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INTERFACES BETWEEN SD AND ABM MODULES IN A HYBRID MODEL

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ABSTRACT

Modelers in various disciplines have applied system dynamics (SD) and agent-based models (ABM) to support decision-makers in managing complex adaptive systems. Combining these methods in a hybrid simulation offers an opportunity to overcome the challenges that modelers face using SD or ABM alone. It also provides a complementary view and rich insight into the problems that modelers investigate. Hence, this approach can offer solutions to a plethora of systems problems. One of the limitations of existing frameworks that guide the process of combining SD and ABM is the lack of detailed guidance describing how the two methods can interact and exchange information. This paper provides guidance for interfacing these simulation modeling methods in a hybrid simulation. In this guidance, we describe interface approaches to exchanging information for different types of information flow between SD and ABM.

1 INTRODUCTION

Despite the potential effects of how information is exchanged between system dynamics (SD) and agent-based (AB) modules of hybrid simulation models on run time and outputs, guidance on designing interfaces between these simulation methods does not exist. For example, Wallentin and Neuwirth (2017) presented a hybrid model of a fish-plankton ecosystem to explore alternative designs of a dynamically switching SD-ABM model. They found that although the population dynamics showed the predicted logistic growth dynamics in all designs, the runtime and outputs of the model varied significantly across these designs. This example demonstrates the effects of interfaces between different simulation methods on the level of insights gained and the balance between the model's computational and predictive performances, which are the benefits of hybrid simulation discussed in the literature (Onggo, Kusano, and Sato 2007; Kieckhäfer et al. 2009; Mazhari et al. 2009; Kazakov, Howick, and Morton 2021; Djanatliev and German 2013). Given the growing interest and a lack of methodological clarity about combining SD and ABM, it would be useful for modelers and practitioners to frame how they combine the two methods explicitly. This paper discusses a methodological aspect of combining SD and ABM, that is how to design interfaces between SD and ABM modules in a hybrid simulation model, in response to a limitation of existing literature in this area.

1.1 Previous Frameworks for Hybrid SD-ABM Simulation: State-of-the-Art

Although the existing frameworks that guide how modelers can combine SD and ABM do not describe detailed designs of interfaces to exchange information between SD and ABM modules in a hybrid simulation, they are helpful to informing guidance on interfaces. We reviewed these frameworks and categorized the existing combinations of SD and ABM into six designs: parallel, sequential, interaction, integration, enrichment, and dynamically switching (Kim and Juhn 1997; Parunak, Savit, and Riolo 1998; Akkermans 2001; Schieritz and GroBler 2003; Borshchev and Filippov 2004; Lorenz and Jost 2006; Martinez-Moyano et al. 2007; Swinerd and McNaught 2012; Wallentin and Neuwirth 2017).

Some frameworks that provide guidance on combining SD and discrete event simulation (DES), mixing analytic and simulations modeling, or mixing methods in general, are also applicable to combining SD and ABM (Shanthikumar and Sargent 1983; Bennett 1985; Chahal and Eldabi 2008; Chahal, Eldabi, and Young 2013; Morgan, Howick, and Belton 2017).

Parallel design includes Class I in Shanthikumar and Sargent (1983), Comparison mode in Bennett (1985), Interfaced class in Swinerd and McNaught (2012), and Parallel in Morgan, Howick, and Belton (2017). In this design, SD and ABM are used to develop independent models either to address different aspects of the same problem which are better suited to one particular simulation method or to represent the same problem for direct comparison. Results of these models are ultimately combined to solve the same problem or compared to enhance confidence in the output produced by each model.

Sequential design has been described in several publications, including Class III and IV in Shanthikumar and Sargent (1983), Scenario explanation or Crisis response in Martinez-Moyano et al. (2007), Sequential class in Swinerd and McNaught (2012), Cyclic interaction in Chahal, Eldabi, and Young (2013), and Sequential design in Morgan, Howick, and Belton (2017). This design includes two or more separate sub-models embedded in different simulation modeling methods in which one model is used to inform the other. One simulation is initially run, and it produces output before terminating; the second simulation starts to run, using as input the output of the first simulation. The information is passed only once from the first to the second simulation. The output of the second simulation represents the final output of the hybrid model.

Interaction design aligns with Hierarchical format in Chahal and Eldabi (2008), Parallel interaction in Chahal, Eldabi, and Young (2013), and Interaction design in Morgan, Howick, and Belton (2017). It comprises different sub-models developed using different simulation modeling approaches which are considered equally important and interact cyclically during run time. Interactions between sub-models occur several times in each direction. A sequential design can be considered a special case of interaction design when the interaction occurs once and in one direction only.

Integration design is in essence Class II in Shanthikumar and Sargent (1983), Integration in Bennett (1985), Intertwined models in Martinez-Moyano et al. (2007), Integration mode in Chahal, Eldabi, and Young (2013), "Holy Grail" in Brailsford, Desai, and Viana (2010), Integrated class in Swinerd and McNaught (2012), and Integration in Morgan, Howick, and Belton (2017). Integration is an approach that combines different simulation modeling methods to create one seamless hybrid model in which it is impossible to explicitly distinguish between the SD and ABM parts and to identify where one simulation approach ends and the other begins. This design offers a coherent view of the problem which enhances continuous flows of information and feedback and captures interactive effects within a system. Although several studies concur on the definition of an integration design, only Swinerd and McNaught (2012) describe in detail different ways to develop an integrated hybrid model. They proposed three designs which belong to the integrated class, including agents with rich internal structure, stocked agents, and parameters with emergent behavior.

Enrichment design has only been discussed in Bennett (1985) and Morgan, Howick, and Belton (2017), and is in line with Process Environment in Chahal, Eldabi, and Young (2013). This design combines different simulation modeling methods to form one unified hybrid model in which one method dominates and is enhanced by elements of another. Enrichment design uses an element of one simulation method to enhance the main method without the need to build an additional model, while integration brings together two full methods to create something new.

Dynamically switching design allows the dynamic switching between SD and ABM in the structure of a model (Bobashev et al. 2007; Vincenot et al. 2011; Wallentin and Neuwirth 2017). It has been applied to efficiently depict the process of an ongoing epidemic as the size of infected populations change (Bobashev et al. 2007).

1.2 Addressing a Limitation of Existing Guidance for Combining SD and ABM

Most frameworks reviewed describe the hybrid design at a high level and emphasize their differences based on the direction of interaction and frequency of interaction over a time window. Enrichment, interaction, and integration designs share many similarities and differ only in terms of the separability and dominance of the SD and ABM modules constituting a hybrid model. The relative nature of these characteristics leads to the difficulty in selecting an appropriate design for a hybrid model. This paper seeks to address this gap by defining clear and logical interfaces between the SD and ABM modules of a hybrid model.

An interface between the two modules defines how the information is passed from the generating module to the receiving module during the running time of the hybrid model. Figure 1 provides an overview of information flows between components of an SD module and an ABM module. A detailed discussion of categories of information flows follows. These categorizations emerged from a literature review of hybrid SD-ABM models across various domains and were based on reflection from the modeling process of our case study (Nguyen, Megiddo, and Howick 2022). For each category of information flow, we provide a description and one or two example models selected from the literature.

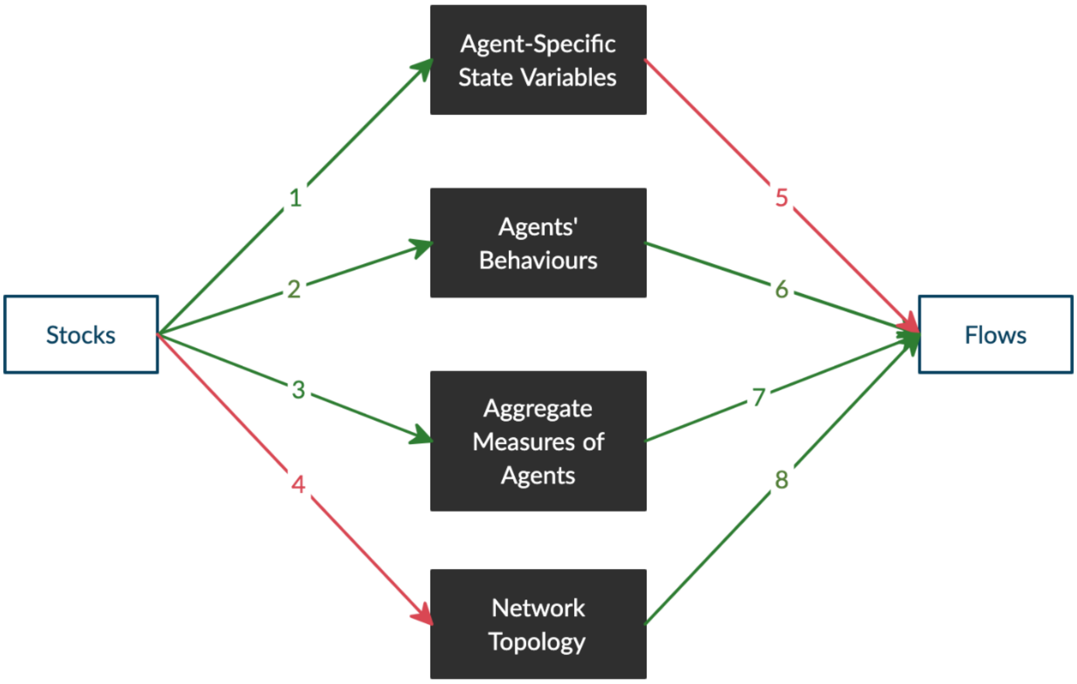

Figure 1: Flows of information between an SD module and an ABM module of a hybrid SD-ABM model. White and black boxes denote elements of an SD and ABM module, respectively. Green arrows denote the flows of information found in the literature, and red arrows denote the proposed flows based on reflection from the modeling process of our case study (Nguyen, Megiddo, and Howick 2022) (1) Stock levels affect agent-specific state variables or are used to generate a small crowd of agents; (2) Stock levels affect agent's behaviors; (3) Stock levels bound aggregate measures of agents; (4) Stock levels affect the network topology of agents; and (5), (6), (7), and (8): Agent-specific state variables, agents' behaviors, aggregated measures of agents, and the network topology of agents affect flows of an SD module respectively.

2 INFORMATION FLOWS FROM SD MODULE TO ABM MODULE

2.1 Stock Levels Define Agent-Specific State Variables (1a)

Description – The level of a stock in an SD module embedded in each agent of an ABM module can determine a characteristic (i.e., state variable) of that agent (Figure 2).

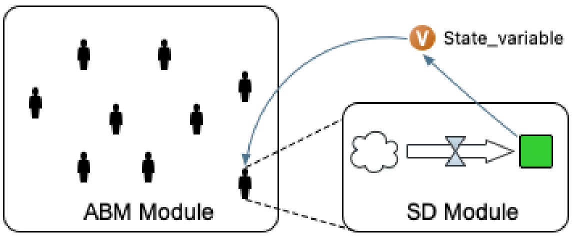

Figure 2: Stock levels define agent-specific state variables.

Example study – The integrated hybrid model in Caudill and Lawson (2013) represents the intra-host dynamics of antibiotic-resistant bacteria and the inter-host transmission dynamics of infections caused by such bacteria occurring among patients and HCWs in a hospital using SD and ABM, respectively. SD modules embedded within patient and HCW agents simulate changes in their internal pathogen population, called the bacteria population vector, over time. The stock level for the bacteria population vector determines the infection state of an agent and influences transmission probabilities when an agent interacts with other agents.

2.2 Stock Levels Define Agent-Specific State Variables (1b)

Description – Small crowds of individual agents with specific characteristics can be generated from stocks representing large population numbers. Individual agents can be generated using distribution functions based on existing empirical data or theories to represent the necessary heterogeneity of these agents.

Example study – Figure 3 shows an example of generating small affected crowds differentiated by age from a larger population in prospective Health Technology Assessment studies (Djanatliev and German 2013; Kolominsky-Rabas et al. 2015). In these studies, a small crowd of affected agents are generated from a stock representing a larger affected population in an SD module. The affected population stock is categorized into different age groups to parametrize agents afterwards. In essence, the different stocks and flows represent different types of agents classified by the age dimension. However, in order to simplify the presentation of the model, as these agent types have the same stock and flow structure, they are presented as one structure with a vector holding the level of the affected population for different age groups. The vector of the affected population is calculated by multiplying the age-specific incidence rates and the corresponding age distribution.

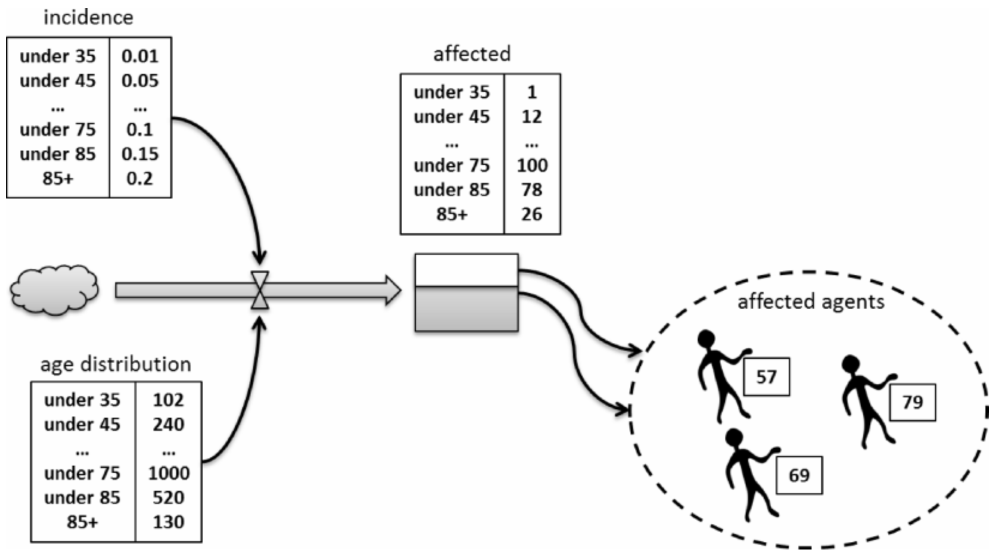

Figure 3: An example of generating agents from stock.

Reproduced from Djanatliev and German (2013). A vector of affected persons can be calculated using the age specific incidence values and the corresponding age distribution which is calculated in parallel by the demographic component. The resulting stock is a vector containing a dedicated number of affected persons with different age groups.

2.3 Stock Levels Define Behaviors of Individual Agents (2)

Description – Stock levels in an SD module determine the corresponding behaviors that individual agents in an ABM module will execute. As shown in Figure 4, if the stock level satisfies Condition 1 (e.g., the level is greater than a threshold or falls within a certain range of values), agents will execute Behavior 1. Example studies – The SD module can act as an environment for which characteristics represented by stock levels influence the behaviors of agents living in it. In a hybrid model for project management, Jo et al. (2015) represents the benefits, cost, and feasibility of an investment project as stocks in the SD module. The stock levels affect the decision-making process of user agents which represent individuals who potentially use and participate in a public investment project.

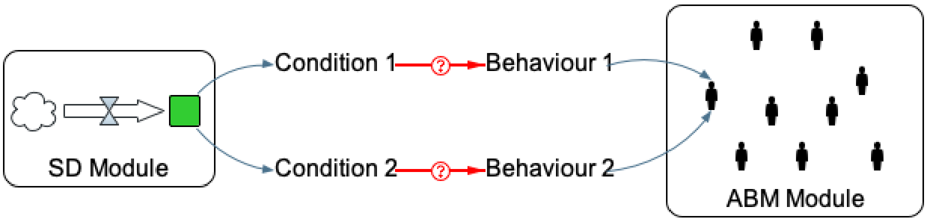

Figure 4: Stock levels in the SD module of a hybrid model define the behaviors of agents in its ABM module.

The levels of stocks of SD modules that are embedded in each agent of an ABM module can also influence the behaviors of these agents. In the hybrid SD-ABM model for public health policy formation published in Cernohorsky and Voracek (2012), an individual agent dies when their health capital stock level, modeled in an SD module, drops below a threshold.

2.4 Stock Levels Bounds Aggregate Measures of Agents (3)

Description – A stock level in an SD module bounds an aggregated measure of agents in an ABM module. The aggregated measure of agents must not exceed the level of a particular stock. Aggregate measures of agents can be the sum of values for an agent-specific state variable or the size of the agent population with a specific characteristic (Figure 5). While a stock level directly affects the behavior of individual agents in interface design (2), in this design, it indirectly affects behavior based on the collective measure of agents, summing up their state variables.

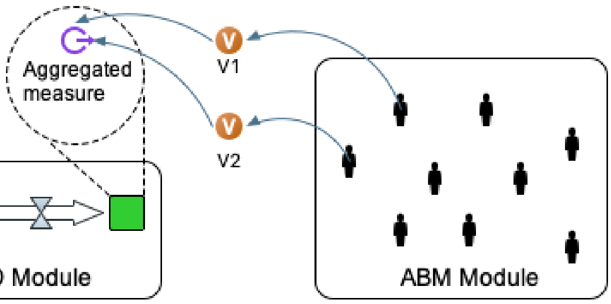

Figure 5: Stock levels bound aggregate measures of the ABM module.

Example studies – In a hybrid model for land use, Verburg and Overmars (2009) models the spatial allocation of demand for urban and agricultural land-use types on a grid. The regional demands for different land use types are represented by stocks in the SD module. The individual cells (agents in the ABM module) on the grid are local pieces of land with different characteristics such as location suitability, neighborhood suitability, and conversion elasticity. The regional level demands are spatially allocated to individual grid cells until the demand is satisfied by iteratively comparing the sum of the allocated area of the land use types with the demand.

Robledo, Sepulveda, and Archer (2013) develops a forecasting enrolment model for resource planning by combining SD and ABM. The SD module represents the overall enrolment system of a university, while the ABM module simulates students' heterogeneous behaviors such as enrolling, dropping a class/course, or transferring to another class at the departmental level. The sum level of stocks for students that have declared their major in Engineering or have not chosen a major bound the headcount of students in that department.

2.5 Stock Levels Define Agents' Network Topologies (4)

Description – The levels of stocks in the SD module determine the corresponding spatial relationship and/or interacting network topology among agents in the ABM module (Figure 6).

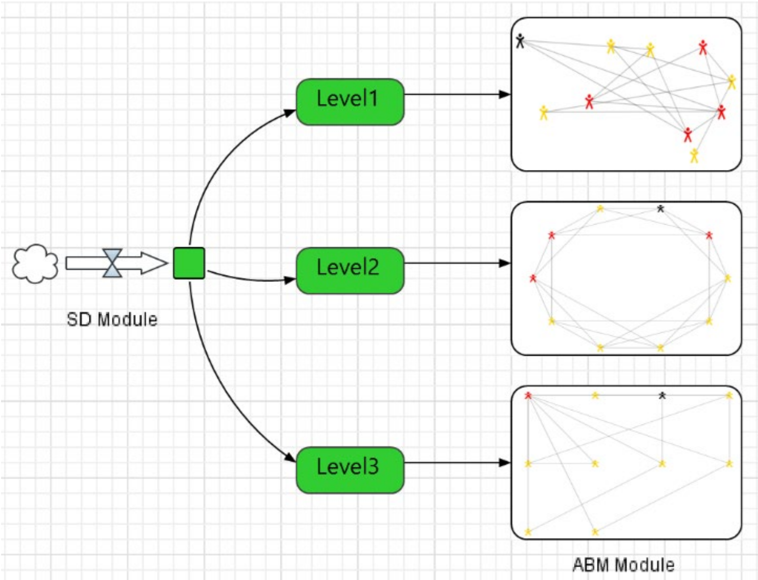

Figure 6: Stock levels in an SD module of a hybrid model define the spatial relationship and/or network topology of agents in an ABM module.

Example study – A hybrid model for a pandemic can comprise an SD module that simulates the spread of an infectious disease in the community and an ABM module that represents a network of healthcare facilities (i.e., agents) in the same area. The network topology defines the transferring pathways between facilities. The level of a stock representing the infected population in the community that require medical care may reach a threshold that the current network topology of healthcare facilities could no longer efficiently handle. When this happens, the transferring pathways between facilities may need to reform to cope with the increasing demand, leading to a change in their network topology.

3 INFORMATION FLOWS FROM ABM MODULE TO SD MODULE

3.1 Agents' State Variables Affect Flows (5)

Description – Agents' state variables may evolve during a simulation as they execute a behavior or interact with other agents and/or the environment. Changes in agents' state variables can affect flows in an SD module (Figure 7)

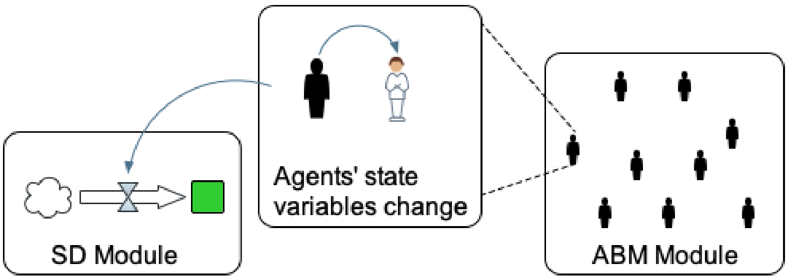

Figure 7: Changes in agents' properties can affect flows in an SD module.

Example study – A hybrid model representing a network of healthcare facilities can include an ABM module representing a care home (i.e., the care home module), where individuals including residents and staff are agents, and an SD module representing its connected hospitals (i.e., the hospital module). Resident agents in the care home can be characterized by their infection status (susceptible or infected). Infected residents are assumed to require acute medical care, and, therefore, they are admitted to hospitals. This means that when a resident agent becomes infected, this change in its infection status will affect the admission inflow to a patient stock in a hospital SD module.

3.2 Behaviors of Agents Affect Flows (6)

Description – Behaviors of agents in an ABM module can influence flows in an SD module (Figure 8).

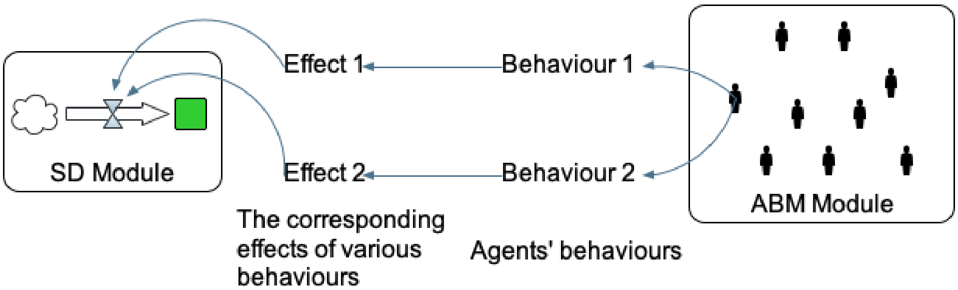

Figure 8: Behaviors of agents in the ABM module of a hybrid model affect flows in the SD module.

Example studies – In Mazhari et al. (2009) hybrid SD-ABM model for capacity planning, the ABM component models the electricity consumption behaviors of household agents. The consumption behavior of household agents affects the flow into the electricity demand stock in the SD component.

Chen and Desiderio (2020) develop a hybrid model to investigate a problem in labor market rigidity and its impact on unemployment. The model is the abstraction of a closed economy with markets for labor and consumption goods. Agents include households (on the supply side in the labor market and on the demand side in the goods market) and firms (on the demand side in the labor market and on the supply side in the goods market). These agents are characterized by internal SD modules representing their balance sheets (stocks), which reflect all of their market transactions undertaken (flows). The relationship between stocks and flows is regulated by rules that follow coherent accounting principles. The actions of agents result in market transactions which influence the flows to the balance sheet stocks within each agent.

3.3 Aggregated Measures of Agents Affect Flows (7)

Description – An aggregated measure of agents in an ABM can influence a flow in an SD module (Figure 9). When SD and ABM modules represent different parts of a system and agents physically move from the ABM module to the SD module, they are removed from the ABM module and aggregated into a stock in the SD module. This movement is represented as an inflow of the stock.

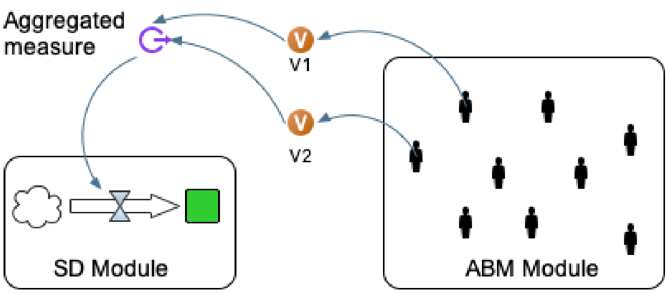

Figure 9: Aggregated measures of the ABM module of a hybrid model affect the flows in its SD module.

Example studies – In the Swinerd and McNaught (2015) hybrid SD-ABM model for the international diffusion of technological innovations, agents describe individual nations. The nations' state of adoption, which, if set to true implies they decide to adopt the innovative technology, are aggregated into the international adoption stock in the SD module.

Jo et al. (2015) models the traffic of road stock in an SD module as the aggregation of driver agents who are potential users of the construction project.

3.4 Network Topologies Affect Flows (8)

Description – The spatial/social relationship and/or network topologies of agents in an ABM module can affect the flows in an SD module (Figure 10).

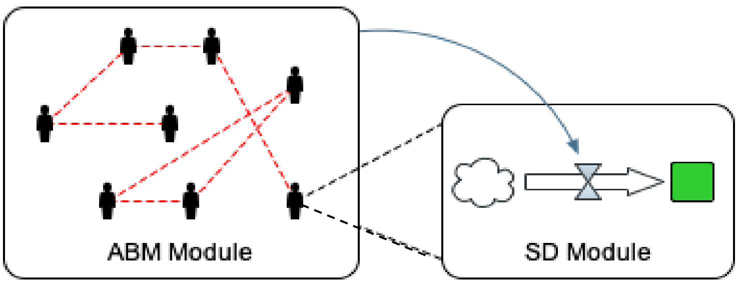

Figure 10: The network topology of agents in the ABM module affects flows in the SD module.

Example study – The hybrid SD-ABM model developed by Vincenot and Moriya (2011) simulates the dynamics of infectious disease transmission in very large fragmented populations at both the local and global scales (Figure 11). It aims to investigate the influence of network topology upon the resurgence of epidemics. Each "site" agent equals one population generated based on a geographic breakdown of metapopulations and is represented by a classic SD module comprising stocks for susceptible, infected, and recovered individuals (Kermack and McKendrick 1927; Anderson and May 1979; Hethcote, Stech, and Van Den Driessche 1981). As individuals within a population could emigrate to other connected populations, the network topology affects the ongoing emigration and immigration of infected individuals

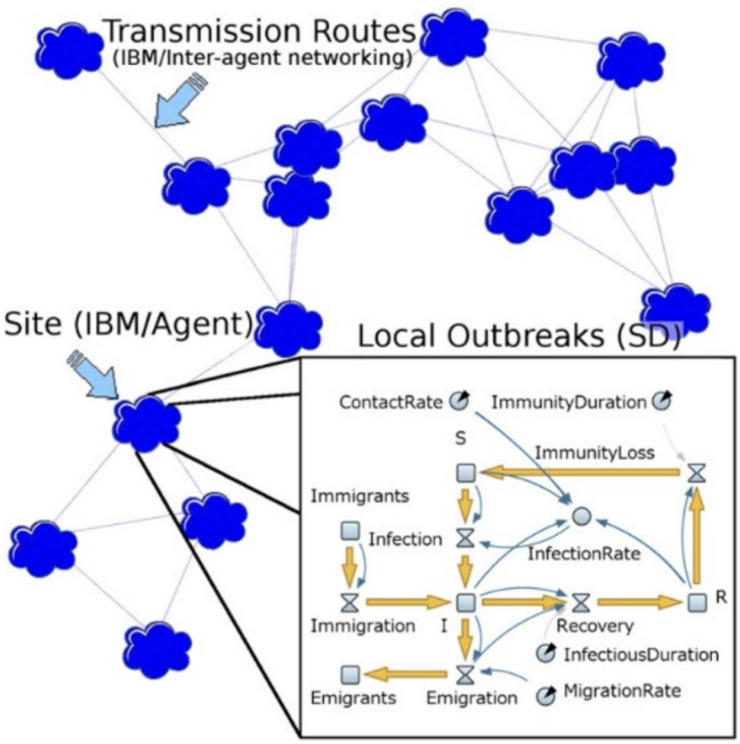

Figure 11: The visual structure of the hybrid SD-ABM model in Vincenot and Moriya (2011). Communicating ABM agents, representing sites (here, visualized as clouds), each incorporate an SD sub-model (a partial view of which is inserted in the bottom-right corner of the figure) computing the evolution of the local outbreaks. These agents are in charge of the exchange of infected individuals between sites composing the network.

4 CONTRIBUTION AND LIMITATION

The methodological contribution of this research is new practices for modelling interfaces between SD and ABM modules in a hybrid simulation model. Previous frameworks for hybrid simulation have described different modes of interaction between simulation methods focusing on the system view, method dominance, and direction and frequency of interaction. However, the description of these interaction modes is still abstract and has not explicitly explained how the information is passed between different simulations. This research addresses this issue by categorizing the designs of an interface between SD and ABM modules and defining how SD/ABM modules generate the information and how the receiving ABM/SD modules handle such information for each design. These interface designs also explain other forms of feedback that go beyond what has been generally discussed in previous hybrid models: i) the SD module generates information that shapes the agents' environment or affects their decision-making and ii) the aggregation of the agents' characteristics or actions represents a stock or parameter in the SD module. The research also proposes two new interface designs: i) a stock level defines the agents' network topology and ii) the agents' state variables affect flows.

Whilst the paper presents a number of possible ways in which modules can be linked, it is not suggested that it provides an exhaustive list. This is particularly due to the 'art' of modelling where different modelers may choose to represent a situation in different ways. However, the paper provides a guiding structure which future research can add to.

5 CONCLUSION

This paper has discussed different designs of interfacing SD and ABM in a hybrid simulation model. Previous frameworks for hybrid simulation have described different modes of interaction between simulation methods focusing on the system view, method dominance, and direction and frequency of interaction. However, the description of these interaction modes is still abstract and has not explicitly explained how the information is passed between different simulations. This work addresses this issue by categorizing the designs of an interface between SD and ABM modules and defining how SD/ABM modules generate the information and how the receiving ABM/SD modules handle such information for each design. These interface designs also explain other forms of feedback that go beyond what has been discussed in previous hybrid models, such as a stock level defining the agents' network topology and agents' state variables affecting flows.

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