Multi-level agent-based modeling

Bibliography

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1   Introduction

Agent-based modeling (ABM) has been recognized has a major modeling paradigm but however, suffers from important limitations:

- ABM is purely bottom-up: microscopic knowledge, *i.e.*, related to system components, is used to construct models while macroscopic knowledge, *i.e.*, related to global system properties, is used to validate models [32].

- Therefor, it is not possible to explicitly introduce bidirectional relations between these two points of view or introduce new ones representing, *e.g.*, different spatial and/or temporal scales or domains of interest.

- Moreover, the role of knowledge depends on its level of observation, not on its epistemic state, which does not seem relevant.

Multi-level[1] agent-based modeling (ML-ABM) aims at extending the classical ABM paradigm to overcome these limitations. It can be defined as *Integrating heterogenous ABM, representing complementary points of view*[2], *so called*

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[1]The terms multi-layer, multi-perspective and multi-view may also be found [81, 83, 84, 132]. The term multi-scale (multi-resolution may also be found) is often used but has a more restrictive meaning as it constraints the definition of levels and their relations.

[2]Points of view are complementary, for a given problem, if they can not be taken in isolation to address it. As [73] note (we translate), "the global behavior of a complex system cannot be understood without making interact a set of points of view."

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levels[3]*, of the same system.* Integration means of course these ABM interact but also they can share environment and agents.

ML-ABM is mainly used to solve two types of *modeling* problems:

- the modeling of **cross-level interactions**, *e.g.*, top-down feedback control,

- the **(dynamic) adaptation of the the level of detail** of simulations, *e.g.*, to save computational resources or use the best available model in a given context[4].

In the first case, the different points of view co-exist, as they integrate interdependent models, while in the latter, levels can be (dis)activated at run time according to the context, as they represent independent models designed for specific situations. *E.g.*, in flow hybrid models, regions of the environment with a simple topology are handled with an equation-based (macroscopic) model, while others are handled with an ABM.

On an other hand, **automated observation and analysis** methods can be introduced at levels not explicitly present in the model, *e.g.*, the group level.

This article aims to bring together the available bibliography[5] on the subject so that it is accessible to interested researchers. Section 2.1 introduces the main theoretical issues that have been addressed so far and section 2.2 presents the different application domains of ML-ABM, with an emphasis on social and flow simulations.

2 Bibliography

The production of scientific articles on ML-ABM has taken off for nearly a decade (fig. 1). However, they have been published in various conferences or journals causing, along with a vocabulary unification problem, a poor visibility of the field.

2.1 Theoretical issues

Three main theoretical issues have been addressed so far:

- the definition of generic meta-models and simulation engines [56–58, 68, 70, 85, 96, 100, 101, 111, 118, 125, 127].

- the detection and reification of emergent phenomena [13–19, 26–29, 43, 64, 86, 87, 121, 128],

- and the definition of generic representations for aggregated entities [82].

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[3]of organization, observation, analysis, granularity, ...

[4]When two levels with static relations are considered, such model is often described as *hybrid* [11, 33–36, 59, 60, 77, 91, 130].

[5]Provided as a bibtex file (Biblio.txt) in the source archive. Bibliographical data used to compute the fig. 1 is also available.
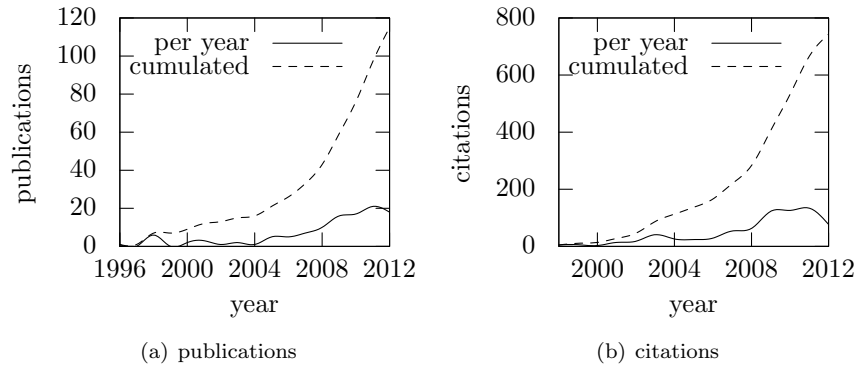
Figure 1: Bibliographical statistics on ML-ABM computed from (a) author's bibliographic database and (b) google scholar data on the May 22, 2012.

2.1.1 Meta-models, simulation engines and platforms

Many meta-models and simulation engine dedicated to ML-ABM have been proposed in the literature. They are are briefly presented in the following, in a chronological order. DEVS[6]-based approaches have been included. Indeed, DEVS, as a generic event-based simulation framework, has been extended to support ABM [72].

GEAMAS [56–58] (GEneric Architecture for MultiAgent Simulation) is a pioneering ML-ABM framework integrating three levels of descriptions (micro, meso, macro). Micro and macro levels represent respectively agent and system points of view while the meso (or middle) level represents an aggregation of agents in a specific context. Communication between levels is asynchronous. **GEAMAS-NG** [29] is a newer version of the framework providing tools to detect and reify emergent phenomena.

tMans[7] [96] is a multi-scale agent-based meta-model and platform. Unfortunately, the project seems to have died in the bud.

ML-DEVS [125] is an extension of DEVS that allows the simulation of multi-scale models (and not only coupled models in which the behavior of a model is determined by the behaviors of its sub-models). Two types of relation between levels are defined: information propagation and event activation. However, ML-DEVS focuses on multi-scale modeling and therefor, only supports pure hierarchies of models, *i.e.*, *interaction graphs* are viewed as *trees* [62].

CRIO [39–41] (Capacity Role Interaction Organization) is an organizational meta-model dedicated to ML-ABM based on the concept of holon [50]. I has been used to develop multi-scale simulations of pedestrian flows (cf. section 2.2.2).

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[6]Discrete Event System Specification [134].
[7]http://tmans.sourceforge.net/

SPARK[8] [111] (Simple Platform for Agent-based Representation of Knowledge) is a framework for multi-scale ABM, dedicated to biomedical research.

IRM4MLS [68, 70] (Influence Reaction Model for Multi-Level Simulation)is an multi-level extension of IRM4S (Influence Reaction Model for Simulation) [63], a meta-model for MABS based on the Influence Reaction (IR) model which views action as a two step process: (1) agents produce "influences", *i.e.*, individual decisions, according to their internal state and perceptions (2) the system "reacts", *i.e.*, computes the consequences of influences, according to the state of the world [37]. Relations (of perception and influence) between levels are specified with digraphs. IRM4MLS focuses multi-level (or perspective) modeling and therefor does not constraint graph structures. This graphs, along with the temporal relations between levels allow to distribute the scheduling of simulations by level. It has been applied to simulate and control intelligent transportation systems composed of autonomous intelligent vehicles (AIV) in flexible manufacturing systems (FMS) [67, 71] and container ports [112, 114] (cf. section 2.2.2).

PADAWAN [85] (Pattern for Accurate Design of Agent Worlds in Agent Nests) is a multi-scale ABM meta-model based on a compact matricial representation of interactions: IODA (Interaction-Oriented Design of Agent simulations) [51], leading to an simple and elegant simulation framework. Relations between levels, representing how they are nested within each others, are specified with an *upper semilattice*.

GAMA[9] [118] is an ABM platform with a dedicated modeling language, GAML, that offers multi-level capabilities. Moreover, it includes a framework (a set of predefined GAML commands) to *agentify* emerging structures [128]. It is certainly the most advanced platform, from an end-user point of view, that integrates a multi-level approach. The multi-scale meta-model focuses on the notion of *situated agent* and therefor, top class abstractions include geometry and topology of simulated entities; however, the meta-model is based on "the fundamental notions of agent modeling (agent/environment/scheduler)" [127]. The notion of level does not appear explicitly but the concept of *species* "defines attributes and behaviors of a class of same type agents" and the multi-scale structure of the model, *i.e.*, how species can be nested within each other.

The **Seck & Honig** model [101] is an extension of DEVS that allows the simulation of multi-level (*i.e.*, non hierarchically coupled) models. The coupling between levels is done through regular DEVS models, named bridge models (fig. 2).

2.1.2 Detection and reification of emergent phenomena

An important problem in ML-ABM is to detect and reify (or more precisely agentity) phenomena emerging from agent interactions. Of course, the question is not to detect any emergent phenomenon but those of interest, to adapt the level of detail of simulations or model cross-level interactions for instance.

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[8]http://www.pitt.edu/~cirm/spark/
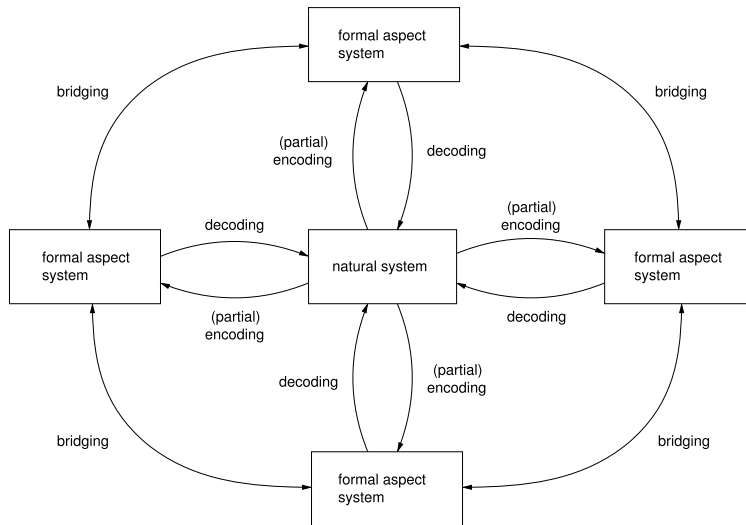[9]http://code.google.com/p/gama-platform/

Figure 2: The Seck & Honig approach (from [101])

Very different approaches have been proposed to detect and reify emergent phenomena. They are briefly presented in a chronological order.

Dedicated clustering methods The pioneering RIVAGE project [105–107] aimed "at modeling runoff, erosion and infiltration on heterogeneous soil surfaces" [106, p. 184]. At the microscopic level, water is viewed as a set of interacting *waterballs*. An indicator characterizes waterball movements to detect two types of remarkable situations: straight trajectories (corresponding to the formation of ravines) and stationary particles (corresponding to the formation of ponds). Close agents sharing such properties are aggregated in ravine or pond macroscopic agents.

[8, 120–122, 124] aim at changing the level of detail of fluid flow simulations based on vortex methods [53]. The goal is, such as in the RIVAGE model, to detect complex structures, *i.e.*, clusters of particles sharing common properties, and aggregate them. However, the detection of emergent phenomena relies on graph-based clustering methods. [64] use a similar approach to detect aggregations of agents in flocking simulations.

Generic frameworks [14–19] define a formalism, the *complex event types* to describe multi-level behaviors. "Conceptually, complex events are a configuration of simple events where each component event can be located in a region or point in a hyperspace that includes time, physical space and any other dimensions" [18, p. 4]. Events can be composed to represent complex multi-level behaviors.

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[26–29] propose a conceptual and technical framework to handle emergence reification . It is included in the GEAMAS-NG platform (cf. GEAMAS paragraph in the previous section) and has been used in DS, a population model of the Reunion Island, to detect and reify new urban areas.

[128] propose a similar framework in the GAMA platform (cf. GAMA paragraph in the previous section). It includes various clustering methods developed in the literature.

[13] propose a tool, SimAnalyzer, to detect and describe group dynamics.

2.1.3 Generic representations for aggregated entities

While developing generic representations for aggregated entities seems an important issue, only one publication is available on the subject. [82] proposes the notion of *pheromone field* (refering to the concept of *mean field* in statistical physics) that "gives the probability of encountering an agent of the type represented by the field at a given location" [82, p. 115]. In this approach, agents act according to their perceptions of pheromone fields (but not of agents).

2.2 Application domains

ML-ABM have been proposed in various fields such as

- biomedical research

  - cancer modeling [6, 10, 31, 54, 79, 91, 135–138],
  - inflammation modeling [4, 5, 129, 130],
  - arterial adaptation [49, 119],
  - stent design [117],
  - vascular tissue engineering [133],
  - bone remodeling [12],

- flow modeling of walking (and running) [39, 75–77], driving [11, 33–36, 67, 71, 112, 114, 131] or streaming [106, 107, 122] agents,

- biology [1, 59, 65, 66, 69, 95, 99, 108–110, 116],

- social simulation [3, 21, 22, 24, 38, 93, 94, 97, 115],

- ecology [20, 52, 87, 90, 92, 102–104, 126],

- geography [46, 55, 80, 88],

- military simulation [60, 61, 84],

- marketing [78],

- epidemiology [25],

- pollution management [98].

An interesting comparative analysis of three of these models can be found in [44, 45, 47].

2.2.1 Social simulation

Social simulation is defined by [115, p. 4] as "the study of social outcomes, let us say a macro regularity, by means of computer simulation where agents' behavior, interactions among agents and the environment are explicitly modeled to explore those micro-based assumptions that explain the macro regularity of interest".

Major social theories developed in the second half of the twentieth century, *e.g.*, *structuration* [42] and *habitus* [9], theories[10], share a common ambition: solving the micro/macro (so called *agency/structure*) problem that can be summarized by the following question: *To understand social systems, should we observe agent interactions (micro level) or structures emerging from these interactions (macro level)?* Such theories tend to consider altogether agent positions in the social space (objective facts) and goals (subjective facts) to explain their beliefs and actions. Their answer to the previous question could be: *social systems can only be understood by considering simultaneously agent interactions and structures in which they occur*:

social structures

$\Big\updownarrow$ social practices

agent interactions.
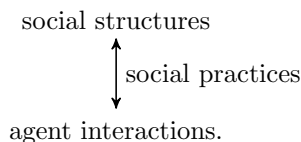
A key concept used by social theorists and modelers to understand downward (or top-down) causation in social systems, *i.e.*, how social structures influence agents, is *reflexivity*. It can be defined as the "regular exercise of the mental ability, shared by all normal people, to consider themselves in relation to their (social) contexts and vice versa" [7, p. 4]. Thus, social systems differ from other types of systems, by the reflexive control that agents have on their actions: "The reflexive capacities of the human actor are characteristically involved in a continuous manner with the flow of day-to-day conduct in the contexts of social activity" [42, p. 22]. Two very different approaches, both from a technical and methodological perspectives, can be considered to simulate systems composed of reflexive agents:

- a purely emergentist approach, only based on the cognitive capabilities of agents to represent and consider themselves in relation to the structures emerging from their interactions (*e.g.*, [23, 48]),

- a multi-level approach based on the cognitive capabilities of agents and the dynamic *reification* of interactions between social structures and agents, *i.e.*, processes that underlie social practices (*e.g.*, [44, 89]).

According to [42], two forms of reflexivity can be distinguished: *practical* (agents are not conscious of their reflexive capabilities, and therefor, are not able to resonate about them) and *discursive* (agents are conscious of their reflexive

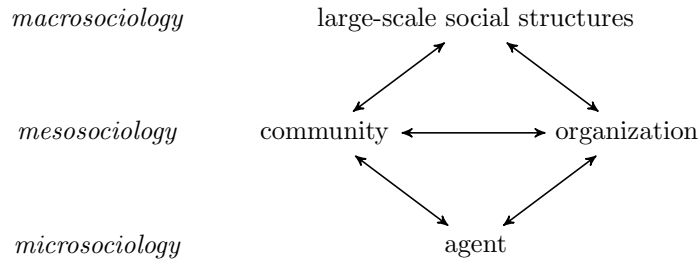---

[10]These theories can be described as hybrid [93]

Figure 3: ML-ABM in social simulation as a link between concepts defined at different levels

capabilities) reflexivity. These two forms are respectively related to the ideas of *immergence*: agent interactions produce emergent properties that modify the way they produce them [21] and *second order emergence*: agent interactions produce emergent properties that are recognized (incorporated) by agents and influence their actions [48].

ML-ABM can also be viewed as a way to link independent social theories (and therefor concepts) defined at different levels (fig. 3) [93, 94, 101]. Readers interested in a more comprehensive presentation of these questions should refer to [97, 115].

2.2.2 Flow modeling

A flow of moving agents can be observed at different scales. Thus, in traffic modeling, three levels are generally considered: the *micro*, *meso* and *macro* levels, modeling respectively the interactions between vehicles, groups of vehicles sharing common properties (such as a common destination or a common localisation) and flows of vehicles. Each approach is useful in a given context: micro models allow to simulate road networks with a complex topology while macro models allow to develop control strategies to prevent traffic jams. However, to simulate a large-scale road network, it can be interesting to integrate these different representations (fig. 4). Similar issues appear in different application domains.

Micro-macro models In environments with simple topologies, a flow a moving agents can be viewed as a fluid in a pipe. In this context a major problem in flow ML-ABM is to determine an appropriate coupling between the different representations in order to preserve simulation consistency [30]. Solutions are domain (or more specifically model) related and therefor will not be presented here in detail. Furthermore, the presentation focuses on "real" ML-ABM: hybrid models based on "simple" microscopic equation-based models are not be presented here.
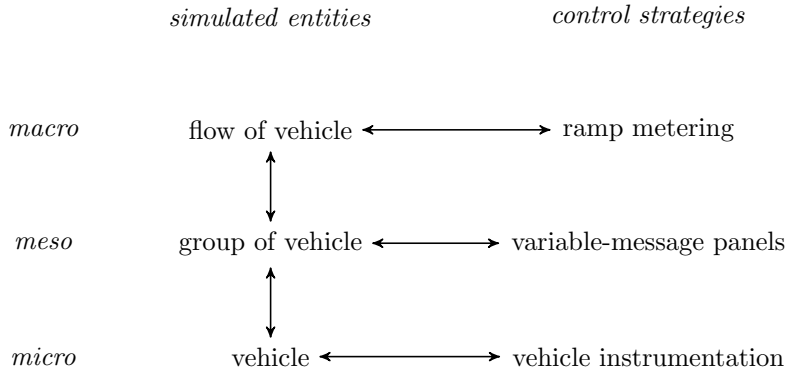
Figure 4: ML-ABM and control in traffic simulation

Micro-meso models   Agents sharing common properties can be aggregated to form-up a higher level (mesoscopic) agent and then, save computer resources or describe group dynamics, such as in the already mentioned RIVAGE [105–107] and DS [29] models (cf. section 2.1.2). Conversely, mesoscopic agents can be disaggregated into lower level agents if related structures vanish.

[67, 71] propose an multi-level approach to solve the dead-lock problem in field-driven AIV systems. Such system rely on self-organization principles to achieve their goals, but AIV can remain trapped into dead-locks. When such a situation is detected (using a similar approach than [105–107]), it is agentified to solve the problem using hierarchical control.

[75] propose an innovative framework for such models: (dis)aggregation functions rely not only on the observable state of simulations (the environment) but also on the internal states of agents. It is used in pedestrian flow simulations. The proximity between agent states (external and internal) is computed by an affinity function. However, their approach is not multi-level (in the sense of the definition proposed in section 1) as mesoscopic agents interact directly with microscopic agents.

[112, 114] extend this framework on the basis of IRM4MLS [68, 70] to allow the definition of "real" ML-ABM. Agents are "cut" into a a set of physical parts (bodies), situated in different levels, and a non-situated part (mind) (fig. 5). Therefor, these different parts can be (dis)aggregated independently. This approach is applied to the simulation of automated container ports.

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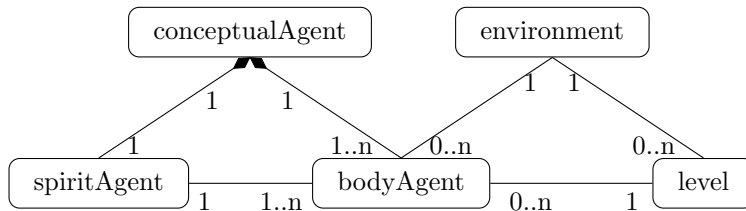
Figure 5: Mind/bodies separation in the Soyez et al. model (from [112])

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