Applications

Simulation

Simulation: Transactions of the Society for Modeling and Simulation International
2018, Vol. 94(6) 493–506

DOI: 10.1177/0037549717737159
journals.sagepub.com/home/sim
SAGE SCS

Observations on the practice and profession of modeling and simulation: A survey approach

Jose J Padilla, Saikou Y Diallo, Christopher J Lynch and Ross Gore

Abstract
This paper reports on a survey capturing modelers' perspectives of Modeling and Simulation (M&S). The survey was completed by a total of 283 respondents from the M&S community with 167 fully completed surveys and 151 respondents identified as model builders. Participants include people from government, academia, and industry in varied roles ranging from researchers to business developers. Respondents also represent a diverse educational background ranging from oceanography, social sciences, and engineering. The survey focuses on three dimensions namely: (a) models and simulations, (b) participants, and (c) how participants interact with models/simulations. We provide six observations from the data analysis: there is no dominating paradigm in M&S, the agent-based community is distinct from the discrete-event community, conceptual modeling is the art of M&S, simulation verification is mostly a trial and error activity, validate by all means necessary, and model accreditation is still too uncommon. A key finding from these observations is the identification of an over-reliance on informal methods for conceptualization and verification in M&S. We posit that this over-reliance on informal methods challenges model/simulation validity.

Keywords
Modeling practice, modeling paradigms, modelers, survey, statistical group comparison

1. Introduction

The discipline of modeling and simulation (M&S) contains many paradigms, methodologies, tools, and practices for creating models and simulations. However, the perception of what constitutes M&S differs not only among the people that apply it but also among the people that contribute directly to the study of such paradigms, methodologies, tools, and practices. In other words, there is a disagreement over what M&S is and does. Considering perspectives of what M&S is, and how we conduct M&S, is important because it permeates how we convey it, teach it, learn it, apply it, sell it, and ultimately on how useful and truthful our simulations and corresponding results are. As such, what we perceive to be M&S permeates the epistemology of models and simulations that we create and the engineering and scientific value that they generate. We present a study that examines perspectives of M&S by surveying people that create models in academia, government, and industry. Our survey obtains this information through questions that focus on: (a) how respondents interact with M&S in their workplaces, and (b) on the role of M&S within the respondents' organizations.

Surveys can illuminate specific M&S topics and contribute to the generation of theories and/or evaluation of hypotheses in general; however, surveys are not one of the most used artifacts in M&S research. The challenges in using surveys lies in gaining access to the broad M&S community while avoiding selection bias. M&S not only has a community of interest reflected in M&S-based conferences such as the Winter Simulation Conference and journals such as the *Journal of Simulation*, but also in conferences and journals in other fields that rely on simulations, such as the disciplines of oceanography and aerospace engineering among others. This challenges the ability to sample the relevant population as experts across these fields that need to be included within the survey's responses. Therefore, the ability to contact M&S experts across different specialties enhances the ability to conduct an M&S specific survey that looks at how models are commonly built across specialty groups and to gain insight into modeling practices of the discipline.

Virginia Modeling, Analysis and Simulation Center, Old Dominion University, Norfolk, VA, USA

Corresponding author:
Christopher J Lynch, Virginia Modeling, Analysis and Simulation Center, Old Dominion University, 1030 University Blvd., Suffolk, VA 23435, USA.
Email: cjlynch@odu.edu

To reach the largest population of people that build models, we distributed our survey electronically using email. Emails were sent to individuals that deal specifically with modeling for dissemination within their groups in order to access desired populations for the study. Additionally, we distributed the survey using LinkedIn, a social media site for business professionals. Distribution through LinkedIn allows individuals that have tagged themselves as having skills pertaining to M&S to share the survey with each other and expand the sample population. We note the risk of sampling bias as we rely on individuals responding to a call and not on randomly selected individuals. Nonetheless, the insights generated provide a starting point for discussion in the M&S community and a platform for research.

2. Survey research: An overview

As surveys are not traditionally used in M&S, this section provides a brief overview on how they are used and how we applied them to this study. Surveys produce information from a population through data collection with the ultimate goal of contributing to developing theory with respect to a topic or explaining some phenomena.[1] The information provided by these surveys can be used for a variety of purposes in both scientific and nonscientific ways. However, survey research specifically focuses on the use of surveys for the advancement of science through increasing knowledge or developing theory. Malhotra and Grover[1] identify three characteristics of survey research: (a) survey research uses structured formats to ask people for information; (b) survey research generally produces quantitative data; and (c) survey research generalizes the results over the population, since only a sample of a population participates in a survey.

Numerous elements can hinder the ability to conduct a survey for a given population, such as reluctance for the target population to participate in taking the survey,[2] and refusing to answer questions, and not following instructions.[3] Specific drawbacks to electronic surveys include the requirement that the target audience have access to a computer[3]; that email surveys can be seen as junk mail and deleted without being opened[2]; and a lack of anonymity if the survey requires return to the surveyor via the participants' personal email address.[4] Participants in face-to-face surveys have a tendency to provide answers that they think please the interviewer and tend to over-report on the socially desirable traits for the review.[3] Highly sought after and frequently targeted groups, such as physicians, may become reluctant to participate in surveys over time.[2] Ansolabehere and Schaffner[5] examine the frequency that distractions occur while taking surveys and find that longer surveys result in more distractions among the respondents, but that these distractions do not affect the quality of the survey results.

Survey research exists within M&S addressing a variety of topics. Boer, de Bruin, and Verbraeck[6,7] surveyed a population of distributed simulation users, vendors, and developers to determine why industry lags behind in the use of distributed simulation. This survey was conducted using questionnaires and interviews to collect data on nine topic areas pertaining to the use of distributed simulation. Boer, de Bruin, and Verbraeck[8] conducted a survey to show that the High-Level Architecture (HLA) standard within M&S is not often applied within industry for distributed simulation. They use the survey: (a) to identify why HLA is not often used by industry, and (b) to identify potential options for fixing this problem. This survey showed that the current view of HLA within industry is that there is too high a cost–benefit tradeoff for using HLA and that current tools for utilizing distributed simulation are too complex. O'Donoghue and Loughrey[9] surveyed modeling teams across the world that examines methodological differences in creating microsimulation models across teams to present a comparative analysis for teams to learn from each other. Ahmed et al.[10] conducted a survey to explore and understand the current state of the art in software process simulation modeling (SPSM). The questions contained in the SPSM survey explored six categories: the modeler; the models; the problems being modeled; model development; the modeling process; and critical problems within SPSM.

Eldredge and Watson[11] conducted a survey within industry of computer simulation with the goal of focusing academia on relevant instructional and research efforts by examining issues including simulation use, simulation hardware, simulation software, advanced simulation methods, and the future use of simulation. Their work provides a longitudinal study of computer simulation compared against two previous surveys to identify changes in perception of the benefits and use of simulation within industry. The longitudinal nature of their study shows that the use of simulation increased between 1977 and 1996 and that simulation is perceived to be a method of analysis within industry. Additionally, their survey revealed an increase in the use of stochastic simulations as well as in the number of software languages used for constructing simulations.

While not broadly used in M&S, surveys have been applied to a variety of questions in the discipline. More importantly, we can surmise that surveys provide, among other things, the context in which M&S exists. This is the main reason for the use of a survey in this study: to capture the content in which M&S exists by inquiring about perspectives of M&S in its community.

3. Methodology

We conducted a three-part survey to explore perspectives of models and simulations within industry and academia by people that build models in performing their work duties. Part 1 focused on how the respondents interact with M&S in their workplaces; part 2 focused on the role of M&S within the individuals' organizations; and part 3 was an optional section that focused on classifying the respondents based on their personal information. Our survey contained 41 questions with the purpose of exploring M&S professionals' perspectives on the key aspects of using and designing models and simulations. Appendix A shows a taxonomical representation of the questions in the survey. The survey was designed using *SurveyMonkey* in an electronic format intended for online distribution as we assume that the use of an electronic survey does not alienate members of our target audience, since builders of models and simulations presumably have the relevant skills to participate in online surveys. The survey was evaluated by a subject matter expert to identify and eliminate ambiguities and poor wording. We distributed the survey via email and LinkedIn, a social media site for professional networking. By distributing the survey on professional networking sites, we made it accessible to both industry and academia professionals worldwide who create agent-based models (ABMs), discrete-event simulations (DESs), and system dynamics (SD) models, among others. Specific M&S practitioner groups were targeted by email and invited to participate and distribute the survey. A drawback of using social media to distribute the survey was that people not affiliated with the intended audience could access the survey. These people likely contribute to partial responses in the survey. The first question of the survey was intended to convey to the respondent that the survey pertains to building and using models and should cause people that do not fall into this group to stop taking the survey. Surveys that target specific populations but receive higher responses from a particular group within that population can affect the analysis through the nonresponse of the other groups.[12] Therefore, distributing the survey via social media removes the ability to evenly sample the target population and may indirectly introduce nonresponse bias into the analysis. This risk is common when using nonprobability sampling[13] and we examined the demographics of the respondents to determine the coverage of the population before drawing any conclusions.

The survey was accessible from January 2014 to February 2015. The survey was completed by a total of 283 respondents with 167 fully completed surveys, and 151 respondents identified as model builders, who were the focus of analysis. Responses specific to model builders were obtained through survey branching.

4. Survey results and analysis

In this section, we present descriptive statistics of the findings from the survey. In addition, we use the automated group comparison feature available in *SurveyMonkey* which uses a Student's t test to determine whether answers from two groups are different at a 95% confidence level ($p = 0.05$). When comparing subgroups of responses, such as ABM versus DES responders that use models for experimentation, the group sizes of respondents vary between 126 and 143 respondents (less than the 151 total respondents). These numbers are less than the total number of respondents because: (a) a single survey question serves as baseline for comparisons and (b) respondents sometimes answered under the open-ended category and added their own responses, which cannot be compared. Therefore, when comparing questions, the numbers of respondents varies based on number of respondents using the open-ended answer option to respond to the question. We use the terms significantly or statistically significant when it comes to statements about category comparison. Comparisons are based on responses.

For the 151 respondents that completed the survey, 44.7% classified themselves with *academia*, 27.8% classified themselves with *private industry*, 15.2% classified themselves with *government*, 7.2% classified themselves as *self-employed or contractor*, and 5.3% classified themselves as *other*. The distribution was 93.3% male and 6.7% female which is representative of the gender gap found in science, technology, engineering and, math (STEM) disciplines.[14] Collectively, the respondents averaged 15.8 years of experience in working with models and simulations. The ages of the respondents were 6.6% under 30 years old, 34.6% between 30 to 40 years old, 14.0% between 41 and 50 years old, 26.0% between 51 to 60 years old, and 18.6% older than 60 years. The educational background of the respondents showed a tendency towards higher degree levels with 49.7% of the respondents having a doctorate, 37.0% having a master's degree, 7.9% having a bachelor's degree, 1.3% having an associate degree, and 3.6% identifying themselves as having completed some courses for the above degree categories. Figure 1 shows the areas that reflect the respondents' formal degree.

A total of 22 countries are identified within the respondent population with the most represented countries including the United States of America at 58%, the United Kingdom at 7.4%, and the Netherlands at 5.4%.

Question 1 of the survey identified two groups of people: (a) people that build models; and (b) people that do not build models. A total of 151 of the 167 respondents were classified as model builders.

4.1. Observation 1: There is no dominating modeling paradigm

We observed that respondents have a diverse modeling background reflective of what is found in the practice of M&S. Figure 2 shows that of the different paradigms

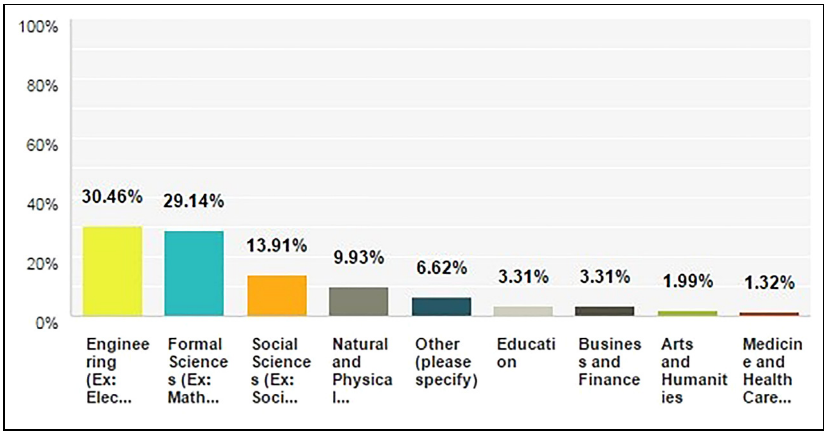

Figure 1. Respondents' formal degree type.

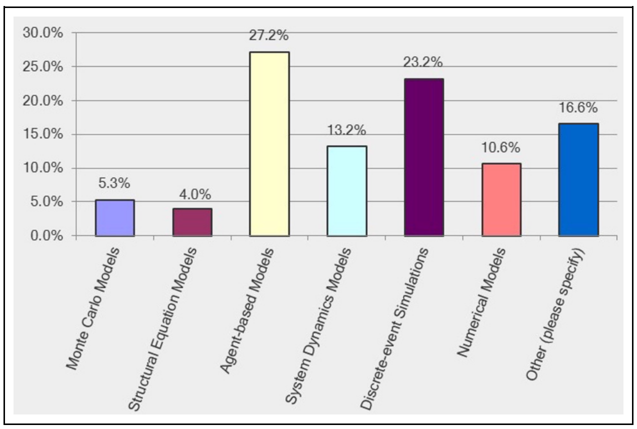

Figure 2. Most commonly constructed model types by model builders.

included in the survey, ABM and DES have a higher percentage of the responses without a large lead over the statistical and mathematical modeling paradigms (Monte Carlo, Structural Equation, and Numerical Models). It is also interesting to note that 16.6% of the respondents did not chose to identify with the proposed categories (chose the "other" category). Of particular note, on the "other" category, was that 6% of respondents favored a combination of two or more paradigms as their most used modeling method, which was a higher percentage of responders than those who identified as Monte Carlo or Structural Equation modelers. This observation is important as it reflects an emergence or resurgence of *multi-paradigm modeling*, either by creating separate or combined models using different paradigms, as a way to model complex systems. Respondents were specific, in several cases, on their preference to combine different paradigms providing responses like "hybrid models that combine discrete and continuous system representations" or "multi-paradigm models (ABM + SD + DES)."

4.2. *Observation 2: There is an ABM community distinct from a DES community*

Table 1 shows that the majority of respondents build models for more than one purpose suggesting that there is not a leading purpose for building models.

However, the data show that the ABM and DES communities are statistically different (refer to the highlighted cells in Table 1). The ABM community focuses on experimentation and explanation (group C/ABMs is significantly higher than group E/DESs with a 95% confidence level), while the DES community focuses on prediction (group E/DESs is significantly higher than group C/ABMs). In this case, 60.98% of responses say that ABMs are for experimentation (compared with 34.29% for DESs) and 73.17% say they are for explanation (compared with 34.29% for DESs). On the other hand, 54.29% of responses say DESs are for prediction (compared with 31.71% for ABMs).

This is supported when comparing other ABM and DES responses on multiple selection questions; ABM modelers rely on theory at a higher rate than DES modelers (82.93% ABM compared with 34.29% DES responses). Furthermore, a statistically significant difference between DES responses come from industry (40%) over academia (25.7%) while a statistically significant difference also occurs between the numbers of ABM responses originating from academia (58.5%) over industry (19.5%). While both ABM and DES groups work in the defense area, the number of DES responses was significantly higher (60%) than the number of ABM (36.59% responses) with the ABM group developing models for research at a significantly higher response percentage (87.8%) than the DES group (60%). Lastly, the ABM group relies on academic/formal sources at a significantly higher rate (87.5%) than their DES counterparts (45.7%).

Interestingly, the survey shows that SD modelers favor building models for experimentation and explanation activities. However, the SD modeler group does not

Table 1. Comparison of modeling purpose by paradigm. Cells display the percentage as well as the number of respondents pertaining to the paradigm and its purpose.

Modeling paradigm	Experimentation	Support for training	Support for decision making	Acquisition	Predict-ion	Explanation	Other - please specify	Total
Monte Carlo models (A)	37.50% 3	37.50% 3	87.50% 7	12.50% 1	25.00% 2	25.00% 2	12.50% 1	15.08% 19
Structural Equation models (B)	0.00% 0	33.33% 2	33.33% 2	0.00% 0	66.67% 4	50.00% 3	0.00% 0	8.73% 11
Agent-based models (C)	60.98% 25 **E**	29.27% 12	51.22% 21	4.88% 2	31.71% 13 **E**	73.17% 30 **E**	12.20% 5	85.71% 108
System Dynamics models (D)	65.00% 13	25.00% 5	50.00% 10	15.00% 3	25.00% 5	65.00% 13	10.00% 2	40.48% 51
Discrete-event simulations (E)	34.29% 12 **C**	34.29% 12	68.57% 24	11.43% 4	54.29% 19 **C**	34.29% 12 **C**	8.57% 3	68.25% 86
Numerical models (F)	43.75% 7	18.75% 3	50.00% 8	6.25% 1	62.50% 10	75.00% 12	0.00% 0	32.54% 41
Total respondents	60	37	72	11	53	72	11	126

significantly differ in that focus from other groups. This may suggest that respondents outside the ABM and DES groups view M&S as a flexible approach and that division into schools of thought or paradigms is more useful in characterizing a set of methods than in representing an M&S worldview.

4.3. Observation 3: Conceptual modeling is still the art of M&S

Modelers have numerous options for designing their models, ranging from informal methods such as sketches or notes taken using pen and paper to more formal methods of creating an initial conceptual model using languages such as the Unified Modeling Language (UML) or the System Modeling Language (SysML). Figure 3 shows that a large portion of respondents focus on what could be called ''informal means'' of creating conceptual models or do not explicitly engage in conceptual modeling activity at all. The use of pen and paper for designing models accounts for 33.8% of responses while designing while building the simulation accounts for 28.5%. Results show that the selection of a modeling paradigm does not significantly impact the way in which a model is designed. However, modelers who rely on theory as the main source of information for their models are significantly more likely to use pen and paper (77.36%) than compared with modelers who use other sources of information to build their models who focus largely on designing while building their simulations (51.02%). We define *designing while building* as occurrences where no explicit informal or formal conceptual models are created in advance of implementation. This may suggest that transitioning theories into models is challenging due to difficulties in conceptualizing the theories, in the lack/scarcity of existing models, the lack/scarcity of experience regarding the implementation of those theories, or the lack/scarcity of an available expert with respect to the theories' subject area, among others. Models that are built or found in education are significantly more likely to have been designed during the development of a simulation than by using pen and paper (34.6% against 16.9%). The same holds true for models found in banking and finance (14.2% to 1.89%), business (18.3% to 5.6%), public services (22.4% to 5.6%), and transportation (30.6% to 5.6%). This may suggest that these models are of systems/phenomena less challenging to create due to, for instance, existing models and experience on their implementation. Lastly, the use of data as the main source for designing models is not a predictor of how one would choose to develop a model. These potential explanations need to be further explored and confirmed.

The survey results suggest that an increased emphasis needs to be placed on getting model builders to follow accepted M&S practices for constructing conceptual

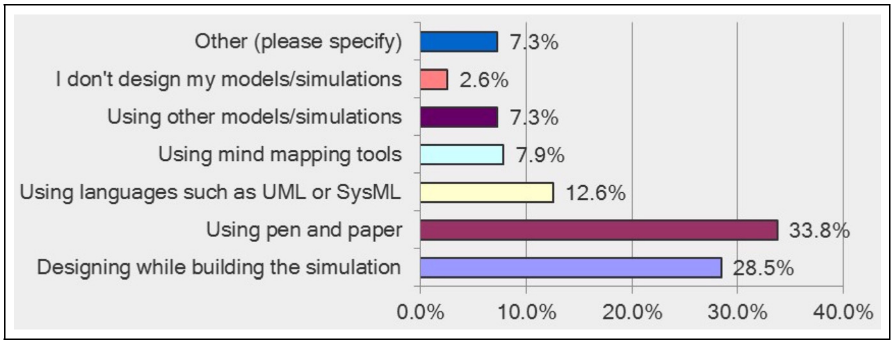

Figure 3. Commonly used methods for designing models.
SysML: System Modeling Language; UML: Unified Modeling Language.

models in a systematic manner before building simulation especially since conceptual modeling is considered a crucial stage in simulation creation.[15,16] While pen and paper is good for initial conceptualization stages, structured approaches such as UML or SysML can provide explicit model descriptions that better facilitate replicability, which is one of the main issues about models in general,[17–20] while helping to transition from model to simulation. In addition, formal conceptual modeling approaches will assist in the verification and validation processes; in terms of verification it allows the simulation implementer to compare against model requirements and in terms of validation it facilitates the comparison of simulation implementation against the system/phenomenon conceptualization. It is noted that we did not inquire about how positively or negatively the use of informal conceptual modeling efforts impact the resulting simulation models or whether modelers encounter difficulties in building models when using formal or informal approaches. We do however, emphasize the use of formal or structured approaches to facilitate the replicability of models and their verification.

4.4. *Observation 4: Simulation verification is a trial and error activity*

Modelers conduct verification to ensure that the simulation is implemented consistently with respect to the model design.[21,22] Techniques for conducting verification range from informal (i.e., visual inspection) to formal methods (i.e., software tools and formal methods). Systematic trial and error comprises 35.8% of respondents with formal methods coming in second at 21.2% and visual inspection third at 19.9%. Over 55% of respondents conduct what could be considered informal means of model verification. Figure 4 displays the breakdown of how the respondents normally conduct verification on their models.

SD models were significantly more likely to have been verified formally (30.5%) than through visual inspection (9.6%) or trial and error (12.9%). On the other side, ABMs were significantly more likely to be verified through visual inspection (38.7%) than formally (13.8%). This shift is in line with our original observation about the existence of those two communities. We also found that simulations built for acquisition were more likely to be formally verified (22.2%) especially in the defense (43.5%) and the healthcare and public health (41.6%) domains. This finding is consistent with our expectations that simulations that support acquisition in those domains are usually safety critical and therefore need more rigor in their development. Not surprisingly, models that were verified through visual inspection were significantly more likely to have been validated through visual inspection. In the same line, models that were formally verified were significantly more likely to have been submitted for third party accreditation (11% as opposed to 1% of models verified through trial and error) whereas models that were verified through visual inspection (58%) or trial and error (43%) were significantly more likely to have never been submitted for accreditation compared with formally verified models (19.4%).

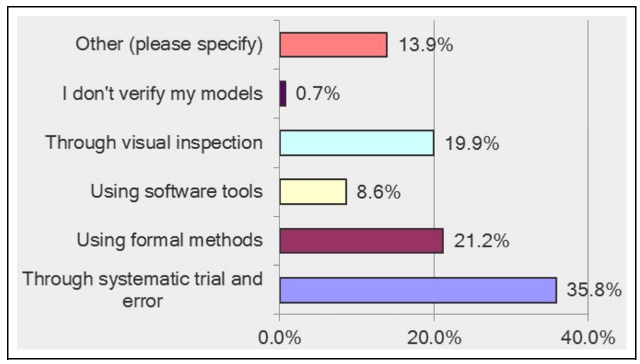

Figure 4. Common practices for verifying models.

Furthermore, standalone models were more likely to have been verified through visual inspection (38.7%)

whereas models that participate in a federation were more likely to have been formally verified (22.2% against 3% of models verified through trial and error). In particular, modelers who use the Test and Training Enabling Architecture were significantly more likely to use formal verification. In more general terms, modelers in the defense, healthcare, and business industry were significantly more likely to formally verify their models whereas modelers in science and engineering are more likely to use systematic trial and error to verify their models. In addition, modelers who rely on professional organizations and textbooks were significantly likely to formally verify their models while those who rely mostly on technical reports were significantly more likely to verify through visual inspection. From a personality standpoint, modelers who describe themselves as introverted, dependable, and self-disciplined tend to verify formally while those who see themselves as critical and quarrelsome tend to prefer trial and error. Finally, organizations that develop models for sale were also more likely to use formal verification.

Responses show that model verification is still a little-used practice among model builders. This finding is consistent with the current literature on verification.[23,24] Techniques are needed for model verification that can help to identify errors within the models that are difficult to catch with visual inspection or systematic trial and error. While there are several techniques for formal model verification like theorem proving, they are time consuming for problems beyond trivial. Simple and accessible means for formal verification are needed so verification can become a central tool of the modeling and simulating process.

4.5. Observation 5: Validate by all means necessary

Validation is the process of checking that the model is a reasonable representation of the system that it represents and, therefore, the model's results can be reasonably trusted to provide insights that are relevant to the questions of interest. A majority of respondents, at 55.6% of the responses, indicated that they validate their models by comparing their models' results directly against the data that they expect the real system to produce. Relying on subject matter experts (SMEs) takes a distant second with 17.2% of responses. Figure 5 provides the breakdown of the primary validation techniques used by respondents.

Of the respondents, SD modelers were significantly more likely to perform data validation (19.32%) than subject matter validation (0%). Not surprisingly, modelers who rely on subject matter expert input tend to validate with SMEs at a significantly higher rate (90%) than using real data (64.7%). This might be due to unavailability of data in those cases. However, this finding points to a bias issue if the same experts providing the input are also doing the validation. We also found that the purpose of the model (experimentation, decision support, etc.) does not influence

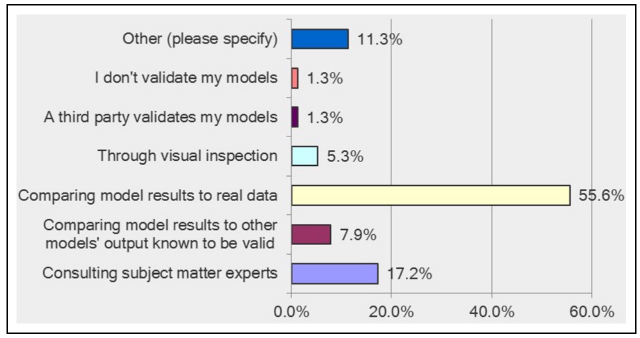

Figure 5. Common practices for validating models.

the type of validation modelers perform. This is problematic especially in cases where we would expect a more rigorous validation procedure when models are developed for explanation or decision support. We also found that a model designed using pen and paper was more likely to undergo empirical validation (comparing with real world data) than it was to undergo SME validation.

Compared with verification, modelers appeared to follow more standard or structured practices for validation. This suggests that validation may be considered more important than verification. However, if we consider verification as a form of structural validation; uncaught model errors may lead to validation issues. In other words, models with errors that are not identified through the verification process can still generate data that matches empirical data.

It is interesting to note the reliance on data for validation in ABMs when a large portion of respondents point on their reliance on theory and explanation when compared with approaches like DESs. It is noted, however, that this difference may likely be due to a slightly higher number of ABM responses. Yet, the data show that ABMs also rely the most on informal modes of conceptual modeling and verification. This insight leads to an interesting question: are we focusing too much on results and not enough on how we build our ABMs? An explanation for this apparent behavior may lie on one or many different factors: lack on agreement on how to conceptualize ABMs, the difficulty on conceptualizing ABMs, and an over-reliance on simulation tools for model conceptualization.

4.6. Observation 6: Model accreditation is still too uncommon

Survey responses show a high number of modelers that either do not, or rarely, conduct accreditation (Figure 6). This may be due to not considering accreditation a necessary, valuable, or practical step in the modeling process. This is understandable as accreditation is usually applied to large and complex modeling initiatives in organizations like the US Department of Defense. Accreditation is the

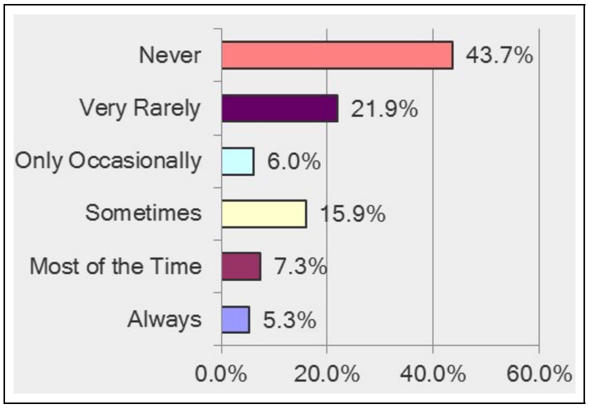

Figure 6. Frequency of submitting models for accreditation.

Figure 7. Word cloud from textual response to the benefits of models/simulations to society.

process of officially determining that a model is acceptable for a specific purpose.[18] Accreditation is commonly regarded as an evaluation by an independent third party of the fulfilment of requirements of a simulation model,[21] a process similar to that of verification and validation; however, accreditation can also involve checking the user-friendliness of the simulation and the model's documentation.[25]

Model accreditation is an underutilized feature within M&S. The challenge lies on how much access to accrediting mechanisms exists. One form of accreditation that is not often used is making simulation design artifacts and/or code available to the M&S community. The community at large becomes the accreditation body. Platforms like Github.com could provide a means for crowd-sourced accreditation. Accreditation, however, relies on the credibility of the accreditor. Journals could take on the task of accrediting simulations of submitted papers and act as initial informal accreditor. While informal, it is a departing point. This indicates that a large number of models may be acceptable for the purposes of experimentation and explanation without the need for accreditation.

5. Final note

An interesting insight comes from the survey's open question. The question reads: "In your opinion, what benefits do models/simulations provide the most to society?" Figure 7 shows a textual representation of the answers (from 65 respondents).

We observed the prevalence of words like explore, understanding, experiments/experimentation, decision making, prediction, cost, training, and insight among others. Manually looking at the responses one at the time resulted in one answer grabbing our attention: *not sure if they provide any* [benefits]. It is difficult to explain this response as more context is required from the respondent. However, this response may point to real or perceived shortcomings of M&S. While only one response, it is important to highlight that the same perspective may be shared by others in the community.

If the reader is interested in a more detailed summary of the survey's statistics see Appendix B. The survey can be viewed at the following link: http://svy.mk/29IiRwm.

6. Discussion

Overall, there are different M&S practices when it comes to activities such as conceptual modeling, the paradigms used for simulation creation, verification and validation of models, among others. Practices range from the informal to the formal, reflecting factors such as the purpose of the models, modelers' personalities, or the foundations of models among others. It may also suggest different standards for model creation and evaluation.

A common theme within the responses is that modelers appear to place greater utilization on informal means for conceptualizing and verifying models and simulations. Further, the application of accreditation, even if informal, is almost absent. We consider that verification in particular is of concern. As previously mentioned, if we consider verification as a form of structural validation, then uncaught model errors will lead to validation issues as invalid models have the potential of generating results that match empirical data. As such, we undermine the contribution and credibility of our models when we build models that do not go through a rigorous and repeatable conceptualization, verification, and validation processes. We acknowledge the challenge of validating models when data is absent or difficult to obtain. Yet, we posit that moving towards formal approaches of conceptualization and verification are within reach. We note, that the survey did not inquire about the impact (positive or negative) the results from approaching modeling activities informally or formally. We acknowledge tradeoffs of time investment and effort when conducting formal verification, for instance and it may not be required for low complexity models. However, the risk of not conducting verification formally and accepting models as verified increases with the complexity of the models.

On the other hand, most of the respondents do conduct some form of verification and validation which indicates that the concept of conducting verification and validation (V&V) is considered of importance to the community in general. The prevalent use of V&V techniques within the respondent community is promising because different groups within M&S utilize V&V techniques differently. It is unsurprising that the use of V&V techniques vary based on the choice of modeling paradigm. Since different industries commonly employ specific types of models (i.e., supply chain using DESs or population dynamics using SDs) to fill specific purposes and answer specific types of questions (and we have already shown selecting a modeling paradigm differs based on the purpose of the model), selecting verification techniques based on: (a) the purpose of the model or (b) the type of industry that the model was created for makes sense within the philosophical context of M&S.

The survey highlights that the M&S community's verification practices range from informal to formal. We did not inquire into the reasons why the range or how or when those approaches are used. We are proponents of more structured, generalized, or standardized approaches to verification as this could assist in preventing factors such as the age of the modeler and the years of M&S-related experience of the modeler from influencing the selection of V&V techniques. A set of standard or community accepted approaches for conducting V&V would allow for a more consistent application of verifying, validating, and accrediting across all models and help increase the credibility and the level of confidence associated with using models.

Lastly, the survey was built to capture an overall picture of the M&S community. We acknowledge the commonly agreed disadvantages of using surveys especially when it comes to sampling bias. We have addressed this challenge by reaching respondents across communities. As such, we encourage other researchers to administer this survey to specialized M&S communities in order to develop a large dataset that informs the profession of M&S over time. Building up the number of responses to the survey is important as this increases the chances that the data reflect the population at large. We also point to a higher reliance on direct contact with respondents (less reliance on social media) to assert inferences on the population. We are firmly convinced that empirical research such as the type we are proposing here is essential in advancing the field of M&S. Our dataset is available to the research community and we are in the process of developing Structural Equation models of the relationship between V&V and the variables captured in this study. These models will more likely require modifications to the survey as to make questions that lead to more precise answers.

7. Conclusions

The paper presents insight into the M&S community by examining survey responses of modelers' relationships with the primary activities of the profession. The survey was completed by 283 total respondents from the M&S community with 167 fully completed surveys and 151 respondents identifying as model builders. Of the 151 model builders we analyzed responses relating to modeling paradigms, model purpose, sources of information when building models and simulations, mechanisms/artifacts for conceptualization, V&V, modelers' education, age, jobs, and organization types among others. Overall, six observations are presented that capture the analysis of survey responses:

- Observation 1: There is no dominating paradigm in M&S.
- Observation 2: There is an ABM community distinct from a DES community.
- Observation 3: Conceptual modeling is still the art of M&S.
- Observation 4: Simulation verification is a trial and error activity.
- Observation 5: Validate by all means necessary.
- Observation 6: Model accreditation is still too uncommon.

The key finding from these observations is the identification of an over-reliance on informal methods for conceptualization and verification in M&S. The use of pen and paper for designing models accounts for 33.8% of responses while designing while building the simulation account for 28.5% and over 55% of respondents conduct what could be considered informal means of model verification (trial and error, and visual inspection). When the M&S community conducts V&V, formal forms of V&V need to be considered. Not only would this facilitate the replication of models/simulations but also increase the credibility of simulation results. Further, we need to consider conceptualization and verification as integral pieces of the validation process. Conceptualization provides a basis for replication by understanding the problem context. Assumptions, required for simplification and verification, provide structural validation by allowing us to know that the system of premises captured in the model are free of contradiction. Validation ultimately becomes a test of how closely results reflect empirical data, if available. In other words, conceptualization and verification provide a large portion of the rigor required in the M&S process. As such, validation is not a separate activity but the culmination of an iterative process undertaken to provide answers or insight about phenomena and systems of interest.

Acknowledgement

The authors would like to thank Joshua Behr, from the Virginia Modeling, Analysis, and Simulation Center at Old Dominion University, for his feedback during the development the survey.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

References

1. Malhotra MK and Grover V. An assessment of survey research in POM: From constructs to theory. *JOM* 1998; 16: 407–425.
2. Flanigan TS, McFarlane E and Cook S. Conducting survey research among physicians and other medical professionals: a review of current literature, In: *Proceedings of the survey research methods section*, American Association for Public Opinion Research, 13–18 May 2008, New Orleans, LA. Oakbrook Terrace, IL, USA: AAPOR, 2008, pp. 4136–4147.
3. Kiesler S and Sproull LS. Response effects in the electronic survey. *Public Opin Q* 1986; 50: 402–413.
4. Daley EM, McDermott RJ, McCormack Brown KR, et al. Conducting web-based survey research: A lesson in internet designs. *Am J Health Behav* 2003; 27: 116–124.
5. Ansolabehere S and Schaffner BF. Distractions: The incidence and consequences of interruptions for survey respondents. *J Surv Stat Methodol* 2015; 3: 216–239.
6. Boer C, De Bruin A and Verbraeck A. Distributed simulation in industry, a survey part 1, the COTS vendors. In: Perrone LF, Wieland FP, Liu J, et al. (eds) *Proceedings of the 2006 Winter Simulation Conference*, 3–6 December 2006, Monterey, CA. Piscataway, NJ, USA: IEEE Press, 2006, pp. 1053–1060.
7. Boer C, De Bruin A and Verbraeck A. Distributed simulation in industry, a survey part 2, experts on distributed simulation. In: Perrone LF, Wieland FP, Liu J, et al. (eds) *Proceedings of the 2006 Winter Simulation Conference*, 3–6 December 2006, Monterey, CA. Piscataway, NJ, USA: IEEE Press, 2006, pp. 1061–1068.
8. Boer C, De Bruin A and Verbraeck A. Distributed simulation in industry, a survey part 3, the HLA standard in industry. In: Mason SJ, Hill RR, Mönch L, et al. (eds) *Proceedings of the 2008 Winter Simulation Conference*, 7–10 December 2008, Miami, FL. Piscataway, NJ, USA: IEEE Press, 2008, pp. 1094–1102.
9. O'Donoghue C and Loughrey J. Nowcasting in microsimulation models: A methodological survey. *J Artif Soc Soc Simulat* 2014; 17: 1–11.
10. Ahmed R, Hall T, Wernick P, et al. Software process simulation modelling: A survey of practice. *J Simulat* 2008; 2: 91–102.
11. Eldredge DL and Watson HJ. An ongoing study of the practice of simulation in industry. *Simul Gaming* 1996; 27: 375–386.
12. Särndal CE and Lundquist P. Accuracy in estimation with nonresponse: A function of degree of imbalance and degree of explanation. *J Surv Stat Methodol* 2014; 2: 361–387.
13. Baker R, Brick JM, Bates NA, et al. Summary report of the AAPOR task force on non-probability sampling. *J Surv Stat Methodol* 2013; 1: 90–143.
14. Beede DN, Julian TA, Langdon D, et al. Women in STEM: A gender gap to innovation. *Economics and Statistics Administration Issue Brief*. Report number 04–11, 2011.
15. Robinson S. Conceptual modeling for simulation: Issues and research requirements. In: Perrone LF, Wieland FP, Liu J, et al. (eds) *Proceedings of the 2006 Winter Simulation Conference*, 3–6 December 2006, Monterey, CA. Piscataway, NJ, USA: IEEE Press, 2006, pp. 792–800.
16. Robinson S. Conceptual modelling for simulation part I: Definition and requirements. *J Oper Res Soc* 2008; 59: 278–290.
17. Davies I, Green P, Rosemann M, et al. How do practitioners use conceptual modeling in practice? *Data Knowl Eng* 2006; 58: 358–380.
18. Davis PK. *Generalizing concepts and methods of verification, validation, and accreditation (VV&A) for military simulations*. RAND CORP: Santa Monica, CA, USA. Report number RAND/R-4249-ACQ, 1992.
19. Epstein JM. *Agent_zero: Toward neurocognitive foundations for generative social science*. Princeton, NJ, USA: Princeton University Press, 2013.
20. McKenzie FD. Systems modeling: analysis and operations research. In: Sokolowski JA and Banks CM (eds) *Modeling and simulation fundamental: Theoretical underpinnings and practical domains*. Hoboken, NJ, USA: John Wiley and Sons, Inc., 2010, pp. 147–180.
21. Balci O. Verification, validation, and accreditation. In: Medeiros DJ, Watson EF, Carson JS, et al. (eds) *Proceedings of the 1998 Winter Simulation Conference*, 13–16 December 1998, Washington, DC. Piscataway, NJ, USA: IEEE Press, 1998, pp. 41–48.
22. Tolk A, Diallo SY, Padilla JJ, et al. Reference modelling in support of M&S: Foundations and applications. *J Simulat* 2013; 7: 69–82.
23. Arthur JD and Nance RE. Independent verification and validation: a missing link in simulation methodology? In: Charnes JM, Morrice DJ, Brunner DT, et al. (eds) *Proceedings of the 1996 Winter Simulation Conference*, 8–11 December 1996, Coronado, CA. Piscataway, NJ, USA: IEEE Press, 1996, pp. 230–236.
24. Pace DK. Modeling and simulation verification and validation challenges. *Johns Hopkins APL Tech Dig* 2004; 25: 163–172.
25. Sargent RG. Verification, validation, and accreditation of simulation models. In: Joines JA, Barton RR, Kang K, et al. (eds) *Proceedings of the 2000 Winter Simulation Conference*, 10–13 December 2000, Orlando, FL. Piscataway, NJ, USA: IEEE Press, 2000, pp. 50–59.

Appendix A: Taxonomical representation of survey questions

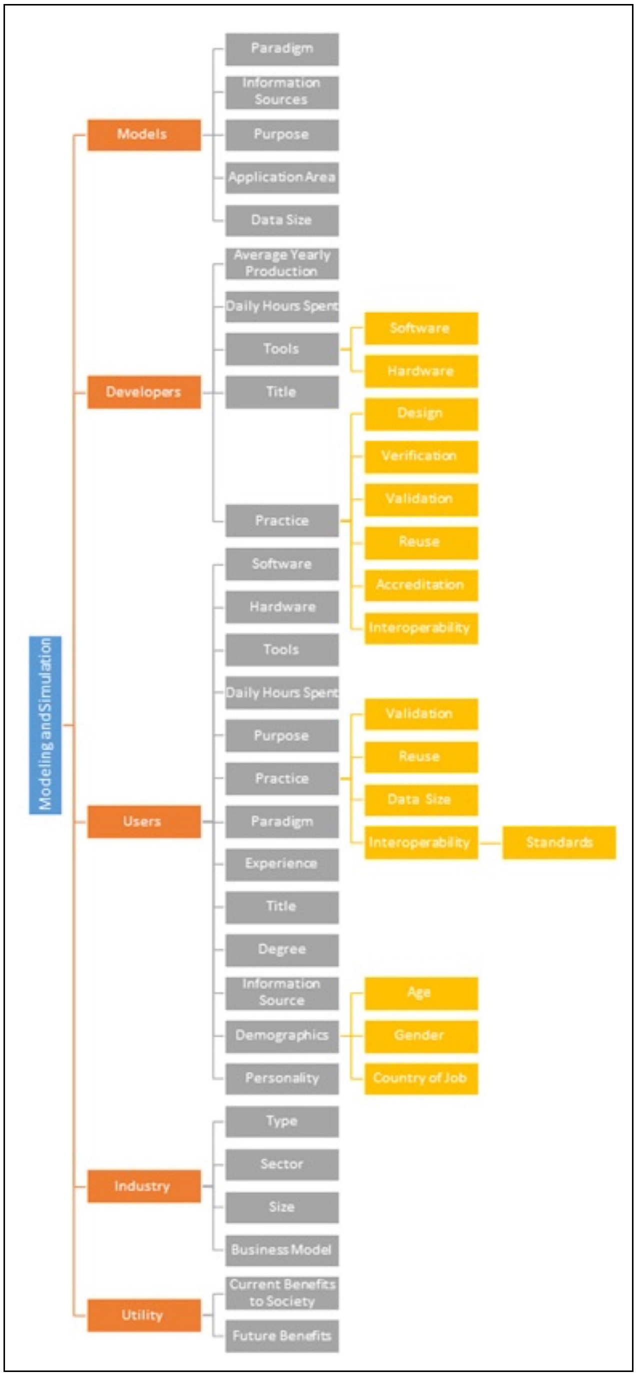

Figure A1. Taxonomical representation of survey results.

Appendix B: Summary of Survey Responses

Table B1. Summary of survey statistics.

Respondent Category	Survey Category	Number/%age of Respondents
Models	Respondents	167
	Paradigm	24.55% Agent-based Models, 20.96% Discrete-event Simulations, 11.98% System Dynamics Models, 9.58% Numerical models, 4.79% Monte Carlo Models, 3.59% Structural Equation models, 14.97% of respondents use a combination of these approaches, and 9.58% do not build models
	Information Sources *	Agent-based Models use theory (82.93%), data (73.17%), SME input (65.85%), and other models (36.59%) Discrete-event Simulations use data (85.71%), SME input (62.86%), theory (34.29%), and other models (28.57%) System Dynamics models use theory (85%), SME input (80%), data (75%), and other models (60%) Numerical Models use data (93.75%), theory (62.5%), SME input (56.25%), and other models (43.75%) Monte Carlo models use data (87.5%), SME input (62.5%), theory (50%), and other models (50%) Structural Equation models use data (83.33%), theory (66.67%), SME input (50%), and other models (33.33%)
	Purpose *	Models are built for their explanatory capabilities (57.62%), decision making support (56.29%), experimentation (45.70%), predictive capabilities (41.06%), support for training (30.46), acquisition (10.60%), among other purposes
	Application Areas *	Defense (50.33%), Science and Engineering (45.70%), Health Care and Public Health (27.15%), Transportation (19.21%), Information Technology and Communications (16.56%), Manufacturing (15.23%), Public Services (14.57%), Energy and Utilities (14.57%), Agriculture and Food (13.25%), Business and Finance (9.93%), Banking and Finance (7.28%), Construction (5.96%), Hospitality, Tourism, and Recreation (2.65%), Arts and Recreation (1.99%), and the remaining respondents do not know the application areas that their models pertain to (1.99%)
	Data Size	Megabytes (60.93%), gigabytes (17.88%), kilobytes (12.58%), smaller than kilobytes (5.30%), and terabytes (3.31%)
	Verification	Informal methods (55.63%), formal methods (21.19%), using software tools (8.61%), a combination of these methods (13.91%), and do not verify models (0.66%)
	Validation	Compare results to real data (55.63%), consult SMEs (17.22%), comparison to other models' outputs (7.95%), visual inspection (5.30%), using a third party to conduct validation (1.32%), a combination of these approaches (11.26%), and do not validate their models (1.32%)
Model Developers	Respondents	151
	Average Yearly Production	None (3.97%), one-to-four (55.63%), five-to-nine (23.84%), nine-to-twelve (9.27%), and twelve-or-more (17.88%)
	Daily Hours Spent	Less than 1 hour (18.54%), 1-3 hours (45.70%), 4-8 hours (29.80%), more than 8 hours (2.65%), and highly variable hours (6.62%)
	Hardware Tools	Off-the-shelf laptop (40.40%), off-the-shelf desktop (37.75%), built-to-order computer station (10.60%), computer cluster (5.30%), dedicated supercomputer (1.32%), scalable environment (0.66%), shared supercomputer (0.66%), dedicated server (0.66%), virtual client (0.66%), GPU-based capability (0.66%), and a combination of laptops and desktops (1.32%)
	Software Tools *	Excel (15.75%), Matlab (15.75%), NetLogo (15.07%), Java (9.59%), AnyLogic (8.90%), Vensim (8.22%), Tools (6.16%), ExtendSim (4.11%), Python (3.42%), Visio (3.42%), Software (2.74%), SAS (2.74%), Access (2.74%), Simul8 (2.74%), Repast Simphony (2.05%), Mathematica (2.05%), SPSS (2.05%), OPNET (2.05%), Powersim (2.05%), Visual Studio (1.37%), LSD (1.37%), GPSS (1.37%), Presagis (1.37%), Expert (1.37%), Lab (1.37%), Libraries (1.37%), and Stella (1.37%)
	Title	Researcher (50.79%), Director (10.32%), Project Manager (10.32%), Simulation Developer (7.94%), Chief Executive Officer (7.14%), Program Manager (3.17%), Teacher (3.17%), Engineer (3.17), Business Development (1.59%), and Chief Technology Officer (1.59%)
Model Users (Non-developers)	Respondents	16
	Software Tools	Enterprise Architect (18.18%), JCATS (18.18%), Excel (18.18%), Matlab (18.18%), and Tools (18.18%)

(continued)

Table B1. Continued

Respondent Category	Survey Category	Number/%age of Respondents
	Hardware Tools	Off-the-shelf laptop (70.0%), off-the-shelf desktop (20.0%), and computer cluster (10.0%)
	Daily Hours Spent	0 hours (37.50%), 0-2 hours (18.75%), 2 to 4 hours (18.75%), 4-6 hours (6.25%), 6-8 hours (12.50%), and unspecified (6.25%)
	Purpose *	Decision making (43.75%), explanatory capabilities (37.50%), support for training (31.25%), predictive capabilities (18.75%), experimentation (12.50%), acquisition (6.25%), and not applicable (12.50%)
	Validation	Comparison to real data (31.25%), consulting SMEs (25%), visual inspection (18.75%), comparing to other models' outputs known to be valid (6.25%), do not validate models (6.25%), and not applicable (12.50%)
	Reuse	None (43.75%), 11-20% (6.25%), 21-30% (12.50%), 31-40% (6.25%), 41-50% (6.25%), 51-60% (6.25%), 61-70% (0%), 71-80% (12.50%), 81-100% (0%)
	Data Size	Megabytes (43.75%), kilobytes (25%), smaller than kilobytes (18.75%), and gigabytes (12.50%)
	Interoperability *	Not used (32.93%), High Level Architecture (30.54%), unknown (27.54%), Distributed Interactive Simulation (19.76%), and the Test and Training Enabling Architecture (8.98%)
	Paradigm	None (37.50%), Discrete-event Simulation (25%), Numerical Models (12.5%), Monte Carlo Models (6.25%), Agent-based Models (6.25%), System Dynamics Models (6.25%), and machine learning (6.25%)
Model Developers and Non-developers	Respondents	167
	Experience	0-5 years (23.35%), 6-10 years (22.75%), 11-15 years (14.37%), 16-20 years (5.39%), and over 20 years (34.13%)
	Title	Researcher (46.11%), Project Manager (10.18%), Director (8.98%), Chief Executive Officer (8.98%), Simulation Developer (7.19%), Business Development (4.19%), Program Manager (3.59%), Teacher (2.99%), Engineer (2.40), Chief Technology Officer (1.80%), and other categories (3.59%)
	Degree	Doctorate (47.90%), Master degree (39.52%), Bachelor's degree (10.18%), Associate's degree (1.20%), and currently pursuing degrees (1.20%)
	Field of Degree	Engineering (32.34%), Formal Sciences (28.74%), Social Sciences (12.57%), Natural and Physical Sciences (9.58%), Business and Finance (4.19%), Education (2.99%), Arts and Humantities (1.80%), and Medicine and Healthcare (1.20%)
	Information Sources *	Academic journals (66.47%), conference proceedings (59.88%), web searches (53.29%), technical reports (49.70%), websites (46.11%), professional organizations (41.92%), book chapters (39.52%), theses and dissertations (39.52%), textbooks (37.72%), organizational meetings (32.93%), newsletters (19.76%), magazines (13.17%), peers and experience (1.80%), databases (1.20%), and standards (0.60%)
	Age	Under 30 years old (6.63%), 31-40 years old (34.34%), 41-50 years old (13.86%), 51-60 years old (27.11%), 61 years and older (18.07%)
	Gender	Male (93.29%) and female (6.71%)
	Country (of Job)	22 countries represented: United States of America (58.0%), United Kingdom (7.2%), Netherlands (5.4%), Australia (4.2%), Germany (3.6%), Canada (3.0%), France (3.0%), Sweden (2.4%), Belgium (1.8%), Argentina (1.2%), China (1.2%), Colombia (1.2%), Italy (1.2%), Luxembourg (1.2%), Norway (1.2%), Norway (0.6%), Chile (0.6%), Georgia (0.6%), Greece (0.6%), India (0.6%), New Zealand (0.6%), South Africa (0.6%), and Barbados (0.6%)
Industry	Respondents	42 model developers and 4 model users (non-developers)
	Type	Model developers build discrete-event simulations (30.43%), agent-based models (17.39%), system dynamics models (10.87%), Monte Carlo models (8.7%), Numerical Models (6.52%), Structural Equation models (4.35%), combinations of these model types (13.04%), and the remaining 8.7% do not build models.
	Sectors Serviced by M&S *	The primary sectors that industry uses models and simulations to support are Defense (56.52%), Science and Engineering (36.96%), Health Care and Public Health (32.61%), Energy and Utilities (30.43%), and Transportation (26.09%).

(continued)

Table B1. Continued

Respondent Category	Survey Category	Number/%age of Respondents
	Size	The size of the industries that use M&S are 65.22% small business (less than 500 employees), 10.87% with 1001-5000 employees, 15.22% with 5001-20000 employees, and 8.7% with more than 20000 employees.
	Business Model *	Develop models and simulations for sale (56.52%) and for research (50.00%), use models previously developed by other people (30.43%), and sell model and simulation software (26.09%).
Utility	Respondents	133 (current benefits) and 126 (future benefits)
	Current Benefits to Society *	Understanding (22.56%), ability (15.0%), explore (13.53%), test (11.28%), decision making (9.77%), cost (9.77%), predictive (9.02%), training (8.27%), complex systems (7.52%), model (7.52%), experimentation (6.02%), experiments (5.26%), efficiency (4.51%), explanations (2.26%), support (2.26%), complex problems (2.26%), cheaper (2.26%), education (2.26%), outcomes (1.50%), exist (1.50%), learn (1.50%), little (1.50%), situations (1.50%), games (1.50%), identify (1.50%), and run (1.50%)
	Future Benefits *	Models (19.84%), decision (14.29%), simulation (12.70%), understanding (10.32%), prediction (9.52%), complex systems (7.14%), training (7.14%), grow (6.35%), research (5.56%), problems (3.97%), live (3.17%), scientific (3.17%), real world (2.38%), knowledge (2.38%), Big Data (1.59%), huge potential (1.59%), policy making (1.59%), agents (1.59%), efficient (1.59%), ideas (1.59%), visualization (1.59%), everyday (1.59%), explore (1.59%), money (1.59%), power (1.59%), and realistic (1.59%)

*Indicates that respondents could select multiple responses for this question.

Author biographies

Jose J Padilla is Research Assistant Professor at the Virginia Modeling, Analysis, and Simulation Center at Old Dominion University. He received his PhD in Engineering Management from Old Dominion University. His email address is jpadilla@odu.edu.

Saikou Y Diallo is Research Associate Professor at the Virginia Modeling, Analysis, and Simulation Center and adjunct Professor of Modeling, Simulation, and Visualization Engineering at Old Dominion University. He received his MS and PhD in Modeling and Simulation from Old Dominion University. His email address is sdiallo@odu.edu.

Christopher J Lynch is a Senior Project Scientist at the Virginia Modeling, Analysis, and Simulation Center. He is currently working on a PhD in Modeling and Simulation at Old Dominion University. He received his MS in Modeling and Simulation from Old Dominion University in Norfolk, VA in 2012 and a BS in Electrical Engineering from Old Dominion University in 2011. His email is cjlynch@odu.edu.

Ross Gore is Research Assistant Professor at the Virginia Modeling, Analysis, and Simulation Center at Old Dominion University. He holds a Doctorate of Philosophy (PhD) and a Master's degree in Computer Science from the University of Virginia and a Bachelor's degree in Computer Science from the University of Richmond. His email address is rgore@odu.edu.