Emergence and Complexity in Agent-based Modeling: Review of State-of-the-art Tools

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Agent-based systems are an important application area of artificial intelligence and are used in decision support systems. Rather than being a problem-solving tool, agent-based system is a tool for developing and testing alternative solutions according to various scenarios. In this context, agent-based modeling is a very effective method to support decision makers in emergency situations to evaluate different risk scenarios and then make decisions quickly and effectively. Moreover, agent-based modeling is a very useful method to support decision makers in situations of high complexity and uncertainty. This paper introduces current studies performed with several agent-based modeling tools and software environments such as NetLogo, AnyLogic, MATSim and Repast. Apart from these, various agent-based modeling tools exist, but these four tools have been chosen because they are still receiving software updates and being widely used in the most current studies. The aims of this study are to review these four agent-based modeling tools, present state-of-the-art research conducted with these tools and provide a reference of agent-based modeling tools for researchers who are developing decision support systems in architectural, urban and transportation design research fields. In this paper, after giving a brief definition of an agent-based system and explaining the importance of concepts such as emergence and complexity in the field of agent-based modeling, it is explained who uses the agent-based models for what purpose, when, where, why and how to use agent-based modeling through selected examples from state-of-the-art studies carried out in different research fields. Furthermore, what current studies and agent-based modeling tools teach us and how future studies can benefit from agent-based models are briefly discussed.

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Etmen-tabanlı Modellemede Belirme ve Karmaşıklık: Güncel Araçların İncelenmesi

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Etmen-tabanlı sistemler, yapay zekanın önemli bir uygulama alanıdır ve karar destek sistemlerinde kullanılmaktadır. Etmen-tabanlı sistem, bir problem çözme aracı olmaktan çok, çeşitli senaryolara göre çözüm alternatiflerini geliştirmek ve test etmek için kullanılan bir araçtır. Bu bağlamda etmen-tabanlı modelleme, acil durumlarda karar vericilerin farklı risk senaryolarını değerlendirip daha sonra hızlı ve etkili kararlar almalarına destek olmak için oldukça etkili bir yöntemdir. Ayrıca etmen-tabanlı modelleme, yüksek karmaşıklık ve belirsizlik durumlarında karar vericileri desteklemek için çok yararlı bir yöntemdir. Bu makale, NetLogo, AnyLogic, MATSim ve Repast gibi çeşitli etmen-tabanlı modelleme araçları ve yazılım ortamları ile gerçekleştirilen güncel çalışmaları tanıtmaktadır. Bunların dışında çeşitli etmen-tabanlı modelleme platformları mevcuttur, ancak bu makalede belirtilen dört araç hala yazılım güncellemeleri almaya devam ettikleri ve en güncel çalışmalarda kullanıldıkları için seçilmiştir. Çalışmanın amaçları, bu dört etmen-tabanlı modelleme aracını incelemek, bunlarla yürütülmüş güncel çalışmaları sunmak ve mimari tasarım, kentsel tasarım ve ulaşım tasarımı araştırma alanlarında karar destek sistemleri geliştirmelerinde araştırmacılara etmen-tabanlı modelleme araçları hakkında kaynak sağlamaktır. Bu makalede, etmen-tabanlı bir sistemin kısa bir tanımı yapıldıktan ve belirme ve karmaşıklık gibi kavramların etmen-tabanlı modelleme alanındaki önemi açıklandıktan sonra, etmen-tabanlı sistemleri kimlerin kullandığı, etmen-tabanlı modellemenin hangi amaçla, ne zaman, nerede, neden ve nasıl kullanıldığı, farklı alanlarda gerçekleştirilmiş en güncel çalışmalardan seçilmiş örnekler üzerinden açıklanmıştır. Ayrıca, mevcut çalışmaların ve etmen-tabanlı modelleme araçlarının bize neler öğrettiği ve gelecekteki çalışmaların etmen-tabanlı modellerden nasıl yararlanabileceği kısaca tartışılmıştır.

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Anahtar Kelimeler: Etmen-tabanlı Modelleme, Belirme, Karmaşıklık, Belirsizlik, Benzetim.

1. INTRODUCTION

Agent-based modeling (ABM) is an analysis tool that has been widely used since the 1990s in various research fields such as healthcare, transportation, urban planning, economics, sociology, e-commerce, web search algorithms, stock market prediction, flight scheduling systems, and even critical systems such as electronic voting systems.

Wooldridge (2009: p.5) defines an agent as "*a computer system that is capable of independent action on behalf of its user or owner.*" This means that an agent can decide what to do to achieve its design goals by itself without any specific instructions. In other words, an agent can be defined as a computer system that can operate autonomously in its environment and interact with other agents to achieve its goal.

In addition to the models developed for the evacuation of public buildings such as schools, hospitals, concert halls, stadiums, theaters or shopping malls in emergency situations, ABM is used to evaluate the evacuation scenarios of cities in urban-scale emergencies such as epidemics, floods, and earthquakes. In this context, ABM is a very effective tool to support decision makers in emergency situations to evaluate different risk scenarios and then make decisions quickly and effectively.

The aim of this study is to review state-of-the-art research conducted by four agent-based modeling tools and give researchers insights into how to use these agent-based modeling tools while developing decision support systems. There are several review papers focusing on ABM. For example, Berger and Mahdavi (2020) prepared a review of current trends in agent-based modeling of building occupants for energy and indoor-environmental performance analysis. There is a review of agent-based modeling for simulation of agricultural systems (Mora-Herrera et al., 2021). Zhuo and Han's (2020) paper reviews agent-based modelling and flood risk management. Additionally, Macal's (2016) study addresses the background and current state of the field of agent-based modelling and simulation. He discusses research challenges for ABM to improve and achieve its potential in the following years. Hawe et al.'s (2012) article reviews existing implementations of ABSs for large-scale

emergency response and presents a taxonomy classifying them by usage. On the other hand, there are many studies focusing on ABM tools/platforms and comparing their features. For instance, Allan (2010) compares several "ABMS software packages" in his study. Railsback et al. (2006) compare five software platforms. Similarly, Fan et al.'s study (2021) compares and analyzes several multi-agent modeling and simulation platforms. Furthermore, Abar et al.'s (2017) study presents comprehensive survey on comparison of the basic features of eighty-five ABM tools. However, this paper does not intend to review and compare features of different ABM tools, it rather aims to present current studies from architectural, urban and transportation design research fields that are conducted with the help of four selected ABM tools. Therefore, in this paper, after giving a brief definition of an agent-based system and explaining the importance of emergence and complexity in ABM, it will be explained who uses the agent-based models for what purpose, when, where, why and how to use ABM through selected examples from state-of-the-art studies carried out in different research fields. In the conclusion section, there will be a discussion about what current studies and ABM tools teach us and how future studies can benefit from ABM.

2. BASICS OF AGENT-BASED MODELING

Agent-based systems are an important application area of artificial intelligence and are used in decision support systems. Rather than being a problem-solving tool, agent-based system is a tool for developing and testing alternative solutions according to various scenarios. In this context, agent-based systems support decision makers during decision-making processes.

According to Wooldridge (2002), the agent takes sensory input from its environment and generates action outputs to affect its environment. This is generally a continuous interaction (Figure 1). Russell and Norvig (2021) indicate that there are many types of environments such as accessible-inaccessible, deterministic - stochastic, static - dynamic, discrete - continuous, fully observable - partially observable, episodic - sequential, and so on. For example, according to Russell and Norvig (2021), characteristics of a medical diagnosis environment are partially

observable, single agent, stochastic, sequential, dynamic, and continuous. Another example they give to better explain type of environments is about the properties of a crossword puzzle environment, which is fully observable, single agent, deterministic, sequential, static, and discrete.

Any control system can be an agent-based system. For example, thermostats, email filtering systems, air traffic control systems, flight scheduling systems are agent-based systems. More complex environments and design tasks need relatively complex decision structures and more complex agent-based systems.

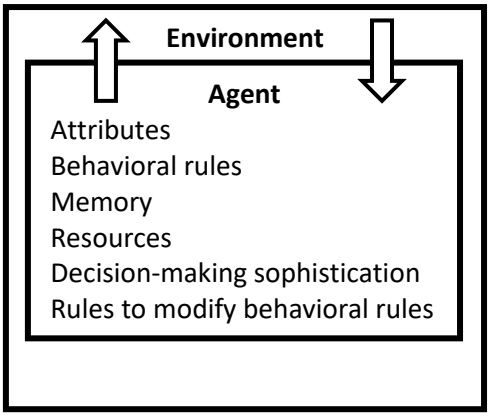

Figure 1: Relationship between the agent and environment (adapted from Macal & North, 2005).

Agent-based models emerge by conceptualizing a real-world system and producing a model in a computer environment using the collected data and presenting it to the evaluation of decision makers using various visualization techniques. According to the evaluations made, various adjustments and changes are made to the model and brought to the optimal version necessary for the solution of the design problem. One of the most important benefits of agent-based modeling is that, within hours or even minutes of operating the system, results related to different scenarios can be obtained. In addition, different scenarios can be tested and compared in a very short time. Thus, decision makers can evaluate different circumstances and choose the most appropriate solution according to the available possibilities and existing conditions. For example, scenarios involving 50 people or 50 million people can be analyzed easily and quickly with agent-based modeling. These features can be considered as the main strengths of ABMs. So, in what kind of

situations should ABM be used? If individual behaviors, simulation of large populations, adaptation, learning, dynamically changing relationships, spatial interactions are important, then ABM is a suitable modeling method.

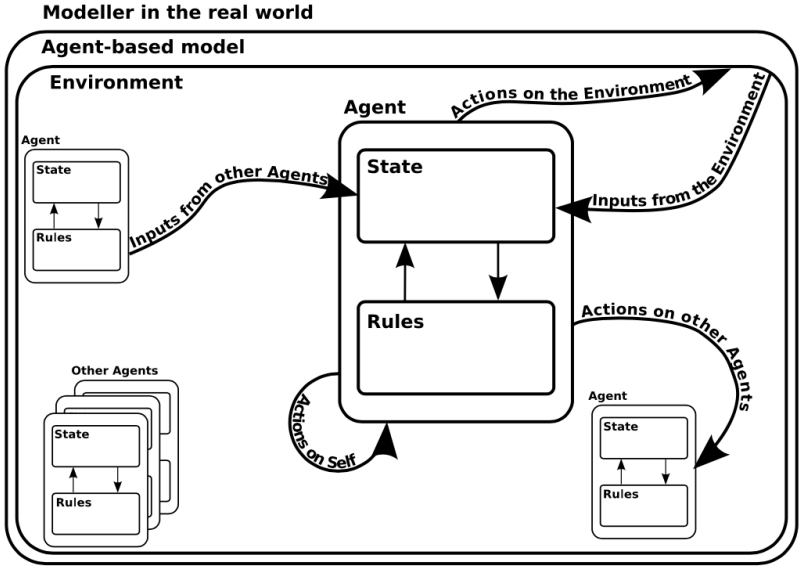

Figure 2: Structure of an agent-based model (Dam, Nikolic and Lukszo, 2013).

In agent-based modeling, the system is built with bottom-up approach. Agents' autonomous and social qualities make modeling of complex interactions possible. Moreover, agents can interact with each other as well as the actors in the real world (Figure 2).

Agent-based models can operate at different abstraction levels. The application areas of agent-based modeling are very diverse. For example, simulations related to the spread of diseases (Hoertel et al., 2020), migration (Hébert et al., 2018), consumer behavior (Caprioli et al., 2020), economics (Glavatskiy et al., 2021), healthcare (Esposito et al., 2020), social interactions and networks (Kaligotla et al. 2018), activity-travel behavior (Cenani et al., 2013; Macal et al., 2018), user/pedestrian movements (Cenani, 2008; Vizari et al., 2020), building/city evacuations in emergency situations (Li et al., 2016), urban and transportation planning (Park et al., 2018), traffic congestions (Vo et al., 2016), terrorist attacks (Lu et al., 2020), natural disasters such as tsunami, flood, earthquake (Costa et al., 2021; Haer et al., 2020; Wang and Jia, 2021) are among the research areas where agent-based models are frequently used.

3. EMERGENCE AND COMPLEXITY IN AGENT-BASED MODELING

Meyers (2012) defines complex systems as "*systems that comprise many interacting parts with the ability to generate a new quality of collective behavior through self-organization, e. g. the spontaneous formation of temporal, spatial or functional structures. They are therefore adaptive as they evolve and may contain self-driving feedback loops. Thus, complex systems are much more than a sum of their parts. Complex systems are often characterized as having extreme sensitivity to initial conditions as well as emergent behavior that are not readily predictable or even completely deterministic*." In addition, complex adaptive systems are made of interacting, adaptive, learning agents (Holland 2006), which have certain features and behaviors. These agents interact with and affect each other, learn from their experiences, and adapt their behaviors, thus making them better fitted to their environments.

ABM is a valuable tool to develop the dynamic behavior of a complex system. In fact, different methods can be integrated into an agent-based model. For example, Cheng and Gan (2013) analyzed evacuation time in different predefined scenarios integrating BIM with behavioral models. Similarly, Marzouk and Daour (2018) used BIM and ABM together for evacuation simulation of labors as an input for a Multi-Criteria Decision-Making process considering total project time, total cost, and evacuation time to achieve the optimum construction method scenario. Also, Bina and Moghadas' (2020) study incorporated BIM with ABM to simulate emergency evacuation from conference hall. Caprioli et al.'s (2020) study applies a hybrid agent-based model integrated with a Geographic Information System (GIS) to simulate a complex socio-economic-architectural adaptive system to study the willingness of inhabitants to adopt photovoltaic systems. Moreover, machine learning algorithms (Yıldız & Çağdaş, 2020), evolutionary computing algorithms (Carta et al., 2020; Guo & Li, 2017) can also be used to develop learning agent-based models. Guo and Li (2017) developed an agent-based topology detection system and used the evolutionary optimization approach with this system. They developed their system with Java programming language. According to their proposed model, plan schemes with the appropriate topology can be

found and the most suitable ones can be selected among these schemes according to several architectural criteria. Their study can be seen as a good example of emergence in an agent-based model. Furthermore, contact transmission in hospital wards is evaluated by Esposito et al.'s (2020) study, which was validated through a simulation built in a Unity 3D environment.

Complexity (see also Batty, 2007; Bedau, 2003; Holland, 1996) and emergence (see also Bedau, 1997, 2003; Silverman et al., 2021) are very important aspects of agent-based models. Emergent behaviors can be best captured with agent-based models. As Klügl stated, agent behavior allows capturing complex, non-linear phenomena, such as emergence, and this phenomenon results in simulation results (Onggo et al., 2019). According to Macal (2020), ABM is "*a modeling and simulation approach applied to a complex system or complex adaptive system, in which the model is comprised of a large number of interacting elements (agents*)". When a scenario is tested with an agent-based model, the result may not always be in line with what was predicted. In other words, emergent user behaviors or emergent results can be observed in agent-based simulations. ABM is a successful method for simulating a process affected by many parameters. Unexpected results may be encountered, especially in agent-based models where problems with high uncertainty exist, therefore, ABM becomes a very useful method to support decision makers in situations of high complexity and uncertainty. So how do we decide under uncertainty? A deterministic and logical approach should be used when uncertainty exists. In other words, the outcome of each action should be evaluated and then the best action should be chosen. Another important question that arises from the previous question is how do we compare possible actions without being sure what the consequences will be? While comparing the weights of possible actions, the option with the highest utility is selected by the decision theory method. Decision theory is a computational method used in decision making under uncertainty (see also Kochenderfer, 2015; Slovic et al., 1977). Decision theory doesn't tell you what your preferences should be, but it does tell you what decisions should be made in complex situations based on your preferences. In an agent-based model, the result with the highest benefit for the decision maker is preferred. For example, when

evaluating different architectural solutions for a hospital building, the most suitable solution for hospital users may not be the most suitable solution for the investor or the municipality. However, the important thing is to find a solution that will keep the benefit of all actors at an optimal level.

4. TOOLS USED IN AGENT-BASED MODELING

This section introduces several tools and software environments (i.e., NetLogo (Wilensky, 1999), AnyLogic (2021), MATSim (2021), Repast (North et al., 2013) used in agent-based modeling. Apart from these, various ABM platforms exist, but these four have been chosen because they are still receiving software updates and being widely used in the most current studies. For more information on other ABM tools/platforms Abar et al.'s study (2017) or Allan's technical report (2010) can be examined. However, it should be noted that this paper does not aim to review and compare features of different ABM tools, instead it presents current studies from the fields of architectural, urban and transportation design research that are conducted with certain ABM tools.

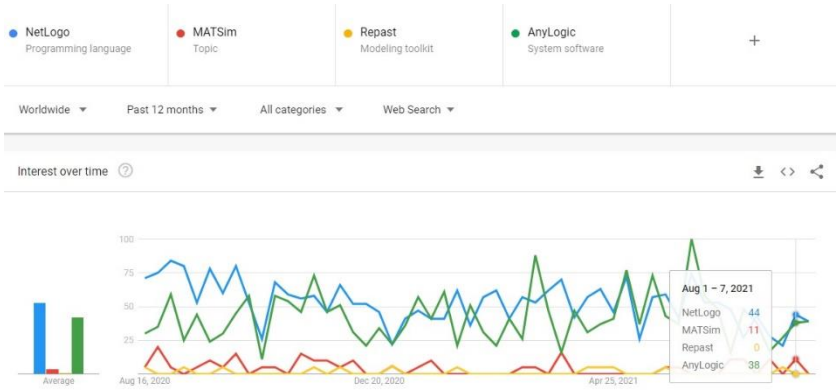

Figure 3: Google search trends for NetLogo, MATSim, Repast and AnyLogic (2021).

ABM is a modeling approach generally used for forecasting, optimization, policy making, and "what if" scenarios. As indicated in the previous sections, ABM is used in various research areas, ranging from healthcare to stock market predictions. **Figure 3** (top) shows the worldwide Google trends for the last 12 months of the software tools mentioned above. According to this chart, NetLogo is the most searched tool, followed by AnyLogic, MATSim, and Repast respectively. **Figure 3** (bottom) indicates compared breakdown by country. Color intensity represents percentage of searches. For instance, 96% out of searches for all 4 terms in Russia belongs to AnyLogic. Furthermore, 68% and 31% out of searches for all 4 terms in USA belongs to NetLogo and AnyLogic, respectively. As shown in **Figure 3**, NetLogo seems to be the worldwide known and searched tool on Google. **Figure 4** illustrates percentage of searches in Turkey.

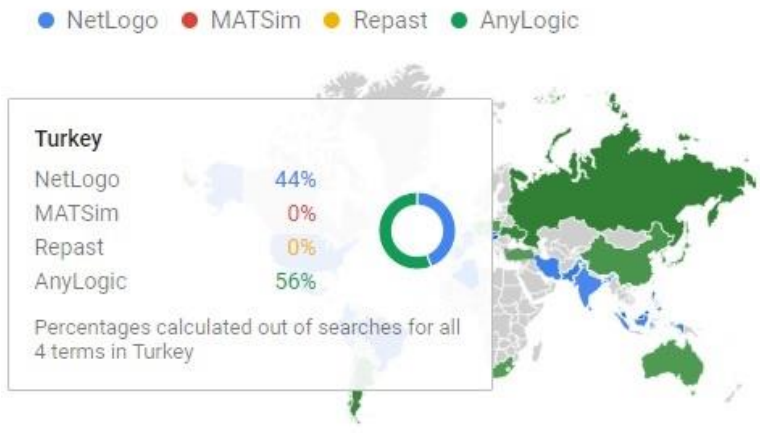

Figure 4: Google search trends for NetLogo, MATSim, Repast and AnyLogic in Turkey (2021).

	NetLogo	AnyLogic	Repast	MATSim
Developer	Northwestern University	The AnyLogic Company	University of Chicago	ETH Zurich
License	Free, open source	Proprietary; Free Personal Learning Edition available	Free, open source	Free, open source
Programming Language	NetLogo	Java	Java	Java
Website	https://ccl.northwestern.edu/netlogo/	https://www.anylogic.com	https://repast.github.io	https://www.matsim.org
Documentation	Good	Limited	Limited	Good
Speed of Execution	Moderate	Fast	Fast	Fast
Ease of learning and programming	Good	Moderate	Moderate	Moderate
Ease of installation	Good	Moderate	Moderate	Moderate
GIS integration	Yes	Yes	Yes	Yes

Table 1: Comparison of NetLogo, AnyLogic, Repast and MATSim (adapted from Chen, 2012; Salgado & Gilbert, 2013).

Table 1 compares four agent-based modeling platforms mentioned in this paper. According to this comparison, NetLogo appears to be a proper choice. Among other advantages, it seems to be NetLogo is easier to learn and program than other tools. AnyLogic is the only non-research group developed and private licensed ABM tool among others. The most crucial feature of the above-mentioned tools is they all have GIS integration that enable them to be used widely in geospatial simulations. Moreover, except for AnyLogic, they are free and open-source tools, which make them easy to modify and publicly accessible to support especially studies of young researchers and students. In the following sub-sections, state-of-the-art research from various research areas using these software toolkits and software environments are explained.

4.1 NetLogo

NetLogo (Wilensky, 1999) is an open-source multi-agent programmable modeling environment. It has GIS support and can save simulations as movies. The variety of sample models and the high number of users have made NetLogo a popular ABM platform.

One of the studies use NetLogo belong to Chennoufi et al. (2018). They proposed a collision avoidance technique for evacuation of individuals which was tested by a simulation developed in NetLogo. Another study focusing on evacuation is Liu et al.'s study (2016). The aim of their study is developing an agent-based simulation to explore the relationships between evacuation efficiency and classroom plans and to design the most appropriate plan schemes for evacuation. Two behavior rules for students have been defined in their study: self-organized and premeditated. It has been observed that the class plan with two exits reduces the evacuation time of the students. In addition, they noticed that students who follow the premeditated instructions leave the classroom faster and are more successful in ensuring their own safety during evacuation procedure. Another pedestrian micro-simulation study focusing on pedestrian evacuation process belongs to Hassanpour et al. (2021). Similarly, Wang and Jia (2021) presented a tsunami evacuation risk assessment. There are also several studies on transportation and urban planning. For example, Dogaroglu et al. (2021) proposed an intelligent parking guidance system model and they compared it with the conventional system where drivers tend to prefer the closest parking utility. They tested five scenarios in NetLogo. On a similar research topic, Vo et al. (2016) developed a micro-simulation for movements of drivers at the car park, while Z. Chen et al. (2016) proposed a model to examine search behaviors of drivers for parking. On the other hand, Lu et al. (2020) developed a model to analyze the effects of terrorist attacks combined with stampedes.

4.2 AnyLogic

AnyLogic is a dynamic and multimethod (i.e., discrete evet, agent-based and system dynamics) simulation modeling platform developed by The AnyLogic Company (AnyLogic, 2021). However, NetLogo is developed by Northwestern University, Repast is developed by University of Chicago, and MATSim is developed by ETH Zurich. Thereby, AnyLogic is

the only non-research group developed and private licensed ABM tool explained in this paper.

The research areas using AnyLogic are very diverse such as groundwater management (Arasteh & Farjami, 2021), coffee shop barista training model (Farhan et al., 2020), or hospital layout design selection (Li et al., 2020). In fact, Kırdar et al.'s (2019) study proposes a smart bike sharing system to promote cycling for tourists as a sightseeing trip in the Historical Peninsula of Istanbul. The proposed bicycle sharing system is modeled by agent-based modeling method in AnyLogic platform. While Antonova et al. (2020) analyzed passenger traffic at an underground station to examine the points of congestion, Koskela et al. (2020) developed a simulation tool that allows the user to explore the effectiveness and impact of a local biorefinery in waste management. Additionally, Kuklowa's (2021) study proposed a highway management model in Prague, whereas Muravev et al. (2021) used AnyLogic platform for optimization of the intermodal terminals on port management.

4.3 MATSim

Multi-Agent Transport Simulation (MATSim) is an activity-based, extendable, open-source multi-agent simulation framework for implementing large-scale agent-based transport simulations (MATSim, 2021). Additionally, it is designed for large-scale scenarios. MATSim currently models a single day; however, in theory, Horni et al. (2012) state that multi-day model could be implemented.

MATSim is applied in several different studies. For instance, it is used to simulate travel demand dynamics (Hörl & Balac, 2021; Llorca & Moeckel 2019; Melnikov et al., 2016), urban air mobility travel time savings (Rothfeld et al., 2021), traffic behavior in growing metropolitan areas (Hager et al., 2015), and carsharing systems (Giorgione et al., 2021). Furthermore, Graur er al. (2021) developed a new simulation core, Hermes, for MATSim to enable efficient large-scale simulations. They state that Hermes is efficient enough to complete simulations of large-scale scenarios within reasonable time frames. Additionally, Ziemke et al. (2021), coupled FEATHERS (Bellemans et al., 2010) activity-based demand model with MATSim to include modeling the

choice of the sequence of activity participation and locations to expand MATSim's analysis capacity.

4.4 Repast

Repast is a software framework for agent-based simulation created by Social Science Research Computing at the University of Chicago (North et al., 2013). It is an open-source agent-based modeling and simulation platform that supports 2D and 3D visualizations as well as GIS.

Many current studies use Repast (Collier et al., 2020; Kono & Haneda, 2021). For example, Macal et al. (2018) developed an agent-based modeling framework to be used in Chicago. Their model simulates daily activity-travel behavior of city residents. Another study is about modeling an information-based community health intervention in Chicago (Kaligotla et al., 2018). Additionally, Manley and Cheng (2018) explored the role of spatial cognition in forecasting urban traffic flow via ABM.

5. CONCLUSION

This paper has examined the state-of-the-art research on ABM, providing basic information and references to several tools and software environments. Moreover, it presents current studies from architectural, urban and transportation design research fields that are conducted with the help of specific ABM tools. In this paper, current ABM studies using tools such as NetLogo, Repast, MATSim and AnyLogic, and in which research areas these tools are used are explained.

As Table 1 demonstrates NetLogo seems to be a good choice among other ABM tools mentioned in this paper. AnyLogic is the only non-research group developed and private licensed ABM tool. However, all four tools/platforms have GIS integration that allow them to be used widely in geospatial simulations. Additionally, except for AnyLogic, they are free and open source, which make them publicly accessible and easy to modify. Moreover, Google search trends in Figure 3 shows that NetLogo is the most searched tool between August 2020 and August 2021, followed by AnyLogic, MATSim, and Repast respectively. These

findings support that NetLogo is a widely known ABM tool. The studies exemplified in this paper are focusing on architectural design, urban and transportation planning research fields, and in this regard, NetLogo and AnyLogic seem to be preferred by researchers from these fields, whereas MATSim and Repast have a relatively narrow usage and not widely used as the other two ABM tools.

Although ABM is a well-known and robust simulation and modelling method that presents the possibility to solve problems that are not easily solved by other modeling approaches, there are still some challenges as Macal (2016) stated in his paper. For example, he specifies the importance of developing better representations of agent behavior (behavioral modelling challenge); developing data analytics and statistical analysis tools, to extract information from simulation results (simulation analytics challenge); understanding how ABM can be efficiently used with other modelling techniques than can operate together (hybrid modeling challenge); developing efficient and effective agent-based models with better computing abilities and simulation workloads (large-scale ABM challenge). Many researchers using ABM in their studies should continue to share their developments on open access platforms, and they should also use easily accessible, open-source tools. Accessibility to both the results of these research and the tools to be used is very important in developing new ABM studies.

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