ТЕОРЕТИЧЕСКИЕ И МЕТОДОЛОГИЧЕСКИЕ ПРОБЛЕМЫ

Agent-based modeling for a complex world. Part 1

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Abstract. The main goal of this paper is 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. 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 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, forecasting, policy) of agent-based modeling. Agent-based models offer a new and powerful alternative, or complement, to traditional mathematical methods for addressing complex challenges.

Keywords: agent-based models, epidemiology, pedestrian traffic, demographic processes, transport systems, ecological forecasting, land use, urban dynamics, historical episodes, conflict simulation, social networks, economic systems.

JEL Classification: C63, D91.

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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 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 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 macro- (aggregated) 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. J.M. 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 decide 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

[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

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 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 was given in the journal article "*Herald 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 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 on the developments of agent-based modeling, though symbiosis with related approaches is a high priority[4].

While the field of artificial societies is our present focus, we do not claim that agent-based modelling 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 studying 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 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 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 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; Parker,

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

Epstein, 2011)). Here we focus only on individual points showing the benefits of the approach. In addition, this is such a rapidly developing area that any review is supposed to be selective and incomplete[5].

This paper consists of 12 sections in two parts. The first one considers the history of agent-based models. The second section is devoted to models of this class related to epidemiology, and the third considers agent-based modeling of pedestrian traffic and population evacuation. The fourth section is devoted to issues of demographic process modeling, and the fifth to the simulation of transport systems. Part two — Ecological forecasting is considered in section six, while the seventh is devoted to issues of land use, and the eighth — to urban dynamics. The ninth section considers models used for the reconstruction of historical episodes, and in the tenth section, we briefly touch on the issues of conflict simulation. In section eleven 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 section. Undoubtedly, the scope of applications of agent-based models is wider, but we focused 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 has 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).

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 was substantially extended and applied to replicate true historical segregation patterns in multiple countries (Hatna, Benenson, 2015).

As proved by Matthew Cook (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.

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, created what was widely called "a foundational trilogy on agent-based modelling". The first volume "*Growing artificial societies: Social science from the bottom up*" (Epstein, Axtell, 1996) examined 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), was not about artificial society, but it was 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.

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

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

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), was 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 (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 was successfully used to solve many problems. Let us now consider several of them in more detail.

Powers of ten

We will see that some scientific and practical fields are already bored under the skin, modeling at the molecular level, while others scaled the agent populations into the billions, modeling at global 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 M.O. Kermack and A.G. 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 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 such a known disease as smallpox (Longini 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.

Fig. 1. The result of a computer simulation of the GSAM model simulating the H1N1 virus pandemic in Tokyo 130 simulated days into the epidemic. 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).

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 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 Medicine, the GSAM was also used to study Ebola in 2014–2015, and 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].

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*" (Piontti 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.

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

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 the people to infection and with their social participation (or withdrawal from circulation due to fear) in the proliferation 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 advance of infection taking into account social (e.g., kinship) connections.

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 was 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 et al., 2017) and the design of interventions (Sabzpoushan, Pourhasanzade, 2018).

For example, the work of researchers from the University of Vigo (Universidade de Vigo, Spain) and the University of Minho (Universidade do 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 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), (Cockrell 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 persons per square meter, as a result of which in some years the number of victims was more than 2400 persons[8].

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 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, Akademia Górniczo-Hutnicza) 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 (at *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 perceived strength of the sound, and the sound fields (*SF*) can be determined using the following simplified formula: $SF_{x,\,y} = \{(x', y'): (x' - x)^2 + (y' - y)^2 \le r^2\}$, 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; $R_i = (r_1, ..., r_n)_i$ is the rule of group i; $S_i \in \{2, 3, ...,\}$ is the size of the group i; r is a separate rule from the number of possible n; and $i \in \{1, 2, ..., m\}$ 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

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

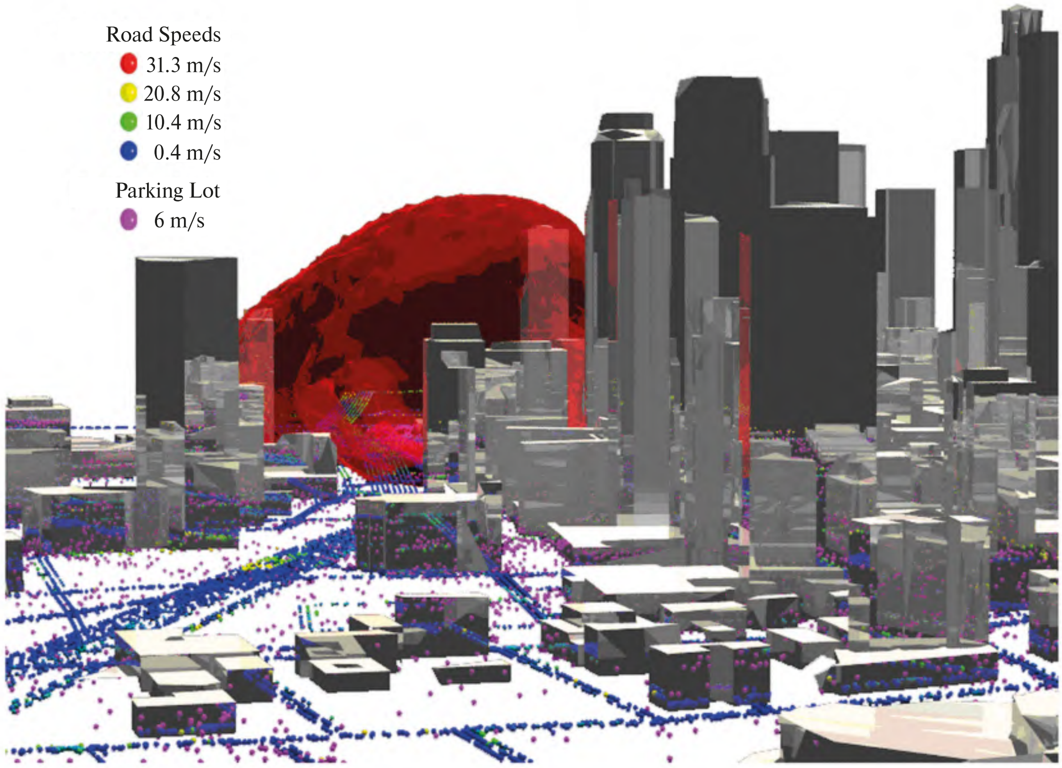

Fig. 2. The result of the model's work — a part of Los Angeles with buildings (rectangles), the plume in the form of a red cloud, and agents (vehicles) colored depending on the speed of movement

A source: Image from "Combining computational fluid dynamics and agent-based modeling: A new approach to evacuation planning" (Epstein, Pankajakshan, Hammond, 2011).

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).

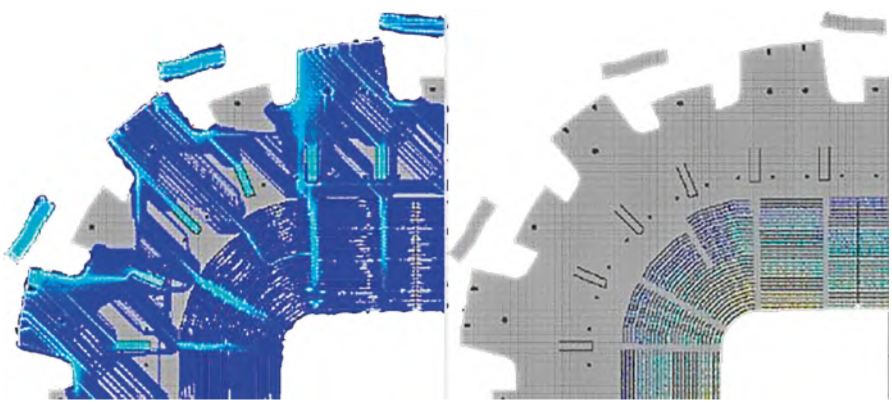

Fig. 3. Visualization of statistics for the evacuation of agents in the lower part of the Allianz Arena stadium: frequency matrix (left), thermal display of evacuation time (right)

A source: Image from "Cellular Automata as the basis of effective and realistic agent-based models of crowd behavior" (Lubaś, Wąs, Porzycki, 2016).

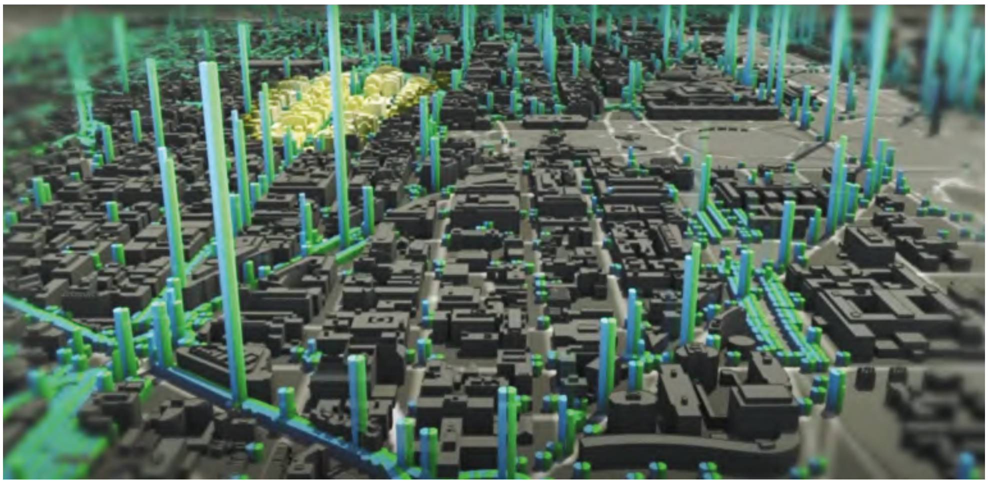

Fig. 4. 3D simulation of the urban landscape in an agent-based model

A source: Image from "What if a nuke goes off in Washington, D.C.? Simulations of artificial societies help planners cope with the unthinkable" (Waldrop, 2018).

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

Fig. 5. A plume of radioactive fallout (yellow) stretches east across Washington, D.C., a few hours after a nuclear bomb (of 12 kilotons capacity) 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)

A source: 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 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 University (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 National Response Scenario 1 (Lewis et al., 2013).

Although damage calculations from such an attack were carried out since the middle of the last century, the increased requirements for realistic simulations lead to 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.

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.

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 grey.

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. One of many combinations that can be explored, is 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.

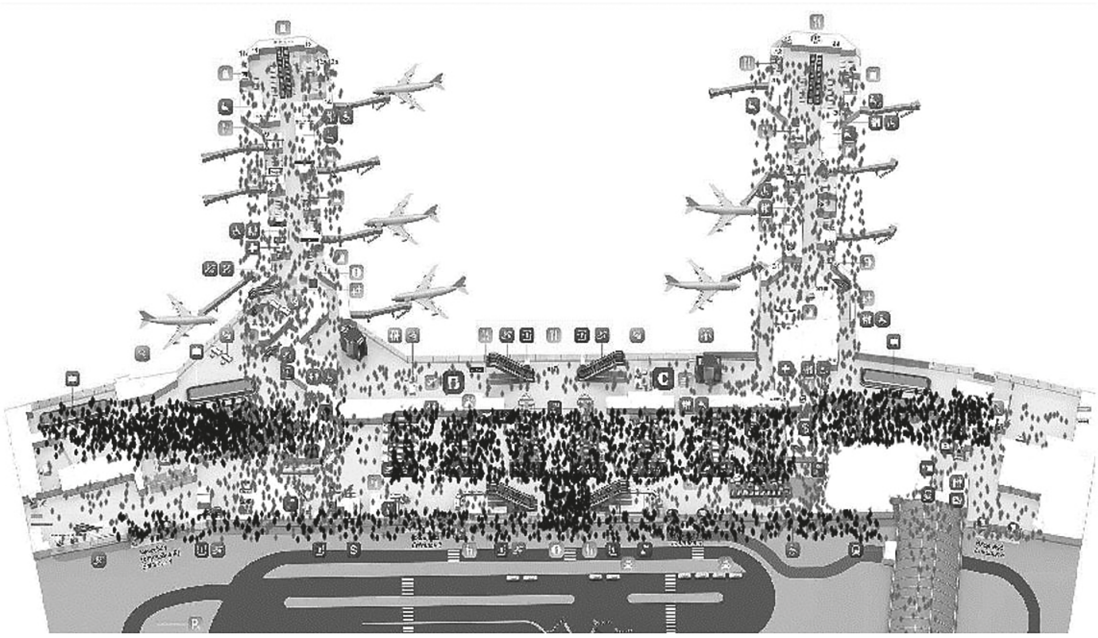

Fig. 6. Distribution of human flows and formation of crowd clusters in the current configuration of the airport interior space. Image from "Development of Software Framework for Large-Scale Agent-Based Modeling of Complex Social Systems" (Makarov, Bakhtizin, Beklaryan et al., 2019)

Table. 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 millions 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

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

animation technologies no longer met the needs of film producers and viewers. For "The Lord of the Rings," about 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 (Reynolds, 1987) and the Artificial Life models of Christopher Langton at the Santa Fe Institute.

Steph. Regelous received numerous awards from film industry for advances in the technology behind MASSIVE, including the "Oscar" for 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 its 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 were 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. DEMOGRAPHIC PROCESSES MODELING

Demographic processes are natural objects 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 the agent-based approach application. It is enough to mention here some distinctive works published over the last years.

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

Artificial population models include models by (Silverman et al., 2013, 2014). These models include agents having complex structures and a large number of states, that makes 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 — were 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, 2003) developed an impressive agent-based model considering the population of Yaffo (an area of about 7 km^2 to the south of 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: 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 developed these models as well, at several scales.

In 2014, the Strategy of Economic and Social Development of St. Petersburg to 2030 was developed (under the guidance of a foreign member of the Russian Academy of Sciences V.L. Kvint) and adopted for implementation in St. Petersburg. The general goal of the Strategy is "to ensure a stable improvement in the

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[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.

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 subject 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 applications to model the emergence of real urban agglomerations from the interaction of agents corresponding to various types of economic actors (Rui, Ban, 2010; Semboloni et al., 2004; Monticino 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 found in 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

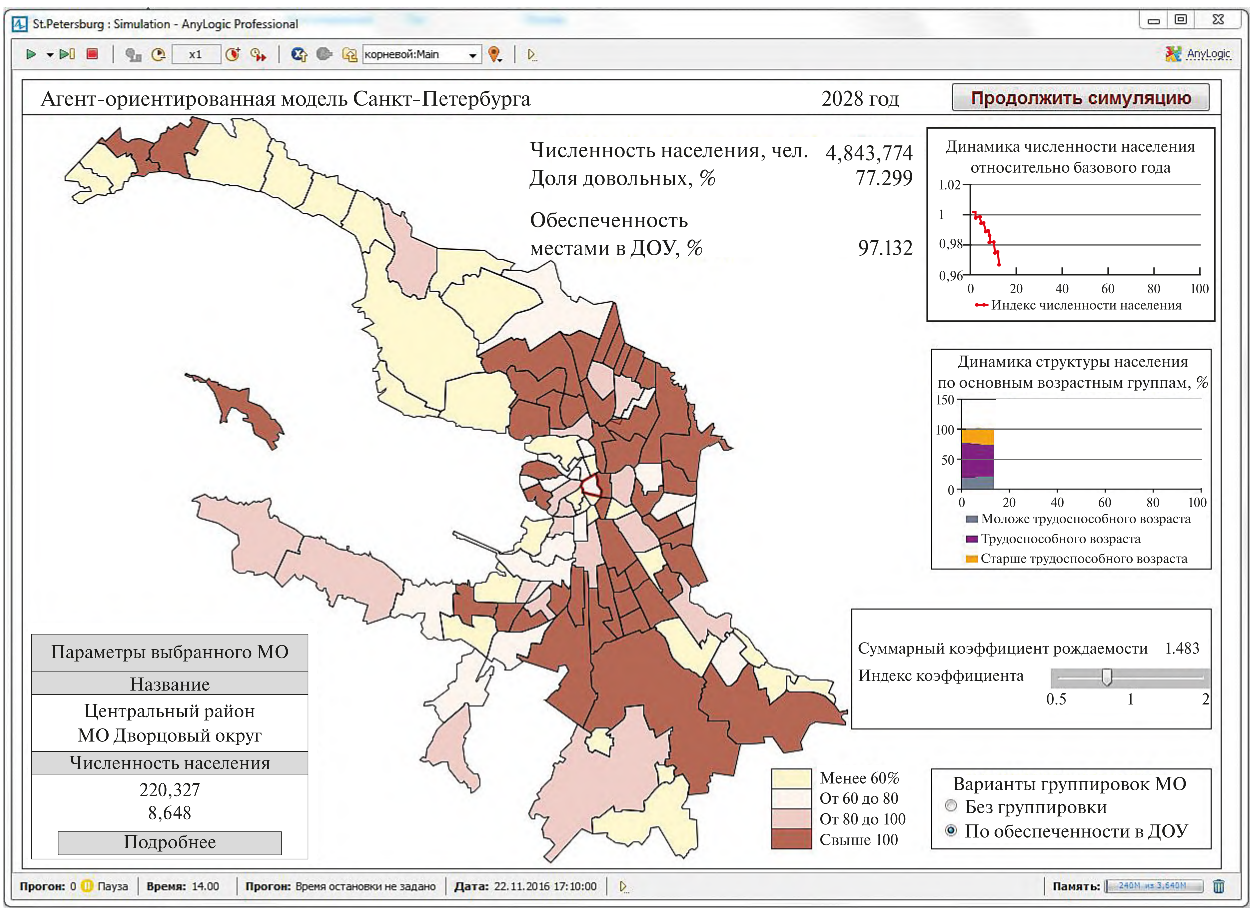

Fig. 7. Main working screen of the Social Petersburg model with an open project creation dialog

A source: Image from "Software and analytical complex 'MÖBIUS' — a tool for planning, monitoring and forecasting the socio-economic system of Russia" (Bakhtizin et al., 2020).

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. Dynamics 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 would 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 iterated 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 working screen of the model interface is shown in Fig. 7.

The working screen 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 employable (able-bodied) population, as well as younger and older cohorts.

The user can also select (mouse click) any district on the schematic map and open (click) the window of the corresponding municipal district. The adjustable parameter of the model is the index of 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.

The Russian demographic model

A bigger example is the Russian demographic model (140 million individual agents). It was developed in 2011, and since was being constantly updated 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 the 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),%.

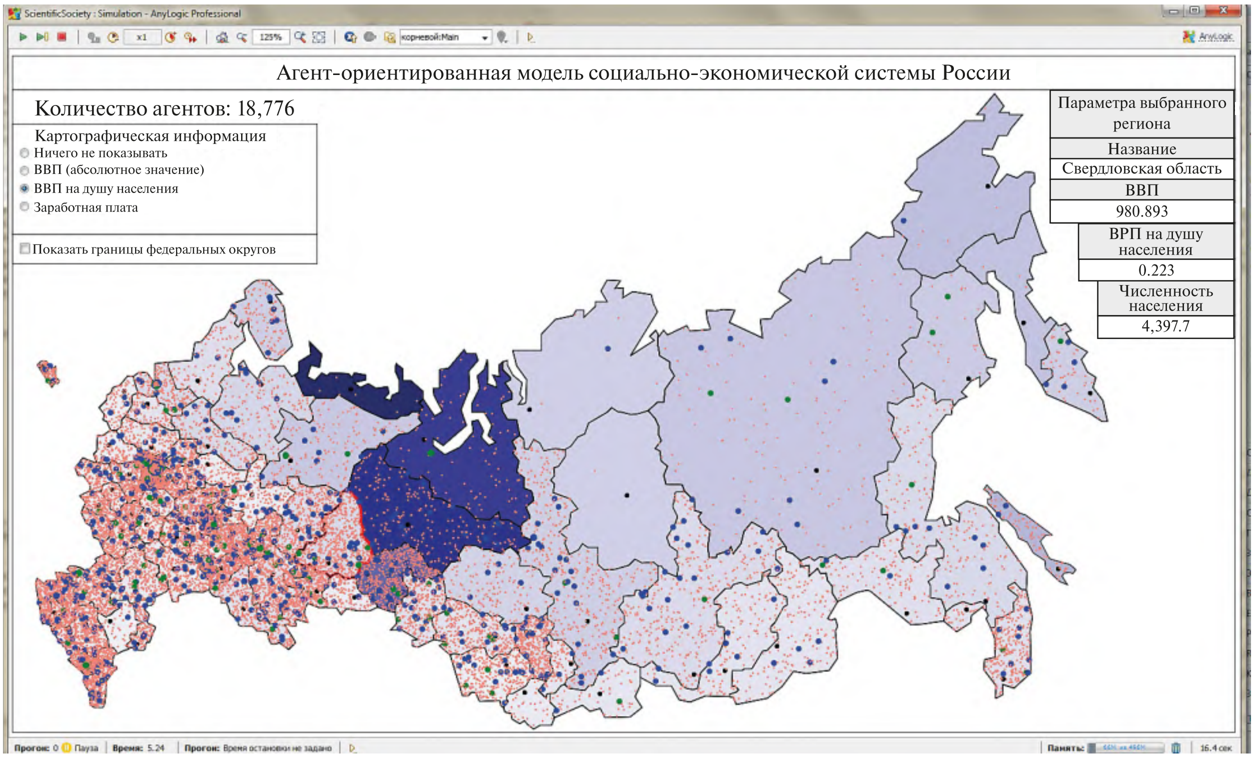

Fig. 8. Working window of the agent-based demographic model of Russia

A source: Image from "Social modeling is a new computer breakthrough (agent-based models)" (Makarov, Bakhtizin, 2013).

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. According to the simulation algorithms, 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 particular 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 probabilities of a particular age for an agent in a given region. A specialized auxiliary module was developed to carry out such scaling and obtain the age (life years) for each agent. The gender of an 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 less 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 chosen 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 the system's 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 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 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 *counterintuitive* policy approaches, it is crucial the model be credible empirically. Program efficiency is also important from a practical standpoint.

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 in many spheres, from urban dynamics to epidemic ones, agent-based transportation modeling is another highly active sphere of application. Indeed, it is fair to say that ABMs are displacing partial diffeential equations in several applications.

5. TRANSPORT SYSTEMS MODELING

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

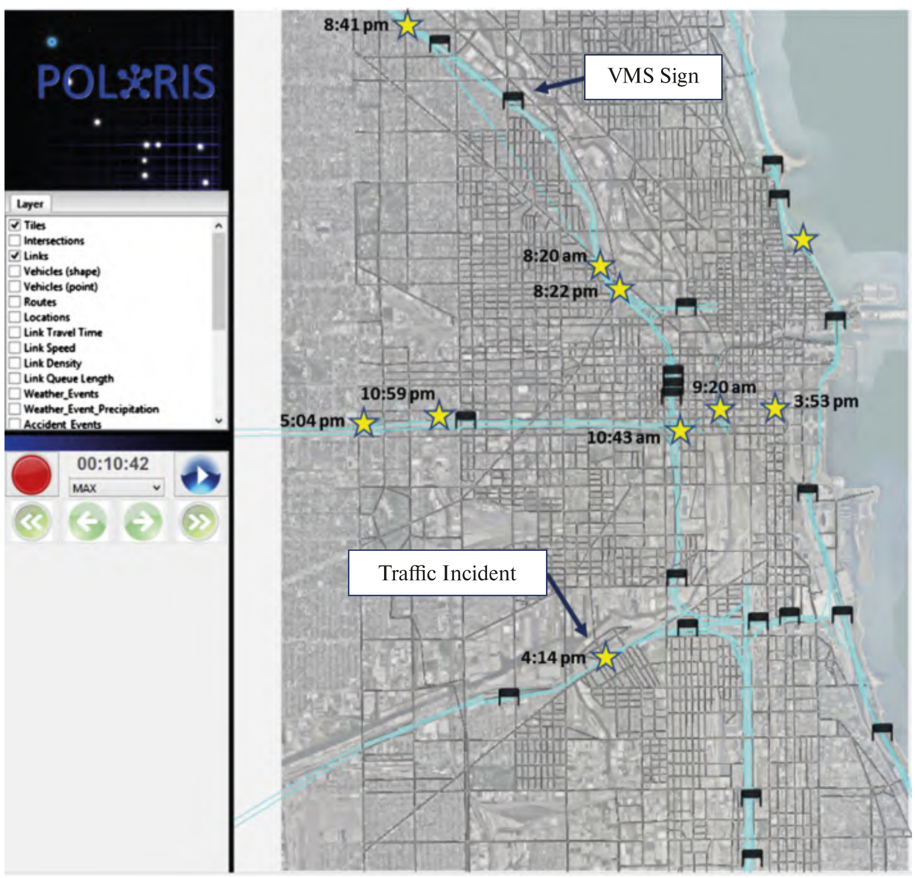

Fig. 9. Road network editor

A source: Image from "POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations" (Auld et al., 2016).

responsible for parallel processing of events; 2) a module implementing 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 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 Fig. 9.

Experts from IBM Research Laboratory in Tokyo in cooperation with the 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 et al., 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 Moscow city transport system, 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

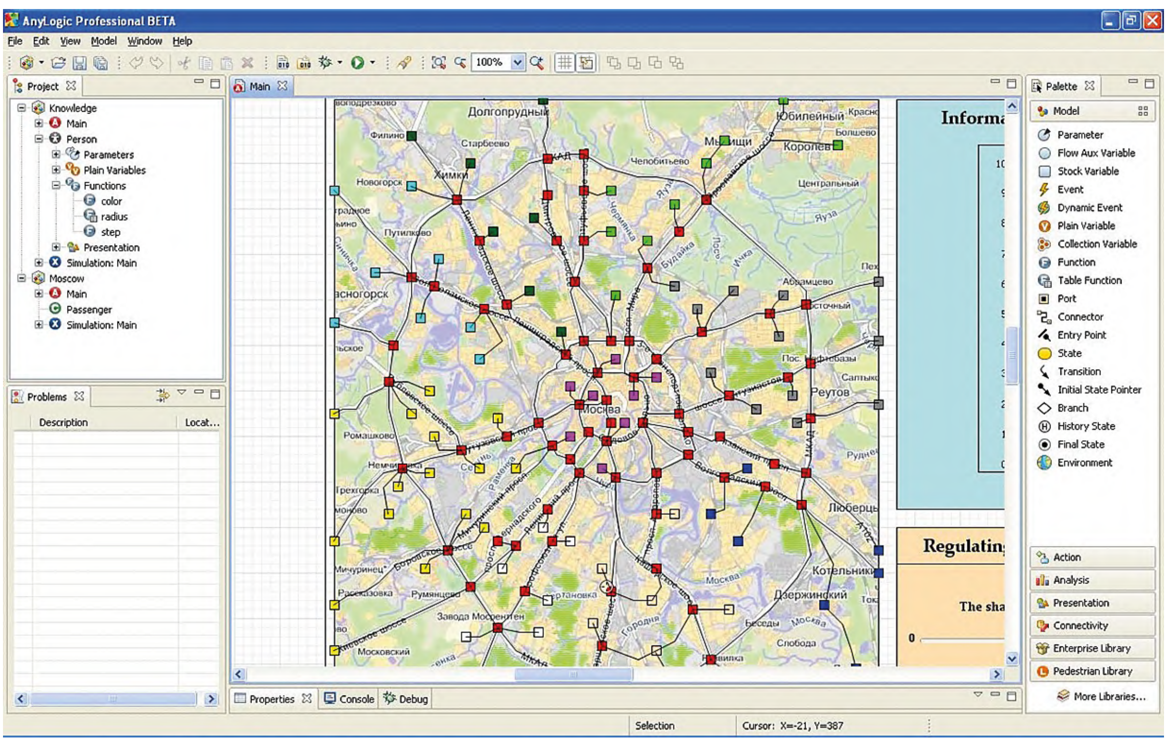

Fig. 10. Implementation of Moscow city transport network using AnyLogic package

A source: Image from "Social modeling is a new computer breakthrough (agent-based models)" (Makarov, Bakhtizin, 2013).

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) intending 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 process 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 social sciences) we could not have built a more realistic simulator with other tools.

REFERENCES / СПИСОК ЛИТЕРАТУРЫ

Auld J., Hope M., Ley H., Sokolov V., Xua B., Zhang K. (2016). POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. *Transportation Research Part C: Emerging Technologies*, 64, March, 101–116.

Bakhtizin A.R. (2008). Agent-based models of the economy. Moscow: Ekonomika (in Russian). [**Бахтизин А.Р.** (2008). Агент-ориентированные модели экономики. М.: Экономика.]

Bakhtizin A.R., Ilyin N.I., Khabriev B.R., Makarov V.L., Sushko E.D. (2020). Software and analytical complex "MÖBIUS" — a tool for planning, monitoring and forecasting the socio-economic system of Russia. *Artificial Societies*, 15 (4). DOI: 10.18254/S207751800012303–2 (in Russian). [**Бахтизин А.Р, Ильин Н.И., Хабриев Б.Р., Макаров В.Л., Сушко Е.Д.** (2020). Программно-аналитический комплекс «МЁБИУС» — инструмент планирования, мониторинга и прогнозирования социально-экономической системы России // *Искусственные общества*. Т. 15. № 4.]

Benenson I., Orner I., Hatna E. (2003). Agent-based modeling of householders' migration behavior and its consequences. *Contributions to Economics,* 97–115. DOI: 10.1007/978-3-7908-2715-6_6

Billari F.C., Prskawetz A. (Eds.) (2003). *Agent-based computational demography: Using simulation to improve our understanding of demographic behaviour*. Heidelberg: Physica-Verlag. 210 p.

Billari F.C., Prskawetz A., Diaz B.A., Fent T. (2007). The "Wedding-Ring": An agent-based marriage model based on social interaction. *Demographic Research*, 17, 3, 59–82.

Boulmakoul A., Karim L., Lbath A. (2021). Vehicle-pedestrian interaction: Distributed intelligence framework. *Procedia Computer Science*, 184, 68–75. DOI: 10.1016/j.procs.2021.03.019

Brauer F. (2005). The Kermack-McKendrick epidemic model revisited. *Mathematical Biosciences*, 198, 2, 119–131. DOI: 10.1016/j.mbs.2005.07.006

Cockrell R.C., Christley S., Chang E., An G. (2015). Towards anatomic scale agent-based modeling with a massively parallel spatially explicit general-purpose model of enteric tissue (SEGMEnT_HPC). *PLOS ONE*, 10(3): e0122192. DOI: 10.1371/journal.pone.0122192

Cook M. (2004). Universality in Elementary Cellular Automata. *Complex Systems*, 15.

Diaz B.A. (2010). *Agent-based models on social interaction and demographic behaviour* (Ph.D. Thesis). Wien: Technische Universität. 93 p.

Ehikioya S., Zhang C. (2018). Real-time multi-agents architecture for e-commerce servers. *International Journal of Networked and Distributed Computing*, 6, 2, 88–98. DOI: 10.2991/ijndc.2018.6.2.4

Epstein J.M., Axtell R. (1996). *Growing artificial societies: Social science from the bottom up*. Washington: Brookings Institution Press, The MIT Press.

Epstein J.M. (1999). Agent-based computational models and generative social science. *Complexity*, 4, 5, 41–60. DOI: 10.1002/(SICI)1099-0526(199905/06)4:5<41:: AID-CPLX9>3.0.CO;2-F

Epstein J.M. (2006). *Generative social science: Studies in agent-based computational modeling*. Princeton: Princeton University Press. 352 p.

Epstein J.M. (2009). Modeling to contain pandemics. *Nature*, 460, 687 (2009). DOI: org/10.1038/460687a

Epstein J.M. (2013). *Agent_Zero: Toward neurocognitive foundations for generative social science*. Princeton: Princeton University Press. 249 p.

Epstein J.M., Hatna E., Crodelle J. (2021). Triple contagion: A two-fears epidemic model. *Journal of the Royal Society Interface*, 18, 81. DOI: 10.1098/rsif.2021.0186

Epstein J.M., Pankajakshan R., Hammond R.A. (2011). Combining computational fluid dynamics and agent-based modeling: A new approach to evacuation planning. *PLOS ONE*, 6, 5. e20139. DOI: 10.1371/journal.pone.0020139

Epstein J.M., Parker J., Cummings D., Hammond R.A. (2008). Coupled contagion dynamics of fear and disease: Mathematical and computational explorations. *PLOS ONE*, 3, 12. e3955. DOI: 10.1371/journal.pone.0003955

Gardner M. (1970). The fantastic combinations of John Conway's new solitaire game "life". *Scientific American*, 4, October.

Guerrero O.A., Axtell R.L. (2011). Using agentization for exploring firm and labor dynamics. In: S. Osinga, G. Hofstede, T. Verwaart (Eds.) *Emergent results of artificial economics*. Lecture notes in economics and mathematical systems, vol. 652. Berlin, Heidelberg: Springer. DOI: 10.1007/978–3–642–21108–9_12

Hatna E., Benenson I. (2015). Combining segregation and integration: Schelling model dynamics for heterogeneous population. *Journal of Artificial Societies and Social Simulation*, 18 (4), 15. Available at: http://jasss.soc.surrey.ac.uk/18/4/15.html DOI: 10.18564/jasss.2824

Ilie S., Bădică C. (2010). Distributed multi-agent system for solving traveling salesman problem using ant colony optimization. In: M. Essaaidi, M. Malgeri, C. Badica (Eds.). *Intelligent distributed computing IV. Studies in computational intelligence*, vol. 315. Berlin, Heidelberg: Springer. DOI: 10.1007/978-3-642-15211-5_13

Ilie S, Bădică C. (2013). Multi-agent distributed framework for swarm intelligence. *Procedia Computer Science*, 18, 611–620. DOI: 10.1016/j.procs.2013.05.225

Janbi N., Katib I., Albeshri A., Mehmood R. (2020). Distributed artificial intelligence-as-a-service (DAIaaS) for smarter IoE and 6G Environments. *Sensors*, 20 (20), 5796. DOI: 10.3390/s20205796

Kermack W.O., McKendrick A.G. (1927). A contribution to the mathematical theory of epidemics. Proceedings of the Royal Society of London. *Series A. Containing Papers of a Mathematical and Physical Character*, 115, 772, 700–721, 1927. DOI: 10.1098/rspa.1927.0118

Langton C.G. (1989). Artificial life. In: C.G. Langton (Ed.). *Artificial Life. SFI Studies in the Sciences of Complexity.* Vol. VI. Cambridge, London: Addison-Wesley.

Lewis B., Swarup S., Bisset K., Eubank S., Marathe M., Barrett C. (2013). A simulation environment for the dynamic evaluation of disaster preparedness policies and interventions. *Journal of Public Health Management and Practice* (JPHMP), 19, Suppl. 2 (02), S42–S48. DOI: 10.1097/PHH.0b013e31829398eb

Longini I.M., Halloran M.E., Nizam A., Yang Y., Xu S., Burke D.S., Cummings D.A., Epstein J.M. (2007). Containing a large bioterrorist smallpox attack: A computer simulation approach. *International Journal of Infectious Diseases*, 11, 2, 98–108. DOI: 10.1016/j.ijid.2006.03.002

Lubaś R., Wąs J., Porzycki J. (2016). Cellular automata as the basis of effective and realistic agent-based models of crowd behavior. *The Journal of Supercomputing*, 72, 6, 2170–2196. DOI: 10.1007/s11227-016-1718-7

Makarov V.L., Bakhtizin A.R. (2013). *Social modeling is a new computer breakthrough (agent-based models).* Moscow: Ekonomika (in Russian). [**Макаров В.Л., Бахтизин А.Р.** (2013). Социальное моделирование — новый компьютерный прорыв (агент-ориентированные модели). М.: Экономика.]

Makarov V.L., Bakhtizin A.R., Beklaryan G.L., Akopov A.S. (2019). Development of software framework for large-scale agent-based modeling of complex social systems. *Software Engineering (Programmnaya Ingeneria)*, 10, 4, 167–177 (in Russian). [**Макаров В.Л.**, **Бахтизин А.Р.**, **Бекларян Г.Л.**, **Акопов А.С.** (2019). Разработка программной платформы для крупномасштабного агент-ориентированного моделирования сложных социальных систем // *Программная инженерия*. Т. 10. № 4. С. 167–177. DOI: 10.17587/prin.10.167–177.]

Makarov V.L., Bakhtizin A.R., Sushko E.D. (2020). Agent-based model as a tool for controlling environment of the region. *Journal of the New Economic Association*, 45, 151–171. DOI: 10.31737/2221-2264-2020-45-1-6 (in Russian). [**Макаров В.Л., Бахтизин А.Р., Сушко Е.Д.** (2020). Агент-ориентированная модель как инструмент регулирования экономики // *Журнал Новой экономической ассоциации*. № 45. С. 151–1712.]

Makarov V.L., Wu J., Wu Z., Khabriev B.R., Bakhtizin A.R. (2019). Modern tools for evaluating the effects of global trade wars. *Herald of the Russian Academy of Sciences*, 89, 7, 432–440. DOI: 10.1134/S1019331619040063 (in Russian). [**Макаров В.Л., Ву Ц., Ву З.** и др. (2019). Современные инструменты оценки последствий мировых торговых войн // *Вестник Российской академии наук*. Т. 89. № 7. С. 745–754. DOI: 10.31857/S0869-5873897745-754]

Makarov V.L., Wu J., Wu Z., Khabriev B.R., Bakhtizin A.R. (2020). World trade wars: Scenario calculations of consequences. *Herald of the Russian Academy of Sciences*, 90, 2, 88–97. DOI: 10.1134/S1019331620010207 (in Russian). [**Макаров В.Л., Ву Ц., Ву З., Хабриев Б.Р., Бахтизин А.Р.** (2020). Мировые торговые войны: сценарные расчеты последствий // *Вестник Российской академии наук*. Т. 90. № 2. С. 169–179.]

Makinoshima F., Imamura F., Abe Y. (2018). Enhancing a tsunami evacuation simulation for a multi-scenario analysis using parallel computing. *Simulation Modeling Practice and Theory*, 83, 36–50. DOI: 10.1016/j.simpat.2017.12.016.

Monticino M.G., Brooks E., Cogdill T., Acevedo M., Callicott B. (2006). Applying a multi-agent model to evaluate effects of development proposals and growth management policies on suburban sprawl. *Proc. of the international environmental modelling and software society. Summit on Environmental modelling and software*. Burlington (USA).

Owaidah A., Olaru D., Bennamoun M., Sohel F., Khan N. (2019). Review of modelling and simulating crowds at mass gathering events: Hajj as a case study. *Journal of Artificial Societies and Social Simulation*, 22 (2), 9. Available at: http://jasss.soc.surrey.ac.uk/22/2/9.html DOI: 10.18564/jasss.3997.

Parker J., Epstein J.M. (2011). A distributed platform for global-scale agent-based models of disease transmission. ACM transactions on modeling and computer simulation: A publication of the Association for computing machinery, 22 (1), 2. DOI: 10.1145/2043635.2043637

Pérez-Rodríguez G., Pérez-Pérez M., Fdez-Riverola F., Lourenço A. (2016). High performance computing for three-dimensional agent-based molecular models. *Journal of Molecular Graphics and Modelling*, 68, 68–77.

Piontti A.P., Perra N., Rossi L., Samay N., Vespignani A. (2018). *Charting the next pandemic: Modeling infectious disease spreading in the data science age*. Social Sciences. Springer Internat. Publishing. DOI: 10.1007/978-3-319-93290-3

Pourhasanzade F., Sabzpoushan S., Alizadeh A.M., Esmati E. (2017). An agent-based model of avascular tumor growth: Immune response tendency to prevent cancer development. *Simulation*, 93 (8), 641–657. DOI: 10.1177/0037549717699072

Reynolds C.W. (1987). Flocks, herds, and schools: A distributed behavioral model. Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH'87). *ACM*, 21 (4), 25–34. DOI: 10.1145/37401.37406

Rui Y., Ban Y. (2010). Multi-agent simulation for modeling urban sprawl in the greater toronto area. *Proc. of the 13th AGILE International Conference on Geographic Information Science*. Guimarães (Portugal).

Sabzpoushan S.H., Pourhasanzade F. (2018). A new method for shrinking tumor based on microenvironmental factors: Introducing a stochastic agent-based model of avascular tumor growth. *Physica A: Statistical Mechanics and its Applications*, 508, 771–787. DOI: 10.1016/j.physa.2018.05.131

Semboloni F., Assfalg J., Armeni S., Gianassi R., Marsoni F. (2004). CityDev, an interactive multi-agents urban model on the web. *Computers, Environment and Urban Systems*, 28, 1, 45–64.

Schelling T.C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, 1 (2), 143–186.

Silverman E., Bijak J., Hilton J., Cao V.D., Noble J. (2013). When demography met social simulation: A tale of two modelling approaches. *Journal of Artificial Societies and Social Simulation (JASSS)*, 16 (4), 9. Available at: http://jasss.soc.surrey.ac.uk/16/4/9.html

Silverman E., Bijak J., Noble J., Cao V., Hilton J. (2014). Semi-artificial models of populations: Connecting demography with agent-based modelling. In: S.-H. Chen et al. (Eds.). *Advances in computational social science: The Fourth world congress*. Agent-Based Social Systems 11, Springer Japan, 177–189. DOI: 10.1007/978-4-431-54847-8_12

Sugumaran V. (2009). Distributed artificial intelligence, agent technology, and collaborative applications. IGI Global. DOI: 10.4018/978-1-60566-144-5

Suzumura T., Kato S., Imamichi T., Takeuchi M., Kanezashi H., Ide T., Onodera T. (2012). X10-based massive parallel large-scale traffic flow simulation. In: *Proceedings of the 2012 ACM SIGPLAN X10 Workshop (X10 '12*). Association for Computing Machinery. New York, USA. Article 3, 1–4. DOI: 10.1145/2246056.2246059

Waldrop M.M. (2018). *What if a nuke goes off in Washington, D.C.? Simulations of artificial societies help planners cope with the unthinkable*. Science AAAS by M. Mitchell Waldrop. Apr. 12. DOI:10.1126/science.aat8553

Wolfram S. (2002). *A new kind of science*. Wolfram Media. ISBN: 1-57955-008-8. Available at: www.wolframscience.com

Yadav S.P., Mahato D.P., Linh N.T.D. (Eds.) (2020). *Distributed artificial intelligence: A modern approach*. 1st ed. CRC Press. DOI: 10.1201/9781003038467

Агент-ориентированное моделирование для сложного мира. Часть 1

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Исследование подготовлено при материальной поддержке Российского научного фонда (проект 21-18-00136 «Разработка программно-аналитического комплекса для оценки последствий межстрановых торговых войн с приложением для функционирования в системе распределенных ситуационных центров России»).

Аннотация. Основная цель статьи состоит в обобщении избранных разработок в области искусственных обществ и агент-ориентированного моделирования и определении того, как этот принципиально новый инструментарий может способствовать решению некоторых из самых сложных научных и практических проблем нашего времени. Сфера применения агентного моделирования значительно расширилась за последнюю четверть века, вобрав множество направлений в самых разных масштабах — от молекулярного до глобального. Описанные в статье модели являются лишь небольшой частью накопленных в мире научных и практических разработок в сфере агент-ориентированного моделирования. Дается представление о широком спектре областей применения моделей этого класса (эпидемиология, экономика, демография, окружающая среда, городская динамика, история, конфликты, стихийные бедствия и др.), масштабах использования (от биологических клеток до планетарного уровня) и целях разработки (исследовательских, генерации искусственных обществ, решения оптимизационных задач, прогнозирования, оценки геополитических сценариев и т.д.). Агент-ориентированные модели предлагают, с одной стороны, новую и мощную альтернативу, а с другой, дополняют традиционные математические методы решения сложных задач.

Ключевые слова: агент-ориентированные модели, эпидемиология, пешеходное движение, демографические процессы, транспортные системы, экологическое прогнозирование, землепользование, городская динамика, исторические эпизоды, моделирование конфликтов, социальные сети, экономические системы.

Классификация JEL: C63, D91.

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