' interests need to be taken into account as well in order to realize their own interest. Yet, another case is the consensus building planning process in which each group attempts to pursue its own objectives yet some level of compromise is acceptable to reach on overall agreement. A specific example is the operation of a large container port. Many different entities, steamship companies, trucking companies, terminal operator, port authority, and local planning agency interact to plan investment strategies and operating regulations. During the process, each tries to guard its own objectives and interests, at the same time each must work with others; in other words, one cannot dominate the others. A sort of balance is kept to sustain the operation of the port, whose objectives are not specific [23].

3.3. Structure of Agent-based Modeling

A typical agent-based model consists of three modules. They are sensor, cognition, and actuator. The sensor module perceives the environment and other agents. The cognition module controls and monitors the agents' individual, communicative, and co-operative activities. It includes the knowledge and beliefs about the environment, a set of goals (or desires), and plans (intentions) to direct the agents' actions. The actuator module carries out the behaviors that have visible effects on the environment.

This structure may vary depending on the characteristics of individual agents as classified earlier. Perhaps the most important aspect of modeling is the representation of the knowledge base, which becomes the base for its action based on beliefs, desires, and intention. The representation of the knowledge base may use rules (e.g., IF-THEN rules, Cellular Automata, fuzzy logic, or any equations of stimulus-response); however, the IF-THEN rules are most commonly seen in agent-based models.

For example, to implement a microscopic traffic simulation model on a highway, the vehicle (or driver-vehicle) elements can be modeled as agents. Each agent takes the following steps. Though the sensor module, an agent holds information (beliefs) about its position, velocity, acceleration, and also about those elements of other agents. Each agent also has information about the environment, such as road geometry and weather conditions. The sensor module then determines the states of the agent, free-drive, following, closing-in, etc. The data provided by the sensor module are evaluated in the cognition module. When a state change occurs, an appropriate desire (plan) is chosen and sent to the actuator module. The actuator executes the commands. Because more than two vehicles or agents are in the system, this type of system is called a multi-agent system (MAS). All agents have the above steps at the same time. Each agent executes the modules, and their collective behavior emerges.

To implement this model, a programming language or "an agent language" that allows efficient execution of the activities of individual agents is necessary. Some of the languages carry the notion of agency, while others do not [40]. The first commercial agent language, TELESCRIPT developed by General Magic, Inc., is a language-based environment for constructing agent societies. Recently, SWARM, developed at the Santa Fe Institute, and CYBELE developed by the Intelligent Automation, Inc., are widely used for agent-based modeling. The popular object oriented program, JAVA or C++, is also used.

The following is presented as an example of the general approach. It is a simulation model of traffic flow at a merging point using the agent-based approach.

- Assume each vehicle (or driver-vehicle pair) as an agent because it is [37] autonomous, [3] has the ability to interact intelligently with other vehicles (for example the use of turning and brake lights to communicate), and [4] has the ability to perceive the environment, such as traffic and road conditions and to respond to events (congestion or accidents).
- Divide the agents into two groups, the ones on the freeway and the others on the ramp since each group has different behavioral characteristics.
- Introduce the rules of behavior (accelerate, decelerate, change lane, etc.) for each agent. This is the rule of "local" behavior as each agent interacts with the neighboring agents and environment. The rule can be derived from the traditional car following theory, gap acceptance model, critical gap distribution model, or the one formulated by Cellular Automata.
- Develop a simulation program that lets the agents have the characteristics and behaviors.
- Test whether the simulation results, which are based on the aggregation of the local behavior, yield realistic global behavior. This requires a comparison of the results with the traffic data at the merging area in real world.

4. AGENT-BASED MODELS APPLIED TO TRANSPORTATION

We review recent literature and examine how agent-based modeling is applied to transportation modeling in this section. It appears that most applications so far utilize the reactive characteristics of the agent, especially in the stimulus-response process, in order to describe interactions between agents. Applications are found mostly in traffic or pedestrian flow.

4.1. Application to Traffic Flow Representation

Burmeister, et al. [12] suggested that the multi-agent system (MAS) helps to conceptualize and describe a complex system under three conditions. They are [37] the problem domain is spatially distributed, [3] the subsystems exist in a dynamic environment, and [4] the subsystems need to interact in a flexible manner. They applied MAS to microscopic traffic simulation, and discussed the advantages as: [37] the rules of vehicle behavior can be changed easily, and [3] the explicit communication and cooperation between vehicles can be represented. They developed a model called

COSY, which consists of the motivation, sensors, cognition, actuators, and communications modules for this work.

Wahle and Schreckenberg [39] presented a framework for online traffic flow simulations, which is based on a multi-agent traffic flow model. The agent architecture consists of two layers that are related to different tasks of a driver. The first layer is the tactical layer, which perceives the environment and reacts in a short time period (about one second.) A cellular automaton model is used to set the rules of car-following. The second layer is the strategic layer, which extends the tactical layer and is responsible for the information (e.g., traffic information), assimilation and the decision-making among different actions (e.g., passing).

Peeta and Pasupathy [35] modeled the changing patterns of traffic flow in a simple network using the MAS framework. They modeled vehicles as agents that are capable of interaction, learning through experience, perception-reaction, and goal-oriented behavior. They examined the stability of the network flow with respect to the rules of driving. MAS is found useful in simulating the evolution of such large aggregates of interacting agents, and they stated that MAS offered a flexible mechanism to represent the heterogeneity and randomness inherent in such systems.

Jiang [27] presents pedestrian flow in an urban environment by the use of MAS. He finds that all pedestrians tend to cluster in their individual destinations. Agents are assumed to be pedestrians and vehicles. Objects are assumed to be buildings, shops, and museums. The physical space of the urban system is regarded as the environment. Communication can occur either between agents or between agents and their environments. The flow simulation was built using StarLogo. He explained that MAS allows the analyst to trace how the global feature emerges as a result of the agent's individual interactions.

Kukla, et al. [29] introduced the autonomous-agent approach for the modeling of pedestrian flow in urban environments. They developed PEDFLOW, a microscopic simulation of pedestrian movement, in which each pedestrian, represented as an agent, is capable of making its own decisions based on the scene observable to that pedestrian. The model, implemented in Java, provides a platform that the movements of the agents are represented by the changes in grid positions. Their behavior is controlled by a set of rules, which relates the environment to a behavior of a person under a specific situation. This cycle is repeated continuously. The aggregate of the individual decisions and their results make up what can be observed as the pedestrian movement. A self-organizing property of the flow emerges as a result of the microscopic interactions between agents with each agent acting only on its local knowledge. No agents have access to all of the globally available data. PEDFLOW reduces the infinite variety of "real life" aspects to a manageable amount.

4.2. Application to ITS and Information Flow Network

Adler and Blue [1] claim that the task of managing roadway traffic meets three conditions of an agent. It is a highly distributed process that involves the coordination of traffic control devices, signals, and sensors. Agents were assigned to model both individual control entities and the regional control centers. Vehicles were modeled as mobile agents that move between regions, or between one agent community to another. They proposed a MAS approach that is called ATMIS. This model facilitates interaction and cooperation between network operators and drivers through mutual information exchange. Network-wide control is achieved through coordination among network operators. Data are collected by network operators and given to the traffic information service provider who synthesizes information and distributes it to the drivers. They claim that better vehicle routing and scheduling is achieved with negotiation between ISP agents and driver agents.

4.3. Representation of Complex Traffic System

Erol et al. [24] explain the limitations of macro models of traffic flow and propose micro modeling. They consider that a complex system is viewed as a large set of small interacting components. The main focus is on identifying the components in a system, and discovering their local behaviors. As reported in many articles, very complex, realistic global behavior can be obtained from simple local behavior. However, two issues with micro simulation are computational performance and software development cost. They state that an agent-based approach is useful because it is a natural successor to the object-oriented paradigm. The authors applied CYBELE, which facilitates communication and interaction among agents. They modeled the ramps, road segments, vehicle interactions, vehicles, traffic lights, signs and sensors, as agents.

4.4. Large Scale Systems

Ljungberg and Lucas [30] adopted an agent-based modeling called OASIS, to manage the flow of aircraft arriving at an airport. The OASIS architecture involves the division of the air traffic management tasks into agents: The aircraft agents are responsible for flying the aircraft, and the global agents are responsible for the overall sequencing and coordination of the aircraft agents. An OASIS implementation comprises one aircraft agent for each arriving/departing aircraft and a number of global agents, sequencers, wind modelers, coordinators, and trajectory checkers. At any time, the system comprises up to seventy or eighty agents controlling aircraft, sequencing, and giving control directives to flow controllers on a real-time basis.

4.5. Travel Behavior

Arentze et al. [2] developed a software called ALBATROSS: a learning based transportation simulation system. ALBATROSS is an activity-based model of activity-travel behavior that is derived from theories of choice heuristics that consumers apply when making decisions in complex travel-making environments. The model predicts which activities are conducted when, where, for how long, with whom, and the transport mode involved. They applied the agent concept to their model architecture, such as activity reporting agent, performance indicators agent, and sequence alignment methods agent.

4.6. Vehicle Routing and Scheduling using biologically inspired multi-agent systems

Perhaps the most known artificial system is the creation of the Ant System. The Ant System [6, 8, 9, 10, 11, 14, 18, 19, 20, 21] is a new metaheuristic for hard combinatorial optimization problems. Dorigo et al. [19] applied the Ant System to the classical traveling salesman problem. They tested the approach on an asymmetric traveling salesman problem, the quadratic assignment, and the job-shop scheduling problem. Bullnheimer et al. [10, 11] used the Ant System to solve the Vehicle Routing Problem for the basic problem [homogenous fleet, capacity restriction, distance restriction, one central depot] and obtained very good results. Teodorović and Lučić [38] developed the Fuzzy Ant System when solving schedule synchronization in public transit. The Fuzzy Ant System represents a combination of the "classical" Ant System and Fuzzy Logic. Lučić and Teodorović [31] developed the Bee System – a new computational paradigm. It is inspirited by Bees' behavior. They explored possible applications of swarm intelligence (particularly collective bees' intelligence) in solving complex engineering and control problems. The traveling salesman problem is only an illustrative example. The proposed Bee System was tested on a large number of benchmark problems found at:
http://www.iwr.uni-eidelberg.de/iwr/comopt/software/TSPLIB95/tsp/.

4.7. Human settlement and society

Drogoul and Ferber [22] proposed the application of multi-agent simulation in ecological or sociological systems. The model simulates the evolution of complex systems where interactions performed between several individuals are responsible for generating general situations observed at the macro level. Multi-agent simulation integrates different partial theories originated in various disciplines such as sociology and ethnology into a general framework by providing tools that allow the integration of different studies.

Dean et al. [15] tried to understand the changes in Anasazi (the precursor of the modern Pueblo cultures of the Colorado Plateau) culture focusing on the relevance of landscapes using agent-based modeling. The landscapes are populated with heterogeneous agents. Each agent is endowed with attributes, such as life-span, vision, movement capabilities, nutritional requirements, consumption and storage capacities in order to replicate important features of individuals or relevant social units such as households, clans, and villages. A set of anthropologically plausible rules defines the ways in which agents interact with the environment and with one another. Altering the agent's attributes, its interaction rules, and the features of the landscape, the model allows examination of behavioral responses to the landscape.

Kohler et al. [28] also tried to model the settlement dynamics of the southwestern region of Colorado from A.D. 900 to 1300 by treating households as agents. They compared simulated settlements with the archaeological records and highlighted the changes in settlement and farming.

Portugali and Benenson [36] examined the evolution of socio-spatial interactions among demographic groups in a city, and modeled the effects on changes in land values of different parts of the city. The model considers humans, plants, or land use as free agents with the capability to plan their actions. The behavior of the individual agents shapes the global make-up of the city.

In order to gain insights into the interplay between microscopic interactions and macroscopic features of a complex system, such as a city or human settlement, one must define specific features at the micro level, but it is not necessary to have detailed descriptions. By changing the rules of interaction or the influence of the environment during the simulation, one may be able to observe different kinds of collective dynamics and the emergence of new properties not readily predicted from the basic equations.

5. DISCUSSION: LIMITATIONS

The usefulness of the agent-based modeling approach is limited by how it handles optimization, evaluation, computation, and actual application environment.

Firstly, in agent-based modeling, the local state and the local knowledge dictate the actions of an agent. This means that the individual agents do not make globally optimal decisions. Reconciling decision-making based on local knowledge with the desire to achieve globally optimal performance is a problem when the agent-based modeling is used for control problems or for representation of choice behavior. Bond and Gasser [7] caution that agent-based modeling may not be appropriate for control problems in which the global constraints and objectives have to be satisfied. Thus, a simulation based on an agent-based model can in fact be interpreted as an image of system behavior when no global control is given.

Secondly, to apply an agent-based model, the analyst needs to feel comfortable with the idea of delegating tasks to the agents, rather than controlling the tasks. The analyst will thus need to become accustomed to and be confident with the notion of autonomous software components. The agents that work on behalf of the analyst eventually exhibit a self-organizing character. To the best of our knowledge, the development of all proposed Multi Agent Systems has been based on a "trial-and-error" approach. Success in solving a particular class of complex problems is the only criterion for evaluating specific multi-agent systems.

Thirdly, computationally, most applications are said to be solved without the agent-based approach. Thus, even if a particular problem has distributed data sources or systems, an agent-based solution is not necessarily the most appropriate one. Computation of agent-based modeling is usually based on a parallel-distributed structure, and the language of programming requires understanding of parallel computing techniques. Further, the calibration of the parameters is not easy because how individual behavior affects overall behavior is not completely known.

Among the remaining questions is: What is the level of "intelligence" that agents should have? What is the best communication between agents? What is the best way for agents to gain experience from different situations and to learn? What is the best way for agents to handle the uncertainty present in many complex problems? These questions need to be asked case by case, and no clear answer seems available at this time.

6. CONCLUSION

As transportation problems become more multi-faceted, and as a result, the behavior of the system becomes more and more difficult to predict, we see the limitations of the traditional top-down analysis approach in handling complexity. The agent-based modeling approach represents a different modeling attitude; it focuses on the interactions of individual elements or agents of the system. Then the overall picture of the system behavior emerges as the interactions are aggregated. Depending on how the agents are defined in its function, the scope of the analysis can be controlled, and the individual agent activities are traced to see how they form the overall image of the system.

The complexity of today's transportation problems is greatly attributed to the interactions and communications among the individual parts (agents) that constitute the system and their greater autonomy to make decisions. Each part participates in interaction according to a rather simple set of rules, which generally leads to maximization of its utility. Intelligent Transportation System (ITS) is a typical example of a complex system where communications play the most significant part. We believe that agent-based modeling may be a useful approach to represent the performance of such a system as the outcome of various control strategies. Advantages of agent-based modeling will be computational simplicity and ease of model formulation because the understanding of the entire system is not critical. However, we need to be mindful that we do not model a phenomenon for the sake of modeling; each application must have specific purpose. Hence, agent-based modeling should be treated as an item on a menu of new approaches that can be used for analysis of a complex and dynamic system.

REFERENCES

[1] Adler, J.L., and Blue, V.J., "Principle negotiation and multiagent transportation management and information systems", *80th Annual Meeting of Transportation Research Board (CD-ROM)*, 2001.

[2] Arentze, T., Hofman, F., Mourik, H.V., and Timmermans, H., "ALBATROSS: A multi-agent rule-based model of activity pattern decisions", *79th Annual Meeting of Transportation Research Board (CD-ROM)*, 2000.

[3] Beni, G., "The concept of cellular robotic system", *Proceedings 1988 IEEE International Symposium on Intelligent Control*, Los Alamitos, CA, IEEE Computer Society Press, 1988, 57-62.

[4] Beni, G., and Wang, J., "Swarm intelligence", *Proceedings Seventh Annual Meeting of the Robotics Society of Japan*, RSJ Press, Tokyo, 1989, 425-428.

[5] Beni, G., and Hackwood, S., "Stationary waves in cyclic swarms", *Proceedings 1992 International Symposium on Intelligent Control*, IEEE Computer Society Press, Los Alamitos, CA, 1992, 234-242.

[6] Bonabeau, E., Dorigo, M., and Theraulaz, G., *Swarm Intelligence*, Oxford University Press, Oxford, 1999.

[7] Bond, A.H., and Gasser, L., *Readings in Distributed Artificial Intelligence*, Morgan Kaufmann, 1988.

[8] Bullnheimer, B., Kotsis, G., and Strauss, C., "Parallelization strategies for the ant system", in: R. De Leone, A. Murli, P. Pardalos, and G. Toraldo (eds.), *High Performance Algorithms and*

Software in Nonlinear Optimization, Series: Applied Optimization, Kluwer Academic Publishers, Boston, 24, 1998, 87-100.

[9] Bullnheimer, B., Hartl, R.F., and Strauss, C., "A new rank based version of the ant system - a computational study", *Central European Journal of Operations Research*, 7 (1999) 25-38.

[10] Bullnheimer, B., Hartl, R.F., and Strauss, C., "An improved ant system algorithm for the vehicle routing problem", *Annals of Operations Research*, 89 (1999) 319-328.

[11] Bullnheimer, B., Hartl, R.F., and Strauss, C., "Applying the ant system to the vehicle routing problem', in: S. Voss, S. Martello, I.H Osman, and C. Roucairol (eds.), *Meta-Heuristics: Advances and Trends in Local Search Paradigms for Optimization*, Kluwer Academic Publishers, Boston, 1999, 285- 296.

[12] Burmeister, B., Doormann, J., and Matylis, G., "Agent-oriented traffic simulation", *Transactions*, 14 (2) (1997) 79-86.

[13] Camazine, S., and Sneyd, J., "A model of collective nectar source by honey bees: self-organization through simple rules, *Journal of Theoretical Biology*, 149 (1991) 547-571.

[14] Colorni, A., Dorigo, M., and Maniezzo, V., "Distributed optimization by ant colonies", in: F. Varela, and P. Bourgine (eds.), *Proceedings of the First European Conference on Artificial Life*, Paris, France, Elsevier, 1991, 134-142.

[15] Dean, J., Gumerman, G., Epstein, J., Axtell, R., Swedlund, A., Parker, M., and McCarroll, S., "Understanding Anasazi culture change through agent-based modeling", in: J. Kohler, and G. Gumerman (eds.), *Dynamics in Human and Primate Societies*, Santa Fe Institute, 2000.

[16] Deneubourg, J. L., Aron, S., Goss, S., and Pasteels, J.M., "The self-organizing exploratory pattern of the Argentine ant", *Journal of Insect Behavior*, 3 (1990) 159-168.

[17] Deneubourg, J.L., Goss, S., Franks, N., and Pasteels, J.M., "The blind leading the blind: Modeling chemically mediated army ant raid patterns", *Journal of Insect Behavior*, 2 (1989) 719-725.

[18] Dorigo, M. "Optimization, learning and natural algorithms", Ph.D. Dissertation, Politecnico di Milano, Milano, Italy, 1992 (in Italian).

[19] Dorigo, M., Maniezzo, V., and Colorni, A., "Ant system: optimization by a colony of cooperating agents", *IEEE Transactions on Systems, Man and Cybernetics, Part B*, 26 (1996) 29-41.

[20] Dorigo, M., and Gambardella, L.M., "Ant colonies for the traveling salesman problem", *BioSystems*, 43 (1997) 73-81.

[21] Dorigo, M., and Gambardella, L.M., "Ant colony system: a cooperative learning approach to the travelling salesman problem", *IEEE Transactions on Evolutionary Computation*, 1 (1997) 53-66.

[22] Drogoul, A., and Ferber, J., "Multi-agent simulation as a tool for studying emergent processes in societies", in: N. Gilbert, and J. Doran (eds.), *Simulating Societies, The Computer Simulation of Social Phenomena*, UCL Press, 1994.

[23] Elterich, J., Kikuchi, S., and Tannian, F., "Maritime infrastructure development: An operations research approach to large scale modeling", Final Report submitted to National Science Foundation Operations Research Program, University of Delaware, 1999.

[24] Erol, K., Levy, R., and Wentworth, J., "Application of agent technology to traffic simulation", *FHWA*, 2000. http:/www.tfhrc.gov/advance/agent.html. Accessed May 2001.

[25] Hewitt, C., "Viewing control structures as patterns of passing messages", *Artificial Intelligence*, 8 (3) (1977) 323-364.

[26] Jeenings, N., and Wooldridge, M., "Applications of intelligent agents. Agent technology, foundations", in: N. Jeenings, and M. Wooldridge (eds.), *Applications and Markets*, Springer, 1998.

[27] Jiang, B., "Multi-agent simulations for pedestrian crowds", *European Simulation Symposium Simulation Technology Science and Art*, 1998, 383-387.

[28] Kohler, T.A., Kresl, J., West, C.V., Carr, E., and Wilshusen, R.H., "Be there then: A modeling approach to settlement determinants and spatial efficiency among late ancestral Pueblo populations of the Mesa Verde region, U.S. Southwest", in: J. Kohler, and G. Gumerman (eds.), *Dynamics in Human and Primate Societies*, Santa Fe Institute, 2000.
[29] Kula, R., Kerridge, J., Wills, A., and Hine, J., "PEDFLOW: Development of an autonomous agent model of pedestrian flow", *80th Annual Meeting of Transportation Research Board (CD-ROM),* 2001.
[30] Ljungberg, M., and Lucas, A., "The OASIS air traffic management system", *Proceedings of the Second Pacific Rim International Conference on Artificial Intelligence*, PRICAI'92, Seoul, Korea.
[31] Lucic, P., and Teodorovic, D., "Bee system: Modeling combinatorial optimization transportation engineering problems by swarm intelligence", in: *Preprints of the Triennial Symposium on Transportation Analysis TRISTAN IV*, Azores, Portugal, June 2001, 13-19.
[32] Moulin, B., and Cabib-Draa, B., "An overview of distribute artificial intelligence", in: G. O'hare, and N. Jennings (eds.), *Foundations of Distributed Artificial Intelligence*, John Wiley and Sons, 1996.
[33] Nwana, H.S., "Towards an approach to designing smart multi-agent systems", Paper presented at CKBS-SIG, University of Keele, September 1992.
[34] Nwana, H.S. "Software agents: an overview", *The Knowledge Engineering Review*, 11 (3) (1996) 205-244.
[35] Peeta, S., and Pasupathy, R., "Analyzing traffic system evolution using multi-agent simulation, *80th Annual Meeting of Transportation Research Board (CD-ROM)*, 2001.
[36] Portugali, J., and Benenson, I., "Human agents between local and global forces in a self-organizing city", in: F. Schweitzer (ed.), *Self-organization of Complex Structures*, Gordon and Breach Science Publishers, 1997.
[37] Resnick, M., *Turtles, Termites, and Traffic Jams: Explorations in Massively Parallel Microworlds*, The MIT Press, 1994.
[38] Teodorovic, D., and Lucic, P., "Schedule synchronization in public transit by fuzzy ant system", Submitted for publishing in European Journal of Operational Research, 2001.
[39] Wahle, J., and Schreckenberg, M., "A multi-agent system for on-line simulations based on real-world traffic data", *Proceedings of Hawaii International Conference on System Science*, IEEE Computer Society, 2001.
[40] Wooldridge, M., and Jennings, N., "Intelligence agents: Theory and practice", *The Knowledge Engineering Review*, 10 (2) (1995) 115-152.