TUTORIAL ON AGENT-BASED MODELLING AND SIMULATION: ABM DESIGN FOR COLLECTIVE BEHAVIOUR IN ROBOTICS

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Abstract

Agent-based modelling(ABM) and simulation is an approach to modelling systems that consist of autonomous agents. ABM applications range from social sciences to various engineering disciplines, as it offers simple and clear methods to model individual behaviours and provides observation and analysis of complex and dynamic systems. Recent advancements in computation tools make agent-based modelling an appealing concept for simulation and therefore a more popular candidate for research purposes. This tutorial presents an introduction to agent-based modelling and simulation by illustrating the main concepts, discussing some applications in various disciplines and describing methods of building agent-based models with an example of collective behaviour in robotics.

Keywords: agent-based modelling, agent-based simulation, collective behaviour in robotics

1 Introduction

Agent-based modelling and simulation is a modelling approach built on individually designed autonomous agents. Although agents play the key role to this modelling paradigm, their interactions and environmental conditions hold equal importance, if not more. ABM has been broadly popular since the beginning of 21st century and has a wide set of applications such as ecology, agriculture, traffic systems, anthropology, economy, social sciences, biology and many more. Table 1 shows some publications of the agent-based models in various fields. The main concept behind ABM is to define required agent behaviours and their surroundings in order to study the overall systems and possible emergent patters that occur which cannot be observed in micro level analysis.

A model is a way of representing the system without all the details and deviations such that it can be investigated corresponding to a certain question or problem. „All models are coarse-grained descriptions of reality; and, in fact, models that are not coarse-grained descriptions are useless as descriptions because they are indistinguishable from the real world and therefore do not assist in our understanding of complex systems(Korzybski, 1990)[WR15]“. A model serves to help understanding and exploring a phenomenon more efficiently than simply by making an observation of reality. Hence, by formulating a model composed of essential elements, emergent outcomes of system mechanisms can be confirmed, explored or even predicted.

A simple agent-based model comprises a group of agents and their interactions. A bottom-up approach is followed while designing an ABM. First the agents are clearly defined and modelled, then the model is extended according to the objectives to be studied. Despite the simplicity of a model, complex behaviour patterns may be exhibited. Moreover, the agents may be affected by their environment, they might evolve and cause unforeseen behaviours to emerge. These properties are what make ABM simple in design, conversely complex in conceptualization.

ABM has various benefits over conventional modelling and simulation techniques; one and possibly the most important being the ability to capture emergent phenomena, second being a natural characterization of a system and third being its flexibility. What makes agent-based modelling stand out among all the modelling and simulation techniques is its capability of dealing with emergency[Bon02]. In contrast to other modelling and simulation techniques -for instance traditional differential equation modelling- ABM does not require an advanced level of mathematical knowledge of the experimenter or homogeneity assumption of the experiment subjects which demands some assumptions to be made. In addition, nonlinear systems can easily be modelled by ABM without a need for linearization.

It is advantageous to use agent-based modelling in several scenarios. First is when dealing with systems whose dynamics are dependent on flexible and local interaction. Second scenario is heterogeneity in the agents themselves, their behaviours and also their environments. This is known to be a challenging task in other modelling and simulation types. Third is multilevel systems to be examined on several levels, especially when no connection is observed between them. Another one is when decision-making relies upon different levels of aggregation. This means that there are feedback mechanisms that affect decision-making of the individuals as well as aggregate levels. Other scenarios include systems where learning or evolutionary processes are present, systems that integrate intelligent human behaviour -socio-technical systems-, systems where the assumptions are needed to form equilibrium and systems with the focus on the transient dynamics rather than the stationary equilibrium [KB12].

There are potential drawbacks to agent-based modelling and simulation as the advantages come at a price. One crucial issue is the designer's decision to include details which he or she considers as 'necessary'. If the model has all the details that it is the exact imitation of reality, the simulation

Application field	Model summary
Agriculture	Agent-based model that investigates the interaction and cumulative impact of the physical water system, local social and institutional structures which regulate water use, and the real estate market on the sustainability of traditional farming as a lifestyle in the northern New Mexico area [WT12].
Air traffic control	Agent-based simulation as a method of predicting the impact of revolutionary changes to an air transportation system [APSB05].
Anthropology	Agent-based model of pastoral nomad/sedentary peasant interaction [KS05].
Archaeology	Agent-based modelling of Aghitu-3 Cave to study upper paleolithic settlement and mobility in the Armenian highlands [EFG19].
Biology	Basic Immune Simulator, an agent-based model to study the interactions between the cells of the innate and adaptive immune system [VAFO07].
Crime analysis	An agent-based model to estimate area-wide impacts of hot spots policing on street robbery [DWW17].
Ecology	Agent-based modelling of deforestation in southern Yucatan, Mexico and reforestation in the Midwest United States [ME08].
Epidemiology	An agent-based model for a fine-grained computational simulation of the ongoing COVID-19 pandemic in Australia [SLCP20].
Evacuation	Agent-based modelling of emergency evacuations considering human panic behaviour [TR18].
Finance	An agent-based model to clarify microscopic and macroscopic links between investor behaviours and price fluctuations in a financial market [HT06].
Healthcare	An agent-based model to examine the impact of the walking school bus on children's active travel to school [YYC14].
Psychology	An agent-based model that simulates the spread of negative mood amongst a group of agents in a social network and integrates elements from Gross' emotion regulation theory [AAAvdW11].
Tourism	An ABM to improve knowledge on tourist decision-making in the selection of a destination to vacation [BPFR17].
Transportation and traffic	An agent-based model for the simulation of road traffic and transport demand of an urban area in south east Sydney, Australia [NNHB14].

Table 1: A list of studies on ABM applications in various disciplines.

might not be needed, and experiments might be conducted instead. Additionally, as the number of details increases, more parameters need to be calibrated, and it becomes more difficult to observe certain patterns. On the other hand, over simplification in modelling might lead to a negotiation in the significance of the results. Another pitfall of ABM is the sensitivity of calibration, insignificant changes in one parameter might induce drastic consequences. The quality of reproduction of results might be a major problem, mostly emerging from deficient documentation of the agent-based models[RAC96].

This paper outlines how to build an agent based model with a simplistic example of collective behaviour in robotics. Section 2 identifies the basics of ABM, adequately exploring its main components and the phenomenon of emergence. Section 3 clarifies the techniques of ABM. Section 4 provides the collective behaviour example by a brief demonstration of the analysis, design and the findings.

2 Understanding agent-based modelling

2.1 Structure of the agent-based model

An agent-based model consists of three main elements: agents, agent interactions and their environment. Agents are the dynamic units of the model, and the environment is their field of action. There can be interactions within the agents, between the agents and the environment, and within the environment itself. There is no definite rule on what the agents and the environment ought to be. The designer is independent to specify these units as long as the model matches the system and is able to meet the motivation of the work. Figure 1 illustrates the workflow in an agent-based model.

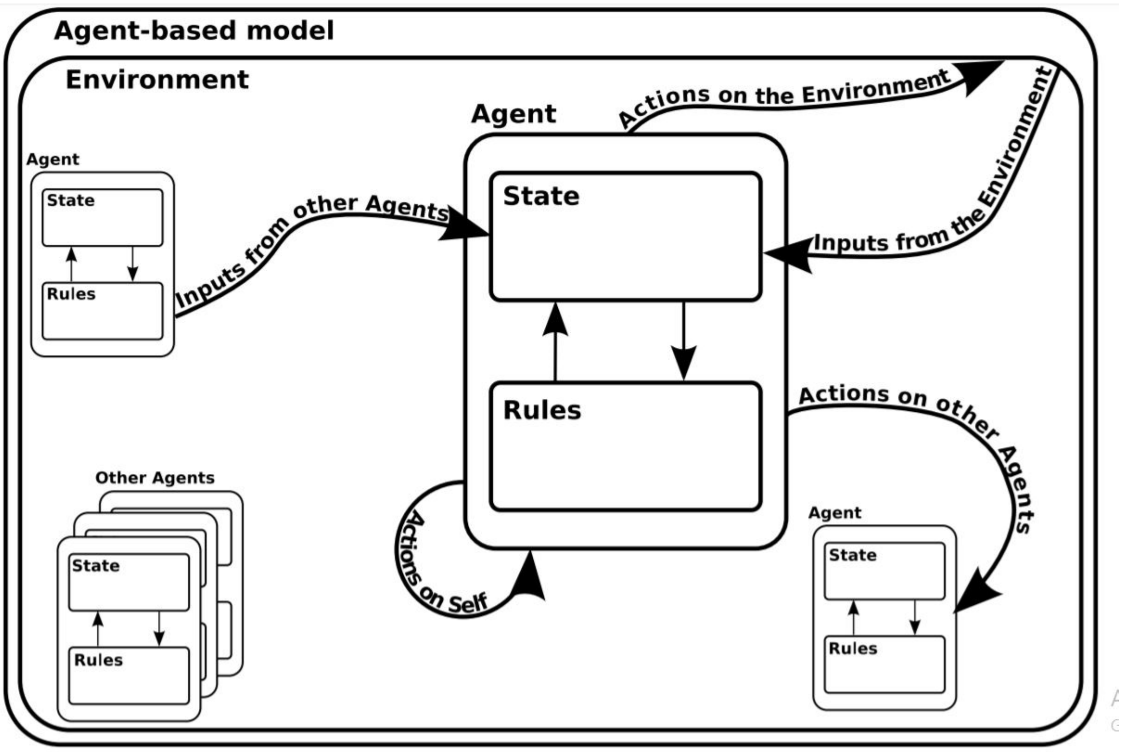

Figure 1: Structure of an agent-based model[NK13].

2.2 Agents

There is no strict definition on what an agent is, and as a matter of fact, this has been a subject of discussion by the academic society. However, it is useful to refer to sources that have been dealing with agent-based modelling since the beginning of this mindset. Wooldridge and Jennings(1995) studied on this question and suggested that „an agent is a system that enjoys the following properties[WJ95]“:

- *Autonomy*: There is no direct intervention by the operator or the outside world on the agent's behaviours and decisions. An agent is a self-sufficient organism that is able to control its actions and states[Cas95]. At the beginning of the modelling process, the agent is equipped with the background of its functionality such that it can sense, process and act on the world around itself.

- *Sociability*: A communication language is established between the agents such that they are able to interact with each other[GK94]. The agents might also have the ability to engage in social activities under the same goal.

- *Reactivity*: Agents are arranged in a way that they are able to perceive their surroundings and are able to react to the occurrences in a timely manner.

- *Pro-activeness*: Agents are able to perform reflexive activities initiatively aside from responding to their environment.

Macal and North(2011) introduced two additional properties to agents[MN11]:

- *Modularity*: An agent has certain characteristics, behaviours and decision-making capability that make them identifiable. This provides that agents are distinguishable by the observers of the system. There is usually a threshold of modularity such that in case of two types of agents having a too complicated and tightly coupled relationship that makes their functional boundary hard to identify, they might as well be modelled as a single type of agent. [RS14].

- *Conditionality*: Agents have time-varying states representing their current conditions. The overall system's state is a collective set of the individual agents' states along with the environment's own state. The reactions and interaction of the agents depend of their states and the environment's state.

Agents may have additional properties that contribute to the agent-based model; nonetheless, these properties are not necessary to form an agent. For example, agents might have the ability to learn and adapt based on their experiences, they may have goals to drive its actions or they may have a full range diversity among them[MN10]. The rule of thumb of the agent-based model design is to select agents to represent the fundamental level of interaction. For example, while modelling a parliament, it doesn't make sense to model every individual representative, but to model each party as a separate agent. This perspective helps the designer to decide what level of complexity the agents comprise.

2.3 Interactions

Wilensky and Rand (2015) categorized ABM interactions in five classes[WR15]: *agent-self, environment-self, agent-agent, environment-environment* and *agent-environment*.

- *Agent-self interactions*: Agents do not always have to interact with their surroundings. One typical example of this type of interaction is *birth*, an agent forming a new agent. Likewise, *suicide* is another self interaction within the agent itself. An agent's decision-making process is also a self interaction, which makes its states and levels of resources change.

- *Environment-self interactions*: Environment-self interactions occur when the environment's state changes, whether the environment expands or narrows, increases or decreases its resources and so on.

- *Agent-agent interactions*: This type of interactions is also called agent relationships. It is not an obligation for the modeller to design all the agents interacting with each other. If the decision-making on an individual agent depends on another agent's state, an interaction must occur. A logical or/and physical map is outlined on the agents' inter-connectivity throughout the design process. *Communication* between the agents is a typical example of this type of interaction.

- *Environment-environment interactions*: This is stated as the least common interaction by Wilensky and Rand (2015). An example for this type of interaction is *diffusion* that can be investigated in the Ants model in NetLogo. A pheromone placed by the ants is diffused throughout the world via an environment-environment interaction.

- *Agent-environment interactions*: If an agent is able to manipulate the world that it lives in, or the environment changes the behaviour or the state of the agent, agent-environment interactions occur. A common type of this interaction is *observation*, when the agents examine their surroundings.

Regardless of the interaction topology of the system, an agent or the environment is only able to interact with a certain number of elements in its local neighborhood. This does not mean that the neighborhood is a physical quantity, the agent or the environment may be members of different networks[Mac18].

2.4 Environment

The environment is the part of the system that agents are in interaction with and it is not considered as an agent itself and is context dependent. „...the system is a particular interpretation of a particular subset of the real world. The 'rest' of the real world is the environment in which the system is situated."The environment is abstracted to the relevant degree of parameters and variables for simplification. Nikolic and Kasmire(2013) focus on the similarities of each agent's environments to define the environment as a shorthand for the information in the global states[NK13]. This information is partly set by the designer, partly provided by the model itself and partly emergent. For instance, time passage is a model provided information, every type of statistics collected during this time is also a model provided information. Global parameters and variables that are set at the beginning of the simulation are designer provided information and these might differ to be static or dynamic. Emergence of the environmental information might arise from the interactions of the agents and/or the environment itself and might not be visible to the agents individually, but to the observer who looks at the overall picture from outside. An adequate example is the market analysis where the prices are emergent because of the single agents' actions.

There are different types of environment structures for different applications.

- *Spatial environments*: Spatial environments are based on a geographical framework and have generally two variants: *discrete* and *continuous* spaces. Because the simulation tools provide discrete implementation, continuous spaces are studied within discrete spaces with an adjustable resolution. *Square* and *hexagonal* lattices are the most common types of discrete spaces. Square lattices consist of squares that can also be categorised into two kinds of neighborhoods: *von Neumann neighborhood* where the square has four neighboring squares (north, south, east and west) and the *Moore neighborhood* where there are four additional neighbors (north-west, north-east, south-west and south-east). The neighborhoods can be extended with further parameters like radius. Hex lattices have a constant number of neighbors and a constant distance to their neighbors which makes them advantageous over square lattices in some applications.

- *Network-based environments*: In social sciences and most real-world applications, agents do not only interact on a geographical basis. For example, a person may only be in touch with people living hundreds of kilometers away from his home and may even not know who his neighbors are, thus not be exchanging any information with them. Network-based environments use the terms *links* and *nodes* to refer to *neighborhoods* and *neighbors* in the spatial terminology. These elements can also have static and dynamic properties just like agents. Three main types of networks are regarded as benchmarks by the network scientists. First one is the *Erdos-Rényi (ER) random graphs* [ER59] where the nodes are randomly connected to each other i.e. agents are equally likely to interact with other agents. This leads to a low clustering coefficient, which means that no subsets of agents interact more than the others, and a short average-path-length, meaning that few steps are taken to reach to a node from another node. Second is *small-world networks* [WS98] where most nodes are not neighbors of each other - they are located in longer distances - but the short average-path-length is preserved. The clustering coefficient becomes high in this case which makes small-world a more realistic approach in real-world scenarios. Third is *scale-free networks* [BA99] which are very similar to small-world networks in terms of clustering coefficient and average-path-length but different in terms of the distribution of connection degrees. In the small-world topology, the popular nodes are as many as the unpopular ones with a Poisson degree distribution. In the scale-free network topology, a small number of nodes - hubs - are highly connected whereas the majority have few connections. Figure 2 illustrates the differences between the networks.

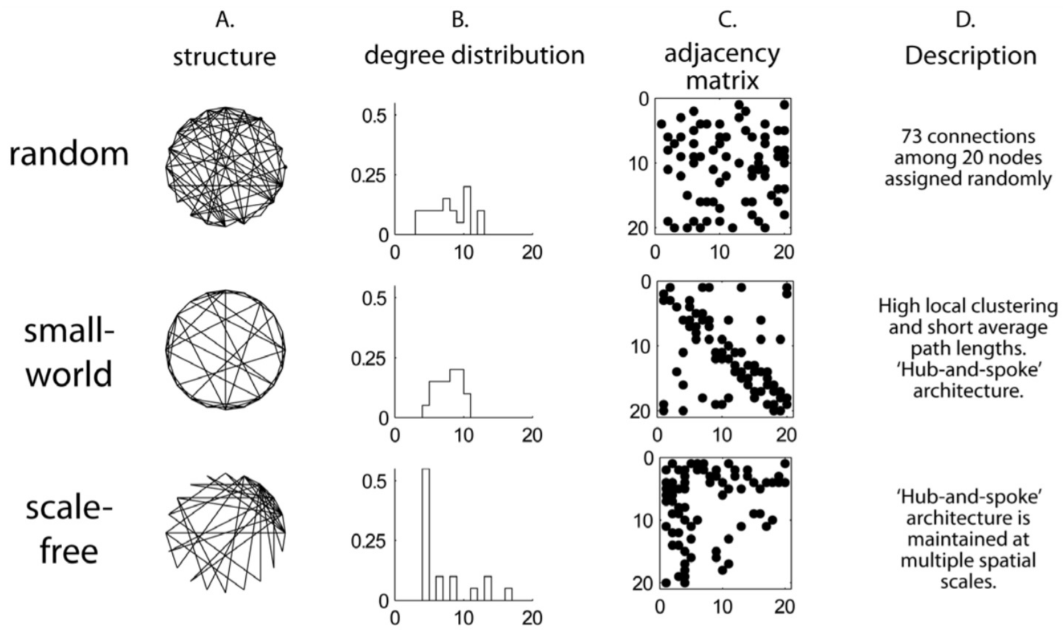

Figure 2: Comparison of random, small-world and scale-free networks[SPMG12].

- *Special environments*: Previously mentioned environment types are based on interaction topologies of the agents. There are other standard topologies that can be considered. *3D* *worlds* are an extension to spacial environments with an additional dimension - a Z coordinate to deal with. However, in 3D worlds, *pitch* and *roll* are used to describe the orientation of the agents. Squares in the 2D spatial environment are replaced by cubes in the 3D worlds. Another special environment type is *GIS* - Geographic Information Systems recording real-data related to the physical locations in the world. GIS are also spatial environments; nevertheless, the data is handled in a different way. The applications are popular among the professionals who process real geographical data such as urban planners, environmental scientists, transportation engineers.

2.5 Complexity and emergence

What makes ABM special? Many users of ABM agree on the idea that its importance stems from its ability to model complex systems and understand emergent phenomena. Hence, it is critical to address the terms *complexity* and *emergence* properly. A complex system is a whole formed out of parts that lead to an over-all emergent behaviour, the system's resulting nature cannot be deduced to the behaviour of its components. The complexity of a system is a measure of how much information and how many details it includes. [BY97] Without a formal definition, complex systems are characterised by three key-features[BY02]:

- *Emergence*: The macro-level behaviour arising from the micro-level parts of the system and not possible to be explained at the agent level alone. [KM09]
- *Interdependence*: Micro-level components depend on each other to a certain degree. Loss of one component might lead to drastic changes on other agents and might alter the whole system behaviour, or the other components might make up for the missing component.
- *Self-organization*: Self-organization is the reallocation of the energy and the action within a system to accomplish a certain mission. It is a collective process of communication, choice and mutual adjustment in behaviour of the agents[Com94]. There is no central-controller, no conductor to manage and organize the behaviours of the agents.

Consciousness was investigated under a large-scale, as the emergent and transient dynamical patterns of brain activity[TJ01]. Molecular crystal growth is an example of emergent phenomena of molecules evolving toward a lowest-energy ordered structure and was modelled with ABM [ATR05]. Basic Immune Simulator (BIS) was developed as an agent-based model to understand the emergence of the immune system's complex behavioural patterns in a generic viral infection scenario[VAFO07]. Herding, queuing and competitive human behaviours are social emergent behaviours in emergency evacuation situations which were also simulated with an ABM[XPL07].

3 Methods for ABM design

There is no specific or obligatory method for designing an agent-based model. Depending on the application, one can extend the existing models, modify them or start from scratch. However, for a model to be scientifically valid, it must be reproducible regardless of the framework it is being implemented at. Sansores and Pavón(2005) addressed this issue as „the lack of a simulation integrated environment that supports the whole research process from conceptual modelling to simulation implementation and analysis"and introduced a high-level conceptual modelling abstraction for simulation development[SP05]. Richiardi(2006) suggested a three-stage process that could lead to the establishment of methodological standards in social and economic simulations in a general sense, rather than the standard itself; first stage being the development of a questionnaire by a working group, second stage being the distribution of the questionnaire by professional simulation journals and final stage being the analysis of the data and a voluntary initial methodological standard recommendation for agent-based simulations[MRS06]. Drogoul(2002) proposed a methodology like a *role-playing game* by assigning tasks to three persons: a thematician who defines the intention of the simulation process, a modeler to clear the concepts and translate the target domain into formality and a computer scientist to implement the model in a computer environment which of course can all be one person altogether[DVM02]. Galan and Izquerdo(2009) outlined a general framework that summarises the process of designing, implementing, and using agent-based models by combining the mentioned approaches[GII$^+$09] which is illustrated in Figure 3. Formal methods, which is an approach developed by computer scientists for the production of high integrity systems, was claimed to be applicable to agent-based modelling by Kehoe(2016) in order to solve the reproducibility problem[Keh16].

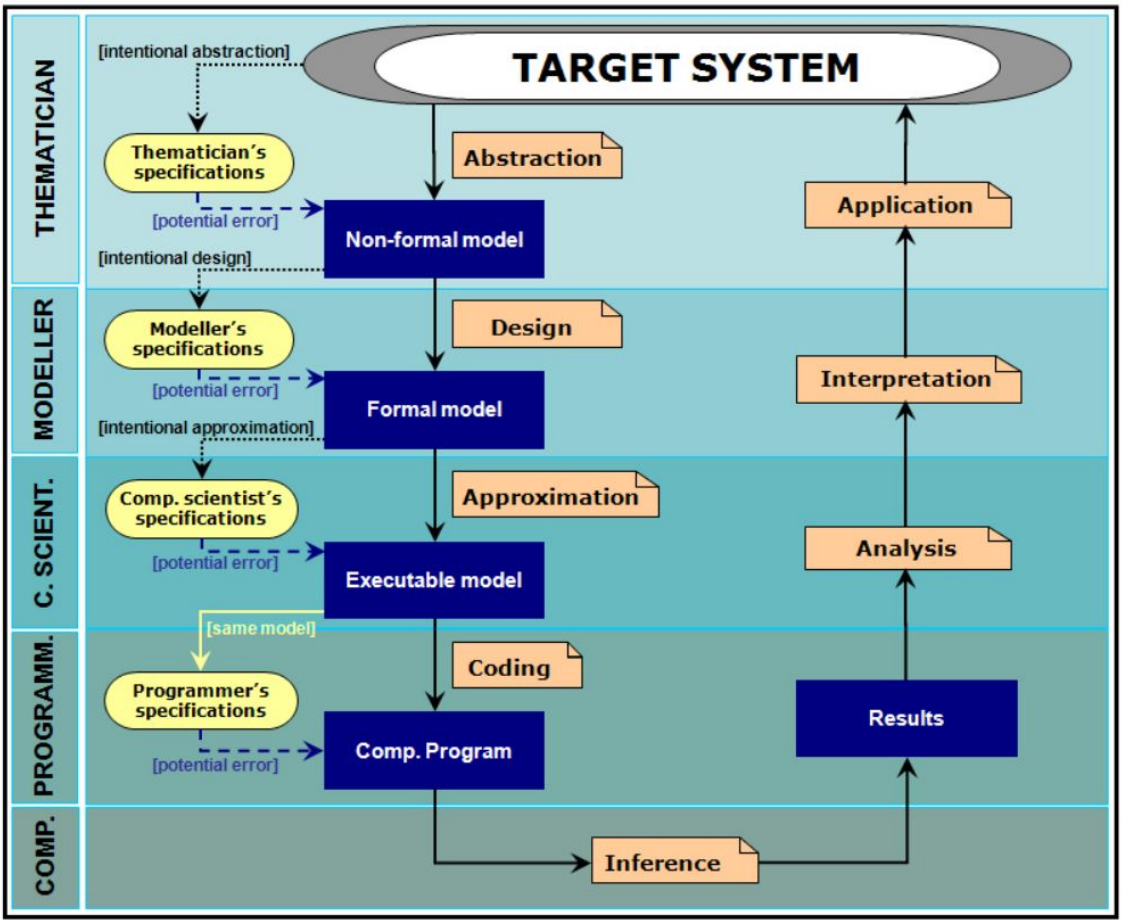

Figure 3: Steps of the design, implementation and application of an ABM[GII$^+$09].

Despite various criticisms, O.D.D. is the most recognized protocol among agent-based model designers[GRV$^+$20]. It was a proposal to overcome the replication problem and was developed and tested by 28 modellers in 2006[GBB$^+$06]. The protocol has been applied by many designers since it was established and has been revised multiple times to eliminate insignificant and manipulable parts. This protocol will be used to understand how to design an agent-based model for the next sections.

3.1 Studying of the system

O.D.D. protocol addresses seven elements, all of which are used as a checklist[GRV$^+$20].

1. **Purpose and patterns**

   A model starts with a purpose that needs to be clearly stated at the beginning of the process. This purpose might be a prediction, an explanation, a description, an illustration or an analogy. The following example is a prediction: „The proximate purpose of the model is to predict the dynamics of the number, location, and size of tiger territories in response to habitat quality and tiger density...The ultimate purpose of the model, which will be presented in follow-up work, is to explore human-tiger interactions“[NCG15].

   The patterns are micro and macro-level observations that are assumed to be driven by the same processes and variables for a certain purpose. They are important to assess the reproducibility of the system.

   Following procedure is to be followed at this stage of the design: *(1) Define a specific purpose which addresses a clear question (2) Include a higher-level purpose (3) Link the purpose with the study's primary results (4) Define the terms in the purpose explicitly (5) Be specific to this version of the model (6) Do not describe the model yet (7) Make the purpose state independent (8) Use qualitative but testable patterns (9) Document the patterns*

2. **Entities, state variables and scales**

   An entity is an object or actor that behaves as a unit. Typical entities are spatial units, agents, environments and collectives(agent collectives with their own type of variables and behaviours).

   State variables characterize the current state of the entities. Same type of agents can be distinguished by their state variables. Temperature is a state variable example for the environment, wealth in Sugarscape[EA96] model is a state variable of an agent.

   Scales are the model's temporal and spatial limitations. The extent and the resolution of the model must be defined by scales. One tick might represent a second, a day or even a year. A square might represent ten square meters or a thousand.

   This stage's guideline is as follows: *(1) Provide a rational outline for the choice of entities (2) Include networks and collectives as entities if they have their own state variables and behaviours (3) Do not explain the change in state variables and the actions of entities at this point (4) Describe the spatial properties of the model if the model represents space (5) Describe the temporal properties (6) Describe the dimensions of the model (7) If there are no specific scales of the model, provide a conceptual definition of the scales or typical values*

3. **Process overview and scheduling**

   Process overview element summarizes what a model does as it runs. What processes are executed in which order(scheduling) is discussed although the details of these processes are fully described later on in Submodels element.

   Following steps are recommended at this stage: *(1) Include everything that is executed at each time step (2) Describe the execution order (3) The schedule must include when state variables are updated (4) Provide a rationale for the process and scheduling (5) Save the* *detailed process explanation for later and keep it simple for now (6) Use flow-charts if possible (7) If necessary, use pseudo-code to clarify execution order*

4. **Design concepts**

   This element contains the justification for the model design decisions. It is often emphasized that the model must include necessary details and exclude irrelevant ones, this is the place to clarify the logic behind the decided details. There are several concepts within this element that are to be discussed individually.

   - *Basic principles*: The general concepts underlying the model design at micro and macro level, how they are handled and whether the model is based on a new or existing theory.
   - *Emergence*: Results of the model that emerge from particular mechanisms, describing those mechanisms by their relevance to the emergence of the model.
   - *Adaptation*: Agent's decisions in response to certain stimuli, internal and external variables that affect the agent's decision-making, the alternative that agents choose from and whether the behaviour is modelled via direct(agents rank alternatives) or indirect objective-seeking(agents follow the rules to reproduce observed behaviours)
   - *Objectives*: The measure that motivates decision-making of the agents with adaptive behaviours that use direct objective-seeking, what variables drive the objective measure.
   - *Learning*: How agents change their decision-making procedure as a consequence of their experiences, how learning is represented and the rationale behind it.
   - *Prediction*: How agents predict future conditions and decision consequences, how models of adaptive behaviour use either explicit or implicit predictions and the rationale behind it.
   - *Sensing*: What state variables are sensed and used by the agents to what extent, how the sensing is implemented and the rationale behind the assumptions.
   - *Interaction*: Types of interactions between the agents, the range of the interactions and the rationale behind.
   - *Stochasticity*: Which processes within the model are designed as stochastic and the reason behind those.
   - *Collectives*: Aggregation of agents that affect and are affected by the agents, whether they are modelled as emerging or explicitly, how they interact to drive the system-level behaviours.
   - *Observation*: The critical outputs of the model to analyse and how they are observed from the simulations, any special techniques used to improve comparison of the model and how to link the results to the purpose.

5. **Initialization**

   This element defines the initialization of the model, how all entities are created before the start of the simulation.

   Following procedure can be pursued: *(1) Define how to setup the model (2) Specify whether initialization intends to be generic or case-specific (3) Explain whether the initialization varies or is the same for multiple simulations (4) If data is imported from the real world, describe it (5) Do not describe parameters and how entities are created*

6. **Input data**

   Time series of variable values or events that drive the model dynamics are input data and they are not affected by the model, but they affect the model. For instance, rain input may affect the moisture variable of the cell and affect the growth of the plants and trees in the model.

   Following steps can be used as a guideline for this element: *(1) Specify whether the model uses input data (2) Note that input data is not initialization data (3) Define the data completely (4) If the model is used for multiple scenarios with different input data, describe the needed input data for each scenario (5) Document the generation of the input data if it comes from another model*

7. **Submodels**

   At this point, every detailed description of each process is explained. These are the submodels that were mentioned in initialization and process overview-scheduling elements.

   Instruction for this element is as follows: *(1) Describe each submodel in detail (2) Break the submodel into submodels if necessary (3) Provide rationale and analyse*

3.2 Implementation and software

Agent-based modelling can be implemented using all-purpose software and programming languages or particularly designed software tools for ABM. Macal(2018) categorizes the tool-kits in three parts[Mac18]: (1) *Desktop computing* which can be used to explore ABM, prototype basic agent behaviours and perform limited analyses. Spreadsheets, i.e. Excel, are known to be the simplest approach; however, they provide limited diversity and scalability. Dedicated ABM tools, such as NetLogo, are capable of a variety of applications and provide an easy user-interface. General computational mathematics systems like MATLAB and Mathematica can also be used for ABM in spite of the fact that the designer has to develop the agent-specific functionality from the very beginning.(2) *Large-scale agent development environments* such as Repast, Swarm, AnyLogic and MASON. (3) *General programming languages*, i.e. C++, Java, Python.

A detailed review on the software tools for ABM was conducted in 2017. Figure 4 demonstrates the classification of the tools with respect to their scalability and development effort[ATLO17]. The comparative literature survey of the state-of-art in software agent-based technology is a valuable document for a potential designer to choose a specific programming environment for his/her implementation.

4 Modelling of collective robotics

Swarm robotics is the study of designing collective robots without a centralized controller or any type of external foundation and is inspired from nature. What distinguishes swarm robotics from multi-robot systems is its emphasis on self-organization and emergence while retaining scalability and robustness[Sah04]. Robots that make up the swarm robotic system have characteristics such as autonomy, homogeneity, local sensing and communication abilities and their actions lead to an emergent collective behaviour to accomplish a certain task. They are simplistically designed robots that are not able to carry out the task on their own and are large in number. All these aspects of swarm robotics make it a suitable candidate for ABM to observe and perform experiments even before realizing the robotic system physically.

Computational Modelling Strength / Models' Scalability Level	Simple/Easy	Moderate	Complex/Hard
Extreme-scale			Repast HPC; MATSIM, PDES-MAS, Swarm
High /Large-scale	Altreva Adaptive Modeler, SeSAM	AnyLogic (2D/3D), AOR Simulation, CloudSim, CybelePro, FLAME, LSD (2D/3D), MASS, Pandora, UrbanSim	Agent Cell (2D/3D), Brahms, BSim (2D/3D), D-OMAR, Echo, Ecolab, FLAME GPU (3D), GridABM, HLA_Agent, HLA_RePast, Repast-J or Repast-3, Repast Symphony (2D/3D)
	NetLogo (2D/3D)	Ascape, CRAFTY, GAMA (2D/3D), SimEvents (MATLAB®), Simio (2D/3D), Simul8 (2D/3D)	MASON (2D/3D)
Medium-scale	JAS, VSEdit	Agent Factory, Breve (3D), Cormas, Envision, GALATEA, IDEA, JAMSIM, Janus, JASA, JAS-mine, MACSimJX, Mathmatica® (Wolfram), Mimosa, MIMOSE, Mobility Testbed, Modgen, OBEUS, SimAgent, SimBioSys, TerraME, Xholon (2D/3D)	DigiHive, MASyV (2D/3D)
	AgentSheets, BehaviourComposer (2D/3D), FlexSim (2D/3D)	Eve, ExtendSim (2D/3D), GROWLab, Insight Maker, Mesa	
Light-weight /Small-scale	AgentScript, Framsticks (2D/3D), JAMEL, JCASim (1D/2D/3D), jES, MOBIDYC, PedSim, PS-I, Scratch (2D/3D), SimJr, SimSketch, SOARS, StarLogo, StarLogoTNG (3D), Sugarscape, VisualBots	SEAS (2D/3D)	

Model Development Effort →

Figure 4: ABMS tools classification table[ATLO17].

4.1 Analysis

The ABM design for this particular application was inspired by the work of Kube and Zhang(1993) who proposed a method for a number of robots to push a box without centralized control and direct communication[KZ94]. Their simulations verified their hypothesis of a team of homogeneous mobile robots' capability of achieving a task without a controller, which was the very definition of *swarm robotics* although the term was not invented yet and there was not much research on the field at the time.

Some modifications were made to the original design and the model was simplified as much as possible. The design will be discussed in detail in the following subsection.

4.2 Design

The O.D.D. protocol is adopted to explain the design of the ABM. The detailed instruction is shown in Table 2. Figures 5 and 6 demonstrate the visualizations of initialization and processes of the simulation respectively.

Purpose and patterns	The general purpose of the model is to investigate the collective behaviour of a number of robots with limited abilities pushing a box. The agents queuing up and piling up at the same edge of the box are the patterns of the model that serve to the purpose.
Entities with state variables and scales	There is one type of agent that represents the robot with the same state variables for each one which are their vision and their speeds. Queueing robots form a collective and have a different speed variable. Spatial units are patches which are square lattices without a certain size corresponding to real life, the scales are relative among the size of the agents, the box, and the environment. The box is a stationary entity belonging to the environment and has the only variable width. The environment has a state variable that can be two ways, narrow or wide.
Initialization	The initialization is a random placement of the agents. The number of agents, their vision angle and radius, average speed and the width of the box are the variables that are set to initalize the model.
Input data	There is no input data other than the changeable average speed of the robots during the simulation.
Process overview and scheduling	'update': At each tick, the visions of the agents are updated in accordance with their headings. 'avoid-obstacle': The obstacle within the vision is detected and avoided. After this point, a state machine approach is implemented so that the agents perform the actions within their states.

Process overview and scheduling	'wander': The agent wanders around, looking for a box or another agent to follow. 'slow': If any other agents are detected within a radius, the speed is reduced to half. 'follow': If another agent is detected, it is followed with the slow speed. 'back-off': To avoid collisions, if the distance is too close to the followed agent, the robot backs off. 'goal': When the box is detected, the speed is reduced to a certain value and the agent gets closer to the box. 'find-spot': When the agent is close to the box but another agent is already placed at the edge in front of it, it turns right and finds an empty spot.
Design concepts	The follow behaviour of the agents emerges a collective group and a pile at one edge on the box. The agents have the ultimate objective to find the box and push it, and medium objectives to follow another agent, avoid collisions etc. There is no learning or prediction in this model. Sensing capabilities of the agents are their front vision with an angle and a radius, and a circular vision to detect neighboring agents. They are able to sense three different entities in the model: other agents, the edges of the environment and the box. The placement of the agents at the beginning and their headings to find a box or another agent when they wander around are random. The observation is only visual, where the agents are placed at the edge of the box. There is no sampled data.
Submodels	This element will not be discussed in detail as the model is already simplified to the maximum extent and the process overview is enough to understand the overall idea.

Table 2: O.D.D. protocol for the design of the model.

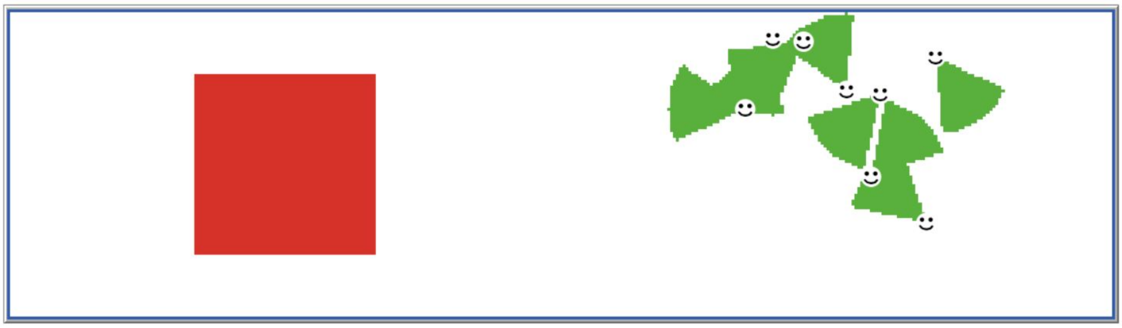

Figure 5: Initialization of the simulation.

4.3 Results

The simulation has been implemented in NetLogo, has provided the desired results and met the purpose of the design which was to verify the hypothesis of robots' capability of pushing a box without control or direct communication. The narrowness of the area has improved the success

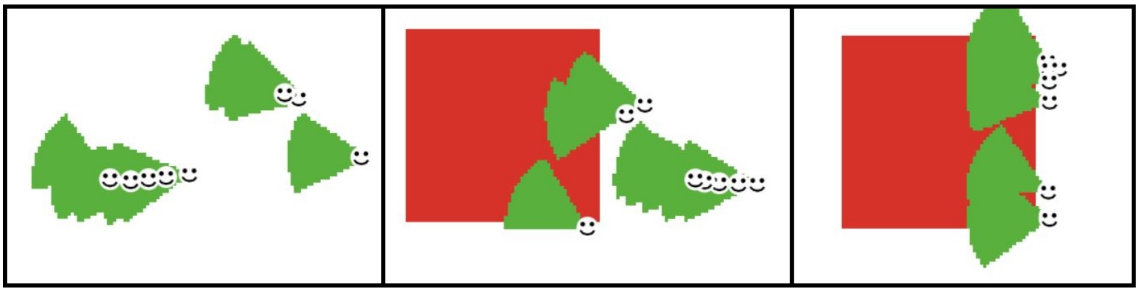

Figure 6: The agents following each other, approaching the box and placed at the edge of the box.

rate and guaranteed an accumulation at one edge of the box which was an issue discussed in Kube and Zhang's paper. Adjusting the temporal and spatial scales to real life conditions will ensure the validity of the hypothesis.

5 Conclusions

This paper has covered the basics and applications of ABM. Throughout each topic, definitions have been explained in detail and various examples have been given. With the demonstration of collective behaviour in robotics, a tutorial on ABM has been presented.

The growing number of applications show that ABM is a promising method for simulation of systems which are relatively more challenging and complex to model with traditional methods. The ongoing advancements of specialized ABM tool-kits, the collective growth of the ABM community, advances in computer performance and especially the appreciation of individual behaviour's importance in modelling are few of the factors that move ABM forward[MN10]. Updates in O.D.D., the most common protocol for ABM, also prove that ABM is advancing its way to being an official procedure adopted by different fields and their contributors.

There are also enduring challenges with ABM, one of them being choosing the right level of description. It is important for the designer to carry out extensive research and use the existing learning tools to understand and embrace ABM fully. Another issue is the computational requirements of ABM, especially with large scale systems. Last but not least, development and sustainability of mechanisms for communities involved as they proceed further with their studies and contribute to the advancements of ABM. Expanding open access to ABM research literature, exchanging information across communities and growing number of applications are helpful developments towards this goal[Mac16].

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