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HYBRID SIMULATION STUDIES AND HYBRID SIMULATION SYSTEMS: DEFINITIONS, CHALLENGES, AND BENEFITS

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ABSTRACT

Hybrid Simulation (HS) is not new. However there is contention in academic discourse as to what qualifies as HS? Is there a distinction between multi-method, multi-paradigm and HS? How do we integrate methods from disciplines like OR and computer science that contribute to the success of a M&S study? How do we validate a hybrid model when the whole (the combined model) is greater than the sum of its parts (the individual models)? Most dynamic simulations have a notion of time, how do we realize a unified representation of simulation time across methodologies, techniques and packages, and how do we prevent causality during inter-model message exchange? These are but some of the questions which we found to be asking ourselves frequently, and this panel paper provided a good opportunity to stimulate a discussion along these lines and to open it up to the M&S community.

1 INTRODUCTION

What is hybrid simulation? Some authors argue that a hybrid model is a mix of continuous and discrete systems wherein differential equations may be used to model continuous behavior together with discrete simulation for representing discontinuous state changes in the system (Mosterman 1999). It is arguable that this definition of hybrid excludes the combined application of M&S techniques that may belong to either the continuous or the discrete space, but not both; for example, discrete-event simulation (DES) and agent-based modelling (ABM) both represent the discrete systems' world view. Mustafee et al. (2015) take a wider view of hybrid to include models that are developed by combining the methodological strengths of individual modelling techniques. Taking the example of ABM and DES, their combined application may be considered as hybrid simulation as DES uses the concept of queues, servers and the three-phase approach (Tocher 1963) and ABS relies on the interaction between individual agents and the resultant patterns and behaviors that emerge (and which are not explicitly programmed); both techniques have their underlying methodological strengths.

The benefits of hybrid simulation is dependent on the methodological strengths of the specific techniques and indeed the synergy that can potentially be realized through their combined application. For example, if we consider hybrid to be continuous time and discrete time, then the combined application of system dynamics (SD) and DES may enable stakeholders to conduct systems' enquiry at both strategic and operational levels; if we consider two continuous approaches to be an example of hybrid, then the combined application of computational fluid dynamics (CFD) and SD, for example, may allow modelling of traffic flow using CFD, as also strategic decision making pertaining to highway development through use of SD; a hybrid simulation definition that includes two or more discrete-time approaches, e.g., DES and ABS, may allow representation of emergent behavior through the interaction of entities that may be queuing for a service to be offered. An example here can be an evacuation scenario that models the exits as queues and servers, and use ABM at the entity level to incorporate agent behavior.

A simulation study consists of several well-defined stages, for example, problem formulation, conceptual modelling, input and output data analysis, model translation/implementation, verification, validation and experimentation. We distinguish between hybrid simulation and a hybrid M&S study based on the techniques applied, as also the stage in which it is applied. The use of multiple M&S techniques in the model implementation stage is referred to as hybrid simulation (see Figure 1; center). A hybrid M&S study, on the other hand, refers to the application of methods and techniques from disciplines like Operations Research (techniques other than M&S), Systems Engineering and Computer Science to one or more stages of a simulation study (Powell and Mustafee 2014). For example, in the problem formulation stage of a M&S study approaches from soft OR (like problem structuring), systems engineering and information systems (like SysML) can be used; for faster execution of simulation in the experimentation stage techniques from computer science can be applied, e.g., the use of GPGPUs and grid/cloud computing (Figure 1). It follows that a combined ABM-DES simulation that uses grid computing for the purposes of faster execution is an example of both hybrid simulation and hybrid M&S study!

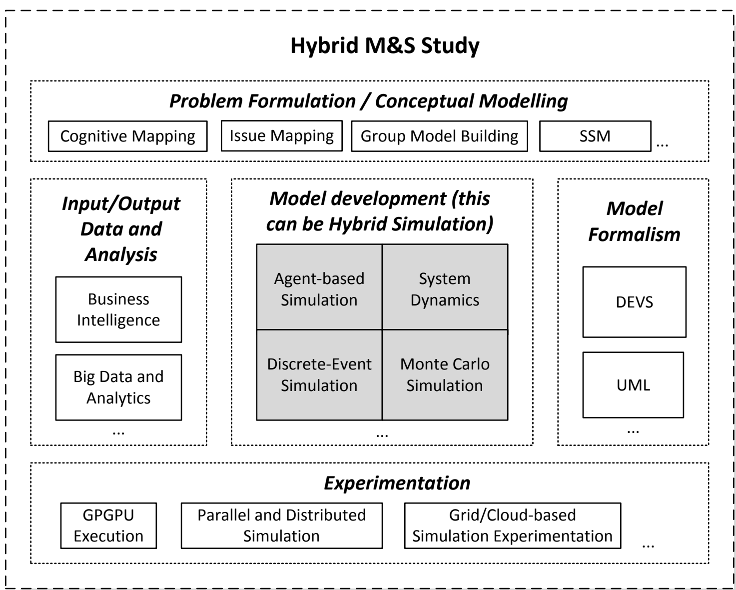

Figure 1: Hybrid Simulation version Hybrid M&S study (Powell and Mustafee 2014).

Our panel paper for the WSC2015 track on hybrid simulation presents two position statements that articulate the need for hybrid in systems biology (Tolk; section 2) and healthcare M&S (Brailsford; section 3). This is followed by a discussion on why we rely on the hybridization of models (Padilla; section 4) and identification of hybrid modeling challenges (Diallo; section 5). The following two sections focus on addressing some of these challenges by widening the scope of what has traditionally been considered as part of M&S study, for example, use of qualitative systems enquiry to support quantitative modeling (Powell and Mustafee; section 6), and by articulating the need for interdisciplinary M&S groups for conducting hybrid studies (Mustafee; section 7). Section 8 is the concluding section.

2 ORCHESTRATING THE MUSIC OF LIFE (TOLK)

Like many other scientific disciplines, biology has been defined by reductionism: instead of evaluating and analyzing highly complex phenomena and systems, biologists focused on simpler and more fundamental subcomponents in order to find sufficient explanations about how these subsystems work. Once this was understood, these subsystems can be recomposed, and the complex system behavior can be explained by the composition of the easier and fundamental behavior on the lower levels.

In his book "The Music of Life: Biology beyond Genes," Denis Noble (2008) makes the argument that such an approach is not appropriate for biology any longer. In order to understand the organism in its environment, a holistic system approach is needed. This has immediate implications for medical simulation support, as understanding of individual phenomena and representation thereof in a simulation is not sufficient. Instead, hybrid simulation systems that span multiple levels, aggregations, scopes, and phases will be needed.

In this section of the position paper, the idea of systems biology will be described first, leading to a hybrid simulation concept that may support the holistic and systemic support of such new ideas for medical simulation, such as digital patients (Combs, Sokolowski, and Banks 2016) or virtual physiological humans (Kohl and Noble 2009).

2.1 Layers of Systems Biology Modeling

Biology has undergone many exciting discoveries in the last century. New technologies have allowed biologists to understand more detail than ever before. Scientists have a good understanding of the various organic systems that make up an organism, like the digestive system, the nervous system, the regenerative system, etc. The organs making up these systems are made up of tissue that is made up of cells. Within these cells, the ribonucleic acid (RNA) and deoxyribonucleic acid (DNA) are found, that produce the important proteins needed for critical life functions. While the DNA contains the genetic instructions needed, the RNA mainly conducts the work of creating, activating, and deactivating certain proteins. For a long time, it was believed that once the DNA's genes are understood and mapped out, life would be better understood from the bottom-up perspective.

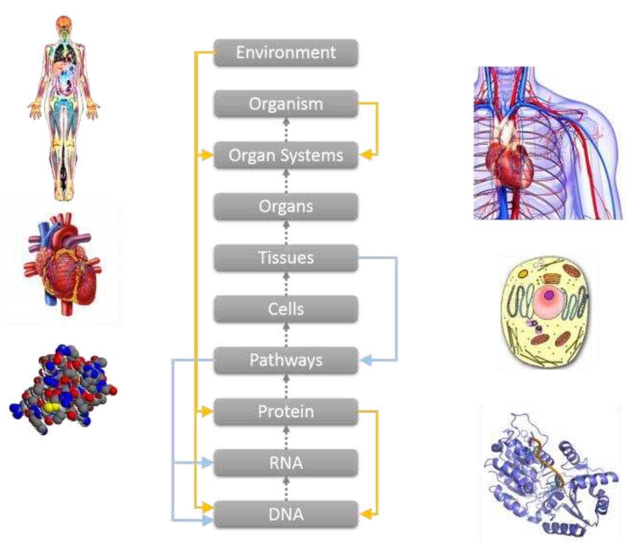

Figure 2: Taxonomy of Systems Biology as proposed by Noble (2008).

Noble (2008) introduced a more complex view. In Figure 2, the interplay of various layers that make up the organism are captured following his ideas. He makes the case that a systems approach is needed to better understand the organism, as the structure is interconnected by feedbacks and connections that bridge other layers. We know, e.g., that strong interrelations can be observed between the environments an organism is in, and the way DNA information is used to produce proteins. In particular when the organism gets injured, many different cells that make up the damaged tissues are collaborating via pathways to trigger the production of proteins, stop the bleeding, produce new cells, etc.

Today, on every level, simulation systems are used successfully. Computational biology and bioinformatics are accepted methods in the domain of biology. However, while models exist for the simulation of organs, tissue and tissue engineering, molecular and protein structure analysis, they are generally used as stand-alone tools supporting their special subdomain. For a systemic and holistic view of the organism, however, they have to be combined in support of systems biology. The following section looks at some alternatives to accomplish this task.

2.2 Modeling Paradigms and Methods and Hybrid Modeling

In his compendium, Fishwick (2007) addresses modeling paradigms regarding modeling methodologies – such as discrete event systems, system dynamics, and agent based approaches – and model types – such as ordinary differential equations, process algebra, and temporal logic. Powell and Mustafee (2014) introduce the idea of hybrid M&S studies, in which various modeling paradigms are applied in an orchestrated set of simulation tools, versus hybrid M&S systems, where several such paradigms are used within one simulation. Balaban, Hester, and Diallo (2014) provide an overview of multi-methodology, multi-method, multi-paradigm, multi-modeling, hybrid, mixed-method, cross-paradigm, and multi-formalism approaches discussed in the M&S community. Turnitsa and Tolk (2008) compiled an overview with focus on the knowledge representation of such views.

The many layers of system biology, that are interconnected in many ways, including feedback loops and connections between layers that are separated by several other layers, clearly show that the traditional reductionism approach leading to a model hierarchy in the form of a pyramid, is unlikely to work. The work published by Tolk et al. (2013) shows that integrated approaches resulting from composing often independently developed simulation systems, as envisioned by hybrid M&S systems, require the conceptual alignment of all contribution solutions, as only the consistent representation of truth in all subsystems ensures a consistent simulation solution. Such an approach is only feasible if the underlying theoretic foundations do not comprise any inconsistencies or contradictions when applied together. If there are inconsistencies in the underlying theory, instead of using one composed hybrid M&S simulation, an orchestrated hybrid M&S study is needed that displays the various results as alternative solutions in one common representation. A good example are the well-known weather forecast maps when a hurricane is approaching. Such maps do not show just one path, but they displays various possible paths based on different models used for the analysis and evaluation. This example also supports the generally observable trend in optimization that it is often more important to avoid insufficient and suboptimal solutions fast than to find the absolute best solution. For many applications, it is more important to find something fast that is sufficient than to find the best solution too late – if a best solution even exists.

A last aspect to consider is the new role that two current research topics will play: Big Data and Deep Learning (Tolk 2015). While big data helps to find information, such as journal papers and other research contributions available online worldwide, that is relevant to solve a medical problem, deep learning helps to discover correlations and relationships that can be used for inter- and extrapolation. An example is the IBM Watson project described by Friedman (2014). These insights can easily be integrated into a hybrid M&S study, but will be challenging to compose seamlessly and consistently into a hybrid M&S system.

In summary, the way forward recommended by Powell and Mustafee (2014) under consideration of the composability foundations published by Tolk et al. (2013) are considered a feasible way forward in support of the vision described by Noble (2008).

3 WHY HEALTHCARE NEEDS HYBRID SIMULATION (BRAILSFORD)

3.1 Background

Over the course of a 25-year career in healthcare simulation modeling, preceded by a decade working in the UK National Health Service (NHS) as a nurse, I have come to the conclusion that healthcare systems are just too complicated to be modeled by one single simulation paradigm. As far back as 2003, I argued (Brailsford, Churilov, and Liew 2003) that "ailing emergency departments" suffer from a collection of complex interrelated problems which require therapeutic treatment with a combination of DES and SD. Seven years later, in a Wintersim paper (Brailsford, Desai, and Viana 2010) I argued that despite software that used both continuous and discrete variables, and despite the success of new multi-paradigm tools such as Anylogic, the "holy grail" of genuinely combining the philosophies of DES and SD had not yet been attained. Moreover, I remain unconvinced that ABM is fundamentally different from DES. In the 1990s I coded all my simulations from scratch and so if some part of the model required a particular logical rule or behavior, then I just coded it without worrying whether it was ABM or DES. In my "DES is Alive and Kicking" paper (Brailsford 2013) I argued that many characteristics of agent-based models can easily be captured in DES and that many of us had been doing ABM for years without even realizing it.

3.2 What's special about Healthcare?

Healthcare is a hugely popular application area for simulation modeling. Literature surveys from the 1980s (Wilson 1981) to the current decade (Katsaliaki and Mustafee 2011) show an increasing trend, with a wider use of SD and ABM. One common feature of all these surveys is the lack of reported implementation of model recommendations. This raises an interesting question: is healthcare special, or different in some way, from other application areas? This question has been widely addressed (Tako and Robinson 2015). The RIGHT study (Brailsford et al. 2009) suggests that healthcare models are implemented far less frequently than models for manufacturing systems or defense applications.

One of the key problems with healthcare is that "everything affects everything else". In my view this is why classical patient flow type DES models for hospital clinics or Emergency Departments are so common in the academic literature but so infrequently used in practice (Fone et al. 2003). It is impossible to isolate one part of a healthcare system from the rest of the system without severely compromising the usefulness of the model in practice. "Optimizing" the flow of patients through the ER will only result in shifting the bottleneck to somewhere else in the hospital. Maybe we need to model the whole hospital? Or maybe the problem lies upstream, outside the hospital? While I love simple models, I have to confess that I have only ever seen one simple DES model that was really useful in practice: Adrian Bagust's model (Bagust, Place, and Posnett 1999) that so nicely illustrates the disastrous outcomes when hospitals strive for 100% bed occupancy.

So, is the solution to use a "whole-systems" approach? Undoubtedly, SD is excellent for capturing the dynamic complexity which is a characteristic feature of healthcare systems. However, and this is a drawback I can identify with as an ex-nurse, it does not easily allow individual patients to be modeled, and it does not easily include variability. Moreover system dynamicists (as users of this approach like to call themselves) simply see the world in a different way to DES/ABM modelers, and even when using a hybrid software tool like Anylogic they conceptualize a model in a different way.

3.3 Health Systems need Hybrid Models

I believe healthcare IS different. The simulated objects in our models, and the users of the models, are human beings. Healthcare systems are not only complicated (and enormous) but dynamically complex, fraught with politics and emotion. The UK NHS is often referred to as an "icon", too precious to be treated as a "political football". Such systems need a multi-layered modeling approach and I believe it is only through the use of hybrid models that we shall eventually reach the Holy Grail.

4 TO HYBRIDIZE OR NOT HYBRIDIZE (PADILLA)

When referring to hybrid models/simulations, we still need consensus not only on defining but also on differentiating the flavors of such models. Terms like multi-method, multi-paradigm and hybrid simulations are used interchangeably nowadays. In addition, consensus regarding their need should be established. It can be argued that their need comes from the idea of "closeness" to a problem situation. In other words, a resulting hybrid model would attempt to closely resemble a system/phenomenon in reality at the expense of its generalizability. As such, this higher level of detail would allow for asking questions not answerable through a more general model. This idea may shed light into the nature of these models as more comprehensive but more difficult to verify and validate. Lastly, I'll report on ongoing research regarding the use of data in ABM which can be seen as a hybrid systems that combines virtual and real worlds.

4.1 Hybrid Model, Multi-paradigm or Multi-method?

Hybrid model is a term widely used when referring to the combination of continuous and discrete models. By correspondence, hybrid simulation would refer to the combination of continuous and discrete simulations (Mosterman 1999). Based on this premise, the combination of models and/or corresponding simulations of the same nature should not be considered hybrid. It is noted that these models do not need to be simulation models. They can be mathematical models as long as they combine continuous and discrete.

Multi-paradigm is a term used when combining at least two simulation out of the three most used paradigms: system dynamics, discrete-event simulation and agent-based modeling (Lorenz and Jost 2006). Multi-method seems to be a newer term and mainly used in the Anylogic community (http://www.anylogic.com) to refer to multi-paradigm modeling, which was also used by Anylogic researchers previously (Borshchev and Filippov 2004). One of the challenges that we (people that build simulations using different paradigms) have is about what term to use that better reflect the resulting simulation. Should we care? Ultimately, a hybrid/multi simulation is a simulation regardless of how it was implemented. Yet, we care about the approaches used and the potential benefits they have when representing systems/phenomena. As such, we (the M&S community) should work towards a consensus based on a formal definition of the term.

4.2 Hybrid Towards Correspondence?

If models are abstractions of systems/phenomena, why can't we abstract them in one paradigm? It can be argued that a hybrid/multi simulation would "better" answer a research question. In this case, a question that cannot be answered by a single paradigm. This case has been made in the interoperability-research community as the reason why existing simulations should be combined.

Like in the interoperability community, the combination of simulations usually goes towards establishing realism in the resulting simulation. Meaning that while we can capture the system using one paradigm, hybrid/multi simulationists look for closer correspondence to reality. Like in the interoperability community, this combination comes with challenges. This closeness, however, comes with its trade-off: higher level of detail. This higher level of detail demands more components and when these components do not exist, more assumptions. Thusly, there will be more simulation components which result in a larger systems with more connections and likely, these connections may be non-linear in nature limiting the traceability of results and validation efforts of the dynamics within the model.

4.3 Complicating Matters: Data-driven Agent-based Simulations

Agent-based models are, in the great majority of cases, rule-driven. Theory, assessments and assumptions are used to create rules at the micro/agent-level that generate a macro behavior of interest. Consequently, agent-based modeling of human behavior follows the same approach. However, while useful, there are challengers of this approach on the basis of validation. According to Kennedy (2012, p. 177): "data for many or most behaviors of interest to the ABM community may not yet exist. The lack of data makes validation and verification of models of human behavior difficult, at best." Further, while we can "validate" a simulation against historical data, we are comparing the simulation output regardless, in some cases, of what input generated such output. The challenge lies on obtaining data not only for validating agent-based models but also for initializing these models. In other words, how do we obtain data at the individual level that can support expected processes like initialization, calibration and validation and others like pattern recognition?

One approach relies on obtaining and analyzing data from one or multiple sources like social media (Padilla et al. 2014) and surveys (Hassan, Pavon, and Gilbert 2010) among others. However, while the data might be available or accessible, its processing is a challenge that is outside of M&S and more into data science. Helbing and Balietti (2011) suggest that data is at the center of the ABM paradigm shift in the social sciences. This shift ranges from mining real-time data ending with the combination of real and virtual worlds. This combination, or system hybridization, has the potential of improving ABMS empirical grounding especially when detailed information is required to answer a research question.

4.4 Final Thoughts

Either via the combination of simulations or the combination of virtual and real worlds, the hybridization movement appears to be fueled by the desire of increasing our trust in models and the results they generate. While the resulting system or simulation may be more complicated in terms of components, relations, type of relations and techniques required to bring them together, the fact they may represent a "closer" reality is appealing. Lastly, we cannot deny the impact that research on interoperability, in terms of standards like HLA for instance, and of tools like Anylogic have had on hybrid/multi simulation movement.

5 CHALLENGING THE CHALLENGES (DIALLO)

Hybrid modeling is attractive because it contains the promise of capturing more details that are relevant to the referent and by doing so it allows us more insights than we could otherwise obtain. While there is no argument that more insight is better, the argument is that we are not guaranteed that adding more details leads to more insight. Furthermore, hybrid modeling is not cost free. From a pure managerial standpoint, it can potentially take longer and cost more to construct a hybrid model; so the question is: is it worth it?. This question is at the basis for intuitively arguing against the use of modeling. However, further exploration shows that the difficulties associated with hybrid modeling are in fact difficulties that exist with modeling.

In order to elaborate this point, it is important to first understand what challenges one might face when attempting to build, execute and analyze a hybrid model. Lynch and Diallo (2015) propose a taxonomy of M&S adapted from Sulisto, Yeo, and Buyya (2004), Fishwick (1995), Sokolowski and Banks (2010) and Tolk (2012). Based on the taxonomy, there are at least six classes of challenges that have to be taken into account. Table 1 summarizes what those challenges are and points to areas where we can find information to deal with some of the challenges. For instance the idea of mixing the static aspects with the dynamic aspects of a system have been studied in Vig and Dooley (1993) to estimate due dates for assignments. Similarly, Ball and Neal (2002) have studied the mix of deterministic and stochastic aspects of a system to model the spread of diseases and Rovers, Kuper, and Smit (2011) discuss the challenges associated with time modeling under mixed continuous and discrete representations.

Table 1: Challenges in hybrid modeling.

Challenge	**Description**	**Area of Study**
Multiple representations of time	Mixing static with dynamic	Operations Management
Multiple bases of value	Mixing discrete time with continuous time	Computer Science

Multiple bases of behavior	Mixing deterministic with stochastic	BioSciences
Multiple Foundations	Mixing Mathematical with Logical	Control systems
Multiple bases for execution	Mixing serial with parallel	Parallel & Discrete Simulation
Multiple resolutions	Mixing entity level with aggregate level	Multi-Resolution Modeling

As Table 1 shows, each of the classes of the challenges is already addressed in a domain inside or outside of M&S. Therefore, we can say that it is worth the effort if we are starting from scratch and deciding whether how to better represent a system as argued in Vangheluwe, de Laura, and Mosterman (2002). In fact, hybrid modeling might be the only option in those cases if we want to formulate a valid model. We posit that the difficulty and reluctance in engaging in hybrid modeling must then originate from the following challenges:

- Building hybrid models through interoperability: In some cases, creating a hybrid model requires combining existing models which means that each of the six classes of challenges have to be addressed individually and in combination. However, this is true every time models have to become interoperable.
- Verifying and validating hybrid models: While an argument can be made that hybrid models are harder to validate, this only makes sense if we consider hybrid models that are built through interoperability. However, this means that validation of hybrid models under those conditions is as complex as validating a composed model. This is a general problem in M&S.
- Explaining hybrid models: Another argument is that hybrid models are harder to explain. This again only makes sense for models built under interoperability. If we consider each component model to be executing independently and interacting with other component models, the hybrid model can be reduced to an agent-based model. Therefore explaining hybrid models under interoperation is as complex as explaining agent-based models.

In all three cases the perceived difficulty is associated with M&S in general and not hybrid modeling. It can therefore be argued that hybrid modeling is not more complex than M&S in general.

6 THE MIRRORED ROOM: THE USE OF QUALITATIVE SYSTEMS DESCRIPTIONS TO INFORM CONCEPTUAL MODELING IN MULTI-STAKEHOLDER ENVIRONMENTS (POWELL AND MUSTAFEE)

6.1 Introduction: the Reality of Realities

Most simulation depends for its validation or verification upon claiming an adjacency with reality: an aircraft approach simulator ‘feels like’ the experience of a pilot in the air; a model of flooding represents accurately the historical behaviour of water in an environment.

Many problems can be constrained so as to make such a claim valid and relevant, but there is a wide set of problems for which such claims are inherently inaccessible (Eden 1989; Checkland 1981; Checkland and Scholes 1990). Any problem which involves diverse perceptions of reality, different valuations of outcomes and, critically, different systems definitions is challenged in this respect. It is as if, in designing and specifying our simulations we seek to create a mirror with but a single reflection of the world, that image being accurate, singular and undistorted (Eden and Ackermann 2004). In reality, however, we have no option but to create a representation of a mirrored room, where different viewpoints carry and create differing images as we observe the reflections in a number of mirrored surfaces (Ulrich 1988; Traoré 2003).

The plurality of such multiple reflections of reality derives from the diversity of observers and their power to create those realities, since in a wide variety of interesting problems, what we need to simulate is socially constructed, in that the very system whose behaviour we need to predict or explain is constructed by the inhabitants of that system. For example, we might consider the simple case of a natural disaster, say, an earthquake or a flood. There is a single, underlying physical reality, of geological dynamics or hydrodynamic flow, but to the extent that we are interested, in our simulation endeavor, in the system outcomes as judged by human agents, we are immediately pushed into the consideration of a socially-constructed valuation system, where the various parties will perceive, value and even define the system we seek to represent. Direct victims of a flood, for example, will define a valuation system centered on perceptions of immediate risk, physical danger or disease, whereas more distant policy agents (regional governments, emergency services) will not only place different valuations (say upon longer term economic effects) but will define the system differently, probably through the possession of more accurate models of physical reality than are available to the victims. In general, the multiple viewpoints of system inhabitants will derive from

- Differing perceptions of system behaviour;
- Differing valuations of system outcomes;
- Differing definitions of the system inhabited.

The first and second of these are relatively easy to accommodate in a single simulation, but the third requires an approach somewhat foreign to the essentially positivist assumptions of most simulators (Kotiadis, Tako, and Vasilakis 2014). There are two difficulties. Firstly, the simulation needs to be sufficiently **flexible in its architecture** to be able to accommodate different understandings of system mechanisms (Chahal and Eldabi 2010). As an example, a study has been carried out of social dynamics and disease transfer mechanisms of Ebola in West Africa during the outbreak of 2014/2015. Disaster management specialists and medical staff will have a Western, 'scientistic' view of the etiology of Ebola, whereas others, in particular certain devout religious groups living away from cities, may have a different view. What is significant in any modeling of the social effects of Ebola is not whether the latter viewpoint is right or wrong, but whether it needs to be differently represented in any overall model of the epidemic. In actuality, modeling the religiously observant behaviors of the religious group is necessary in order to represent disease transfer mechanisms effectively and accurately. Since those behaviors are posited on a particular ('non-scientific') set of assumptions of disease transmission, any 'more informed' set of assumptions made in a model will be an inadequate basis on which to explain the behaviors.

Secondly, verification/validation cannot be based on any direct appeal to a single, uncontested reality, as is the case in most engineering or scientific simulation/modeling exercises. In the case of the Ebola exercise, while an appeal for validity can be made on the basis of, say, accurate predictions of disease transmission in the actual population(s), it must be remembered that this measurement of system output is, in fact, conditioned by the assumptions of a particular observer. In particular, definitions of constitutes an Ebola case, while appearing incontestable to the Western scientific mind, is, in fact contestable within an up-country Nigerian, Guinean or Liberian social context.

6.2 Support to Simulation Modeling Specification Work

We are concerned in our research, then, with a class of problems in which an undeniable 'scientific' reality underlies the experience of the effects and judgment of that reality by human beings acting in a social sphere. Examples of this include

- the diverse experiences, valuations and political responses of people in a community affected by an environmental disaster (where, for example, inhabitants of Fortuneswell, Isle of Portland might view a bi-annual flood event as 'business as usual' while the townsfolk of the Thames Valley, an area closer to political centers and media, might take a different view)
- the interactions of (scientifically discoverable) pharmacological effectiveness with social context, psychological mechanisms (e.g. placebo) patient expectations etcetera. The experiences, for

example, of plastic surgery patients, cardiac disease suffers and cancer patients are not merely the product of a scientific prediction extrapolated into the lifeworld.

In both cases we see, firstly, an indeterminacy of valuation of effect imposed by the plural nature of the social receipt context (in other words, we have to take into account varying valuations and definitions in deciding whether our system interventions are ‘desirable’), and, secondly, a feedback mechanism by which those definitions and valuations affect the very system which we are modeling (in other words, we as modelers cannot simply decide unilaterally what is important, a situation made more inconvenient by the disagreement in the receiver community as to what is important).

We can simplify this interactive problem as simulation designers by taking a series of positivist assumptions, but the problem of which sets of assumptions to take still remains. A suitable approach may be to use a modeling method in which a variety of system assumptions can co-exist in order to explore the (plural) social system context. Soft System Methodology (SSM) would claim to fulfill this role but Checkland’s work tends towards the participative action research assumption of completeness (Lehaney and Paul 1996), and there are no examples to hand of SSM being used to target specific simulation representations. SSM is very effective in identifying potential action agendas but poor in predicting the effects of those actions (Lehaney and Paul 1994). Particularly in the case of health systems and crisis management, where very substantial resources are applicable, this prediction of effect is essential (Robinson 2011).

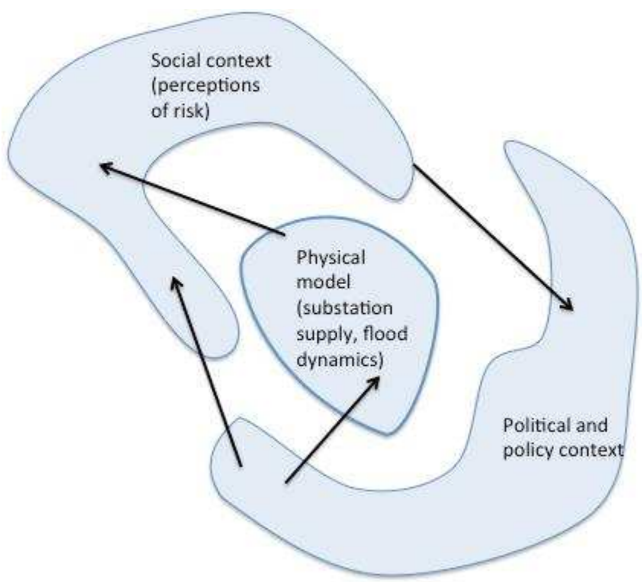

Figure 3: Example of a soft metamodel structure (here a flood event).

An alternative approach to SSM is qualitative systems dynamics (QSD) which has the merit of being more similar in its representative structure to that of simulations (and indeed through toolsets like iThink© and Vensim© can be translated, with chosen boundary conditions, into a quantitative simulation format) (Sterman 2000; Powell and Coyle 2005; Powell and Swart 2010; Swart and Powell 2006)

In summary the approach consists of using a soft systems approach prior to simulation specification (Viana et al. 2014; Djanatliev and German 2013) in order to identify the key mechanisms which span a physical infra-system and the surrounding socially-constructed systems (typically, a local social valuation system, such as the direct victims of flood and a more distant political valuation system (Liddell and Powell 2004), as depicted in Figure 3.

7 HYBRID TEAMS FOR HYBRID SIMULATION (MUSTAFEE)

I use the term hybrid teams to emphasize the need for interdisciplinary M&S groups that bring together problem stakeholders, researchers and practitioners. They are essentially composed of individuals specializing in specific fields of study or, as in the case of problem stakeholders, having tacit knowledge of the underlying system of enquiry. When considered as a whole, such hybrid teams will have recourse to knowledge constructs (theories, methodologies, techniques, applications, etc.) that have not traditionally been applied to M&S studies. Such teams are arguably better poised to address challenges pertinent with hybrid systems as the very constitution of the team allows for opportunities to leverage from the diverse body of knowledge and individual expertise and skillsets and make it possible to work towards common end goals.

The importance of interdisciplinary research is widely recognized; however, the question to be asked is whether our community has sufficiently embraced the opportunities that it brings? Looking at this from the perspective of a computer scientist, advances in computing (computer hardware, distributed systems, programming models, communication networks) have led to the recognition of one particular research community that utilizes non-trivial amounts of computing resources, accesses large data sets, and engages in collaborative scientific enquiry made possible by experts from different organizations and knowledge domains – this is the e-Science community (Mustafee 2010). For a hybrid M&S community to gain the same recognition it is argued that we look wider than our immediate discipline (M&S in the context of Operations Management) and reach out to communities like Operations Research (OR), Software Engineering and Computer Science; we debate and agree on conceptual representations of these inter-disciplinary methods and techniques and where they can be applied in relation to our well-defined stages of a simulation study (Figure 1 is an attempt along those lines); we develop multi-paradigm/multi-method/multi-technique frameworks with the aim of facilitation wider adoption of hybrid (section 6 is an attempt towards this); we conduct research that demonstrates the need for diverse research communities working together in realizing the methodological and technical aspects of a simulation study and which goes beyond only the development of the model itself; we aim for a critical mass of hybrid systems' modelling research and practice in communities wider than M&S (similar to the WSC track but in conferences like ACM SIGSIM PADS and Distributed Simulation and Real-Time Applications which have traditionally focused on the interface of Computer Science/Applied Computing and discrete systems, and UK OR Society (UKORS) Annual Conference and EURO which showcase wider OR research).

Some readers may critique the idea of the need for a concerted effort to build such a community arguing that our discipline has always been outward looking! This is recognized by the panelist and indeed some of his M&S work has used techniques from OR, e.g., application of Cutting and Packing Optimization with ABM (Mustafee et al. 2013) and Qualitative System Dynamics to informs DES studies (Powell and Mustafee 2014), as also from distributed systems, e.g., grid computing (Mustafee and Taylor 2009) and PADS/HLA (Mustafee et al. 2009; Mustafee et al. 2015). It is recognized that there are pockets of interdisciplinary research clusters on M&S. However, it is also true that most journals, conferences, journal/conference quality rankings, special interest groups and arguably departmental structures continue to maintain their focus on specific subject areas (this does not however mean they do not offer a conduit for hybrid systems research), and the development of a hybrid M&S community could enable us to "look wider" and more horizontally and help facilitate a more integrated and inter-disciplinary approach to systems modelling.

8 CONCLUSION

This is the first year that Hybrid Simulation has featured as a full track. Prior to this it was organized as a mini-track (@ WSC2014) and as a thematic session (@WSC2012 and WSC2013). The progression of this track from relatively small thematic sessions to a full track is in a way representative of the increasing number of hybrid simulation studies being reported in literature. Application of hybrid techniques bring with it a number of opportunities as well as challenges, and the panel paper allowed us to explore some of them and provided pointers for future research.

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