Enhancing ABM into an Inevitable Tool for Policy Analysis

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Social systems consist of many heterogeneous decision-making entities who create complexity through their interactions. These systems are governed by policies in a multi-scale institutional context. While policy is a top-down instrument, its effect is determined by a bottom-up process, in the sense that the aggregate behavior of the social system is the result of interaction and reasoning on the level of individuals. We argue that understanding social systems at the individual level significantly contributes to understanding and predicting the effectiveness of policies. Given that agent-based modeling (ABM) allows for rich representation of individuals, it is well suited for providing necessary insights for policy analysis. To support this claim, in this paper, we give a systematic overview of the requirements that policy analysis puts forward. By viewing policy analysis as a cycle of activities, we discuss five categories: problem definition, policy evaluation, identification of alternative policies, decision support, and monitoring. Moreover, we evaluate mathematical and computational tools with respect to these requirements. Finally, we propose a list of extensions to ABM for monitoring, decision making, and participatory design in the policy analysis cycle.

Keywords: *agent-based modeling, policy analysis, tool selection, policy cycle*

1. Introduction

How would taxation on light bulbs or subsidies on LED lamps influence the behavior of consumers toward more energy saving habits? Can investment on manure-based biogas systems improve farming prospects for animal farmers? And, does fining recyclers in a developing country prevent them from hiring children and using dangerous chemicals when they are recycling electronic appliances? These questions all address policy problems, exploring the long-term effect of strategic decisions on the operational behavior of individuals and on the global outcomes of the complex social system.

Policies are rules or instruments guiding actions and decision making by people in order to achieve desired outcomes in social systems. The design of effective policies is a cyclic process of identifying the objective, defining alternative policies, selecting the one that would best address the objective, and finally monitoring and evaluating the implemented policies' effects on the system (Weimer and Vining 2005). Throughout this cycle various tools ranging

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from benchmarking and historical analysis (Scharpf 1997) to computational simulations (Gilbert 2004) are used.

Policies are implemented as top-down decisions but their acceptance is—at least partly—a bottom-up process. This calls for a system understanding at the microlevel in order to find out which of the alternative policies are most effective (Scharpf 1997). Microlevel analysis contributes an insight into the individual's unanticipated adaptive behavior, decision making, and interactions, facilitating the improvement of conditions for effective policy solutions.

The need for micro-level analysis has a good fit with what agent-based modeling (ABM) offers. ABM, as a bottom-up simulation approach, builds artificial societies from individual agents and their interaction, giving insight into how people may react toward different situations (Banks et al. 2000). Compared to other computational approaches such as differential equations and statistical modeling, ABM imposes less assumptions on linearity, homogeneity, normality, and stationarity (Banks et al. 2000). In addition, agent-based models have the power to demonstrate emergent phenomena at system level. This is especially instrumental for policy problems where the influence of individual behavior on system properties is under study (Conte et al. 2001).

However, to use ABM for policy analysis there are additional requirements. For example, for evaluating policy alternatives, the policy analyst also needs means of imposing policies (or rules) to the simulated system in order to study individual reaction and adoption to these impulsions. Therefore, building a system purely from bottom-up may not be entirely instrumental for policy analysis. Furthermore, since the subjects of policy problems are societies with real people, the reliability of an agent simulation and the results it provides are a sensitive issue that require careful evaluation.

The goal of this paper is to show the suitability of ABM as an approach to analyze policy problems and how it can be enhanced to address even more requirements for policy analysis. To achieve this goal, we first explain the policy analysis cycle and introduce the various steps and requirements in the analysis process in Sections 2 and 3. We then introduce the computational tools that are commonly used for policy analysis and reflect on the benefits and drawbacks of each, in Section 4. We explain how ABM can be used as a comprehensive approach for policy analysis and discuss areas for further enhancement in Section 5. Finally, we conclude our findings in Section 6.

2. The Process of Policy Analysis

A policy is a set of principles or rules to guide a social system toward those actions that are most likely to achieve a desired outcome. Policies can be implemented as social norms (e.g., switching off lights when leaving a place which must be internalized by people, for example, through advertisement campaigns), legal impositions (e.g., subsidies and taxes on the different consumer products such as milk, LED light bulbs, etc.) or technological artifacts (e.g., electronic gates at stations).

The practical activities of policy-making and implementation are distinguished from the more reflective activities of policy analysis which aim at determining which alternative policies may most likely achieve desired goals and outcomes. Policy analysis is specifically complex because the consequences of implementing a policy "are the outcomes under external constraints of intentional action" (Scharpf 1997). In other words, human actors are driven by a combination of internal intentions, natural impulses, and/or external factors that make modeling behavior complex.

In the first step the policy analyst verifies, defines, and details the given problem by characterizing the social context in which the problem is embedded and identifying the independent variables that affect policy outcomes. The identification of the problem source and the independent variables is a major milestone in policy analysis because the objective of the problem owner is often either not clear or appears to be in conflict. In fact, most often, different actors view the problem in their own perspective. It is the role of the analysts to understand the positions and influence of various stakeholders and choose the definition that the problem owner/decision maker has control on (Patton and Sawicki 1993). Clarification of the problem takes place with consultation, brainstorming, narratives, and scientific research. Often, the problem is redefined many times during the process of analysis.

In the second phase, the policy analyst identifies the criteria that show when the problem is solved or a goal is accomplished. The analyst aims to select those criteria that are central to the problem and most relevant to the decision makers in the implementation process (Patton and Sawicki 1993). This also facilitates the comparison between policy alternatives. During comparison, new criteria may also be identified.

Once the analyst knows the values, objectives, and goals of the stakeholders and the evaluation criteria for judging policies, he can generate alternative policies (Patton and Sawicki 1993) . The list of possible alternatives is usually long since there are many variations and combinations for the policies. Benchmarking and past experience are common approaches for identifying policy alternatives (Scharpf 1997; Patton and Sawicki 1993).

Among policy alternatives, the most appropriate options are selected using the already defined evaluation criteria. The alternatives are compared based on the potential effects and their chain of causation. Since not every policy can be tested with the same method, analysts have access to various methods (e.g., cost–benefit analysis, programming, institutional analysis, and quantitative analysis) to evaluate different policies. It is important to identify economically, technically, and politically feasible alternatives. This is where many institutional analysis theories and frameworks (i.e., IAD (Ostrom 2005), Actor Centred Institutionalism (Scharpf 1997)) are frequently applied. Furthermore, it is important to clarify the distinction between possible policies and to be able to display them to the problem owners. Consultation commonly takes place to increase the efficiency and transparency of policy implementation (Althaus, Bridgman, and Davis 2007).

The final phase of policy analysis is the monitoring, maintenance, and evaluation of the implemented policy. In most instances, the analyst develops implementation guidelines and procedures rather than being involved directly in the implementation of the selected policy. It is important for the analyst to know whether a failed policy could not be implemented as designed or the policy did not produce the desired results because the underlying theory was incorrect (Patton and Sawicki 1993). Therefore, policy analysts are highly involved in the postevaluation of implemented policies. In general, this phase is about monitoring the use of inputs and the achievement of outputs, and evaluating the direct effects and long-term impacts of the policy.

In the next section, we discuss what kind of requirements the different steps of the process put forward for policy analysis tools.

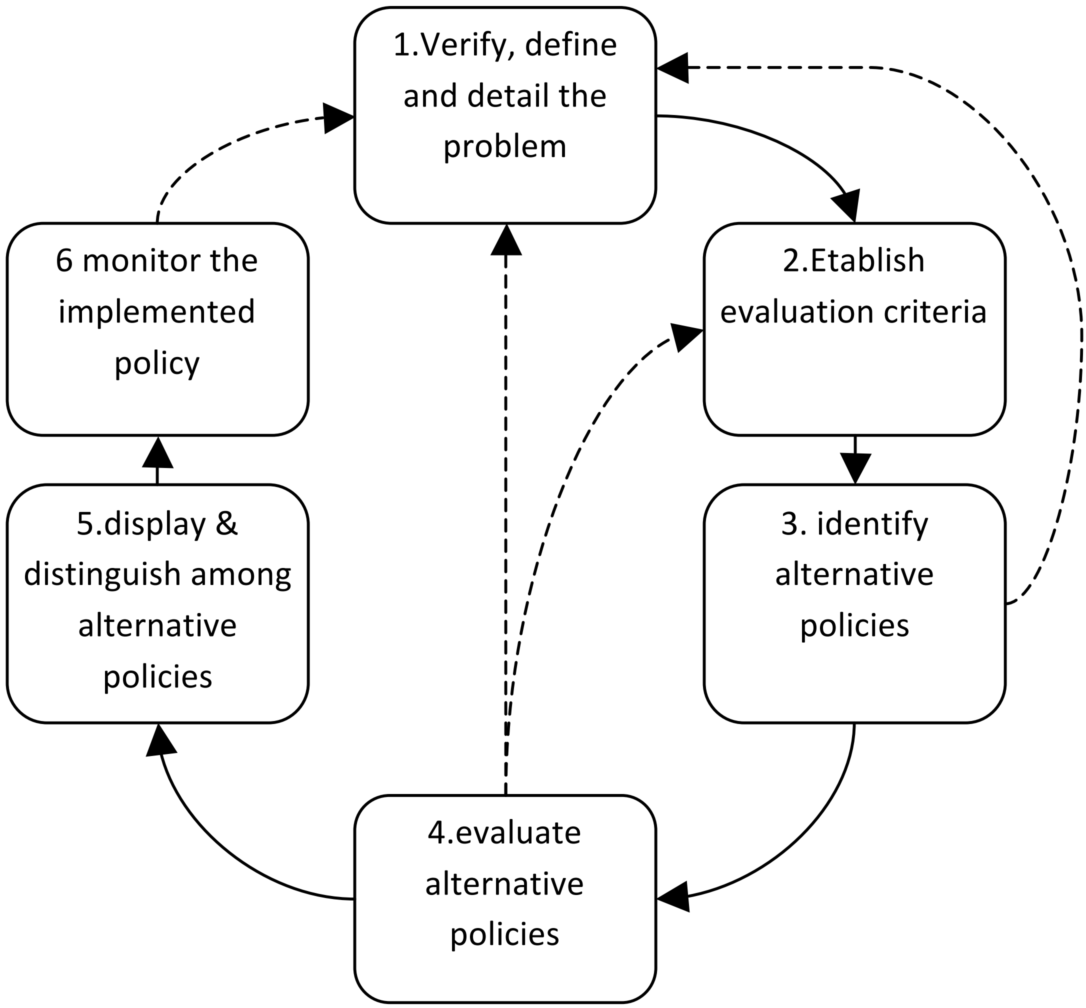

Fig. 1. Policy analysis cycle (Patton and Sawicki 1993)

3. Requirements for Policy Analysis Tools

The main objective of policy analysis tools is to support a better understanding of the policy problem and the context in which the problem is situated, and to support the evaluation of policy solutions. To reach this objective, there are several aspects that need to be taken into account. First, even though policy implementation is a top-down procedure, policies affect individuals. It is the combination of individuals' reactions that determines the success of a policy implementation. While for some problems, it may suffice to capture and understand the overall emergent behavior of the population, for others, a deep understanding of individuals, their unanticipated behavior, and decision making and interactions is essential (Scharpf 1997). Therefore, it is important that policy tools provide a suitable level of system analysis to link between individual behavior and global outcomes. Second, to better understand the problem and its context, the policy instruments need to reflect reality to a required extent depending on the type of problem. Therefore, it is important to consider to what extent the underlying assumptions for any tool (e.g., rationality and complete information) match the characteristics of a specific policy problem.

Each step in the policy analysis cycle (Figure 1) has specific requirements which are classified into five areas discussed below:

1. Problem definition
   Policy analysis requires the means to clarify the problem itself including:
   a) Techniques that facilitate communication with domain experts and stakeholders (Moss 2002).
   b) Techniques to parameterize the problem or problematic behavior.
   c) Means of understanding and defining the population. Even though a detailed understanding of individuals may not be a key element for every policy problem, a general understanding of the population that will be affected by the policy is a minimum requirement. In most cases, the context has a large number of active entities and there is very little knowledge about the global interdependencies.
   d) Means of identifying the available resources, processes, physical and environmental characteristics, and boundaries of the system where the policy is conducted.
2. Evaluation Criteria
   Support for policy evaluation includes:
   a) Specific measures such as cost, benefit, effectiveness, and legality. The problem owner provides these measures directly or indirectly.
   b) Means of clarifying, deducing, and confirming measures whether or not provided by the problem owner (Patton and Sawicki 1993) and associating the measure specifications with problem definition.
   c) Tools for identification and consideration of extreme values and worst-case scenarios.
3. Identification of Policy Alternatives
   Identifying alternative policies is closely related to the problem definition and the set of evaluation criteria. To identify policy alternatives, the analyst requires:
   a) Means for identifying the attributes of each policy.
   b) Means of linking policies to evaluation measures.
   c) Inclusion of technical, economical, societal, and political aspects of each alternative (Patton and Sawicki 1993).

d) Tools to display and present alternative policies.

4. Decision Support for Selecting Policy Alternatives
    a) Instruments to distinguish, categorize, and compare policies.
    b) Tools to support participatory decision making.
    a) Means of answering what-if scenarios.
    b) Tools for tracking the behaviors and reactions toward policies, before policy implementation (e.g., gaming and simulation).
    c) Tools for testing extreme values and worst-case scenarios.
5. Monitoring implemented policies
   After implementation, policies can be monitored and evaluated using the evaluation criteria identified in the second step of the cycle. The policy analyst requires:
    a) Tools and methods to compare and illustrate the before-and-after situations in order to evaluate the effects of a policy.
    b) Tools for tracking the behaviors and the reactions.

Besides the specific requirements mentioned above, data collection, data analysis, and research are the common requirements for every step of the process. For an effective policy, consultation is also essential throughout the policy analysis process (Hodge and Davies 2006). There are different levels of consultation; for some projects, public opinion is taken into consideration while for others, this may need to be more limited due to, for example, security reasons (Althaus, Bridgman, and Davis 2007). Furthermore, for selecting any policy instruments, the time constraints that the policy analysts work under need to be considered (Patton and Sawicki 1993).

Policy analysts use various tools in different phases of the policy analysis cycle (e.g., surveys, brainstorming, sensitivity analysis, institutional analysis, etc.) (Patton and Sawicki 1993). It is common practice to select a combination of tools that complement each other for different policy cases. Computational tools are in particular frequently applied to cover more scenarios and possibilities than normally possible with non-computational tools (e.g., scenario writing). In this research, we especially focus on the computational tools that are used for policy analysis. We will compare these tools and reflect on the benefits and limitations of each in order to identify areas for improvement.

4. Computational Approaches for Policy Analysis

Different policy tools focus on different aspects of the policy analysis cycle. Given the importance of computational tools, we introduce the major approaches that are currently in use, namely: Neo-classical Equilibrium Modeling (NEM), Traditional Game Theory (TGT), System Dynamics (SD), Serious Gaming (SG), and Agent-based Modeling (ABM). We then discuss the benefits and drawbacks of each as a policy analysis tool.

Neo-classical Equilibrium Modeling

Neo-classical Equilibrium Modeling (NEM) is a frequently applied tool for market-related policy problems. NEM provides mathematical models of markets and has special focus on maximizing profit, competition, and income distributions in markets through supply and demand (Jones 1965).

Neo-classical models take into account many aspects of a real economy including commodities, production, growth, and money (King, Plosser, and Rebelo 1988). However, they mostly address centralized market economy and therefore are not suitable for other types of decentralized markets.

The underlying assumptions in NE models such as full rationality of parties, complete information, and certainty also create concerns about their reliability on the insights they provide. Although this line of research is gradually moving toward higher uncertainty approaches, rationality of individuals and complete information are the necessary pillars in equilibrium modeling.

Traditional Game Theory (TGT)

Game theory is the most frequently applied tool for understanding actor behavior and decision making in policy problems (Gibbons 1992). The fundamental concepts in game theory are players, strategies, and payoffs. A player may be an individual or a composite actor that is capable of making choices. Strategies are lists of consecutive actions for a player, or functions assigning actions to each decision point of a player on the basis of previous actions by the opponents.

The limited number of actors and outcomes, the joint product of separate choices, and the actors being aware of their interdependence, make game theory useful for policy analysis (Scharpf 1997).

However, there are a number of strong assumptions in TGT that make it less suitable for many policy problems (Scharpf 1997): perfectly rational actors, complete information, self-interest, and unlimited computational and cognitive ability. Another limitation of game theory is that it does not provide a macroperspective explanation of policy choices, which is commonly required for policy analysis (Scharpf 1997). One other limitation of TGT is that the number of interactions between actors is very limited (interactions between three agents (Moss 2001)) while for policy problems, hundreds or thousands of actors may be involved.

System Dynamics

System dynamics (SD) is a computational simulation approach which has its roots in differential equations. With this approach, a system is described using a system of equations with which future states of the system are derived from its current state. In system dynamics (SD), real world problems are represented in terms of stocks, flows, and information. SD ignores single events and entities and takes an aggregate perspective (Borshchev and Filippov 2004).

The ease of use and availability of packages and tools makes system dynamics one of the most popular computer-based analysis tools among policy analysts. However, as the simulations grow bigger, the number of assumptions increases, introducing additional questions of validation to support the reliability of the simulated model.

The high number of assumptions thereby also makes the model less flexible. Essentially, SD is a one-layer approach which means that the focal system is simulated as an indivisible whole. It does not take into account the fact that the actual system consists of individual people and it is their behavior and reaction that actually results in global outcomes.

Serious Gaming

Serious games can be designed to gain insights into policy problems. These types of games are a simulation of real world systems and events where players get the chance to make decisions about virtual events. The purpose of a serious game is to put actors in situations representing reality, in order to understand their decision process and then study the possible outcomes of the aggregation of those decisions. These situations can be virtual (i.e., computer games) or real (i.e., a setting that would represent the real world situation).

Games provide the possibility to learn on multiple levels. While the involved players may learn from the contextual information provided by the game or the decision making as it takes place during the game, useful material is gathered by the designers of the game to solve the underlying policy problem (Raybourn and Waern 2004). Serious games do not necessarily have to be computer-based; they could also be role-plays among human players.

While serious gaming (SG) reflects a great part of real actor decision making, compared to other models, the population that can be considered for a game is normally much smaller than the real population and therefore unreliable to extrapolate to real world scenarios.

Agent-based Modeling

Agent-based modelling (ABM) is a computer-based modeling approach that enables the exploration of the consequences of complex assumptions (Janssen and Ostrom 2006). In ABM, models are inherently bottom-up and decentralized. Therefore, ABM describes those situations where the standard methods of predictive policy analysis are least effective (Moss 2002). With ABM, it is possible to design irrational agents with incomplete information in relatively uncertain situations.

The main advantage of ABM over other modeling approaches is that it captures emergence, linking individual behavior to system level behaviors. This results in a natural representation of a system's global behavior as well as adding more flexibility to possible outcomes (Bonabeau 2002). However, since ABM is a bottom-up approach to problem solving and the global behaviors of the system are emergent outcomes rather than being implemented into the system (Epstein 2006), techniques for representing policies as top-down structures into the simulation are neither common nor straightforward.

Functionality of the Tools for Policy Analysis

The tools introduced in this section are all used for policy analysis. In fact, in most cases the policy analyst uses a selection of these tools along with the non-computational methods. Therefore, highlighting which part of the policy analysis cycle each tool supports will be informative for choosing an effective combination of the tools. Table 1 shows where in the policy analysis cycle the aforementioned tools can be helpful. The letters in the second column show which requirement of Section 3 is addressed.

NEM can be used to parameterize the policies and make an association between different dimensions using equations. NEM does not support the identification of the resources, processes, characteristics, and boundaries of the system. However, once they are detected, it also helps parameterize these attributes for problem attributes. This also holds for the evaluation measures and policy definition. A limitation of this mathematical method is that it does not facilitate communication with domain experts because mathematical equations are not understandable to everyone. Also, NEM does not help to gain insights into individual behavior and decision making, as it describes the system from a macro perspective. In terms of decision support, NEM can be used to categorize and distinguish policies through mathematical equations. However, since certainty is one of the assumptions in this approach, the answer to what-if scenarios using this approach are not always reliable. This also holds for tracking behaviors because not only the system is analyzed at macrolevel, individuals are considered fully rational with complete information. These assumptions may also not justify answers for certain behaviors and reactions when monitoring the implemented policies.

Unlike NEM, traditional game theory takes an individual-based approach, which provides a means of specifying the population in the problem definition. However, TGT is about outcomes rather than individual behavior. Therefore, it is not the most suitable tool for tracking individual behaviors and reactions for selecting a policy or monitoring an implemented one. While TGT can be used to define evaluation measures and identify extreme values and worst case scenarios through computing equilibria, as a standalone tool, it has other limitations. For example, it does not provide a test bed for participatory decision making unless it is used with serious gaming (SG). TGT does not support the identification of policy alternatives either: there is no way of identifying the attributes for policy alternatives and it is infeasible to link policies to evaluation measures.

System dynamics (SD) is a computer simulation approach that makes use of differential equations. Therefore, all the benefits of mathematical descriptions, such as formulating policies and their attributes and defining evaluation measures, are facilitated with SD. Owing to the availability of tools, displaying and presenting various policies is practical. In addition, SD like other simulation approaches enables tracking of system behavior. However, the major limitation of SD is that the system is not viewed as a collection of individuals. Therefore, it is infeasible to gain insights into populations and the decision-making behavior of individuals and thus not possible to track behaviors and reactions at individual level toward a policy. Nonetheless, the general processes and outcomes are traceable. Furthermore, instead of identifying boundaries and resources for a policy problem, to make a system dynamics simulation, these aspects need to be defined beforehand.

Serious gaming (SG) is one of the most useful tools to define a policy problem. It also facilitates the definition of evaluation measures and identification of their link with the problem definition. When the players become involved in a serious game, they are able to place themselves in the situation to find out how policies would affect them. This facilitates the identification of the association between policy alternatives and evaluation measures. The limitations of serious gaming (SG) are all related to the limited number of players in a game which is normally much smaller than the number of agents in the system in which the policy would actually be implemented. This limitation makes it difficult to:

– rely on the results for what if scenarios,
– test extreme values and worst case scenarios, and
– track reactions toward policies before and after a policy implementation.

Agent-based modelling (ABM) is similar to SG, with the difference that the people in serious games are represented as artificial agents in ABM. ABM covers many of the benefits of SG because both tools deal with populations of individuals. Since ABM is aimed at existing systems (Moss 2002), and is descriptive rather than predictive (Lempert 2002), it is instrumental for comparing and illustrating the before-and-after situations of a policy implementation. In addition, ABM also provides valuable insights into the emergent outcomes of policy implementation which are the result of individual behaviors and reactions. In fact, ABM combines the benefits of the aforementioned tools. However, there are still areas for improvement.

The issues related to emergence in simulations are (1) the type of emergence: are they physical (e.g., traffic patterns)? or social (e.g., punishment for stealing)?, and (2) the detection, analysis, and possibly control of emergence. In current ABM research, physical emergence is extensively addressed in simulations especially when using visual tools such as Netlogo. It is, however, more difficult to address social emergence because it is not always visually recognizable in a simulation.

One other drawback of ABM is that since the systems are simulated from bottom-up, there is no straightforward method to simulate the social or technical environment of the system, or to define the boundaries. This also makes it difficult to include the technical, economical, societal, and political aspects of policies into simulations. Currently, these factors are either not considered in the simulations or they are modeled as part of the agents. Modeling social structures within agents is not realistic because agents and structures are interrelated but separate concepts. The primary consequence of simulating the combination of the two as one entity is that we would not be able to study the influence of social structures on individual behavior and the system as a whole. Furthermore, social structures are also influenced by individuals. If they are modeled within agents, it is not possible to model global changes in these structures and observe how they evolve and diminish, and how new structures emerge. In current agent-based models, it is difficult to explicitly display and present policies because of the inability to model social structures. Therefore, being able to model policies as a purposive design of social structure also facilitates their presentations.

final drawback of ABM for policy analysis is related to participatory model development. Although simulation results can be communicated to problem owners to facilitate participatory decision making, building collaborative agent-based models is not a common process.

5. Enhancing ABM for policy analysis

Although ABM addresses various requirements for policy analysis, there are still areas for further extending its applicability in this area. In this section, we discuss how ABM can be improved at each of the requirement levels of Section 3.

Enhancements for Problem Definition in Policy Analysis

While there are visual tools and techniques for ABM that facilitate communication with domain experts by showing results of simulation runs, consultation with stakeholders for problem clarification is not a built-in facility for ABM. There-

		NEM	TGT	SD	SG	ABM
Problem definition	communicate with experts	✗	✗	✔	✔	✗
	parametrize problem	✔	✔	✔	✔	✔
	identify and define population	✗	✔	✗	✔	✔
	identify resources, system characteristics & boundaries	✗	✗	✗	✔	✗
Evaluation Criteria	specify measures	✗	✗	✗	✔	✗
	measure clarification & link with problem definition	✔	✔	✔	✔	✔
	identify & consider extreme values	✔	✔	✔	✗	✔
Identification of Policy Alternatives	identify policy attributes	✗	✗	✔	✔	✔
	link policies to evaluation measures	✔	✗	✔	✔	✔
	include technical, political & economical aspects	✔	✗	✔	✔	✗
	present policy alternatives	✗	✗	✔	✔	✗
Decision Support for Selecting Policy Alternatives	compare alternatives	✔	✗	✔	✗	✔
	participatory decision making	✗	✗	✗	✔	✔
	answer what-if scenarios	✔	✗	✔	✔	✔
	explore possible reactions towards policies	✗	✗	✗	✗	✔
	test extreme values	✔	✔	✔	✗	✔
Monitoring	compare before & after situations	✔	✔	✔	✔	✔
	track reactions	✗	✗	✗	✗	✔

Table 1. Policy analysis approaches and the type of problems they can be used for

NEM: Neo-classical Equilibrium Modeling, TGT: Traditional Game Theory, SD: System Dynamics, SG: Serious Gaming, ABM: Agent-based Modeling fore, ABM for policy analysis requires tools for involving stakeholders when developing the agent-based model. This can be achieved by combining serious games and real actors into agent-based models (Castella, Trung, and Boissau 2005; Guyot and Honiden 2006).

The integration of ABM and SG would also facilitate and improve the parameterization of the problem or problematic behavior. While it is possible to develop highly sophisticated intelligent agents who are capable of making realistic decisions for their actions and interactions, the agents are still predictable to a great extent. Incorporating real actors in the agent-based model covers uncertain and unanticipated behaviors.

Enhancements for Dealing with Evaluation Criteria in Policy Analysis

Evaluation of policies is important because a faulty choice can have expensive consequences in terms of health, money, time, and security. Agent-based modelling (ABM) can have several added values in terms of policy evaluation. First, involving real actors in simulated scenarios in an agent-based model can help them identify measures. Second, by providing consistency between policy measures and those evaluations performed on the agent-based models, the results of the simulated system can be highly reliable for the policy analysts. Currently, verification and validation of agent-based models is more geared toward the actual software model rather than real world implications. Finally, using serious games and involving problem owners and domain experts in agent-based simulations would also facilitate the definitions of evaluation measures.

Enhancements for Dealing with Policy Alternatives

Many ABM tools and packages provide visualization facilities (e.g., Tisue 2004; North, Collier, and Vos 2006). However, it is highly instrumental if ABM tools have explicit policy representation so that it is possible to enable/disable each policy alternative in order to observe the effects. As we previously discussed, having an explicit structure for policies re- quires the incorporation of top-down social structures in agent-based models rather than building them purely from bottom-up (Conte et al. 2001).

Another issue for studying policy alternatives is the exploration of the emergent consequences of a policy implementation. As previously discussed, emergent behavior in a social system (i.e., the global reaction toward an implemented policy) is different compared to other emergent properties existing in physical and natural systems which are commonly recognized as emergence in ABM (Epstein 2006). Emergence in a social system is recognized and identified by the individuals and reacted on, while in other types of emergence, the individuals (e.g., birds in a flock) are not conscious about the emergent structure they have created. For example, in a flock, the birds form a shape while they are not aware of the flock shape and do not make an effort to influence the shape in any particular way. They do, however, try to position themselves according to their neighbors. In a social system on the other hand, an individual recognizes an economic crisis (an emergent pattern). He tries to change the situation if powerful enough or adjust his own status according to the global situation rather than his own surroundings and neighbors.

For policy analysis, not only artificial agents should be able to recognize a policy change in the system, they need to identify the global behaviors and adjust their behavior accordingly (i.e., adaptability). For example, if inefficient light bulbs are banned in one country, an agent may start buying LED lamps because they are the only ones available in the market. Another consequence of such a policy may be the formation of black markets. The rich cognitive agent must be able to recognize this emergent phenomenon and make decision on whether to continue buying LEDs or buy banned light bulbs from the emergent black market.

The emergence and evolution of social structures is studied both in the social sciences (Axelrod 1986; Janssen 2005; Smajgl, Izquierdo, and Huigen. 2010) and computer science (Holland 2001; Smajgl, Izquierdo, and Huigen 2008). This line of research can be further enhanced to explore the effect of imposing policies on the emergence of social structures.

Enhancements for Decision Support for Policy Selection

ABM is a bottom-up approach which models individuals rather than top-down principles (Epstein 2006). Policy analysis by definition is about imposing guiding principles into a social system. Therefore, ABM for policy analysis should be a combination of bottom-up and top-down model development to facilitate explicit and elaborate policy comparison and evaluation. Using System Dynamics (SD) techniques is one way of facilitating this combination (Scholl 2001; Castella et al. 2007). Furthermore, participatory decision making is a new line of research in ABM where enhancements can be highly instrumental for selecting policies (Barreteau, Bousquet, and Attonaty, 2001).

Finally, advances in verification and validation of agent-based models are required to be able to trust the results of comparison between policy alternatives using ABM. Results from agent-based simulations are difficult to interpret due to their size and complexity. Even more, as there is usually no test using empirical data, most evaluations do not normally go beyond a proof of concept (Janssen and Ostrom 2006).

Enhancements for Monitoring Implemented Policies

Improving cognitivity in agents can provide more insights into why people give certain reactions toward an implemented policy. Furthermore, the artificial intelligence literature which provides means of implementing cognitive agents needs to be more accessible to social scientists. Currently, this line of research provides sophisticated tools that are difficult to comprehend and use by social scientists and policy analysts who are less familiar with computational sciences.

6. Conclusion

The goal of this research was to explore the potential of ABM as a tool for policy analysis.

To perform this research, we presented a systematic overview of the policy analysis cycle to identify the requirements it puts forward. We then compared various tools that are used for policy analysis, including ABM, to identify the benefits and drawbacks of each.

The comparison between the different tools provides our hypothesis that ABM can indeed be considered as an inevitable tool for policy analysis under the condition that some enhancements are made. Therefore, by using the results of our comparison, we identified areas where ABM can be enhanced:

– Enabling participatory model development to enhance problem definition and identification of evaluation criteria.
– Enabling the detection, exploration, and control of social emergence to empower the selection of policy alternatives by gaining more insights into possible outcomes.
– Combining bottom-up and top-down modeling, so that agents can make decisions and act in a more realistic environment where social and physical structures are present and influence their behavior. This would support the selection process of policy alternatives by also providing explicit representation of policies as social structures.
– Enabling conceptual as well as computational evaluation of agent-based model to increase the reliability of such models.
– Increasing the accessibility of agent-related research for social scientists and policy analysts who are less experienced in computational sciences.

In conclusion, we believe that because of the importance of individual-based study of policy problems and to make use of the computation power of simulations, ABM is one of the most instrumental tools for policy analysis. To enhance ABM in the identified areas, combining this approach with SG and SD can be effective. In addition, uncertainty analysis, case loading, and data calibration are some of the methods that need to be focused on when choosing alternative policies using ABM (Bankes 2002). Also, complex agent-based models result in enormous amount of data which require powerful data analysis tools.

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