HOW CAN WE PROVIDE BETTER SIMULATION-BASED POLICY SUPPORT?

Andreas Tolk

The MITRE Corporation
Charlottesville, VA, USA
atolk@mitre.org

Thomas Clemen

Hamburg University of Applied Sciences
Hamburg, GERMANY
thomas.clemen@haw-hamburg.de

Nigel Gilbert

University of Surrey
Guildford, UK
n.gilbert@surrey.ac.uk

Charles M. Macal

Argonne National Laboratory
Lemont, IL, USA
macal@anl.gov

ABSTRACT

This paper collects the positions of four experts who participated in a panel on simulation-based policy support. The experts are well known for their contributions in this domain, predominantly for their use of agent-based approaches. The first section addresses the increasing requirements to integrate social modeling to support the evaluation of the socio-economic impact of policies, including questions of equity. Artificial societies are presented as enablers. The second section observes that the purpose of a simulation model is very much linked to its usefulness for supporting policy decisions. This implies requirements for learning agents and better representation of time and space. The third section focuses on the need to give agents more active behavior, to let them drive the action. While digital twin technology promises to help, the current state of the art seems insufficient. The section closes by looking at trust in simulation models, which will be needed for policy support.

Keywords: agent-based model, artificial society, policy support, spatial-temporal models, trust.

1 INTRODUCTION

This paper summarizes the answers of the four participating experts on the panel to the question "How can human, social, and cultural aspects be brought into simulation-based policy support?' The panel has been conducted within the track on Humans, Societies and Artificial Agents (HSAA).

In their paper on policy evaluation using simulation, Gilbert et al. (2018) state that "*where the costs or risks associated with a policy change are high, and the context is complex, it is not only common sense to use policy modelling to inform decision making, but it would be unethical not to.*" But are our simulation systems ready? Why do we think that policy decision support is becoming increasingly important? What is the role of simulation in policy decision support? What are the requirements for simulation Research and Development (R&D)? Do we need a research agenda that can be shared with other disciplines?

We are holding the expert panel to address this kind of question in preparation for a more direct call to action in the future. This accompanying paper collects the position statements of our experts, who all are well known for their contributions on the use of agent-based approaches. We provide a preliminary synthesis at the end of the paper, and hope that during the panel discussion many more interesting points will be raised in the panel, the discussion with the audience, and any follow-on exchanges. Communication is therefore welcomed!

2 CAN WE PRESENT EQUITY AND INTEGRATION IN SIMULATIONS? (TOLK)

Policy always works within socio-technical systems. If we want to support the evaluation of policies, our simulation systems must represent these socio-technical systems as well as the policies themselves. The Modeling and Simulation (M&S) community is used to dealing with physical-technical systems and many introductory texts to M&S focus on engineering challenges and their computational and software engineering-oriented solutions. But policies happen not in physics-based systems with well understood causes and effects, but in socio-technical systems, which are themselves topics of ongoing research. After describing some requirements for social modeling, we will investigate artificial societies as technical enablers for evaluating such systems and derive some additional principles that are good practice when thinking about the use of simulation for policy evaluation.

2.1 Requirements for Social Modeling

Davis et al. (2019) compiled contributions on social-behavioral modeling for national health and national security, using theory-driven, data-driven, and hybrid approaches. One of their main insights is that strategic planning is not about simply predicting and acting. Decision makers need a clear understanding about the solution space and which areas are relatively stable. While optimization in technical systems is usually possible, social systems often quickly adapt to new situations, and these adaptations do change the system itself, an effect observed by Suarez and Demerath (2019) as well as many others.

Diallo et al. (2019) argued that the Humanities and Social Sciences should ‘take the wheel’ of such developments more than the engineering-focused simulation community has been used to. The simulation modelers were the experts on implementation and execution, but the conceptual models of the examples featured in their book were motivated by insights from experts in philosophical theology, philosophy of religion, philosophical ethics, religion and science, the scientific study of religion, computational humanities, computational social sciences, and other fields within the intersection of humanities and simulation.

One of the common observations is the need for a much better representation of the cultural, economic, and social aspects that are influenced by politics, but that also are influencing politics. Diversity, equity, and inclusion are increasingly recognized to be important. Within the United States, President Biden issued an executive order in January 2021 ensuring that policies do not violate principles of equity and create hardships for minority and underserved communities (White House, 2021). But even without such an executive order, explicitly modeling these factors in simulation approaches is useful for policy evaluation. The challenge, however, is how to use the numerical and computational tools utilized by simulation experts to represent the often vague and ambiguous theories used to address such concerns.

This is the moment where simulation comes into play. First, as discussed by Tolk et al. (2018), simulation can become the common language in which experts from many domains, including those of the Humanities, express their concepts and theories in executable form. Second, as discussed in Tolk et al. (2021), using hybrid approaches for modeling and simulation allows bringing diverse ideas from a range of disciplines into a common framework. These two developments allow to bring cognitive diversity into a common model, which is needed to contribute to solving the complex problems policy makers are faced with. As Page (2008) observes, it is this cognitive diversity that allows us to solve problems under complexity better than approaches limited to a set of experts with the same background.

In various research projects, simulations are used claiming to provide outputs based on gender, race, and ethnicity, but they have not yet been featured in the conferences and workshops organized by professional simulation societies. Some of them can be found in the collection supporting Social Justice modeling (MITRE, 2022), but most of them are feasibility demonstrations. As stated by Bullinaria (2018), the simulation is used to provide a *"representative series of abstract case studies involving innate or culturally-acquired gender-based ability differences, gender-based discrimination, and various forms of gender-specific career preferences, demonstrate the power of the approach. These simulations will hopefully inspire and facilitate better approaches for dealing with these issues in real life."* When the objective is policy support, providing good examples are helpful, but they are not sufficient when the objective is simulation-based policy support.

2.2 Artificial Societies as Technical Enablers

Artificial societies advance the agent-based modeling paradigm by integrating human and social factors into the model. The rules followed by the agents are not based on engineering principles but implement research findings from computational social science. The resulting artificial society has three components:

- a population of individual agents reflecting demographics and attributes of interest,
- the social networks in which an individual is engaged, and
- the situated environment with its infrastructure and social determinants.

The idea of artificial societies is not new, and it has been dealt with as a subtopic of agent-based applications for some time, such as described by Parker and Epstein (2011) or Macal et al. (2018). What is new in recent approaches is the use of data analytics to instantiate and initialize the model (Tolk, 2022). To instantiate and initialize an artificial society of Washington, DC, with 500,000 individuals, 260,000 households, and 50,000 locations of interest (e.g., workplaces, schools, and malls) to better understand the effect of health policy decisions, we used data from a variety of sources, including the U.S. Census Bureau's American Community Survey (ACS); the U.S. Department of Health & Human Services' National Survey on Drug Use and Health (NSDUH); the Center for Disease Control and Prevention's (CDC) Social Vulnerability Index; and Pew Research Center's Religious Landscape Study. We also used synthetic data representing the typical health records of individuals to avoid the use of Protected Health Information (PHI). We also used information contained in journal articles about the subject of interest.

The result is a realistic representation of the Capital region with its important infrastructure, the social, economic, and health status of the individuals, and the social groups and networks of interest. Policies become additional constraints for the rules that the individuals follow to compute their daily actions. As the individuals are situated in a representation of their environment, additional models can be used to simulate changes to this environment, such as climate change effects, to evaluate the social-economic effects of such events, including the context of the social networks of the individuals.

Different individuals and population groups represent different views and value systems, social groups and networks capture different affiliations, and multiple rules can be used to be selected based on the status of individuals as well as of embedding social networks, making the approach very flexible. Overall, the method of artificial societies allows to integrate multiple viewpoints and solution strategies, such as often seen in cross-disciplinary teams. This includes the option to represent views of minority groups, allowing the analysts to focus on minority concerns and - as the socio-economic factors are part of the modeled characteristics - evaluate policy effects with focus on these groups.

2.3 Principles of Good Practice

The last section showed how artificial societies provide a method to cope with social, economic, and cultural aspects of a socio-technical system necessary to support policy makers. In addition to these technical capabilities, there are several good practices to consider for this work.

- *No model without the modeled!* This phrase was coined in the context of establishing an equity-focused participatory modeling framework, the Social Justice Platform (MITRE, 2022), and states that to model systems, problems, and policies with an equity lens, using quantitative, empirical data is often not sufficient. An integrative approach with insights from social science research is needed. Of special interest is the integration of the lived experience of communities and partners, and only they themselves can communicate their experiences.
  Currently, we have neither a good common concept for participatory modeling, nor an approach wide enough to include minority groups and underserved communities, as these groups usually do not participate in serious games or peer-reviews of agent rules, but without their input, the resulting model will remain guesswork.
- *Democratizing simulation!* This good practice is closely related with the first one, but with a slightly broader scope. While the first one focuses on directly affected communities, this second one states the general necessity for increased integration of diverse viewpoints, as recommended by Page (2008). Understanding socio-technical systems often requires new ways to look at the systems. This requires a much broader approach to obtain input for models, beyond the software engineering tools used today. Again, better methods for participatory modeling are needed.
- *Project management for multidisciplinary Integration!* To orchestrate the multiple views and facets of problem understanding in multidisciplinary teams, Shults and Wildman (2020) propose a six-phase project plan that focuses on ensuring that all ideas and viewpoints are captured, documented, and utilized within the project. This can happen in the form of model contributions, measures of merit and associated metrics, or contribution of report components.

The method underlying artificial societies welcomes this kind of diversity needed to identify causes of observed problems, assess equity impacts of policies when exploring solutions, and analyze or predict policy impact within such a socio-technical system. What policy makers expect from simulation-based support is to get informed about possible options and their effects and side effects, and to get recommendations which option to choose under various circumstances. By taking all the various aspects of a complex, adaptive, socio-technical system with its multiple facets and viewpoints into account, such option awareness can be provided by an artificial society.

Artificial societies benefit from all contributions in this position paper, as the call for better agent-based model concepts given by Clemen are as useful as the critical observations on the application of digital twins and trust by Gilbert. Analysis and synthesis are supported by rigorous data analytics as well, but the principles are organizational pinnacles of the solution and its acceptance, which will also help to fulfill the promise of simulation, as formulated by Macal.

3 UNCERTAINTY, PURPOSEFUL MODELS, LEARNING AGENTS, AND SPATIO-TEMPORAL CONSIDERATIONS (CLEMEN)

“The role of the scientist is not to decide between the possibilities but to determine what the possibilities are.” (Lord May, former UK government chief scientific adviser, as quoted in Pielke 2007). Undoubtedly, the creation of models and executing them in simulations can support decision-makers in exploring the state space of a problem, hopefully raising new ideas about how to solve them. Unfortunately, there is no free lunch. All co-authors of this paper mentioned the aspect of uncertainty. Generating synthetic populations (Jiang et al. 2021) or artificial societies, as Andreas Tolk stated before, requires a large number of assumptions that are difficult to validate. The “trust” that Nigel Gilbert is writing about origins from the individual and personal evaluation of a stakeholder and whether this model helps support their intentions. That holds much uncertainty and is furthermore a temporal variable. Thus, if a decision-maker expects a significant decrease in uncertainty by utilizing a model, this might lead to disappointment. Therefore, one essential question to us, as the modelers, is how we can support decision-makers in accepting uncertainty as an indispensable part of the game.

3.1 Purposeful models

Norbert Wiener stated in a prescient paper (Wiener 1960): “If we use, to achieve our purposes, a mechanical agency with whose operation we cannot interfere effectively […] we had better be quite sure that the purpose put into the machine is the purpose which we really desire”.

The question about the purpose of an (agent-based) simulation model is very much linked to its usefulness for supporting policy decisions. When teaching Agent-based Modeling & Simulation (ABMS) classes at university, we emphasize the essential necessity to become clear about the specific research question before starting to model.

Creating and applying simulation models in academia and research aim to gain a deeper mechanistic understanding of the systems in focus — the more finely granular the results, the better. For use in the political arena, this approach needs to be abandoned. Complexity has to be transformed into applicable messages. The purpose here is not to enhance understanding but to find appropriate handles for targeted changes. If the purpose is different, the models need to be different either.

3.2 Learning agents

Multi-Agent Systems (MAS) and the deriving paradigm of ABMS unite the general concepts of AI and simulation in a straightforward manner (Russell 2019). Intelligent agents perceive their immediate environment, including other agents, and act according to their inner logic.

Although various agent architectures exist, the simple reflex agent (Russell 2019) or variations of it are the most commonly used ones. Here, the 'perceive-and-act' cycle is mainly implemented by if-then-else control statements and probability rules. One reason might be the relative *explainability* of such sequences and their proximity to standard programming languages.

One generally accepted result from AI research is that rules, probabilities, and logic seem insufficient to create intelligent behavior. However, how complex do our agents need to be? All considerations with the original question in mind that we want to make simulation useful for policy support.

One core aspect that needs to be incorporated into ABMS is learning. Authentic behavior of (human) agents requires adaptation to environmental changes. Wouldn't it be exciting if an agent-based model suggested alternative courses of action for dealing with global climate change that no human has come up with before?

Machine learning (ML), as a current dominant part of AI, mainly focuses on applying ML algorithms to datasets in order to create models. Liu (2017) called this paradigm 'isolated learning' and suggested focusing on the “lifelong machine learning (LML)” paradigm (Thrun & Mitchell 1995) instead. The major difference to regular ML is that LML includes a memory component that keeps track of the learning history. This paradigm is currently much discussed in the AI community. Further research is needed to evaluate its value to ABMS.

3.3 The importance of time and space

Most published ABMS studies utilize what Stuart Russell called the ‘standard model’ of computation (Russell 2019); a set of input data objects is fed into a parameterized and calibrated simulation engine, which generates, after a specific timespan, a set of results.

The human decision-making process, in comparison, works entirely differently. In an ongoing cognitive process, sensed and perceived input is evaluated, categorized, retained, or discarded. Conscious and unconscious decisions are made in alignment with our cognitive model.

This approach has been adapted partially to crisis management, military operations, and other team challenges. Paper-based or digital situation maps are continuously updated, using various forms of intelligence, surveillance, and expert knowledge.

Transferred back to the topic of this paper, future (agent-based) simulation models might run incessantly, reflecting the current state of the system a policy decision is needed for. The model structure and state-space of these potentially very large simulation models will be adapted to the physical system, forming so-called Digital Twins (Clemen et al. 2021) or Digital Shadows (Fuller et al. 2020). The necessary real-time data may origin from satellite imagery, IoT sensors, or other data sources.

A crucial factor for such a system will be the availability, precision, and correctness of the underlying spatio-temporal data (Glake et al. 2021). Both time and space aspects should be addressed in future research.

4 ACTIONS, DIGITAL TWINS, AND TRUST (GILBERT)

4.1 Incorporating not just behavior but action into ABMs

Bringing in human, social, and cultural aspects into simulation-based policy support inevitably involves modeling people, organizations and perhaps even national states as agents. Such agents are, as is widely recognised, not well represented as mere objects, but need to be considered to have behavior, i.e., they react to the environment in which they are put. But, as we are increasingly becoming aware, even this is not enough. We need in addition to model intentions and plans, as meaningful behavior or action, as well as the ‘upward’ effect of action on the social world and correspondingly, the ‘downward’ effect of social systems on actions.

The work on modeling COVID over the last two years makes for an interesting case study. For many reasons, the earliest models (of those that went beyond just extrapolation) were SEIR models that represented the course of the infections but had only the crudest notion about the effect of behavior (e.g., school closure as an intervention was modeled by assuming that school age children no longer contacted each other). Then we got a generation of models that did attempt to model ‘behavior’ although this was thought of as primarily reactive (e.g., lockdown was modeled as a reduced probability of meeting other agents). What is still missing from most models is consideration of the thinking that lies behind people’s reactions to COVID, and the effect of the social (e.g., peer pressure, media, community and subcultures, and the distribution of knowledge). For example, whether one wears a mask or not depends on whether one thinks mask wearing is efficacious, whether peers expect one to wear a mask, whether masks are easily available, and whether there are regulations requiring mask wearing, among other factors. Moreover, each of these factors may be changing dynamically, including there being feedback effects (e.g., your mask-wearing may persuade your peers to wear a mask also, and vice versa). Such considerations are just beginning to be incorporated into COVID models. A similar progression can be applied equally to most current policy modeling efforts, which typically include some simple representation of behavior, but as yet little or no representation of intention, knowledge or action.

4.2 Digital twins

While I admire Thomas Clemen's call (section 3.3) for work on Digital Twins (DTs), actual implementations are (as far as I know) still far in the future. At least in the United Kingdom, DTs are rapidly becoming a buzz word, but are as yet thought of only in relation to ‘cyber-physical systems’, i.e., not in relation to socio-economic systems. I am sure that we will get to the latter sometime, but there is a lot of development work to do first. This includes some important issues about privacy and surveillance, and correspondingly about obtaining data at the appropriate level of granularity and in a timely fashion. Moreover, if the DT is to ‘evolve’ to match the real world, we will also have to consider the problem that ML faces, about making the DT ‘explainable’. The more that DTs have ambitions to influence the ‘real world’, the more important it is that the way they work is available to inspection, so that they can be tested for bias, error and even corruption.

4.3 Can models be trusted?

A third issue of importance for the use of models to support policy making is how to persuade policymakers to trust our models. My short answer to this is that we won't usually be able to obtain trust in our models – the only, or the best, way to get policymakers to use models is for them to create the models themselves, with our help. Then they will have a degree of ownership of the model and will have committed their time and resources to its development, and we can be sure that the model is on a topic that they care about. However, moving in this direction would need a re-think about both the methodology and the technology of modeling. As noted in section 3.1 above, the academic tradition insists that there is a clear and precise research question and preferably a hypothesis before modeling begins. But in the policy context, there may be no research question and even if there is, it is likely to change, not only as the modeling domain becomes better understood, but also as the policy environment alters. This means that the modeling methodology must be dynamic and participative. To achieve co-design and co-development with policy makers, the technologies must provide accessible tools and displays. And since policymaking is often fast paced, these tools must be capable of being brought to bear rapidly and generate results quickly.

Even if we do manage to develop such tools and techniques, there will still be an issue about the kind of knowledge that modeling generates. The UK Prime Minister, Boris Johnson, is reported as requiring his aides to send him shorter memos, limiting papers to just two sides of A4 (Sunday Times, 23 February 2020). The output from most models will exceed this limit. And one must also explain that models of complex social systems do not yield point predictions about the future, but rather offer understanding of a range of possible scenarios - it is likely to be a tough job for a policy analyst to boil down the results of a policy simulation to two pages.

5 THE PROMISE OF SIMULATION (MACAL)

Policymakers face many important challenges ranging from climate change to social inequality, from the threat of nuclear war to pandemics and misinformation spread, and many more (Reese 2018). Many simulation professionals (simulationists) believe that simulation modeling can provide policymakers with critically needed information to answer their pressing questions. Simulations can provide "science-based" information as a basis for policymakers' decisions. Simulation modeling has the unique capability among modeling approaches to forecast, if not predict, the future and explore alternate worlds in silico. Using simulation, policymakers can test policies to see the possibilities for the future and the likely effects of their policy decisions before they make them. By simulation as used here, it is meant the mathematical/computational modeling of the sequential steps of a dynamic process that plays out over simulated time, and that emphasizes the causal mechanisms and factors that govern the system behavior.

5.1 Simulation's Value Proposition

The ongoing COVID-19 Pandemic provides the context for the use of simulation to support policy making and is a basis for thoughts on the ingredients for simulation to better support policymakers. My views are based on the experience in using CityCOVID, a highly granular agent-based epidemiological simulation model (Macal 2020; Ozik et al. 2021), in supporting analysts and policymakers in the public health departments of City of Chicago and the State of Illinois USA (Mahr 2021; Thomas 2021).

Simulation has a unique capability among modeling alternatives to create and provide information on the past, the present and the future to policy makers. For successful engagements with simulationists, policymakers need to understand the benefits that simulation can provide in supporting science-based decision making. We find four reasons that policy makers might find engagement with simulationists to be beneficial: (1) simulating the past (backcasting): we would like to simulate the past to identify the causal mechanisms that could have produced observed real-world outcomes, (2) simulating the future (forecasting): simulation can provide information on how the future could evolve, given several assumptions, while propagating the impact of uncertainties in the data and structural relationships on model outcomes, (3) simulating a set of possible alternative interventions on a "what-if" basis provides valuable information to policymakers on their choices, and (4) choosing our future: simulation offers us the possibility of choosing the future we would like to live in through the choices that policymakers make. Simulation can be a basis for optimizing these choices and selecting the "best" outcome(s) we would like to achieve by whatever criteria policymakers choose to value the outcomes.

5.2 Lessons Learned and Facilitators for Successful Support to Policymakers

Based on our Covid-19 experience, we postulate these ingredients for successful engagements between simulationists and policymakers.

- Sustaining commitment on the part of the policymaker to making decisions based on science. This translates into basing the modeling work on empirical data and evidence from the peer-reviewed literature.
- Trusted and credible simulationists: (1) there is trust between the policymakers and the simulationists, (2) simulationists who are credible scientists to build and use the models to produce, analyze, and interpret the information provided to policymakers, and (3) the simulationists can produce useful information that directly answers policymakers' well-defined questions in the time frame in which the information is relevant.
- Trusted and credible models, either by being peer-reviewed or being able to directly answer the policymakers' specific questions. Directly means here the model contains minimal abstraction, approximation, and aggregation and minimal interpretation and translation of model results by simulationists.
- Providing information to policy makers in an appropriate form. Providing information in plain "English" in a summary form that policy makers can readily understand is essential. This is very different from writing a technical paper for a peer-reviewed journal as many simulationists are accustomed.

6 SUMMARY

Simulation systems - not only agent-based ones - are showing potential to support policy making, particularly when the identified gaps are closed by ongoing research. One often required capability is to better cope with uncertainty, and simulation systems can either amplify or help reduce uncertainties among policymakers. It is primarily up to the simulation experts to make the process of utilizing models for decision-support as comfortable and smooth as possible. But coping with uncertainty is not the only identified goal. All four position statements contribute different ideas to what may easily become a research agenda for simulation-based policy support. They all recognize the need to cope with socio-technical systems, which are recognized to be complex and coping with new challenges, in particular when research insights from social science and the humanities are integrated. But policy evaluations have increasingly to address social, economic, and cultural challenges. One challenge of the real system is that the individuals making up the society are constantly learning and adapting, which needs to be captured in simulation systems for policy support, but current approaches of AI and ML often fall short. We need a clearer understanding of the cognitive models used by humans in order to capture these processes in our simulations. The emerging method of digital twins may support, but also fall short for complex, socio-technical systems. All this raises the question if we can trust such models (Harper et al. 2021), particularly when applied in complex situations under uncertainty? But nonetheless the various challenges, simulation can provide policymakers with critically needed information or "possibilities", as Lord May stated in (Pielke 2007), to answer their pressing questions using science-based insights.

Besides all technical and conceptual concerns, we like to point out the necessity of incorporating a management-of-change strategy into our objective to support decision-makers. Software companies learned early that without taking the users by the hand, the introduction of new tools and methods is seldom successful. This principle is not only valid when providing simulation software to political organizations.

We need to include it in every communication with the stakeholders. Moreover, we also need to teach our students to follow this guideline.

As mentioned in the introduction, the authors believe that a call for action to provide better simulation capabilities to support policy evaluation in complex problem spaces may be helpful to focus the efforts of our community to meet this new set of challenges. The position topics are neither complete nor exclusive. They were selected to show the need and give examples. This is not a task for a subset of experts. We will need community engagement to make this happen.

DISCLAIMER

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AUTHOR BIOGRAPHIES

ANDREAS TOLK (0000-0002-4201-8757) is Chief Scientist for Complex Systems Modeling with The MITRE Corporation in Charlottesville, VA. He holds a Ph.D. and M.S. in Computer Science from the University of the Federal Armed Forces in Munich, Germany. He is a Fellow of the Society for Modeling and Simulation and a senior member of ACM and IEEE. His email address is atolk@mitre.org.

THOMAS CLEMEN (0000-0002-8200-5141) is a Full Professor of Database Systems and Artificial Intelligence at Hamburg University of Applied Sciences, Germany. He holds a Ph.D. in Computer Science from the University of Kiel, Germany. His research interests include multi-agent systems, digital twins, spatio-temporal data, and human behavior modeling. Thomas regularly advice policy stakeholders on national security, civil protection, and other topics. His email address is thomas.clemen@haw-hamburg.de.

NIGEL GILBERT (0000-0002-5937-2410) is Distinguished Professor of Computational Sociology at the University of Surrey, UK. He was one of the first to use agent-based models in the social sciences, in the early 1990s, and has since published widely on the methodology underlying computer modelling, and on the application of simulation for applied and policy related problems and to support public policy decision-making. He can be reached at n.gilbert@surrey.ac.uk.

CHARLES M. MACAL (0000-0001-9167-0699) is the Group Leader of the Social and Behavioral Systems Group in the Systems Science Center of the Global Security Sciences Division at Argonne National Laboratory. He has a PhD in Industrial Engineering & Management Sciences from Northwestern University and a Master's Degree in Industrial Engineering from Purdue University. His email address is macal@anl.gov.