AGENT BASED MODELING
FOR ORGANIZATIONS AND POLICYMAKERS

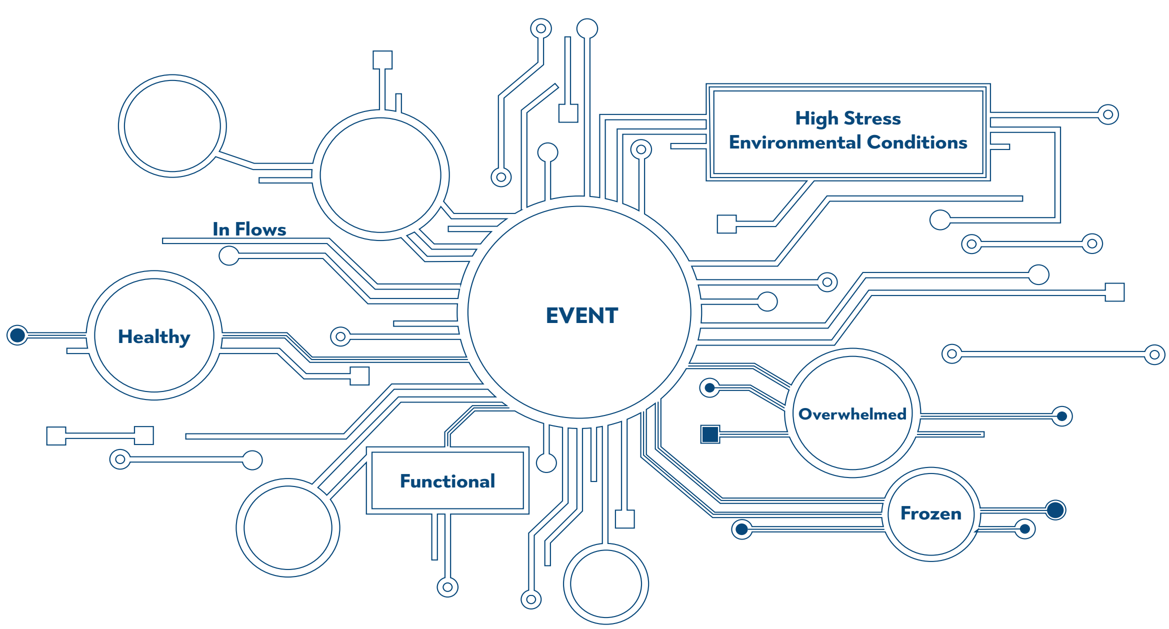
MARCH 2019

Bottom Line Up Front

One of the ever-present challenges for organizations and policymakers in achieving desired outcomes is knowing what structures and processes will support and produce them. Well-intentioned approaches often fail to achieve desired ends, and worse, produce unintended consequences that may even run counter to what is desired, e.g. building additional roads that result in increased traffic, or "streamlining" a business process only to discover bottlenecks under periods of high throughput.

Modeling candidate approaches is one method organizations can use to lower the risk of unintended consequences; however, traditional modeling methodologies often fail because they don't take into account the way the interactions among components of a system give rise to macroscopic outcomes, leading to unintended consequences being discovered only after implementation—an extremely costly process.

Agent Based Modeling (ABM), however, is a non-traditional modeling and simulation tool that is well suited to help bridge the gap between intentions and outcomes in complex human systems. By drawing explicit attention to the way an organizational or policy change can affect both components and their interactions, non-obvious consequences that follow can be discovered and highlighted. As organizations and policymakers seek to address perceived inefficiencies and poor results, ABM should be leveraged as part of an active design process.



Agent and environment interactions. Visual depiction of interconnected agents and events in an ABM highlighting functional and non-functional responses among various components.

AGENT BASED MODELING: WHAT AND WHY

ABM is uniquely suited for practical applications in complex and dynamic systems because it is the system and the problem-set that determine the form and resolution of the model, rather than being bound to or dependent on specific types of components. For instance, if we wish to model crowd behavior in an emergency situation, we can model the behaviors and interactions of people interacting without having to model the biological cells that compose each individual. Moreover, one would not need to model all aspects of each individual, such as their taste in movies or favorite color, only those relevant to the behavior of interest, for instance their susceptibility to panic. There is a 'practical resolution' for any given problem, and that informs the granularity of the model.

The "agents" in ABM can be any entities that are sensible for the problem: if we are interested in chemical systems reasonable agents would be chemicals; if we are interested in an ecosystem the agents might be various species; if we are interested in how riots emerge in a crowd the agents might be individuals.

A classical example of how ABM can illuminate unexpected dynamics comes from a model of predator-prey dynamics. The so-called Lotka-Volterra model is a relatively simple ABM, where there are only two agents, one representing a population of the predator, the other the prey. Prior to the development of this model, predator and prey populations that reproduced and hunted at constant rates were assumed to produce a static equilibrium—yet the model showed sustained oscillations were also possible with no external force causing them. And indeed oscillations of this type are observed in ecosystems, among other more complex dynamical phenomena. The interactions between predator and prey produce behavior that is not observed in either one in isolation, thus the interactions are essential to capture in order to understand the behavior.

This simple insight has far reaching implications—where else have we expected static equilibrium where it does not exist? Markets? Cultures? Nations?

The systems and environments that we face both in business and governance are not only complex, but are rapidly growing more so, enabled primarily by information and transportation technologies. The interdependencies created by our dense interconnectedness exacerbate the challenges associated with understanding the consequences of any policy or organizational decision, and generate novel kinds of events that we must grapple with.

Events are no longer isolated, but can spread and cascade, transform and mutate. The Arab Spring, the 2008 financial crisis, Ebola flare ups and outbreaks, rapid cultural shifts like the #MeToo movement, leaderless protests and riots such as the current Yellow Vest movement in France.

Traditional mathematical and statistical tools are not well suited to problems with strong interdependencies such as those above, but that is the new normal—on all scales and across the globe. These tools fail to work in complex systems because of the simplifying assumptions of independence and linearity that make them tractable with limited computing power. But these assumptions don't reflect real world conditions, where systems of interest are generally non-linear and interdependent, and thus don't lend insight into it.

ABM does not depend on these simplifying assumptions, but rather relies on computing power that has only recently become widely available. Ensembles of large-scale simulations can be performed in which assumptions are chosen that best reflect relevant realities. Biological and memetic contagion, cultural paradigm shifts, social and political unrest, fads and trends, as examples, all become amenable to analysis and exploration.

	ABM	TRADITIONAL MODELING
Assumptions	Explicit, non-linear, interdependent, micro, flexible	Hidden, linear, independent, macro, fixed
Output	Ensembles, possible futures, data, analyses and visualizations of computational "experiments"	Single trajectory, "Optimal" parameters, analytical proofs
Scales	Micro-to-macro (multiscale)	Single scale
Tactical use	Exploratory, option-generating, focus on robustness, adaptation, and evolution	Proof based, analytical, deriving 'optimal' solutions given (often faulty) assumptions
Well suited for	Complex, not well understood, uncertain, interconnected, contextually embedded	Simple, well-understood, certain, isolated
Based on	Reasonable assumptions, relevant agents and behaviors, inductive probing	Fundamental laws, deductive inference
Engagement	Intuitive, articulable, general	Technical, arcane, specialized
Scope	Extendable, iterable, able to be built upon as more is learned	Fixed, one-shot, new information requires complete reformulation

ABM vs. Traditional Approaches. ABM and more traditional modeling tools are suited to differnt kinds of problems. Readily available computing power has made it possible to leverage ABM for complex systems.

MODELING CONSIDERATIONS

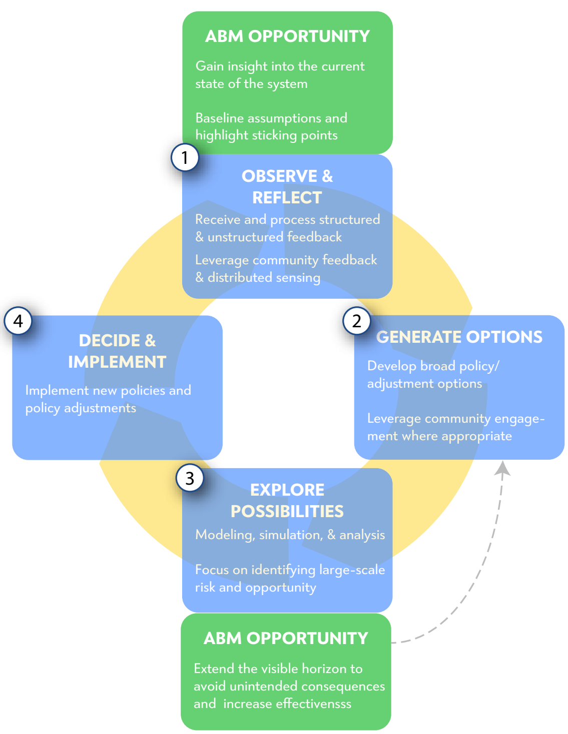
For organizations and policymaking, choosing *individuals* as agents of interest often makes sense, but depending on context, choosing departments, firms, or political units such as towns or states, for instance, is also reasonable. It is also possible to define multiple kinds of agents at the same or different scales.

The key is to select agents for which we have a relatively clear understanding and access, such that we can define their relevant behaviors, ability to learn and adapt, and interactions with other agents and the environment. These "micro-assumptions," which may be formulated as deterministic or probabilistic, are what drive the model, and ultimately produce the emergent behavior of the whole system.

Where we have behavioral uncertainty, which is often the case in human systems, both agent behaviors and environmental variables can be modeled in a probabilistic way. This implies that each model instantiation will produce an ensemble of outcomes, rather than a single one. The distribution of outcomes present in such an ensemble can contain crucial information about the possible behaviors of a system. For instance, the very same system under the same circumstances could in some cases function properly, and in others break down catastrophically, simply due to how chance events unfold.

Gaining foresight into the range of possible outcomes increases decision-making sophistication especially with respect to rare but costly events.

Crucially, we can vary the micro-assumptions, environmental conditions, policies, organizational structures, and any other potentially relevant features, and analyze and compare outcomes across model instantiations to both identify promising approaches as well as rule out candidates for which unfavorable effects are uncovered. This process does not guarantee that the implementation will achieve its intended effects, but it does (1) enable deeper insight into the current state of a system and the sources and mechanisms of problems and sticking points, (2) make assumptions about component behaviors and interactions explicit so that if they are found to be faulty they can be refined for all future work, facilitating organizational learning, and (3) enable rapid iteration in the idea-generation phase of a project to produce a larger set of possible approaches for consideration which can be ruled out or selected for implementation against simulated outcomes.



Active Design. Iterative and exploratory, active design leverages feedback and can be catalyzed by ABM.

ABM IN AN ACTIVE DESIGN PROCESS

ABMs are most powerful when leveraged as a tool in an active design process in which feedback and iterative refinement are used in the implementation of policy and organizational changes.

Ultimately, reality will be the judge of any policy or organizational decision, and in a complex and dynamic environment it is essential that relevant feedback is leveraged when observing outcomes and assessing effectiveness.

Each iteration of an active design process begins with an observation period (stage 1 in the figure), which establishes to the greatest degree possible the current state of the system and its performance—including how prior policy or organizational changes have contributed to improvement or degradation.

In this process ABM can be used to better understand a system's current behavior, both functional and pathological, and to baseline assumptions about the behavior of relevant agents and environmental variables. For instance, reproducing a known challenge or sticking point can help to clarify the underlying mechanisms that are causing it, and may suggest ways to overcome those challenges in addition to building confidence in a model's assumptions and ability to capture relevant system behavior.

After using feedback and any relevant modeling to observe the current state of the system, an active design process entails generating options for moving forward (stage 2 in the figure). Exploring the possible consequences of those options generated (stage 3 in the figure) can be enhanced by leveraging ABM here as well, as potential solutions can be clearly articulated and consequences explored, prior to selecting an approach and implementing it. In an actual active design process using ABM, it may be sensible to cycle between stages 2 and 3 (dashed arrow in figure) before moving on to implementation, as novel options might emerge as part of the possibility exploration stage, which can be further considered.

After an approach is implemented in a real world setting, the active design process renews itself with another period of observation.

ABM is uniquely suited to catalyze an active design process for organizations and policymakers grappling with complex and dynamic challenges, both internally and in their environment. As part of an active design process, ABM can reduce risk and clarify potential outcomes, effectively extending the visible horizon.

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