

# A Study on Agent Based Modeling - Topological Interactions

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**Abstract:** - Agent Based Model (ABM) is a class of computational models for simulating the actions and interactions of autonomous agents with a view to accessing their effects on the system as a whole. It combines elements of game theory, complex system, emergence, computational sociology, multi-agents system and evolutionary programming. ABMs are also called individual-based models (IBMs). ABMs are a kind of micro scale model that simulate the simultaneous operations and interactions of multiple agents to re-create and predict the appearance of complex phenomena. The key notion is that simple behavioral rules generate complex behavior. Most Agent Based Models are composed of numerous agents specified at various scales, Decision making heuristics, Learning rules or adaptive processes, An interaction topology, Non agent environment. ABMs are typically implemented as computer simulations, either as custom software or via ABM toolkit, and this software can be used to test how changes in individual behavior will affect the system's emerging overall behavior. This paper presents an overview of how agents communicate agent communication languages and interaction protocols.

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## I. INTRODUCTION

The advent of widespread fast computing has enabled us to work on more complex problems and to build and analyze more complex models. ABM is applicable to complex systems embedded in natural, social, and engineered contexts, across domains that range from engineering to ecology. It may be noted that an Agent Based Model is a computer program that creates a world of heterogeneous agents in which each other agents interacts with other agents and environment. These interactions can generate simple, complex behavior patterns. The ABM has been used to study the traffic regulation within a city, region or even a whole country.

## II. ABM FRAMEWORK

Since agent-based models describe the behavior and interactions of a system's Constituent parts from the bottom up, they are the canonical approach for modeling emergent phenomena. Bonabeau (2002) has identified a (non-exhaustive) list of situations where agent-based models can be useful for capturing emergent behavior:

- Complex interactions: Interaction between agents is complicated, non-linear, discontinuous, or discrete (i.e. the behavior of an agent can be altered dramatically, even discontinuously, by other agents). This can be particularly

useful if describing discontinuity of individual behavior is difficult, for example, using differential equations

- Heterogeneous populations: The ability to design a heterogeneous population of agents with an agent-based model is significant. Agents can represent any type of unit, from which intuitive collections of individual units can be formed, from the bottom up. Unlike agent-based models, aggregate differential equations tend to smooth out fluctuations. This is important because under certain conditions, fluctuations can be amplified: a system can be stable (approximately constant or exhibiting a linear trend) but susceptible to large perturbations. Heterogeneity also allows for the specification of agents with varying degrees of rationality (see above)

- Topological complexity: The topology of agent interactions is heterogeneous and complex. Aggregate flow equations usually assume global homogeneous mixing, but the topology of an interaction network can lead to significant deviations from predicted aggregate behavior. This is particularly poignant for social processes, because physical or social networks matter; and, when agents exhibit complex behavior, including learning and adaptation

- Appropriate model framework: In many cases ABM is a natural method for describing and simulating a system composed of real-world entities. The agent-based approach is more akin to reality than other modeling approaches, rendering ABM inherently suited to simulating people and objects in very realistic ways. For example, it is arguably

easier to conceptualize and model how evacuees exit a building during an emergency, than to produce equations that govern the dynamics of evacuee densities. Nonetheless, because equations regarding evacuee density result from the behavior of evacuees, the agent-based approach will also enable the user to study aggregate properties. In particular, the agent-based approach can be useful when it is more natural to describe the constituent units of a system under some or all of the following conditions:

(i) The behavior of individuals cannot clearly be defined through aggregate transition rates (e.g. panic within a fleeing crowd)

(ii) Individual behavior is complex. Although hypothetically any process can be explained by an equation, the complexity of differential equations increases exponentially as the complexity of behavior increases. Describing complex individual behavior with equations can therefore become intractable

(iii) Agent behavior is stochastic. Points of randomness can be applied strategically within agent-based models, as opposed to arbitrarily within aggregate equations

- **Flexibility:** Finally, the agent-based approach to modeling is flexible, particularly in relation to geospatial modeling. Notably, spatial simulations benefit from the mobility that agent-based models offer. To reiterate, an agent-based model can be defined within any given system environment (e.g. a building, a city, a road network, a computer network, etc.). Furthermore, agents have the ability to move within their environment, in different directions and at different velocities. Agent mobility makes ABM very flexible in terms of potential variables and parameters that can be specified. Neighborhoods can also be specified using a variety of mechanisms. The implementation of agent interactions can easily be governed by space, networks, or a combination of structures. This would be far more complex to model using mathematics, for example. Significantly, agent-based models can regulate behaviors based on interactions at a specific distance and direction. Agent-based models also provide a robust and flexible framework for tuning the complexity of agents (i.e. their behavior, degree of rationality, ability to learn and evolve, and rules of interaction). Another dimension of flexibility is the ability to adjust levels of description and aggregation. It is easy to experiment with aggregate agents, sub groups of agents, and single agents, with different levels of description coexisting within a model. Thus, the agent-based approach can be used when the appropriate level of description or complexity is unknown, and finding a suitable level requires exploration of scenarios.

### III. NEED FOR AGENT BASED MODELING

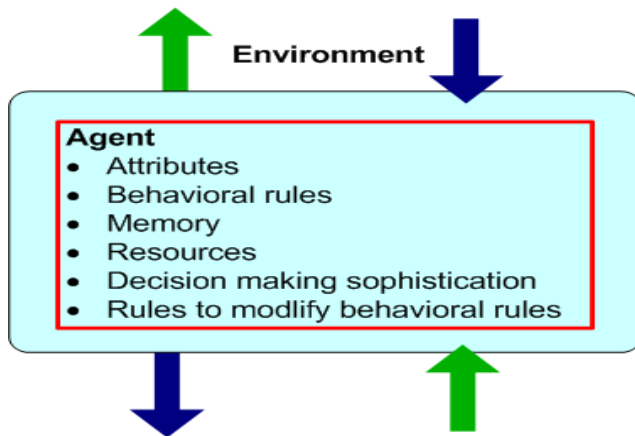
Agent-based models are a kind of microscale model that simulate the simultaneous operations and interactions of multiple agents in an attempt to re-create and predict the appearance of complex phenomena. The process is one of emergence from the lower (micro) level of systems to a higher (macro) level. As such, a key notion is that simple behavioral rules generate complex behavior. This principle, known as K.I.S.S. ("Keep it simple, stupid"), is extensively adopted in the modeling community. Another central tenet is that the whole is greater than the sum of the parts. Most agent-based models are composed of: (1) numerous agents specified at various scales (typically referred to as agent-granularity); (2) decision-making heuristics; (3) learning rules or adaptive processes; (4) an interaction topology; and (5) an environment. ABMs are typically implemented as computer simulations, either as custom software, or via ABM toolkits, and this software can be then used to test how changes in individual behaviors will affect the system's emerging overall behavior.

### IV. FRAMEWORK

Recent work on the Modeling and simulation of Complex Adaptive Systems has demonstrated the need for combining agent-based and complex network based models. Describe a framework consisting of four levels of developing models of complex adaptive systems described using several example multidisciplinary case studies:

Complex Network Modeling Level for developing models using interaction data of various system components.  
Exploratory Agent-based Modeling Level for developing agent-based models for assessing the feasibility of further research. This can e.g. be useful for developing proof-of-concept models such as for funding applications without requiring an extensive learning curve for the researchers.  
Descriptive Agent-based Modeling (DREAM) for developing descriptions of agent-based models by means of using templates and complex network-based models. Building DREAM models allows model comparison across scientific disciplines.

Validated agent-based modeling using Virtual Overlay Multiagent system (VOMAS) for the development of verified and validated models in a formal manner. Other methods of describing agent-based models include code templates and text-based methods such as the ODD (Overview, Design concepts, and Design Details) protocol. The role of the environment where agents live, both macro and micro, is also becoming an important factor in agent-based modeling and simulation work. Simple environment affords simple agents, but complex environments generate diversity of behavior.



## V. AGENT INTERACTION TOPOLOGIES

A manufacturing system, modelled by agents, is a loosely coupled network of communicating and cooperating Production entities. In such a network, the connection method between these entities, together with their interaction rules, significantly affect the functionality of the system. research efforts in dynamic distributed scheduling have widely used market mechanisms, particularly the standard Contract Net Protocol (CNP) or its variations for the allocation of tasks to resources. Smith first proposed CNP as a simple and efficient tool, which has been later

standardised by the Foundation for Intelligent Physical Agents

The following steps are a summary of the CNP task allocation process among the contractor agents (known also as participants) by manager agent (also known as initiator)

1. Task Announcement by initiator
2. Task announcement processing by participant
3. Bidding by participant
4. Bid processing by initiator, and awarding the contract
5. Contract processing, reporting result and termination.

### 5.1 STAR MODEL

Star model CNP in its simplest form, where contractors are only connected to the central manager, forms a Star network.

Figure illustrates CNP-based interaction in such a network, where logical topology and interactions of its members occur regardless of the physical arrangement of its resources.

Messages are exchanged in this interaction protocol in the form of FIPA-ACL (Agent Communications Language)

### 5.2 PEER TO PEER MODEL

Peer-to-Peer model The CNP as seen in the Star model is flexible, but the model is still too centralized with only one

manager. All resource agents in the Star model can be connected to one another to produce a Peer-to-Peer (P2P) model, as shown in Figure 2. Here no single central manager or broker exists. This means that any resource can itself be a manager as well. In contrast with the Star model, such a P2P model is more robust due to redundancy of autonomous Resource/Manager (R/M) agents [2]. When an agent plays the role of Manager (R/M) it interacts with all available Resources (R/M) similar to the Star model. To ensure central coordination among the managers and global knowledge in the system, a higher-level supervisory agent is added to this P2P model.

### 5.3 RING MODEL

Ring model Resource agents could be arranged to form a Ring as illustrated in Figure 3. There would be no manager agent as in the previous cases. A higher-level supervisory agent is in charge of the coordination among agents similar to the P2P model. The main issue with the classical ring topology is that the failure of one network member brings the entire network to a halt. In this model, however, the role of supervisor precludes such a situation, in addition to offering other benefits for P2P model, as already mentioned. Upon the arrival of a manufacturing order (set of tasks), a table of tasks to include all their specifications is created. The tasks are sorted in the table according to their priority, which is determined by pre-defined rules and user inputs. The supervisor agent successively circulates and monitors the task table among the resource agents

## VI. CONCLUSION AND EVALUATION OF MODELS

In order to conduct the task allocation experiments and to compare performance of the models described in Section 5 the following quantitative parameters are calculated from simulations output data as performance indicators in this research:

**Total time:** This is the time elapsed to complete a manufacturing order (set of tasks), and contains any time spent on scheduling and operations until the last resource finishes the last task.

**Costs:** This consists of three major cost elements of the resources (machines). The first element is the cost when a machine is busy with a task. This is calculated by the rate of machine occupation, and depends on depreciation and running costs of each machine and the duration of operations including set-up times. The second element is penalty cost when a task passes its due time. The rate of penalty for each task is defined in the manufacturing order. Penalty cost is also an indication of tardiness. The third element is related to idleness (i.e. non-operating) status of machines.

**Utilization:** Defined as the percentage of processing time against the total order execution time. It will be indicated by busy/idle percentage of the machines.

The results show that in most cases the proposed Modified Ring and CNP-based P2P models give superior performance output compared to the Star and Ring models.

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