STATE ACADEMIC UNIVERSITY FOR THE HUMANITIES
SCIENTIFIC PUBLICATIONS DEPARTMENT

Makarov V.L., Bakhtizin A.R., Epstein J.M.

Agent-Based Modeling for a Complex World

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The main goal of this paper has been to summarize selected developments in the field of artificial societies and agent-based modeling and to suggest how this fundamentally new toolkit can contribute to solving some of the most complex scientific and practical problems of our time. This paper consists of several parts. The first one considers the history of agent-based models. The second part is devoted to models of this class related to epidemiology, and the third considers agent-based modeling of pedestrian traffic and evacuation of the population. The fourth part is devoted to issues of demographic process modeling, and the fifth to the simulation of transport systems. Ecological forecasting is considered in part six, while the seventh is devoted to issues of land use, and the eighth to urban dynamics. The ninth part considers models used for the reconstruction of historical episodes, and in the tenth part, we will briefly touch on the issues of conflict simulation. In the eleventh part of the paper, we consider issues related to studying social networks using an agent-based approach. Agent-based models of economic systems are considered in the twelfth part. Undoubtedly, the scope of applications of agent-based models is wider, but we elected to focus on these indisputably significant areas.

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INTRODUCTION: COMPLEXITY DEMANDS NEW MODELING TOOLS

Recent global shocks have demonstrated the coupling of large-scale systems. The COVID-19 pandemic was not only a public health catastrophe, but an economic one as well, with combined effects distributed very unevenly within and between countries. However, in its cascading effects, the pandemic was not unique. Disruptive technologies and seemingly local political or economic shocks can have system-wide ramifications, to say nothing of climate change and other environmental perturbations. By any definition, we are living in a complex system requiring new tools and new ways of thinking. One of these is Agent-Based Modeling, which we will review here.

What are Agent-Based Models?

What are agent-based models and how can they help us navigate a complex world? The classic agent-based model is an artificial society of software individuals. They interact directly with one another in some artificial environment, which could be a geographical landscape, an organization, or a social network. These interactions can alter the agents and can alter their environment, which in turn affects the agents, and so forth, often producing complex non-equilibrium dynamics. These micro-scale agent interactions can also generate stable macroscopic social patterns, such as spatial segregation patterns, statistical distributions of wealth, or dynamic epidemic trajectories. While, in the beginning, "Toy" agent-based models were used to illuminate counter-intuitive mechanisms of herd immunity, economic scaling laws, and racial residential clustering, they have grown into mature scientific instruments, where model-generated patterns (model outputs) are compared to real-world macroscopic data. When they agree, the micro-scale agent-based model reveals a generative mechanism, and constitutes a candidate generative explanation, of the macro-scale phenomenon. Epstein uses the term Generative Social Science for the approach (Epstein, Axtell, 1996; Epstein, 2006). There may be other generative explanatory candidates, in which case further data or experiments may be required to adjudicate between them, as in any science where theories compete. But, generative sufficiency is a necessary condition for explanation. As Epstein, puts it, "If you didn't grow it, you didn't explain it" (Epstein, 2006, p. 51).

Some social-level phenomena are difficult (even impossible) to "grow" in homogeneous populations of perfectly-informed utility maximizers, of the sort one encounters in neoclassical microeconomics and game theory. Rather, agents are typically heterogeneous, have imperfect information, and are *boundedly* rational, to use Herbert Simon's famous term. Recent agents, such as *Agent_Zero* (Epstein, 2013), even include a fear module grounded in cognitive neuroscience, which can override the agent's conscious deliberations, about risk for example.

Finally, due to the explosive growth of computing power, and the advent of specialized programming languages for agent-based modeling, very large-scale agent-based models have been constructed in epidemiology, economics, and related fields.

What *distinctive* contributions can the agent-based approach make in understanding and shaping what, by any definition, is an increasingly complex world? One contribution is to close the micro-macro gap.

The micro-to-macro gap

For example, methods of multivariate regression analysis have been used to determine the relationships between macroscopic socio-economic indicators. The resulting regression equations can be very useful in predicting how a change in some aggregate variable (e.g., income taxes) will affect another aggregate variable (e.g., total consumption). But, by definition, the regression equations are aggregate (macro-to-macro) functions. As such, they can give no account of *how the macroscopic patterns emerge* from the bottom up, through interactions at the micro scale. As we will review, the evolution of large-scale agent-based modeling promises to fill this gap, allowing generative explanations of macro phenomena, in turn allowing us to explore how policies applied at the *micro* level may "bubble up" to alter social level patterns in desirable ways. Moreover, the micro interactions typically involve *heterogeneous* agents interacting in *networks*, both of which are difficult to capture in well-mixed compartmental differential equations. Finally, the micro world (and the macro patterns) may be highly dynamic and far from equilibrium, eluding static equilibrium approaches. One important development propelling large-scale agent modeling has been computing power.

Explosive growth in computational power

From the 1990s to the present day, the power of computing systems has grown almost exponentially. In comparison with 1993, the total performance of the 500 fastest supercomputers has grown almost 2 million times and is more than 2.5 exaFLOPS[1], and the performance of the top-end FUGAKU[2] and LUMI[3] systems is approximately 0.5 exaFLOPS. Presumably, the exaFLOP barrier for one supercomputer will be overcome within a year or two.

The shear computational barriers to large-scale heterogeneous agent modeling have largely been overcome. The main challenge now is to populate large models with cognitively plausible software individuals for purposes ranging from fundamental understanding of social dynamics to the design of policies. Prediction is often assumed to be the goal. But often it isn't. For example, the literal prediction of not-yet-evolved viruses is not in sight. However, agent-based modeling can help prepare for events we cannot, and may never be able to, predict. Novel pathogens and pandemics are prime examples, but the economic, political, and environmental spheres provide others requiring new tools and new ways of thinking. Recent global shocks illustrate, moreover, that in a connected word, they are coupled, as in the COVID-19 pandemic and economic crises of 2020–2021.

Adjacent Worlds

We note that many research centers worldwide are certainly involved in large-scale computational modeling. Among these, one might point

1 Data of the portal containing the rating and descriptions of the 500 most powerful computing systems in the world: https://www.top500.org
2 FUGAKU supercomputer website: https://www.fujitsu.com/global/about/innovation/fugaku
3 LUMI supercomputer website: https://www.lumi-supercomputer.eu

to: GTAP, MIRAGRODEP, MIRAGE, GLOBE, MULTIMOD, GEM, Global Macrofinancial Model, The Long Term Growth Model, Moody's Research LabsInc. Model, WorldScan, LINK, WEFM, KPMG-MACRO, NiGEM. A more detailed overview is given in the journal article "*Vestnik of Russian Academy of Sciences*" (Makarov, Wu et al., 2019; Makarov, Wu et al., 2020). Generally speaking, however, these models are based mainly on the "top-down" equilibrium approach, and do not purport to identify "bottom-up" (micro-to-macro) mechanisms, which have loomed large in the epidemic and economic "black swans" of 2020. So, they belong to a different research *programme*.

Agent-Based Modeling, Multi-Agent Systems, and Distributed Artificial Intelligence

Likewise, we distinguish between the research *programme* for Agent-Based Modeling and the Multi-Agent Simulation agenda. While these communities overlap, at its core, Multi-Agent Simulation is in the distributed artificial intelligence (DAI) tradition and is oriented primarily toward applied mechanism design and system optimization. For example, in the field of electronic commerce (Ehikioya, Zhang, 2018) DAI is used to develop optimal trading strategies (Sugumaran, 2009), to plan optimal transport networks (Boulmakoul, Karim, Lbath, 2021), or plan the effective use of network resources (Janbi, Katib, Albeshri et al., 2020; Yadav, Mahato, Linh, 2020). By contrast, agent-based modeling is focused on generative explanations of social dynamics as in the Schelling segregation model, the Epstein-Axtell Sugarscape model, and the Alife (Artificial Life) tradition. While these communities have largely separate journals, conferences, methods, applications, and audiences, there are intersections of note (Corea, 2019).

Swarm intelligence is an example (Ilie, Bădică, 2013). It is a decentralized self-organizing system used to solve optimization problems. For example, ant colony optimization algorithms, which simulate the actions of ants, can be used to solve graph-based route finding problems (the traveling salesman problem) (Ilie, Bădică, 2010). Our focus here will be developments on the side of agent-based modeling, though symbioses with related approaches is a high priority[4].

[4] The authors thank Robert Axtell for a very useful discussion of this distinction

While the field of artificial societies is our present focus, we do not claim that agent-based modeling is the best tool for all purposes. There are many other analytical tools that may be more effective for particular tasks and that also have software implementations including neural networks and other machine learning methods, not to mention differential equations. These approaches can often complement one another.

The Dialogue Between Methods

For example, in epidemiology, we often start by building a deterministic well-mixed (non-spatial) ordinary differential equations model with homogeneous pools (e.g., susceptibles and infectives) and study its dynamics and equilibria analytically. These have given fundamental insights into core phenomena like herd immunity and the vaccine levels required to induce it. Then we "agentize" the classic model, relaxing these stringent mean field assumptions, introducing randomness (stochasticity), space (which could be a physical landscape, a network, or both), heterogeneous agents and behavioral adaptation, to study the robustness of the classical results. The ordinary differential equations and agent-based modeling results can differ radically, suggesting novel approaches to epidemic containment (Epstein, Parker, Cummings et al., 2008). To date, many specialized software tools for building agent models (NetLogo, RePast, MASON, AnyLogic and others) have been developed.

Aims and Organization

With this as motivation, our aims are (a) to invite the reader to consider the potential of agent-based models for studying the world around us, (b) to review selected results in several important fields, and (c) to suggest fertile lines of future research. The authors of the paper have published scientific works in which they gave characteristics and described successful examples of the implementation of agent-based models (see, for example, Bakhtizin (2008); Makarov, Bakhtizin (2013); Epstein, Axtell (1996); Epstein (2006, 2013) and Parker, Epstein (2011). Here we will focus only on individual points showing the benefits of the approach. In addition, this is such a rapidly developing area that any review must be selective and incomplete[5].

5 The largest bibliographic databases Web of Science and SCOPUS show publications to have grown by 120 fold over the period 2000–2020

This paper consists of several parts. The first one considers the history of agent-based models. The second part is devoted to models of this class related to epidemiology, and the third considers agent-based modeling of pedestrian traffic and evacuation of the population. The fourth part is devoted to issues of demographic process modeling, and the fifth to the simulation of transport systems. Ecological forecasting is considered in part six, while the seventh is devoted to issues of land use, and the eighth to urban dynamics. The ninth part considers models used for the reconstruction of historical episodes, and in the tenth part, we will briefly touch on the issues of conflict simulation. In the eleventh part of the paper, we consider issues related to studying social networks using an agent-based approach. Agent-based models of economic systems are considered in the twelfth part. Undoubtedly, the scope of applications of agent-based models is wider, but we elected to focus on these indisputably significant areas.

1. HISTORICAL EXCURSION

It is difficult to identify the exact dawn of the agent-based approach. Some researchers link the emergence of agent models with cellular automata (CAs) of the 1940s. The great mathematician, John von Neumann laid foundations for modern computing (the von Neumann architecture), participated in the Manhattan Project, and dealt with issues of self-replicating systems. He proposed the concept of CAs, further developed by his colleague, Stanislav Ulam. Over the next decades, a large number of CAs with a wide variety of rules for the transition between states have been developed, and myriad articles and books have been written on this topic[6]. One of the most famous of these CAs is the game “Life,” developed by the English mathematician John Horton Conway in 1970. It not only became a classic, but also gave rise to a huge number of variations (Gardner, 1970).

[6] Data from the bibliographic and abstract base of scientific publications: https://www.scopus.com

The American economist and 2005 Nobel Laureate in game theory — Thomas Schelling, in a 1971 article "*Dynamic models of segregation*" proposed a cellular automaton describing the process of segregation and showed, surprisingly, that strong spatial segregation can emerge even when the individual agents have an extremely weak preference for neighbours of their own colour (Schelling, 1971). The Shelling model has been substantially extended and applied to replicate true historical segregation patterns in multiple countries (Hatna, Benenson, 2015).

As proved by Matthew Cook (2004), CAs are capable of universal computation, as are Turing Machines, the Lambda calculus, partial recursive functions and other inter-translatable formalisms. So CAs, while hardly unique in this respect, are in good computational company and have the distinct advantage of being simple to program and easy to visualize. For many examples, see "*A New Kind of Science*" (Wolfram, 2002).

One outgrowth of CAs is the field of Artificial Life, pioneered by Christopher Langton at the Santa Fe Institute in the US (Langton, 1989). The field of CAs is a fast-moving area, and with the wide availability of high-performance computing, this direction may be expected to advance dramatically.

For all their interest, classic CAs do not have heterogeneous agents, or ones who interact with (and alter) an external landscape, or engage in sexual reproduction, form networks and tribes, or engage in resource conflict, trade, and the transmission of cultures, immune systems, and diseases in a single unified artificial society. This is the realm of Agent-Based Modeling.

The first such integrated Artificial Society model, named Sugarscape, was developed (without knowledge of Schelling's model) in the early 1990s. An author of the present article, Epstein, has written what is widely seen as a foundational trilogy on agent-based modeling. The first volume "*Growing artificial societies*: *Social science from the bottom up*" (Epstein, Axtell, 1996) examines the now classic Sugarscape, which despite its relative simplicity, made a significant contribution to the development of the *generative epistemology* discussed earlier.

The second volume, "*Generative Social Science*: *Studies in Agent-Based Computational Modeling*" (Epstein, 2006), is not an artificial society, but a collection of focused studies demonstrating the agent-based approach as applied to a host of scientific fields including evolutionary games, economics, epidemiology, archaeology, organizations, and conflict. These include several realistic empirical studies and practical applications.

Dostoevsky

One of the challenges posed by Epstein at the end of "*Generative Social Science*" (Epstein, 2006) was to "grow Raskolnikov" an internally conflicted agent whose behavior results from an internal competition between reason and passion. Hume famously wrote that "Reason is… the slave of the passions" and so it was for Dostoevsky's immortal character, in which rational forces compete (unsuccessfully) with brooding murderous emotional ones. Is there a way to build software agents that include some simple representation of *emotions*, of *bounded rationality*, and of *social connection* (or isolation as the case may be)? These would appear to be minimal constituents of a cognitively plausible agent.

The third volume, "*Agent_Zero*: *Toward Neurocognitive Foundations for Generative Social Science*" (Epstein, 2013), is Epstein's answer. Unlike the perfectly informed utility maximizer of economic theory, *Agent_Zero's* behavior results from the interaction of an affective module (based on the neuroscience of fear), and a boundedly rational deliberative module exhibiting some systematic errors established by experimental psychologists from Herbert Simon to Daniel Kahnemann and others. *Agent_Zero* is also a social animal, influenced by other (emotionally driven and statistically hobbled) agents in her network (networks are in fact endogenous). When ensembles of *Agent_Zeros* interact, they replicate several important social psychology experiments, and generate collective phenomena from contagious violence to seasonal economic cycles to flight from contaminated areas and war zones. Because these are idealized exercises, Epstein (1999, 2013) called them "computational parables," but they have since led to current empirical research on the ways in which contagious fear can drive pandemic waves, addictive behaviors, and financial panics.

Since the mid-1990s, agent-based modeling has penetrated a wide variety of scientific and practical fields and has been successfully used to solve many problems. Let us now consider several of them in more detail.

Powers of Ten

We will see that some have bored under the skin, modeling at the molecular level, while others have scaled the agent populations into the billions, modeling at planetary scale.

2. EPIDEMIOLOGY

To begin, let us focus on a pressing problem: the spread of infectious diseases (i.e., epidemics and pandemics). The classic differential equations model was published by Kermack and McKendrick in "*A contribution to the mathematical theory of epidemics*" (Kermack, McKendrick, 1927). It is a so-called compartmental model with three homogeneous pools — the susceptibles (S), the infectives (I), and the recovered (R). This SIR model posits perfect mixing (mass action kinetics) between the S and I pools and yields fundamental insights about the nonlinear threshold nature of epidemics, and the conditions for herd immunity among other phenomena. For a full review, see "*The Kermack-McKendrick epidemic model revisited*" (Brauer, 2005). Applied to well-mixed homogeneous settings, the model performs well.

However, the modern world is highly heterogeneous (e.g., by immune status) and, as COVID-19 has demonstrated, transmission exploits contact networks on many scales, from local to global. Moreover, the classical models ignore endogenous behavioral adaptations. Some of these, like social distancing and mask-wearing, can supress transmission, while others, like vaccine refusal, can amplify it. These behaviors, furthermore, may be driven not by conscious "rational" deliberations but by unconscious "irrational" contagious fears. For models coupling fear transmission and disease transmission, see "*Coupled Contagion Dynamics of Fear and Disease*: *Mathematical and Computational Explorations*" (Epstein, Parker, Cummings et al., 2008) and "*Triple Contagion*: *a Two-Fears Epidemic Model*" (Epstein, Hatna, Crodelle, 2021). Fear of illness can be contagious in the absence of disease. In 1994, hundreds of thousands of people fled the Indian city of Surat, fearing a pneumonic plague epidemic, although at the time of the mass exodus the World Health Organization had not confirmed a single case (Epstein, Hatna, Crodelle, 2021).

Agent-based models can represent, albeit crudely, the behavioral adaptations of heterogeneous individuals, which together represent an artificial society. The computational agent model is able to track each agent's network and spatial contacts, disease state, movements, distancing and vaccine behavior, and so forth. To test and calibrate the parameters of the model, it can be run many times to match statistics regarding the spread of a known disease such as smallpox (Longini, Halloran, Nizam et al., 2007). Within the framework of the constructed agent-based model, the transmission of infection from one person to another is tracked (in a so-called dendrogram) but equally important, agent behaviors resemble those of real people under stress, with inherent errors, biases, and other departures from textbook rationality. These behaviors have shaped global pandemic dynamics, including the multiple waves of the 1918 Spanish Flu and those of the ongoing pandemic of SARS-Cov-2 and its variants.

Planetary-Scale Agent Models

Under Epstein's direction, the Brookings Institution's Center on Social and Economic Dynamics, developed a Global-Scale Agent Model (GSAM). It simulates the interaction of 6.5 billion individuals moving on a world map, including intra- and inter-country contact dynamics (Parker, Epstein, 2011; Epstein, 2009). It was the first infectious disease model on this scale and to our knowledge remains the largest. Its development was funded by the US National Institutes of Health in response to the Bird Flu H5N1 crisis.

Data on contact patterns are better for some countries than others, but the advent of geo-coded location data from blue-tooth enabled devices (notably cell phones) promises a watershed in contact modeling, and is already central to contact tracing for COVID-19 pandemic containment.

Fig. 1 displays a global spread scenario for an H1N1 Swine Flu variant beginning in Tokyo (Epstein, 2009). Black pixels are healthy individuals, red are infected, and blue are recovered or dead. This screen shot is the state of affairs 130 simulated days into the epidemic, illustrating starkly

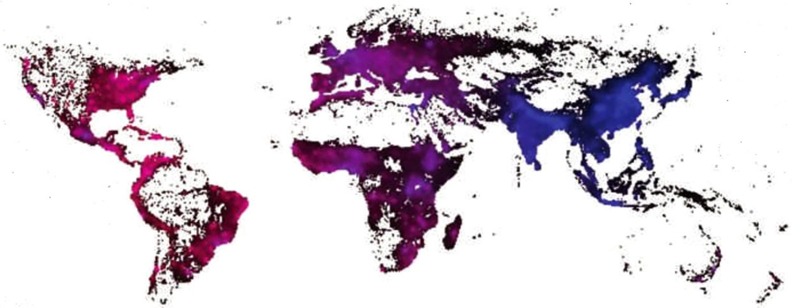

Figure 1. The result of a computer simulation of the GSAM model simulating the H1N1 virus pandemic that began in Tokyo 130 days ago. Each diseased agent is marked with a dot (black is healthy, red is sick, blue is recovered). Image from "Modeling to contain pandemics" (Epstein, 2009).

our overarching point that the world is indeed highly connected. The model is stochastic so there are run-to-run variations even for the same initial conditions and parameter values. So, any particular simulation, such simulation is shown in Fig. 1, is but one sample path of a stochastic process. Typically, one will run the agent-based model many times to build up a robust statistical portrait of its performance.

At Epstein's Center for Advanced Modeling at Johns Hopkins, the GSAM was also used to study Ebola in 2014–2015, and has been configured to represent hemispheric seasonal oscillations and other planetary-scale dynamics.

The US National submodel of the GSAM includes 300 million agents, matched to US Census data. It includes workplaces, schools, and hospitals. Travel between the US's 30,000 zip codes is estimated econometrically. The US model was used to study the value of school closures, travel restrictions, and other interventions. Since viruses are constantly mutating, the arsenal of tools for combating them must constantly expand, including through agent-based models. A variety of these models, including the above, are posted at the New York University's Agent-Based Modeling Laboratory directed by Epstein[7].

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[7] https://publichealth.nyu.edu/research-scholarship/centers-labs-initiatives/agent-based-modeling-lab

Developing general purpose infectious disease models on these scales faces many software engineering problems (e.g., load balancing, parallelization, network modeling). For the GSAM, see "*A Distributed Platform for Global-Scale Agent-Based Models of Disease Transmission*" (Parker, Epstein, 2011). For more recent developments, see "*Charting the Next Pandemic*: *Modeling Infectious Disease Spreading in the Data Science Age*" (y Piontti, Perra, Rossi et al., 2018). Not only does behavior affect global spread, but it also shapes dynamics at the level of urban health care systems, as we now discuss.

Related International Efforts

At Central Economics and Mathematics Institute of the Russian Academy of Sciences (CEMI RAS), a model was developed for predicting epidemiological dynamics depending on quarantine measures to estimate peak loads on the healthcare system. To this end, an agent-based model was constructed, in which human agents go through the stages of disease from infection to recovery or death. These transitions are modeled not at the level of the homogenous group (as in the classical models), but at the individual level. This makes it possible to take into account the heterogeneity of the population in terms of characteristics associated with the biological sensitivity of people to infection and with their social participation (or withdrawal from circulation due to fear) in the spread of the disease. Thus, the probability of severe disease complications (stressing the health care system) depends on the individuals' basic level of health, and on the spread of infection taking into account social (e.g., kinship) ties.

The model was tested on the example of the COVID-19 epidemic in Moscow. The epidemiological characteristics of COVID-19, given by expert practitioners involved in the examination and treatment of patients, were used to plausibly mimic the course of disease within agents. Using computer simulations, estimates of the social course of the epidemic were obtained for various values of the model parameters, including the effect of quarantine measures on the number of infected and dead over the entire period of the epidemic; the date of the onset of the peak of infection and its extent; peak demand for hospital beds, including intensive care. The socio-demographic structure of the population and the epidemiological characteristics of a specific infection are the parameters of the model, which can be adjusted for other regions and infections for practical use as a decision support tool in regional and sectoral situation centers (Makarov, Bakhtizin, Sushko et al., 2020).

Since the onset of the coronavirus pandemic, there has been a sharp increase in the number of publications that use an agent-based approach to estimate the rate of spread of the disease, depending on scenario conditions.

Under the Skin Agent-Based Modeling

We have "zoomed in" from the global scale to the urban scale. We can go further. Agent-based modeling has also bored under the skin to model intra-agent biological processes. These new directions include modeling drugs and their effect on the body at the molecular level and studying processes of inflammation and even tumor growth in cancers (Pourhasanzade, Sabzpoushan, Alizadeh et al., 2017) and the design of interventions (see Sabzpoushan, Pourhasanzade, 2018).

For example, the work of researchers from the University of Vigo (Spain) and the University of Minho (Portugal) examines sequential and parallel algorithms as applied to three-dimensional modeling of individual molecules in complex structures using an agent-based approach. The space for all simulations is a real and measurable object (bacterial cytoplasm). The approaches developed make it possible to determine the arrangement of molecules with a sufficiently high accuracy to reveal possible critical states of the objects under study. In addition, these approaches are implemented in a cross-platform application, which facilitating the construction of three-dimensional models on several hardware platforms and operating systems (Pérez-Rodríguez, Pérez-Pérez, Fdez-Riverola et al., 2016).

Agent-based modeling in medicine

An agent-based parallel-computing model of intestinal epithelium has been developed at the University of Chicago to simulate ileal inflammation in ulcerative colitis. According to the scientists, the use of an agent-based approach is natural for displaying the activity of billions of cells containing DNA and RNA; on the other hand, processing such an array of information requires the use of supercomputers, and in this regard, researchers have developed a general-purpose spatial model for studying intestinal tissue (Spatially Explicit General — purpose Model of Enteric Tissue (SEGMEnT), see Cockrell, Christley, Chang et al. (2015).

To model more complex processes, for example, simulating the work of all cells of the colon for one year, according to the developers of SEGMEnT, 450,000 processors will be required for 30 hours. And to simulate the cells of the whole organism, taking into account the development of various diseases, the research group links this possibility with the emergence of supercomputers with exascale performance, though algorithmically, SEGMEnT is already capable of this.

Concluding the topic of biological processes, we simply note that agent-based models are also used to study (a) tissue morphogenesis, (b) the spread of invasive plant species, (c) the effect of environmental changes on living organisms, and (d) population dynamics of several interacting species, to name a few related directions.

3. PEDESTRIAN TRAFFIC INCLUDING EVACUATION

Another major application of agent-based modeling is the simulation and optimization of pedestrian and vehicular traffic, congestion modeling, and evacuation.

As an example, a model developed at the University of Western Australia and the University of Murdoch (Australia) considers the pilgrimage to Mecca, including the ritual of stoning the Shaitan, the culminating part of the Hajj. The number of pilgrims is constantly increasing (except for 2020 due to COVID-19), and therefore, the number of casualties is also increasing — due to illness, heat, accidents and, mainly, crush injuries. During the Shaitan ritual, the density of the crowd reaches 6–8 people per square meter, as a result of which in some years the number of victims was more than 2400 people[8].

[8] UK Web Publishing: https://www.independent.co.uk/news/world/middle-east/iran-saudi-arabia-murdering-pilgrims-hajj-stampede-a7228466.html

Although the Saudi Arabian authorities use modern video monitoring, communications, and crowd analysis software, there is a danger of unexpected problems. In response, the Australian model was developed using an agent-based approach to simulate various scenarios of the Hajj and the mentioned rite through computational experiments. The scenarios included both minor adjustments to the routes, and the introduction of a timetable for pilgrims to travel to individual sections, laying routes for people to pass, and so forth. Through the use of hybrid tools (combining operational monitoring technologies and agent-based simulators), it was possible to optimize flows and significantly reduce the number of casualties (Owaidah, Olaru, Bennamoun et al., 2019).

A different urban congestion model was developed in 2011 by specialists from Epstein's Center at Brookings and the National Center for Computational Engineering at the University of Tennessee. They developed the Los Angeles Plume-Agent Hybrid Model, which uses computational fluid dynamics to calculate the dynamics of airborne toxic contaminants and an agent-based model to simulate pedestrian and vehicular traffic (Fig. 2). The behavior of the model agents is largely determined by fear of exposure to toxic emissions. The high performance computing application allows one to quickly calculate many scenarios and receive forecasts faster than in real time. In practical application these could be interactively transmitted to dispatchers, so to ensure effective selection of escape routes (Epstein, Pankajakshan, Hammond, 2011).

Evacuation issues

Relatedly, scientists at the University of Science and Technology in Krakow (AGH University of Science and Technology) built an agent-based platform to simulate crowd behavior at various scales — from small rooms to large centers of attraction for a large number of people (e.g., stadiums, high-rise buildings). (Lubaś, Wąs, Porzycki, 2016),

Most of the models considering the movement of agents operate with fairly simple rules of behavior (*operational* and occasionally *tactical level*). In the model proposed by the authors above, many additional factors affect the decision-making process — the dissemination of information through the broadcasting system, instructions for staff, etc. Depending on the location of the loudspeakers in the venue, the cells differ in the

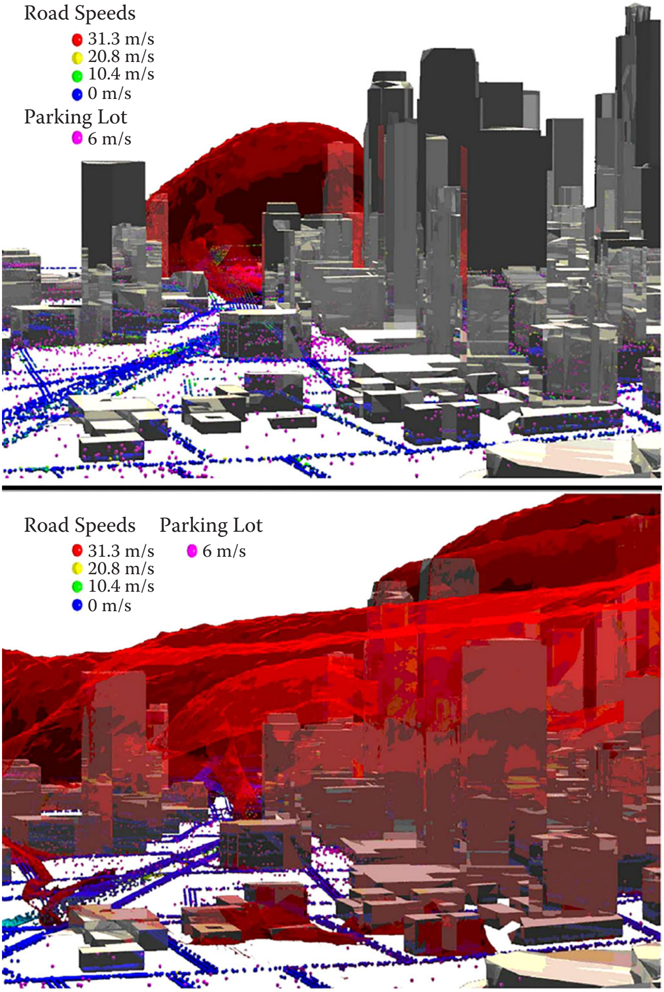


Figure 2. The result of the model's work — a part of Los Angeles with buildings (rectangles), the plume in the form of a red cloud, and agents (vehicles) colored depending on the speed of movement. Image from "Combining Computational Fluid Dynamics and Agent-Based Modeling: A New Approach to Evacuation Planning" (Epstein, Pankajakshan, Hammond, 2011)

perceived strength of the sound, and the sound fields (*SF*) can be determined using the following simplified formula:

$$SF_{x,y} = \{(x', y') : (x' - x)^2 + (y' - y)^2 \leq r^2\},$$

where x, y are the coordinates of the sound source, and r is the omnidirectional radius of the spherical wave. When the agent enters the zone of sound fields, he can hear the message with probability P_{SF} and change his behavior (go to another emergency exit, increase/decrease speed, etc.). Another important opportunity for adjusting decision-making at the *strategic level* is communication within a group of agents in close proximity (using mobile communication devices) defined by the set (L_i, R_i, S_i), where $L_i = (x_i, y_i)$ is the leader of group i, and x, y are its coordinates; $R_i = (r_1, r_2, ..., r_n)_i$ is the rule of group i; $S_i \in \{2, 3, 4, ...\}$ is the size of the group i; r is a separate rule from the number of possible n; and $i \in \{1, 2, 3, ..., m\}$ is the group index.

The same group conducted simulations for the eastern stand of the Wisla stadium. The total number of agents in the simulation is 11,808, the evacuation time for 95% of agents is 653 seconds, the fastest evacuation is 3 seconds, the slowest is 653 seconds, the average speed of movement of agents is 0.316 m/s. Note that over time, the average speed decreased, a congestion effect associated with the filling of the nearest exits. According to the developers of the simulator, such a result indicates errors in the design of the stadium. Observational data of fans exiting the eastern stand of the Wisla stadium corroborate the simulation results.

For the larger stadium, the Allianz Arena, with a capacity of 70,000 spectators, simulations were carried out for 58,000 agents. The average evacuation time after multiple runs was 1117 seconds, the average movement speed of agents was 0.726 m/sec. The fastest evacuation was 2 seconds, and the slowest was 1117 seconds (Fig. 3).

Because the simulator can be used to identify bottlenecks in the evaluated venues (stadiums, buildings, etc.), it can also be fused with online monitoring systems of crowded areas using CCTV cameras, depth sensors, GPS trackers, and other devices. The fusion of such systems and the described model will make it possible to anticipate crowd behavior in real time to forestall hazardous congestions, providing an additional analytical tool for decision support during public events (Lubaś, Wąs, Porzycki, 2016).

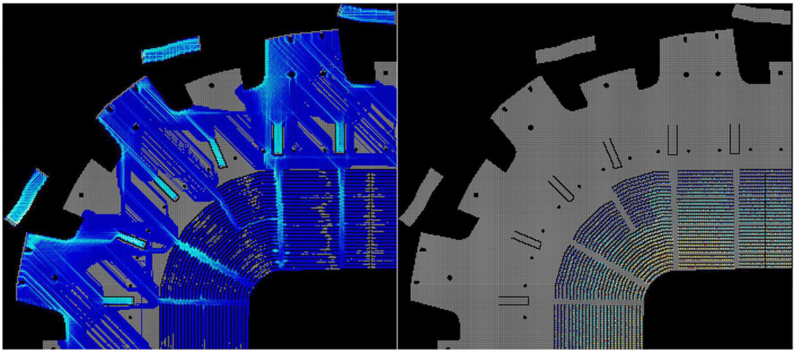


Figure 3. Visualization of statistics for the evacuation of agents in the lower part of the Allianz Arena stadium: frequency matrix (left), thermal display of evacuation time (right). Image from "Cellular Automata as the basis of effective and realistic agent-based models of crowd behavior" (Lubaś, Wąs, Porzycki, 2016)

In a study by scientists at Tohoku University (Japan), (Makinoshima, Imamura, Abe, 2018), an agent-based model is presented that simulates the process of evacuation in an urban environment as a result of a tsunami collapse. The model was built for technical implementation on supercomputers based on hybrid parallelization technology using the MPI and OpenMP software interfaces. The calculations executed using it demonstrated the high realism of the results obtained. For example, the tsunami caused by the earthquake that occurred on March 11, 2011 in the area of the island of Honshu was reproduced. According to the estimates of seismologists, this was the strongest earthquake in Japan for the entire observation period.

Statistical data on the behavior of a large number of pedestrians were used to adjust the parameters of the model. For example, the speeds of movement of individual agents were determined taking into account the average speed of their movement (1.34 ± 0.26 m/s) so that the entire set of numbers corresponded to the normal distribution.

Scientists at Virginia Tech (now at the Biocomplexity Institute at the University of Virginia) developed an agent-based model for assessing the effectiveness of the United States federal government's response to a nuclear attack on major cities (Washington DC, New York, Los Angeles etc.) which is known as known as National Response Scenario 1. (Lewis, Swarup, Bisset et al., 2013).

Although damage calculations from such an attack have been carried out since the middle of the last century, the increased requirements for realistic simulations lead to use of an agent-based approach. This permits the representation of several million mobile heterogeneous agents, differing across a wide set of parameters and behavior modes, interacting with a detailed multilayer geographic information system containing information on all houses, road networks, facilities, and other infrastructure. Figures 4 and 5 are from simulations for Washington DC.

The Virginia Tech developers calibrated the model as closely as possible to reality, given incomplete data. Some uncertain parameters were estimated by averaging the results from multiple model runs, during which the values of the output indicators were compared with their postulated targets. This calibration of the model was carried out sequentially for each of its parts.

Based on analyses of disaster behavior in numerous emergencies (fires, floods, earthquakes, etc.), the developers argue that in severe crises, the agents' behavioral repertoire shrinks from its normal variety (which might include recreation, for example) to several core options ("seeking refuge," "search for relatives," "search for a doctor," etc.). Accordingly, their behavioral model implementation is minimal.

Supplementing this was data obtained from the American Community Survey, annually carried out by the United States Census Bureau. This is one of the largest such surveys, covering approximately 3.5 million people each year.

The geographic location of the population was customized using data from NAVTEQ, the world's leading manufacturer of digital maps and other data for geographic information systems used both in navigation systems and in numerous online maps.

The population of the artificial Washington metropolitan area, calculated on the basis of statistics, is 4 million people (in reality, according to 2017 data, about 6.2 million), the number of model agents living in the territory subject to the attack is 730 833, and the number of possible locations for them is 146,337.

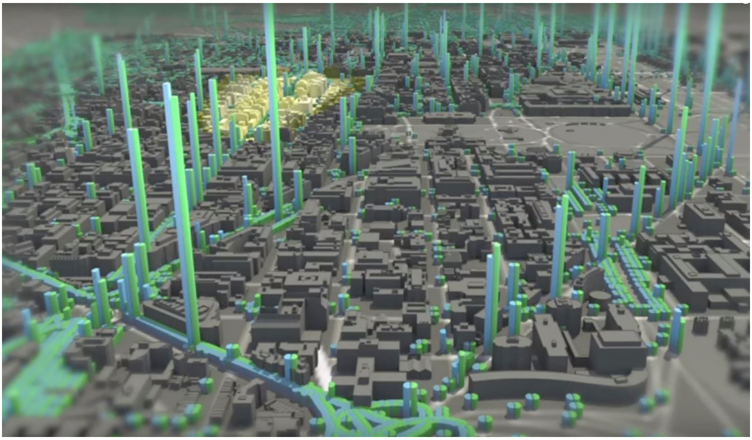


Figure 4. 3D simulation of the urban landscape in an agent-based model. Image from "What if a nuke goes off in Washington, D.C.? Simulations of artificial societies help planners cope with the unthinkable" (Waldrop, 2018)

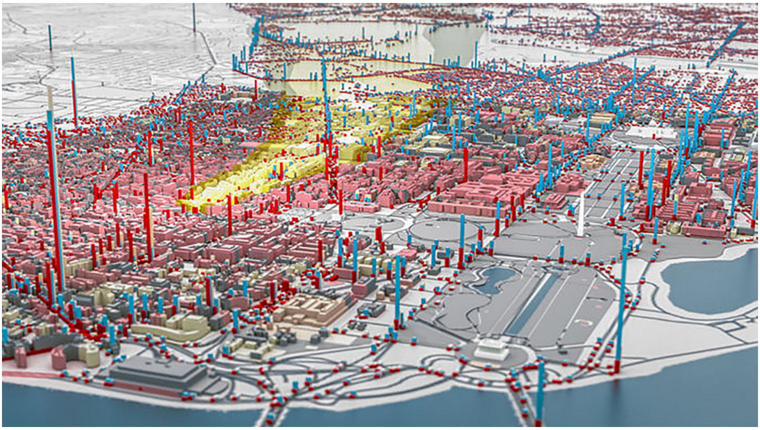


Figure 5. A plume of radioactive fallout (yellow) stretches east across Washington, D.C., a few hours after a nuclear bomb (with a capacity of 12 kilotons) goes off near the White House in this snapshot of an agent-based model. Bar heights show the number of people in a particular place and the color indicates their health (red represents sickness or death). Image from "What if a nuke goes off in Washington, D.C.? Simulations of artificial societies help planners cope with the unthinkable" (Waldrop, 2018)

The health indicators of agents change over time and are calculated based on data from medical examinations of people exposed to radiation.

CEMI RAS model of passenger behavior at an airport

In 2019, CEMI RAS developed an agent-based model of crowd behavior at airports (Makarov, Bakhtizin, Beklaryan et al., 2019). It takes into account the influence of various factors (for example, the number of entrances and exits, the number of check-in counters, physical dimensions of premises, the number of passport control points, waiting time in the baggage claim areas, etc.). It also allows one to determine the best values of the most important resource characteristics of the airport ensuring the elimination (dissipation) of crowd clusters. Computational experiments were carried out using the example of Domodedovo airport (Moscow). Its basic characteristics are presented in Table 1.

We would note that further parameters are taken into account when modeling the dynamics of passenger traffic at the airport (the waiting time for entering the airport and passing through security scanners, the number and capacity of waiting rooms and business lounges, etc.). Computational experiments were aimed at determining areas of crowd cluster formation (populated areas) that affect the average time spent by an agent-passenger at the airport. In Fig. 6 agents belonging to high-density crowd clusters are highlighted in black, with all other agents highlighted in gray.

According to the calculations, the main factors influencing the formation of crowd clusters at Domodedovo airport are the number of entrances, the number of operating passport control points and the average waiting time at baggage claim areas. As one of many combinations that can be expored, the construction of one more entrance to the airport building, a twofold increase in the number of passport control points, a decrease in the average waiting time at baggage claim areas to a 30 minute maximum, and the opening of 20 additional check-in counters effectively eliminates (dissipates) crowd clusters, reduces queues, and thus improves passenger flow. Here, the agent-based approach made it possible to significantly increase the realism of the results obtained.

Table 1

Basic characteristics of Domodedovo airport affecting the dynamics of passenger traffic

No.	Parameter	Value
1	Average passenger traffic per day	60,000 persons
2	The average number of persons at the same time (including passengers, accompanying persons, employees, etc.)	7,000 persons
3	Total area of all terminals	135 ths. m.
4	Number of runways	2
5	Runway capacity (average number of landings per hour)	80
6	Average number of passengers per flight	200 persons
7	Number of check-in counters	130
8	Check-in counter capacity	80 persons / hour
9	Number of self-service kiosks	24
10	Self-service kiosks capacity	20 persons / hour
11	Number of passport control points	128
12	Passport control point capacity	10 persons / hour
13	Number of inspection lines in the pre-flight control area	15
14	Inspection lines capacity	360 persons / hour
15	Average waiting time in the baggage claim area	20 min
16	Number of airport entrances	4

Lord of the Rings

As an interesting aside, agent-based models have found applications outside the sciences. One area is entertainment, for example, in the film industry. In the early 2000s, the MASSIVE software product (Multiple Agent Simulation System In a Virtual Environment) was developed. It can simultaneously process tens, hundreds of thousands and up to mil-

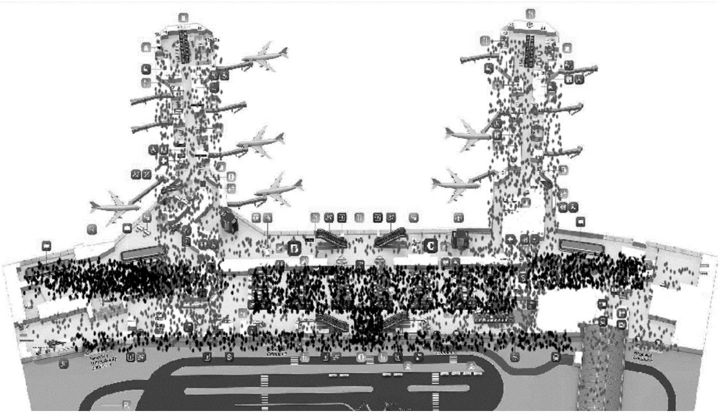


Figure 6. Distribution of human flows and formation of crowd clusters in the current configuration of the airport interior space. Image from "Development of Software Framework for Large-Scale Agent-Based Modeling of Complex Social Systems" (Makarov, Bakhtizin, Beklaryan et al., 2019)

lions of animated objects, such as pedestrians and vehicles[9]. MASSIVE was originally developed during the filming of "The Lord of the Rings." The Director made a request for software realistically animating the interaction of many software entities, such as in virtual crowds and armies. Stephen Regelous, the founder of MASSIVE, answered the call by applying the concept of artificial societies. This was a breakthrough for the film industry, since the previously used stop-motion animation technologies no longer met the needs of film producers and viewers. For "The Lord of the Rings," roughly 200,000 agents were generated, each of which had primitive rules of behavior: dodge obstacles; follow the direction of general movement; leave if dissimilar to nearest neighbours in the crowd, etc.

While new to the film industry, earlier models of this type included the famous "Boids" flocking and obstacle-avoiding model of Craig Reynolds (1987) and the Artificial Life models of Christopher Langton at the Santa Fe Institute.

Regelous has received numerous awards from film industry for advances in the technology behind MASSIVE, including the "Oscar" for

9 MASSIVE product website: http://www.massivesoftware.com

scientific and engineering achievements (Scientific and Engineering Award) and for the autonomous animation system of agents used for action scenes in "The Lord of the Rings" trilogy[10], which led to applications in many other hit films[11].

MASSIVE is an example of a very successful application of the agent-based approach in the film industry, particularly for animating geographically distributed battle scenes.

Of course, none of these animated battles have been compared to actual wartime battle data. Therefore, this entire line of work, while a delightful (and lucrative) application of simple agents, is not properly part of the method's scientific advance, to which we now return.

4. MODELING OF DEMOGRAPHIC PROCESSES

Demographic processes are natural topics for agent-based modeling, as individual-level phenomena like birth rates, mortality, and migration generate aggregate spatio-temporal population dynamics. Not surprisingly, demography is a widespread area of application of the agent-based approach. It is enough here to mention some distinctive works published over the last years.

Agent-based models of social interactions and demographic behavior include Billari, Prskawetz, Diaz et al. (2007) and Diaz (2010). These consider various components of the demographic system, such as marriage and changes in the birth rate, etc. In addition, these works investigate differences in peoples' behavior associated with their belonging to different cultures with corresponding differences in reproductive norms and behavior.

[10] Section of the official website of the American Academy of Motion Picture Arts and Sciences, dedicated to the awards ceremony in 2004: https: //www.oscars.org/sci-tech/ceremonies/2004

[11] "Avatar," "Edge of Tomorrow," "Tron: Legacy," "2012," "Harry Potter," "Pirates of the Caribbean," "King Kong," "Ben Hur," "Aquaman," "Resident Evil," "300," "I, Robot," "Godzilla," "Pompeii," "Game of Thrones" among others

Artificial population models include Silverman, Bijak, Hilton et al. (2013) and Silverman, Bijak, Noble et al. (2014). These models include agents having complex structures and a large number of states, which make it possible to predict demographic dynamics at various levels — from households to the entire population of the UK.

Diverse applications of agent-based modeling to simulate processes associated with population movement — from the creation of married couples and the impact of social norms on the birth rate, to residential decision-making — are presented in the book "*Agent-Based Computational Demography. Using Simulation to Improve Our Understanding of Demographic Behavior*" (Billari, Prskawetz, 2003)

Scientists from Tel Aviv University and New York University (Benenson, Orner, Hatna, 2011) developed an impressive agent-based model considering the population of Yaffo (an area of about 7 km^2 of southern Tel Aviv officially called Tel-Aviv-Yaffo). The ethnic composition of this settlement is as follows — the Jewish majority (70%) and the Arab minority (30%), which tends to increase. The principal result obtained during the experiments was that the resettlement of resident agents in the area depends to a great extent on the ethnic composition of neighbors.

Earlier, we discussed Multi-Agent Systems and Distributed Artificial Intelligence as areas related to agent-based models. Another and powerful relative of agent-based modeling is Stochastic Microsimulation. These are detailed individual-based models, but agents do not interact directly with one another, as in the classic agent-based models. Rather, agents' states and behaviors, like one's retirement age, are updated by drawing from distributions. When these are known, the method is capable of reproducing observed patterns accurately, and is a crucial step toward full "agentization" (on agentization, see Guerrero, Axtell, 2011). CEMI RAS has developed these models as well, at several scales.

In 2014 in St. Petersburg, the Strategy of Economic and Social Development of St. Petersburg to 2030 was developed and adopted for implementation (developed under the guidance of a foreign member of the Russian Academy of Sciences V.L. Kvint). The general goal of the Strategy is "to ensure a stable improvement in the quality of life of citizens and increase the global competitiveness of St. Petersburg based on the implementation of national development priorities, provision of sustainable economic growth and use of the results of innovative and technological activities.”

One of the main metrics for growth of the city’s economy, and the main measure of success of its socio-economic policy is human capital accumulated by the residents of the city. Indeed, the first area of the Strategy is “Human capital development.”

The goal of CEMI RAS was to develop an individual-based model of St. Petersburg to be used as a planning tool for implementation of the Strategy and to test various control actions in the course of computer experiments. It is no accident that CEMI RAS chose a bottom up individual-based approach. There are many examples of its successful application to model the emergence of real urban agglomerations from the interaction of agents corresponding to various types of economic actors (Rui, Ban, 2010; Semboloni, Assfalg, Armeni et al., 2004; Monticino, Brooks, Cogdill et al., 2006).

The first stage of the work was to create a demographic model of St. Petersburg. It was required to accurately reproduce the age/gender structure of the city’s population at the predetermined initial point of time, and also to adequately simulate processes of natural movement of this population.

At the beginning of the model’s operation, arrays of initial information are read from the empirical database. These data include characteristics of the municipal districts of St. Petersburg, demographic data including the age pyramid, the distribution of population by municipal districts, mortality rates by gender and age, the total birth rate (the average number of children born by a woman during the reproductive period), as well as the distribution of births by the age of the mother.

After that a population of agents (50,000) is created. They are assigned individual characteristics — like gender and age structure– in such a way that structure of the artificial population accurately reproduces the one calculated on the basis of the initial input data. The created agents are then settled in municipal districts (with a common age sructure). Thus, an empricially accurate starting state of the agent-based system is established.

From there, the program iterates forward in time. Movement of the city’s population — as well as mortality and birth rates — are simulated step by step (one iteration of the model corresponds to one calendar year).

From mortality rate distributions differentiated by gender and age, the probability of dying for each agent of the population is drawn. After that its fate is determined in this probabilistic manner, some agents are removed, and the rest became one year older.

Then, based on the number of women of reproductive age, the total birth rate, and the distribution of births by the mother's age, the probability of having a child for women of each age was calculated. After that, it was probabilistically determined for each female agent of reproductive age, whether she will give birth to a child in the current year. If so, a new agent aged zero was created the mother's place of residence in the municipal district.. It was assigned the male or female gender with a probability of 0.512/0.488 and iterates forward as described.

To track the state of the model, and for the user to institute various control actions, the main indicators of the simulation are shown on model interface screens at each step of the simulation (e.g., the number, the proportion of satisfied residents).The main screen of the model interface is shown in Fig. 7.

The main window also contains a schematic map of the city, grouping municipal districts forecasted for the current year in terms of the provision of the population with places in preschool establishments.

In addition, the screen shows the following diagrams: the dynamics of population change relative to the base year (also one of the target indicators for the St. Petersburg Development Strategy) and the dynamics of the population structure by the main age groups — the able-bodied population, as well as younger and older cohorts.

The user can also select (click with the mouse) any district on the schematic map and go to the window of the corresponding municipal district. The adjustable parameter of the model is the index of the aggregate birth rate. The user can change this in the course of the model's operation.

Given the detailed elaboration of the social system and the need to assess the level of life satisfaction of *individuals*, the agent-level approach turned out to be a more effective and realistic means of Strategy monitoring than other tools.

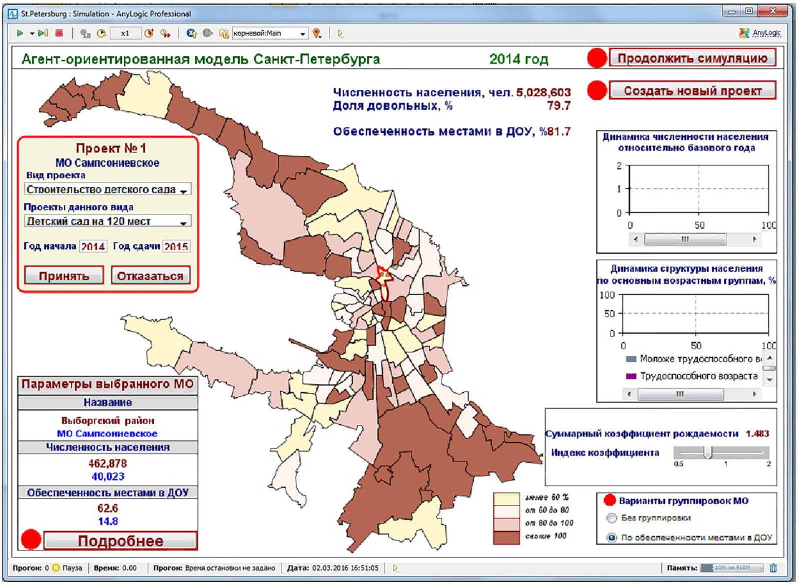


Figure 7. Main working window of the Social Petersburg model with an open project creation dialog. Image from "Software and analytical complex 'MÖBIUS' — a tool for planning, monitoring and forecasting the socio-economic system of Russia" (Bakhtizin, Ilyin, Khabriev et al., 2020)

The Russian Demographic Model

A larger example is the Russia demographic model (140 million individual agents). This was developed in 2011, and has been constantly refined since. The model was tested against real data according to the following metrics: a) the quality of reconstructing the age/gender structure of the population using agents both in the country as a whole and in the context of regions; b) model stability and low error of the obtained results of forecasting the main demographic indicators in comparison with the variants of the official forecast provided by the Federal State Statistics Service; c) the efficiency of program code parallelization when running on supercomputers.

The initial information for the model is the following statistical data for the base year:

- At the level of the country as a whole:
  - Distribution of the population by gender and age (age/gender pyramid), thousand people;
  - Mortality rates (per 1000 people) differentiated by gender and age;
  - Retirement age for men and women by years of the transition period corresponding to the 2018 pension reform.
- At the level of individual regions:
  - Population, thousand people;
  - Share of the population under the working age, %;
  - Share of the population of the working age, %;
  - Share of the population over the working age, %;
  - Aggregate birth rate;
  - Distribution of births by the age of mothers (share of births attributable to mothers from cohorts of five-year age intervals within the reproductive age: 15–19; 20–24; 25–29; 30–34; 35–39; 40–44 and 45–49 years), %.

At the beginning of the model's operation (initialization), the model loads the initial data, scaling the given number of agents by region and creating the calculated number of agents. It then determines values of individual properties associated with the simulated processes of population reproduction for each agent. In accordance with the simulation algorithms employed, these properties are: the agent's age, gender, the maximum desired number of children in the family and the number of children already born. In addition, the agent "remembers" its family ties. Its individual collections (lists) are used in this case — collections of parents, children, brothers and sisters, and other relatives.

Agents' age and gender values are distributed in such a way as to reproduce as accurately as possible the age/gender structure of the population specified in the initial data both for the country as a whole and at the level of individual regions. For this purpose, further scaling of the obtained values related to the number of agents in each region was performed: (a) by shares of the main age groups of the population in each region: younger than the working age, the working age, and older than the working age (taking into account the observed retirement ages for women and men for the base year); and also (b) by shares of each age cohort in the population.

The obtained values of the shares of the total number of agents within a region are then used as the probability of a particular age for an agent belonging to a given region. A specialized auxiliary module was developed to carry out such scaling and obtain the age value for each agent. The gender of the agent is also determined in a probabilistic way taking into account the gender ratio for the obtained age cohort.

In the model the maximum desired number of children in a family is a random variable from one to seven with a given beta distribution shifted to the left (the maximum value is two children). A specialized auxiliary module was also developed to determine the specific value of the desired number of children for each agent.

The stage of establishing family ties between agents is executed after gender and age properties are assigned First, a “mother” is selected for each agent from the collection of agents of the same region. This is a female agent of a random age having the number of children, which is fewer than the maximum desired number. The ages of mother agents are based on the distribution of births by the age of mothers given in the initial data. As model runs proceed, the number of children of the selected mother agent increases, and the child agent, mother agent, and mother’s closely related agents introduce new relatives in the corresponding collections.

Fig. 8 shows the working window of the developed model (the points are agents). During system operation it is possible to obtain the latest information on the socio-economic situation of all regions of Russia (including with the use of cartographic information that changes in real time depending on the values of endogenous variables).

In the course of computer experiments aimed at forecasting the main demographic characteristics of the population, the model showed good results when tested according to the performance metrics discussed above (accurate age/gender stucture, model stability, and code efficiency). Testing using these metrics was fundamentally important, since the model was developed as a testing ground for developing socio-economic policies and assessing their consequences. Particularly when computer simulations produce *conterintuitive* policy approaches, it is crucial that the model be credible empirically. Program efficiency is also important from a practical standpoint.

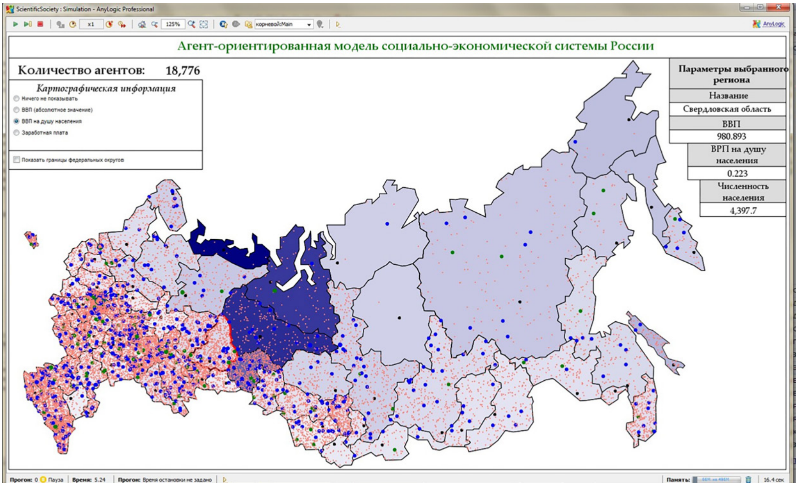


Figure 8. Working window of the agent-based demographic model of Russia. Image from "Social modeling is a new computer breakthrough (agent-based models)" (Makarov, Bakhtizin, 2013)

To estimate the efficiency of the algorithms used to parallelize the agent-based model, CEMI RAS evaluated the dependence of the acceleration of parallel computations on the number of processors with curves constructed in accordance with Amdahl's law. Runs were also carried out using the resources of the Lomonosov Moscow State University (supercomputer "Lomonosov-2") and the National Supercomputer Center of the People's Republic of China (supercomputer "Tianhe-2") to test the portability of the software package. The absolute value of the simulation time due to newer processors in these cases was lower, but the acceleration curves remained the same. Since agent mobility is crucial to many spheres, from urban dynamics to epidemic ones, agent-based transportation modeling is another highly active field. Indeed, it is fair to say that ABMs are displacing partial diffeential equations in several applications.

5. MODELING OF TRANSPORT SYSTEMS

Argonne National Laboratory developed software for building agent-based models to simulate traffic flows (Fig. 9). The main utilities of the developed package, named POLARIS, are as follows: (1) a module responsible for parallel processing of events; (2) a module that implements

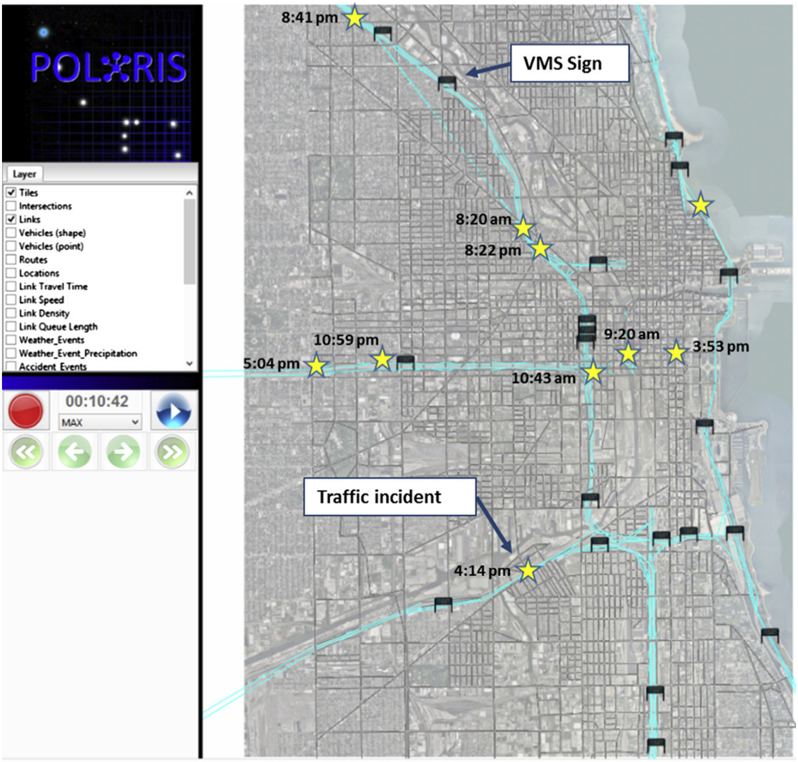


Figure 9. Road network editor. Image from "POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations" (Auld, Hope, Ley et al., 2016).

interprocess communication; (3) a library for visualization; (4) a library for data input/output, etc.

The POLARIS software platform allows integrating various procedures (distribution of traffic flow calculations among processors, agents' demand for trips) within a single model with a shared memory that processes all events occurring during urban system simulation (Auld, Hope, Ley et al., 2016).

The project developers note that until recently individual components of models considering transport systems, such as traffic flows, gas emissions, the formation of a request for a particular type of urban transport, and other factors were not simultaneously taken into account. However, it is precisely the nonlinear interactions among these dynamics that is of greatest concern. Hence, the need for high performance integrated traffic modeling frameworks like POLARIS, whose in interface for Chicago Central Area is shown in Figure 9.

Experts from IBM Research Laboratory in Tokyo jointly with scientists from the Tokyo Institute of Technology developed a platform for building large-scale traffic flow simulators using the new X10 parallel programming language (Suzumura, Kato, Imamichi, 2012). Experiments with the developed models for more than 100 cities around the world demonstrated a linear performance gain depending on the number of processor cores used.

In addition to the platform mentioned, a traffic flow simulator called Megaffic (derived from IBM Mega Traffic Simulator) was developed. It also uses the X10 programming language developed for parallel programming. This language is essentially an extension of the Java language with additional support for arrays and processes, as well as shared global address space.

Agent-based model of the Moscow transport system

In turn, CEMI RAS developed an agent-based model of the transport system of Moscow city, which makes it possible to assess the consequences of changes in its operation within the framework of urban agglomeration resulting from: 1) the introduction of new radial or circular highways; 2) temporary closure or elimination of any element of the transport system; 3) introduction of economic sanctions (highway toll, congestion charge, etc.).

The greatest challenge in building the model was a shortage of detailed inter-district traffic data. A common surrogate in such cases is to use a so-called "gravity model." This class of model assumes that the traffic from one district to another varies directly with the capacity of the arrival and departure districts and inversely with the distance (or cost of travel) between these districts. Typically, the denominator is the distance raised to a power (estimated econometrically); hence its name.

There are three Types of agents in the Moscow model: 1) agents (persons) who wish to get from point A to point B; 2) passenger cars carrying an average of two people; and 3) a public transport carrying approximately 150 people.

Agents of the first Type make a decision on the choice of transportation mode, i.e. on the choice of an agent of the second or third Type (based on of factors discussed below. Agents of the second and third Types are tied to an animation diagram that changes in real time, according to their speed of movement and location at time *t*, all of which varies with the specific situation.

The animation diagram is a city map (in this case, Moscow, although this is not essential) elaborated up to the level of major transport arteries (Fig. 10).

When modeling, we determined the behavior of individual agents, while more general phenomena — traffic jams or a parameter reflecting the level of traffic congestion — emerge from the bottom-up in the course of the model's operation. As discussed at the outset, a distinct advantage of agent-based modeling is the ability to generate global dependencies and patterns through agent interactions without prior knowledge *of them*. It is crucial to credibly represent the logic of individual agent behavior. While this is an empirical challenge (as in all the social sciences) we could not have built a more realistic simulator with other tools.

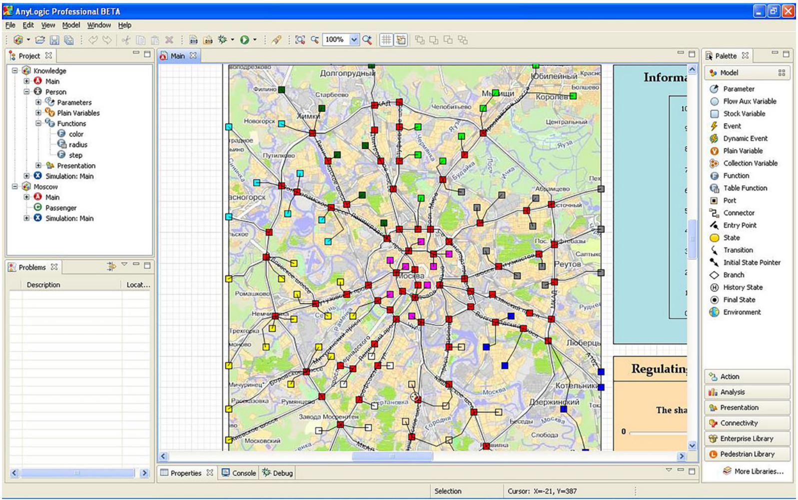


Figure 10. Implementation of Moscow city transport network using AnyLogic package. Image from "Social modeling is a new computer breakthrough (agent-based models)" (Makarov, Bakhtizin, 2013)

6. GEOGRAPHY AND ENVIRONMENT

Forecasting the state of the environment using an agent-based approach can be distinguished as a separate major area. An overview of the most well-known models simulating the processes of environmental pollution due to human activities, the influence of the state of the environment on the morbidity and mortality of the population, as well as the processes of managing the environmental load are given in a recent publication by the staff of Central Economics and Mathematics Institute of the Russian Academy of Sciences (Makarov, Bakhtizin, Sushko, 2020). This also reviews best practices in socio-ecological-economic agent-based modeling. The CEMI RAS Model includes two types of agents — people and enterprises. The first type of agents determines the demographic dynamics and participates in the work of enterprises, and the second type of agents produces products and releases emissions into the ecosystem of the territory (atmosphere and water). The polluted environment affects the level of health and mortality of people, but the model provides for a mechanism for regulating emissions, which affects their volumes.

An important challenge is to populate large-scale climate models with agents whose behaviors affect the climate itself — at the October 8–9, 2020 meeting of the BRICS[12]. Working Group on information and communication technologies (ICT) and High-Performance Computing Systems, this was chosen as a flagship priority for all participating countries. The project "*Digital Modeling of the Earth system*" was unanimously supported, and will couple an agent-based model representing human behaviors to the large scale climate model developed at Moscow State University by M.V. Lomonosov. This model forecasts the weather and climate of the Earth, taking into account a large number of factors (atmospheric, oceanic changes, ocean biogeochemistry, ionospheric dynamics, ice sheet evolution) — for several dozen simulated layers of our planet with a resolution of 10 km (Stepanenko, Bopape, Glazunov et al., 2020).

It will be among the first such integrated human-climate models, and will advance the monitoring and prediction of feedback effects between individual behaviors and environmental effects on worldwide scales.

7. LAND USE

Agent-based modeling of land use methods should be recognized as a separate area. An early example is a model of irrigation systems in Indonesia (Lansing, Kremer, 1993). Since then, many agent-based land use models have been developed (Matthews, Gilbert, Roach, 2007).

Interesting results were obtained by researchers from the University of Edinburgh, Heriot-Watt University (United Kingdom), the University

12 BRICS is the acronym coined to associate five major emerging economies: Brazil, Russia, India, China, and South Africa.

of Waterloo (Canada), and the University of Ljubljana (Slovenia). They developed an agent-based model for the municipality of Koper (Slovenia), which considers the impact of changes in the land use regime on the quality of life of the population. In particular, it showed an important trade-off, industrial development results in loss of high-quality agricultural land. However, new residential areas improve the quality of life of the population (Murray-Rust, Rieser, Robinson et al., 2013).

A broader model by scientists form five countries (USA, Netherlands, UK, Brazil, China) included international effects. See Dou, Millington, Bicudo Da Silva et al. (2019). To study how changes in land use regimes are influenced by international trade of agricultural products, an agent-based model (TeleABM) was developed. It was applied to the trade of soybeans between China and Brazil. One of the model's governing parameters is the price of a traded product, which influences decisions related to land use made at the farm-agent level. Recalling the micro-macro gap discussed earlier, the following feedback was found — changes in land use at the micro level affect the balance of supply and demand at the macro level.

To say a bit more about the trading mechanics, farmer agents in the receiving system allocate their resources to grow soybeans, rice, and corn. Farmer agents in the sending system allocate their resources to grow a single-season of soybeans, a double-season of soybeans and corn, and/or a double-season of soybeans and cotton (Dou, Millington, Bicudo Da Silva et al., 2019). Fig. 11 shows the interface of the TeleABM model designed to change the control parameters and view the results. In the case under consideration, the screen displays two municipalities: (a) Sinop, Mato Grosso, Brazil and (b) Gannan, Qiqihaer, China, in which land use regime depends on the values of exogenous parameters entered by the user (panels (c) and (d)). It thus permits many experiments.

Another related field is natural disaster resilience. Damage minimization against possible floods was studied with an agent-based model developed at RWTH[13] Aachen University, Germany. Micro-level agent farmers make decisions on land use based on climatic conditions, crop yields, price levels, and anticipated flood damage (Nabinejad, Schüt-

13 Rheinisch-Westfälische Technische Hochschule

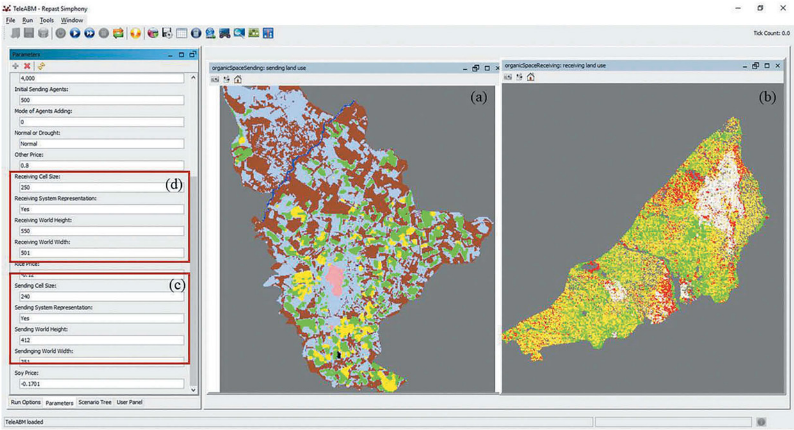


Figure 11. TeleABM model interface: on the left panel (a): light blue — grassland, brown — forest, green — yellow — soybean-corn, black — cotton; on the right panel (b): blue — water body, green-soybean land, yellow — corn, white — rice paddy, and brown — built-up land. Image from "Land-use changes across distant places: design of a telecoupled agent-based model" (Dou, Millington, Bicudo Da Silva et al., 2019)

trumpf, 2017). Fig. 12 displays the work window of the model, showing how agent farmers (in yellow) are distributed over the territory, areas of which are partially flooded (highlighted in red). Each farmer interacts with its neighbours within a certain radius. Incoming information influences the decisions of the agents who receive it.

The diversity of agent-based land use models prompted researchers from three countries (USA, UK, Germany) to suggest using a common ODD (Overview, Design concepts, and Details) protocol to categorize the many simulators being developed (Polhill, Parker, Brown et al., 2008).

Figure 12. Work window of the model: agricultural land (damaged and used), farmers and their social networks. Image from "An Agent-Based Model For Land Use Policies In Coastal Areas" (Nabinejad, Schüttrumpf, 2017)

8. URBAN DYNAMICS

Closely related to the previous discussions, we turn now to agent-based models of urban agglomeration. Recall that strength of ABMs is to give a formal account of how interactions at the micro-scale generate the macro-scale patterns and dynamics of interest, in this case at the City level. Ideally, these ABMs would include micro modules simulating social, transport, environmental/ecological and other systems, interacting within a unified model. These would reveal how aggregate urban dynamics emerge 'from the bottom up.'

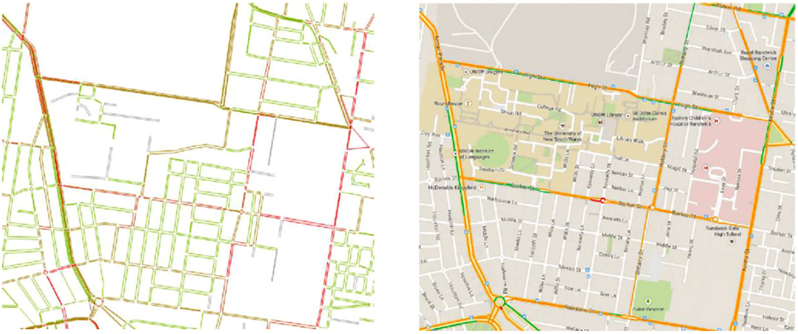
An example is a paper by researchers from several French research centers: "*Exploring Intra-Urban Accessibility and Impacts of Pollution Policies with an Agent-Based Simulation Platform*" (Fosset, Banos, Beck et al., 2016).

It represents a digital twin of Grenoble, a city of 160,000. The agents of the model reproduce daily activities of the townspeople (trips from home to work or school, business trips, walks, etc.) in accordance with the schedules compiled from surveys and statistical data collected from various sources. The simulator contains infrastructure facilities (schools, enterprises, etc.), a transport system, houses, etc., implemented on a geographic information system.

A module of the system calculates the changing environmental situation in the city and its impact on the residents. This project is demanding both in terms of resources and time, and has been underway for more than 15 years (Fosset, Banos, Beck et al., 2016).

Relatedly, a team of researchers from the University of Wollongong, Australia, describes an agent-based TransMob simulator that examines people living in Southeast Sydney and their needs for housing, transportation and social infrastructure. One of the output parameters of the model is the level of satisfaction of residents, which depends on a number of influencing factors. The authors note that TransMob is one of few models that combine population dynamics, a traffic simulator, various land use modes, and other modules (Huynh, Perez, Berryman et al., 2015). This ABM reproduces the daily life of the city quite accurately (Fig. 13). Planned extensions include traffic of freight transport and non-working trips of agent residents.

This research area has been actively developing, with international conferences dedicated to urban dynamics studied with the use of agent-based models. For example, one of the latest conferences on this topic — The 6th International Workshop on Agent-Based Modeling of Urban Systems — was held in May 2021, and abstracts of selected reports are



(a) (b)

Figure 13. Traffic density around the University of New South Wales at 8:00 am: (a) screenshot of the TransMob simulator; (b) screenshot of Google Traffic Map. Image from "Simulating Transport and Land Use Interdependencies for Strategic Urban Planning — An Agent Based Modeling Approach. Systems" (Huynh, Perez, Berryman et al., 2015)

available here: http://modelling-urban-systems.com/abmus2021/proceedings/main.pdf

A common feature in this field is the use of geoinformation technologies; here we would mention an aggregator site that collects information about projects implemented in this area: "*GIS and Agent-Based Modeling*."[14]

9. COMPUTATIONAL RECONSTRUCTION OF HISTORICAL EPISODES

The Artificial Anasazi Project, whose origins are recounted in Epstein (2006) was a collaboration between the Brookings Institution, the Santa Fe Institute, and the World Resources Institute. It sought to model the

[14] https://www.gisagents.org

rise and fall of the American Kayenta Anasazi over the period 900 AD to 1350 AD, at which point this civilization vanished from its lands. For archaeologists, the central puzzle was, why? On the model of Sugarscape (Epstein, Axtell, 1996), the project digitized the entire environmental history (hydrology, soil fertility, maize potential, drought severity) and settlement patterns of the Anasazi from data accumulated by the Tree Ring Laboratory at the University of Arizona. Then, Artificial Anasazi households were built, with ethnographically based nutritional requirements, and rules for the founding of new families and households. Left to their own devices, the Artificial Anasazi replicated the main population and spatial dynamics of the true history over the entire period, with populations tracking the rise and fall of environmental conditions. The model showed that the environment proper could have sustained a small population of Anasazi, pointing to a combination of purely environmental and social factors to explain their enigmatic abandonment of the Longhouse Valley study area (see Axtell, et al., 2002) For a colorful popular account of the research in *Nature*, see "*Life with the artificial Anasazi*" (Diamond, 2002). Note that agent-based archaeology has grown into a vibrant field (e.g., Kohler, Gumerman, 2000).

The Anasazi model has been replicated many times (Janssen, 2009). This is an important point. Not only are agent-based models frequently calibrated to data, they are also replicated. Indeed, it is a strong norm in the agent-based modeling community that code should be open source. And, in fact, the open source libraries available are now extensive (e.g., Netlogo, OpenABM).

Ancient Warfare

Ancient warfare is another area where the agent-based computational reconstruction of historical events is promising. An impressive example is "*Modelling medieval military logistics*: *an agent-based simulation of a Byzantine army on the march*" by Murgatroyd, Craenen, Theodoropoulos et al. (2012). This is part of their larger modeling project, "Medieval Warfare on the Grid" (MWGrid). They write "MWGrid seeks to study behaviour dynamics at a larger scale, involving tens of thousands of agents, all within the context of modelling logistical arrangements relating to the march of the Byzantine army to the battle of Manzikert

(AD1071). The defeat of Emperor Romanus Diogenes IV's army at Manzikert was a key event in Byzantine history, resulting in the collapse of Byzantine power in central Anatolia (Haldon, 2005).

Needless to say, in explaining this crucial military outcome, historians face many gaps in the data, notably regarding the size of the Byzantine army. Without the check of a model, a consensus can form around certain assumptions despite a lack of hard evidence. Models can function as checks on these assumptions. One notable example is the assumption that the Manzikert army of Emperor Romanus Diogenes IV numbered up to 100 thousand people. Is this plausble, given what *can* be reconstructed?

As the authors write, "This was a major logistical challenge that involved the largest Byzantine army in over 50 years travelling more than 700 miles across what is now part of the modern state of Turkey, from near Constantinople (modern Istanbul) to Manzikert (modern Malazgirt) just north of Lake Van" (Fig. 14).

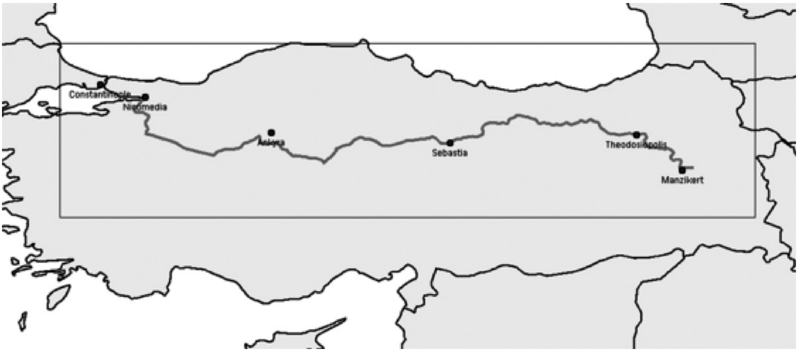


Figure 14. Anatolia: possible route. Image from "Modelling medieval military logistics: an agent-based simulation of a Byzantine army on the march" (Murgatroyd, Craenen, Theodoropoulos et al., 2012)

Through a very careful reconstruction of the landscape proper, the food supplies available from settlements along the route, cattle, grain and other logistical demands and constraints, their agent-based modeling (conducted at full population scale) calls the prevailing wisdom into question. And the difficulty of sustaining large armies over such great distances sheds new light on the calamitous defeat of the Byzantine army.

This kind of imperial over-reach has foundered on logistics more recently, the failed invasions of Russia by Napolean and Hitler being examples. On the centrality of logistics in military history see Martin van Crevald's "*Supplying War*: *Logistics from Wallenstein to Patton*" (1977). Agent-based models have also illuminated the size distribution of wars between states (see Cederman, 2003).

10. SIMULATION OF CIVIL CONFLICT

Turning from inter-state to intra-state conflict, agent-based models have been used to explain revolutions and rebellions. Epstein's (2002) civil violence model has been replicated many times. An implementation of it downloads with Netlogo and has been extended and calibrated empirically by Lemos (2017). See also Lemos, Coelho, Lopes (2013). In the original model, there are civilian agents and cop agents. These agents move and interact on a landscape of sites.

Civilians can be actively rebellious or quiescent; they rebel if their grievance against the central authority exceeds their (risk-adjusted) likelihood of arrest[15]. A civilian estimates his arrest probability as the ratio of cops to active rebels within his vision. Specifically, he asks, "Were I to rebel, what would be the ratio of Cops to Actives within my vision (so the denominator can never be zero)"[16]. Grievance is the product of economic hardship and the perceived illegitimacy of the regime. If Grievance exceeds the arrest probability, the agent rebels. Otherwise, she remains quiescent.

15 Technically, grievance minus arrest probability must exceed a threshold, normally set to zero.

16 This is misunderstood by several commentators, who correct for the alleged division by zero, which is not possible if the agent includes itself in the denominator, as stipulated.

The theoretical model produces several stylized dynamics and counterintuitive results. Among the former are punctuated equilibrium in outbursts, and their spatially localized occurrence. A core experiment compares two runs. In the first, the regime's legitimacy is reduced from its maximum (100) all the way to zero, but *in small increments*. Each time legitimacy falls incrementally, some agent's threshold is exceeded and he rebels. But he rebels alone and is picked off. No rebellion occurs.

By contrast, if from the maximum of 100, legitimacy is reduced only to 80, *but in a single shock*, many agents go active at once, reducing the Cop-to-Active ratio for others, who then join and amplify the rebellion. It is not the absolute legitimacy reduction, but the shock that drives the rebellious cascade. Or, as Levitsky and Ziblatt warn us in their 2018 book, "*How Democracies Die*," it is precisely the slow incremental imperceptible erosion of liberties that requires vigilance.

11. RESEARCH ON SOCIAL NETWORKS

Social networks have long been recognized as central to the study of group formation, information diffusion, and disease transmission, for example. Agent-based modeling is changing the study of social networks as well.

Researchers from the University of Surrey, in their paper "*Social Circles*: *A Simple Structure for Agent-Based Social Network Models*" built an agent-based framework for the creation of social networks with various topologies (Hamill, Gilbert, 2009). In addition to traditional network models (e.g., regular lattice, random network, small world network, scale-free network), their program uses a geometric property of circles (hence their title). As they write, "Taking the idea of social circles, it incorporates key aspects of large social networks such as low density, high clustering and assortativity of degree of connectivity. The model is very flexible and can be used to create a wide variety of artificial social worlds." Network topology can also be dynamic, as where the duration of ties (friends, sexual partners) is heterogeneous and drawn from distributions, or generated endogenously, as in Epstein (2013).

By contrast to the transient ties above, the GECS-Research Group on Experimental and Computational Sociology is focused on permanent changes in social network stucture related to the level of trust between market exchange participants. Their experiments on network topologies showed how dynamically changing networks can lead to increased collaboration between agents. Indeed, this suggests that dynamic networks generated endogenously can outperform those with a fixed topology (Bravo, Squazzoni, Boero, 2012).

An overview of agent-based models applied to study social networks is given by the German scholars Will, Groeneveld, Frank et al. (2020) in "*Combining social network analysis and agent-based modeling to explore dynamics of human interaction*: *A review*." More than 120 scientific publications on this topic were analyzed. A central conclusion is that the quantitative analysis of causal relationships between agent behaviors and network structures can illuminate their coevolution.

12. ECONOMICS

Agent-based modeling is changing the field of economics, at scales from the micro to the macro. At the micro-scale, there is a broad effort to develop next-generation agents that are more realistic cognitively than the canonical rational (expected utility maximizing) actor of traditional economics and game theory. Well-established human departures from textbook rationality include: base rate neglect, asymmetric weighting of gains and losses (Prospect Theory), framing effects, anchoring, conformity effects, confirmation bias, contagious fear, and violations of the standard preference axioms (e.g., 'more is preferred to less') as in the Ultimatum Game and other experiments studied in Behavioral Economics. Moreover, the cognitive underpinnings of these departures from rationality are being identified by neuroscientists in the field of Neuroeconomics (Glimcher, Fehr eds., 2013). Agent-based modelers are building these cognitive mechanisms into next-generation agents. One recent attempt to incorporate cognitive drivers into an advanced agent is Epstein's Agent-Zero (2013), discussed earlier.

At a far larger scale, one of the most famous agent economics projects is a massively parallel agent-based model of the European economy — EURACE (EURope Agent-based Computational Economics). This is a collaboration of scientists from eight research centers in Great Britain, Germany, France and Italy, as well as the 2001 Nobel Laureate in Economics Joseph Stiglitz (Deissenberg, van der Hoog, Dawid, 2008).

There are three types of agents in the model — households (tens of millions), manufacturing enterprises (hundreds of thousands), and financial organizations (hundreds). Regulators (government, central bank, etc.) are specified as a set of restrictions for the agents listed above. The model includes five types of markets (consumer, investment, labor, financial, and credit). For greater realism, agents are geo-referenced and data for model initialization is presented in the form of a geographic information system, which also contains infrastructure facilities — roads, educational institutions, shops, etc.

The calculations using the EURACE basic module made it possible to assess the degree of impact of the quantitative easing mechanism (after the 2008 financial crisis) on the duration of the economic downturn and the effectiveness of this method of monetary policy in combination with fiscal measures (Raberto, Cincotti, Teglio, 2014; Teglio, Mazzocchetti, Ponta et al., 2015).

On another topic, markets and inequality, German sociologist Niklas Luhmann famously hypthesized that economic systems amplify, and must amplify, initial inequalities in order to persist (see Luhmann 1988, p. 112). His ideas were tested in an agent-based Luhmann Economy model by Fleischmann (2005). The author is very guarded in his support of Luhman's hypothesis, writing that "This timeframe may be long enough (our example with only 36 agents, 3 goods altogether 900 in number needed more than 150,000 trade runs) to justify Niklas Luhmann's observation that the economy produces unevenness from unevenness." Fleischmann goes on to note several important qualifications and to suggest extensions required for a more decisive test. This illustrates how ABMs are being used not just to generate hyotheseis, but to challenge them.

Agent-based modeling of financial markets should be singled out as a separate area. The Web of Science and SCOPUS bibliographic databases show that hundreds of agent-based models related to financial markets have been developed. The use of this tool is illuminating the micro-mechanisms of financial market operation through simulation[17]. Among the most cited agent-based modelers of financial markets is Thomas Lux, a professor at Keele University. In his recent public lecture "Agent-Based Models in Finance: Foundations, Explanatory Power and Application" delivered on February 3, 2021, he noted that over the past decade, the validation of agent-based finance models has progressed dramatically with our ability "to extract information on 'hidden' variables such as sentiment which constitutes a salient building block of such models."[18] For a thorough review of agent-based computational models in finance, see Blake LeBaron (2006). More recently, LeBaron (2019) obtained fundamental results relating the trajectory of stock indices to expansions in the strategy sets available to traders.

In 2016, Robert Axtell published a model in which 120 million agents self-organize into 6 million firms (Axtell, 2016). This built on his earlier agent model of firm formation dynamics, which successfully generated the observed Zipf distribution of firms sizes in the US Economy, a statistical regularity that he also established and published in *Science* (Axtell, 2001). In contrast to classical models, which assume that the economy is in the state of equilibrium, in reality there is significant flux in almost all areas. For example, Axtell notes that (at the time of his publication) in the United States about 3 million employees find new jobs every month, i.e. about 1 of 40 employees change their jobs and 1 of 60 firms close. Indeed, For example, one of Axtell's results is that there are no stable equilibrium states in the labor market (Axtell, 2015). Yet, despite this turbulence at the micro level, the skewed Zipf distribution of firm sizes is stationary.

The emergence of stationary distributions in the economy is a central concern of Econophysics, another recent development, which uses the

[17] Agent-based modeling for central counterparty clearing risk, April, 2020. https://www2.deloitte.com/uk/en/pages/audit/articles/agent-based-modelling-for-central-clearing-risk.html

[18] https://wilmott.com/agent-based-models-in-finance-foundations-explanatory-power-and-applications

tools of statistical mechanics to understand emergent phenomena in agent economies, with power law distributions in financial markets a prominent topic. The approach is well-illustrated in "Colloquium: Statistical mechanics of money, wealth, and income" (Yakovenko, Rosser, 2009).

In this connection, a very interesting study was carried out by Robert Peckham (2013) at the University of Hong Kong. He investigated the spread of various kinds of infections (H1N1, H5N1, SARS, HIV/AIDS, etc.) *in conjunction with* the development of financial crises. The author identifies couplings between these processes noting the similarity of their transmission mechanisms. His research indicates that problems in financial markets, conjoined with the spread of a pandemic, cause panic and economic instability, suggesting that the tools of epidemiology may offer economists promising avenues to "inoculate" agents against financial panics, often stimulated by speculators (the initial infectious agents).

According to the physicist and chairman and head of research at Capital Fund Management (Paris) Jean-Philippe Bouchaud, "the study of "*complex physical systems*" has made significant progress in the last 40 years and offers new ideas and methods. It is relevant for economics because it has had some success in modeling many systems exhibiting abrupt phenomena and tipping points that closely resemble crises. One of the best adapted tools to address these complex systems are agent-based models, which offer much more realism and flexibility than purely formal models from classical economics. Unlike these models, agent-based models are able to encapsulate the inherent "human desires and misunderstandings" that lead to "manias and panics." Advanced economies are still dealing with the fallout from the 2008 crisis and economists still do not agree on its fundamental causes. We can certainly do better."[19]

In applied economics, Agent Based Computational Economics (ACE), should not go without mention. Leigh Tesfatsion, at Iowa State University, one of the pioneers of this area, defines the process of building models in accordance with the ACE methodology as analogous to labora-

[19] https://www.ft.com/content/f653a4ee-2dce-11e8-a34a-7e7563b0b0f4

tory biological experiments with the use of a Petri dish. It is assumed that the developer sets the initial conditions and agent rules for the modeled system including its goals. Then the dynamics of this virtual world are generated endogenously, purely through the interaction of its agent constituents. Tesfatsion emphasizes that the ACE approach was developed as an addition to modern economic theory but without presupposing classic rationality, optimal choice, or equilibrium. (Tesfatsion, 2002). For example, ACE posits unpredictable behavior by agents in relation to one other, and also models their adaptation to exogenous macro shocks. Many researchers are involved in the ACE project with several results available at http://www2.econ.iastate.edu/tesfatsi/ace.htm.

Since Alan Kirman's influential critique of the Representative Agent model of macroeconomics (Kirman, 1992), there has been an attempt to develop Heterogeneous Agent Macroeconomics.

Included in this general movement, there are some attempts to relax several assumptions of Computable General Equilibrium Theory (CGE) and its extension, Dynamic Stochastic General Equilibrium Theory (DSGE), to obtain more realistic results. Central to this is a replacement of the single Representative Agent of macroeconomics with a larger number of heterogeneous agents. Diverse efforts are collected in "*Computational Economics*: *Heterogeneous Agent Modeling*" (Hommes, LeBaron, eds., 2018).

All of this has led to several high visibility popular calls for agent modeling in Economics. In the 2003 article "*Agents of creation*"[20] in the *The Economist*, agent-based models were advocated as a new tool for modeling complex systems, an appeal reiterated in the 2010 Economist article "*Agents of change*."[21] There, agents are considered as an alternative to dynamic stochastic general economic equilibrium models. In an editorial in the journal *Nature*, agent-based modeling was advocated as a promising tool for studying complex socio-economic processes including markets. (Farmer, Foley, 2009).

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[20] An article from The Economist magazine published in 2003: https://www.economist.com/science-and-technology/2003/10/09/agents-of-creation

[21] Article from The Economist magazine, published in 2010: https://www.economist.com/finance-and-economics/2010/07/22/agents-of-change

Agent-Based Modeling in the Private Sector

The agent-based approach is also used in modeling business processes. In their paper, "*Agent-based modeling in marketing*: *Guidelines for rigor*," Rand and Rust (2011) discuss agent-based applications. They write, "Agent-based modeling can illuminate how complex marketing phenomena emerge from simple decision rules. Marketing phenomena that are too complex for conventional analytical or empirical approaches can often be modeled using this approach. Agent-based modeling investigates aggregate phenomena by simulating the behavior of individual 'agents' such as consumers or organizations." The authors use an agent-based model to replicate the Bass model of the diffusion of innovations. They also show how extensions of the Bass model that would be difficult using traditional marketing research techniques can be executed with a rigorous agent-based approach.

At a more detailed level, researchers (Halaška, Šperka, 2018) from Silesian University (Czech Republic) with colleagues from Denmark developed a Multi-Agent Resource-Event-Agent framework (MAREA) integrated with an ERP (Enterprise Resource Planning) system. Their paper, "*Is there a Need for Agent-Based Modeling and Simulation in Business Process Management*?" presents the results of a model simulating a trading company selling computer cables. The impact of changes in a set of various kinds of input resources on the company's financial results was specifically assessed. Calculations showed that even small mico-level input changes have a statistically significant effect on the company's aggregate output and financial performance.

Software-analytical complex "MÖBIUS"

Over the course of many years, the Central Economics and Mathematics Institute of the Russian Academy of Sciences has developed methodological principles for constructing complex software-analytical complexes combining approaches to model socio-economic processes, agent-based being prominent. Evolutionarily, CEMI RAS has built a model complex "MÖBIUS"[22], which has incorporated the advantages of different approaches and consists of several blocks (Fig. 15).

[22] The name of the software-analytical complex is associated with two circumstances. First, the Möbius strip is the main symbol of the Central Economics and

All blocks of the MÖBIUS complex, although they were originally developed separately, are closely related to one another and represent a

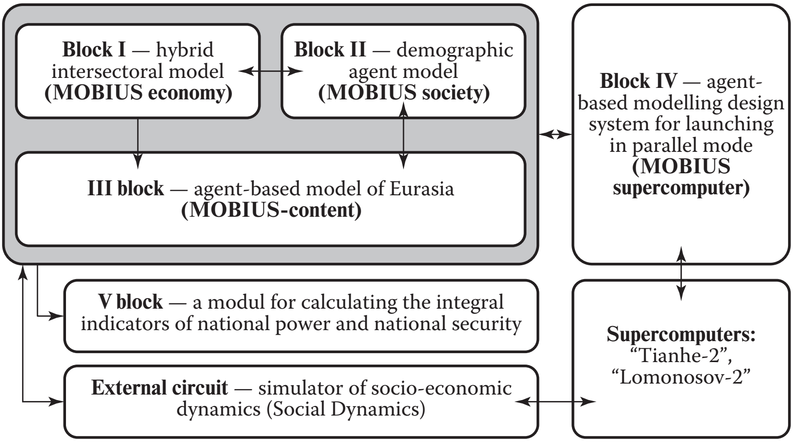

Figure 15. Schema of the software-analytical complex "MÖBIUS". Image from "Software and analytical complex 'MÖBIUS' — a tool for planning, monitoring and forecasting the socio-economic system of Russia" (Bakhtizin, Ilyin, Khabriev et al., 2020)

single integrated whole. The demographic agent module is the basic element for the agent-based model of the Eurasian continent, and also governs the dynamics of households for the inter-sectoral block "MÖBIUS-economy." This, in turn, is linked to the Eurasian scale model. To speed up the calculations, the "MÖBIUS-supercomputer" system can be connected to tools which automatically distribute the executable program code over a user-specified number of processors for parallel execution (Bakhtizin, Ilyin, Khabriev et al., 2020).

Diverse calculations have been carried out using MÖBIUS, including the following:

Mathematics Institute of the Russian Academy of Sciences, and its high relief adorns the Institute building. Secondly, this sign is the physical embodiment of infinity, which corresponds to the scale of the computational capabilities of one of the modules — "MÖBIUS-supercomputer", capable of technically implementing models with about 10^9 agents on the world's most productive systems (including exascale supercomputers).

- forecast of changes in the age-sex structure of the population of Russian regions (Bakhtizin, Makarov, Maksakov et al., 2021);
- demographic changes in the European Union, taking into account important factors, such as the internal attitudes of people, influencing their reproductive behavior, as well as in-migration (Makarov, Bakhtizin, Beklaryan et al., 2019);
- dynamics of labor migration between Russia and China (Makarov, Bakhtizin, Sushko et al., 2017);
- the level of pollution in some regions of the Russian Federation, taking into account the spatial location of industries and stationary sources of emissions (Makarov, Bakhtizin, Sushko, 2020);
- forecast of the main macroeconomic indicators of Russia and its constituent entities as a result of changes in the rates of basic taxes, budget subsidies, the volume of the money supply, the key interest rate, prices for basic energy resources, the dollar exchange rate, and other variables (Makarov, Bakhtizin, Khabriev, 2018).

A separate block is a module for calculating integral indicators of national power and national security for 193 UN member states. The weights of the several dozen selected factors were calculated using methods of multivariate statistics.

CONCLUSION

The models described in this paper are a small part of worldwide scientific and practical developments in the field of agent-based modelling and related areas. We have attempted to give an impression of the vast range of application areas (epidemiology, economics, demography, environment, urban dynamics, history, conflict, disaster preparedness), scales (from cellular to local to urban to planetary), and goals (simple exploratory models, optimization, generative explanation, forecsting, policy) of agent-based modeling. Agent-based models offer a new and powerful alternative, or complement, to traditional mathematical methods for addressing complex challenges. Ubiquitous processes in which heterogeneous individuals interact in space and in networks, driven by internal cognitive, and external social, dynamics invite the use of agent-based models.

There are specialized journals publishing agent-based models developed for various spheres (for example, The Journal of Artificial Societies and Social Simulation), and a growing number of Centers internationally. At our Centers specifically, on the Russian side, an international online-seminar "Artificial societies and information technologies"[23] has been held at the premises of CEMI RAS since 2020. Scientists from many countries have made reports on the developed agent-based models during the first year of its operation:

(1) Russia (over 10 organizations);

(2) China (Guangdong Science & Technology Infrastructure Center, Milestone software company, Joint Center for Mathematical and Economic Research, Sichuan Normal University, Guangdong University of Finance & Economics, Shanghai company Tianjin, University of Chinese Academy of Sciences);

(3) Switzerland (Swiss Federal Institute of Technology in Zurich);

(4) Germany (Technical University of Munich, University of Hamburg);

(5) India (National Institute of Technology Durgapur, West Bengal);

(6) Bulgaria (American University in Bulgaria);

(7) Kazakhstan (L.N. Gumilyov, Eurasian National University, Nur-Sultan);

(8) Ireland (University College Dublin);

(9) France (Institut national de la recherche agronomique);

(10) Korea (Korea Advanced Institute of Science and Technology, Department of Industrial and Systems Engineering);

(11) Canada (University of Alberta);

(12) Brazil (Institute for Applied Economic Research, Pontifical Catholic University of Rio de Janeiro, Federal University of Juiz de Fora);

(13) Colombia (Pontificia Universidad Javeriana);

(14) Sweden (The Institute for Analytical Sociology);

(15) Japan (Computational design studio ATLV);

(16) United Kingdom (Simudyne) etc.

[23] https://www.abm-online.org

In the US, Epstein's NYU Agent-Based Modeling Lab offers a two-semester curriculum, plus an online Introductory Course, on Agent-Based Modeling. NYU has also held international conferences on Agent-based modeling in global health and has recently formalized a collaboration with the New Approaches to Economic Challenges (NAEC) initiative at the OECD in Paris to apply *Agent_Zero* epidemiology to economic and financial dynamics. In collaboration with NYU's Courant Institute for Mathematical Science, Epstein plans to build very large-scale epidemic models populated with cognitively plausible agents to forecast the effects of behavioral adaptation on global pandemic dynamics.

A Cautionary Note

While the future of agent-based modeling is bright, an important imperative — in terms of model transparency and statistical testing — is to follow Einstein's admonition to keep the models "as simple as possible, but no simpler." Freely adjustable parameters and agent decision rules should be added only if they truly add explanatory power. It is too easy to make complex agent models using the friendly development environments that have emerged of late. This temptation must be avoided. Even with elegant parameter sampling approaches (a simple example being Latin Hypercube), the evaluation of large-scale models with many parameters, each of which can assume many values, with many stochastic realizations for each combination quickly becomes computationally daunting. While large mathematical models are rarely tractable analytically, large agent-based ones must be, in this sense, "tractable computationally" if they are to fill the gap.

Important Directions and Challenges

The main goal of this paper has been to summarize selected developments in the field of artificial societies and agent-based modeling and to suggest how this fundamentally new toolkit can contribute to solving some of the most complex scientific and practical problems of our time.

Clearly, the entire field of Agent-Based Modeling has expanded dramatically over the last quarter century, with applications across a remarkable array of fields, at scales ranging from molecular to global. The early (ca. 1990s) computational challenges to large-scale explanatory modeling have been largely overcome, with real-time policy modeling visible on the horizon. Of the many fruitful directions the field might take, we feel that three are especially fertile.

One of them is to continue building models at the scale of entire economic, ecological, and epidemiologic regions — whether these correspond to existing political units or not. Obviously, pandemic diseases like COVID-19 are oblivious to political boundaries in a highly connected world, but so are climate change and other forces.

Second, many of these phenomena are coupled. Disease epidemics affect economic dynamics. Climate change pushes mosquito ranges north, driving new diseases to mega-cities of the northern hemisphere. How will urbanization itself affect access to health and economic opportunity, with what effects on political stability? These are huge questions. While the data landscape is changing dramatically with the advent of massive geospatial and social media, we cannot wait for "validation data" build these models. They are essential headlights in a highly uncertain future.

Third, we must populate models with cognitively plausible agents. In some settings, human behavior is canonically rational, with well-informed individuals maximizing utility subject to budget constraints. But in other settings, non-deliberative emotional forces, like contagious fear, can eclipse deliberations, igniting collective behaviors like financial panics, ethnic violence, and the refusal of safe and effective vaccines (which WHO ranks in the top ten threats to global health) that are very far from optimal.

While focused calibrated agent-based models will continue to advance specific fields, we urge the development of coupled large-scale agent-based models populated by cognitively plausible agents. At the very least, these can inspire an integrated vision of our connected future and perhaps help us shape it in equitable and peaceful directions.

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for a complex world

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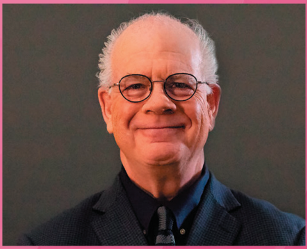

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