Model-Based Systems Engineering Uptake in Engineering Practice

By

Dr. Bruce Cameron
Massachusetts Institute of Technology (MIT)
bcameron@mit.edu

Daniel Mark Adsit
Massachusetts Institute of Technology (MIT)
adsit@sdm.mit.edu

Abstract

Modeling is ubiquitous in engineering, but data on model use and user sophistication in engineering-driven firms is remarkably sparse. Some authors have predicted a sea change in engineering workflow through Model-Based Systems Engineering (MBSE). Despite benefits, the prevalence of effective modeling techniques in industry is an open question. Massive open online courses (MOOCs) and similar online offerings are a new opportunity to learn about industry practices. In this paper, we draw on data from the "Architecture and Systems Engineering" online program from the Massachusetts Institute of Technology (MIT), which has enrolled 4200 participants, to understand how models are used in practice. We use aggregated data from questions to investigate model use by participants and their organizations. The results demonstrate that whereas modeling is widely recognized for its potential, the actual deployment against problems of interest is substantially lower than the participant-stated potential. We also find that many participants reported low use of basic modeling best practices, such as specialized programs. We propose that this research is a fresh use of descriptive analysis to uncover actual modeling practices. Future research should target more detail about modeling practices in engineering-driven firms, and the reasons why modeling adoption is low or overstated.

I. Introduction

The use of models spans nearly all disciplines in history. Early examples include dioramas of buildings and battlefields, computer simulations, and engineering. Models are a mechanism to simplify complex information for a specific "purpose" [1]. Recent technical advancements in software promise to reduce cost, improve performance, and make collaboration more effective in engineering. Model-Based Systems Engineering (MBSE) refers to a specific recent trend that argues for a central model to serve as a means of coordinating system design.

While modeling has a rich history, profound benefits from sophisticated modeling techniques depend entirely on awareness, application, and adoption by engineering-driven firms [2], [3]. One of the challenges to MBSE is a reliance on network effects where benefits grow nonlinearly with the adoption by other users on the team. The conclusion that "the biggest challenge to wide-scale MBSE adoption is gaining acceptance in the SE, program management,

Accepted for publication in IEEE Transactions in Engineering Management.

and acquisition communities, because MBSE does not readily fit the traditional documentation and review process" personifies this problem [1]. Prior research has cited many other specific challenges. Practical adoption challenges include discrepancies with standards such as SysML between different engineering disciplines [4], the "complexity of cyber-physical" systems that inhibits modeling [5], lack of support for "full-system lifecycle" [1], and "expense" of creating models [6]. Organizational challenges to adoption include a "culture change" away from documents [1], an incomplete transition from "traditional-document based development" [4], and the "challenge organizations face when attempting to adopt more advanced model-driven techniques" [7]. Other challenges are strategic, including a perception that "none of the existing approaches has established" despite the maturity of SysML [4] and uncertainty about the overall "value proposition" of MBSE [1]. Finally, studies in specific domains such as the battery [6] and manufacturing [8] industries cite supposedly unique characteristics that inhibit model development.

Despite these many perceived challenges, there is scarce data about modeling adoption by engineering-driven firms. Leveraging data in this area is important to assess whether engineers apply effective modeling techniques in practice. Prior research has attempted to build an image of the existing state of MBSE adoption through several mechanisms. A survey of 50 academic and industry experts attempted to assess systems engineering competence among respondents [4], while another gathered responses from approximately 200 respondents about MBSE "adoption" at firms [9]. Case studies address specific challenges with a vehicle's fuel management subsystem [5] and a healthcare information system [10]. Others have worked to catalogue existing research and "methodologies" into practical conclusions [1], [6], [7]. However, in many cases the number of samples in preceding studies appear small or the sample profiles do not represent all industry.

Modern educational experiences that include environments beyond the traditional classroom are an opportunity to improve data. Massive open online courses (MOOC) assemble learners from around the world from different backgrounds. For example, edX.org lists over 1900 courses at the time of this writing. These programs extend reach across geographies, industries, firms, and knowledge silos through interactive videos, surveys, and discussion boards. Beyond exposure to course content, MOOC participants engage in both individually-paced and community learning environments. MOOCs connect orders of magnitude larger groups of participants simultaneously than is otherwise practical within traditional education. A prior study of participant "subpopulations" in MOOCs concludes that effectively leveraging participants' "prior knowledge" enhances MOOC content effectiveness because it "mediates encounters with new information" [11]. We propose that the overall MOOC environment and interactive mechanisms facilitate a practice-sharing role, in addition to the traditional content delivery style of online and video education.

The "Architecture and Systems Engineering: Models and Methods to Manage Complex Systems" certificate program offered by the Massachusetts Institute of Technology (MIT) is a series of four online courses with enrollment of 4200 participants with common interest in MBSE over the past two years. As career opportunity becomes increasingly chaotic and professionals endure a "life-long" state of "transition" [12], the participants who enroll in these courses represent a potential population sample to learn about engineering practices. Whereas it is debatable whether the scale or economic model fits the established MOOC definition, experienced participants engage through both public and corporate-supported enrollments.

During the "Architecture and Systems Engineering" program at MIT, participants complete an enrollment survey and respond to interactive polls about modeling in engineering. Participant responses are an opportunity to learn about the modeling practices in engineering-driven firms. This data is sufficiently anonymized for learning without privacy risks. This paper begins with a research outline and analysis of methods used on survey and polls data. The results are then presented, followed by a discussion of the use of models and MBSE in industry.

II. Literature review

Models have "been part of the systems engineering (SE) profession for decades," whereas Model-Based Systems Engineering (MBSE) is a more disciplined set of practices that "places models at the center of the system development process" [1]. This broadly defines how models are "represented," ranging from "modeling language" to "text description" to even a "cartoon" [13], [14], [15], [16]. Ramos et al. [17] contrasts "traditional" SE regimes with an optimistic near-future view of MBSE where the "prominence of controlling documents is now replaced by controlling the model of the system." Others take an industry specific approach to modeling [18], [19]. Selic [20] defines "model-driven development" as the exploitation of unique modeling advantages within the software engineering field despite acknowledging modeling practices in engineering from ancient Rome. It will be necessary to identify the current state and barriers in context in order to evaluate the prevalence and forecasts of MBSE adoption.

Despite the extensive history of modeling, many efforts have attempted to catalog challenges with MBSE adoption [21]. A review of MBSE industry methodologies acknowledges that "traditional document-driven approaches" utilizing programs such as Microsoft Word and PowerPoint show few signs of retreat even though current modeling "technology" is entirely capable and despite adoption of SE process standards [7]. Another study characterizes MBSE as a puzzle beyond simple technical application and identifies "cultural" challenges during an extensive enumeration of current academic enthusiasm about MBSE subject matter [17]. Results from industry "surveys" attribute an MBSE adoption gap to pending transition from "traditional" documents to models within engineering disciplines [4]. However, incremental modeling does not necessarily indicate effective practice. Madni and Sievers [1] argue that the "current culture of relying on document-centric systems engineering is arguably the most serious impediment to adopting MBSE in most organizations." While consistent with specific modeling obstacles in construction engineering [22], these broader MBSE assessments suggest that modeling obstacles are not limited to any specific area of engineering.

Past analyses have attempted to identify solutions to MBSE adoption challenges. Technical proposals include improvements to languages and "modeling tools," [4] in addition to enhanced "interoperation" [5]. Certain proposals argue that custom "specialized, domain specific" modeling solutions are needed [5], whereas others cite broader collaborative efforts from "working groups," "case studies," and "courses" [1]. Prescriptive studies propose solutions for specific domains, such as the battery [6], construction [22], software engineering [10], [16], and aerospace [23] industries. Whereas all these approaches may seem reasonable at face value,

Accepted for publication in IEEE Transactions in Engineering Management.

the underlying state of MBSE adoption across engineering remains unclear. Without a landscape view, local optimization may come at the expense of solving systematic MBSE adoption problems.

Dominant practice is one explanation for modeling adoption challenges. Estefan [7] attributes continuous model revision and refinement, versus the static nature of traditional documents, as a "communication barrier." This appears to align with the observation that SE "functions are captured in multiple text documents" by established practices [1]. The claim that "MBSE does not readily fit the traditional documentation and review process" that is ingrained into established organizational practices may explain dependence on text documents and the struggle to grow beyond them [1]. Challenges transitioning from modeling theory to practice are also cited. These includes the perception that most achievements are limited to "academic and research domains rather than industry" [22]. Phrases such as SE "approaches have been used in battery literature in the past" from a study of lithium ion batteries suggest that modeling remains an academic rather than industry exercise, whereas "the eventual goal" and "next two decades" sets an enormously long timeline for modeling achievements [6]. Meanwhile, quantitative data about the actual use of models in industry is mostly omitted from many sources.

General modeling obstacles imply adoption obstacles for formal MBSE applications [24], [25]. Madni and Sievers [1] acknowledge the dilemma that MBSE "value proposition needs to be convincingly demonstrated on real-world problems," but suggests that shortcomings are addressed through discourse activities such as INCOSE, case studies, laboratory research, and academic courses similar to the MIT program used in this study. However, regardless of whether this value refers to higher performance at higher cost or improved performance-to-cost ratio against the current state, association and academic programs may not be directly connected enough to actual business results to demonstrate value. In the end, advancement of MBSE depends on what engineers do, not what they say they will do.

Other solutions take approaches that make modeling more appealing. Despite optimism about models for software engineering, acknowledgment that "development process and environment used to produce it must be integrated into the legacy development process and environment" appears related to the document patterns revealed in more recent sources [20]. "Collaboration" between academia and industry has enabled specific achievements for construction engineering and references specific case studies [22]. However, "high risk, project uniqueness, and short decision making time" obstacles appear easily extensible to many other engineering disciplines. Therefore, similar collaborative techniques between academia and industry to develop modeling competence could impact broader adoption. Albers and Zingel [4] suggest that in order to address the systematic organizational nature of this problem as presented, "advancements" in MBSE languages and tools must support a foothold for modeling in regular practice that overcomes dominant industry practices. After all, at some level, the languages and tools appear too far a reach. MBSE facilitates a description of the system that "evolves" and is "integrated" in ways that are less achievable using documents [1]. The question why organizations remain dependent on documents and how to overcome this inertia remains.

Despite the apparent organizational challenges to model adoption, proposed solutions still attempt to encourage technical advancement and increased sophistication. Derler et al. [5] proposes "technologies" that mitigate six "modeling challenges" including consistency and

Accepted for publication in IEEE Transactions in Engineering Management.

connectivity problems. Whereas this analysis lists ten “wide range applications” spanning signal processing to financial engineering, the prescriptive recommendations for “modeling and simulation environments” primarily leverage a military aircraft subsystem example as the data source. Therefore, the paper extrapolates conclusions about intricacies of modeling techniques to broader “cyber-physical systems.” However, additional sophistication in languages and tools might make modeling and MBSE more difficult to adopt in practice based on challenges related to documentation and dominant practices as inferred from the earlier discussed surveys of MBSE and modeling in engineering.

Technical solutions that aim to make modeling appear less daunting and lower the barriers to entry are another approach. Even very early, Selic [20] concludes that resources already exist to produce software in “large-scale industrial applications” and suggests this might be possible by “domain experts” using automated code generation from models without intervention by traditional software developers. This appears very similar to the use of SysML to describe systems. Beyond identifying text documents as models, documents may also be a product of models [1]. Therefore, this raises questions about the underlying goals for producing models, documents, the entire system, or some intermediate state.

Educational data is another area, unrelated to modeling and MBSE, that affects this research. Massive open online courses (MOOCs) can be defined as “distributed classrooms...that emphasize instructional videos and regular assessments, centralizing activities on a single platform” and “provide an unprecedented volume of data” [11]. This classification of “large repositories of data” extends beyond MOOCs across similar educational formats that apply new types of technology [26]. Breslow et al. [27] moves beyond the presence of this data by acknowledging that this “tremendous amount of data opens up considerable opportunities for educational research.” Whereas analysis of data from “online learners’ activities” has transformed into “emerging” but distinct Educational Data Mining (EDM) and Learning Analytics (LA) research subjects, the body of existing literature lacked an “accredited overview” of the current state [28]. The multiple “learning settings,” “research objectives,” and “analysis methods” uncovered in the subsequent survey suggests significant variation in the research body.

Goals in EDM and LA can be broadly defined as a “focus where learning science and data-driven analytics intersect” [28] or more narrowly scoped to “design better and smarter learning technology and better inform learners and educators” [29]. This focus on educational improvements aligns with research about other sources including “low completion rates” among students in MOOC courses themselves [11] and “what advanced or hindered their achievement” regarding student use of course materials [27]. Romero and Ventura [26] acknowledges an opportunity to analyze data from broad types of educational programs and data, including student “demographic data,” but distinguishes between “human judgement” techniques in LA versus “automated” techniques in EDM. Quantitative techniques are evident in “clustering” to analyze student subpopulations in MOOC courses [11]. However, this distinction may not firmly regulate opportunities to learn using data because even elements of EDM move outside automation and into human factors, including “choosing what data to collect, focusing on the questions to be answered, and making sure that the data align with the questions” and “summarization, visualization, and interactive interfaces to highlight useful information and support decision-making” [26]. The use of a formal survey with explicit questions to obtain data from and about

Accepted for publication in IEEE Transactions in Engineering Management.

students in a MOOC [27] and acknowledgement that data from educational sources does not necessary originate in a single "data stream" [29] suggests that methods beyond automated analysis are appropriate.

Variations in this field may arise from more recent establishment and limited deployment outside the laboratory. Opportunities to leverage "unimaginably large datasets" appeared later in education compared to other "scientific" fields [29] and the "unprecedented" rise of MOOCs in higher education has revealed "numerous and finer grain" data from within a single course [27]. Romero and Ventura [26] concludes that despite analytical advancements to leverage this data, "it is necessary to move from the lab to the general market, and to achieve this objective it is necessary to carry out the next stages of future work." However, even though "calibrating prior knowledge" of students is an open opportunity that could improve the learning process and course materials [11], none of these sources thoroughly address the impact of educational and MOOC data beyond the educational classroom.

From the literature, we conclude that there is a substantial gap in the data surrounding deployment of MBSE practices, as well as an opportunity to identify potential barriers to adoption using data from online learning environments.

III. Research outline & analysis methods

This paper analyzes modelling sophistication in engineering-driven firms using participant data from two sources in the MIT "Architecture and Systems Engineering" program:

1. An enrollment survey with answers to questions about participant backgrounds submitted at the beginning of the program.
2. Polls responses with answers to questions related to course material submitted throughout the program courses. Polls are similar to multiple-choice quizzes.

The question responses from MIT classes were used because they present a unique data opportunity that is absent from the existing research, were available based on permissions provided by course participants, and were readily accessible by the authors through existing involvement in the courses. A subset of questions is analyzed based on relevance to the research objective. Several important limitations are discussed that impact this analysis and research.

Survey and polls analyses

The enrollment survey and polls questions enable participants to report details about themselves and their organizations. In order for an analysis of the survey and polls to effectively address the research objective, conditions about the population sample, question responses, and questions themselves must be met. It is possible to extract meaningful conclusions about the research objective using data from the participants for three reasons.

First, the participants in the course must reflect an appropriate population sample to address the research objective by responding to the polls. This means that the respondents must have some affinity with engineering-driven firms. Course participants have already self-

Accepted for publication in IEEE Transactions in Engineering Management.

identified with models in engineering based on the course subject matter. Additionally, course participants are analyzed based on age, educational, and career details reported through the enrollment survey. We propose that this detail sufficiently identifies these participants as an appropriate population sample to represent modeling use and user sophistication in engineering-driven firms.

Second, the total number of responses to each polls question used in this analysis ranges from 637 to 803. This number is a range because some participants declined to answer certain poll questions. We argue that this is a sufficient number of qualified responses for the research objective, although further discussion is included for specific questions.

Third, the polls questions must reveal the details about the use of models. This presents several data challenges that are covered in the limitations section. Nonetheless, responses from six polls questions that cover MBSE, documentation, languages, programs, and queries provide insight into model use and user sophistication in engineering-driven firms.

Limitations of the survey and polls analyses

The analysis methods used for the enrollment survey and polls data are subject to several important limitations that impact the research objective.

First, we assert that participants in this course reflect a broad population of engineering practice. This assumption relies on awareness about current practices inside organizations. However, some participants might have insufficient exposure to their organizations to accurately report in the polls. Other participants might not be familiar enough with modeling technology and tools to accurately answer the questions. Whereas the results from the enrollment survey indicate that participants have enough exposure to accurately respond to the polls, this uncertainty poses a risk to the research objective.

Second, participants in the courses self-report answers to the survey and polls questions. Therefore, responses that do not represent the accurate or complete situation are possible for many related reasons. Participants might misunderstand the question. They may mislead for privacy reasons or answer randomly to advance to the next screen as quickly as possible. Finally, reported results might be less accurate than results that are obtained through observation. Therefore, self-reported results pose a risk to the research objective.

Third, the polls questions were originally designed for the MIT courses to facilitate participant engagement. Therefore, certain aspects of the data are inconvenient for this research purpose. For example, the respondents are not necessarily the same across all polls because some participants may have added or dropped between courses in the program, and furthermore, participation in the polls is not mandatory for course completion. Additionally, there is no data linkage between enrollment survey and polls responses. This means that it is not possible to analyze polls responses from specific population subsets. Finally, there is no linkage in the data between different polls questions. While we argue that the content of the survey questions is sufficient for the intended purpose, these factors limit the possible analysis options and pose a risk to the research objectives.

Based on these limitations, we proceed to showcase the population sample surveyed in the MIT courses followed by a discussion of the data results.

Accepted for publication in IEEE Transactions in Engineering Management.

IV. Results

This section presents the analysis of model use and user sophistication in engineering-driven firms using enrolment survey and polls question data.

Results: Participant backgrounds from enrollment survey

This section analyzes survey responses about age, education, and careers. These responses provide insight into later responses for the polls questions about models, but we present them here in “Results” because they also represent an answer to the question “What populations are interested in MBSE?”

Age details from survey

Age distribution is important because it may reflect whether participants are working-age, versus still in school or retired. It may also indicate whether participants are in early, mid, or late career stages. These factors could impact participant knowledge about industry practices.

Fig. 1 indicates the distribution of participant ages. Approximately 80 percent of participants reported ages younger than 50 years old. The largest fraction of participants reported ages in the 30s (33 percent), while approximately equal numbers reported ages in the 20s and 40s (23 and 22 percent, respectively). We conclude that this distribution likely reflects many mid-career professionals with multiple years of experience in their organizations and industries, and incorporates a fraction of younger professionals with possible exposure to recent modeling technology trends in academia.

Accepted for publication in IEEE Transactions in Engineering Management.

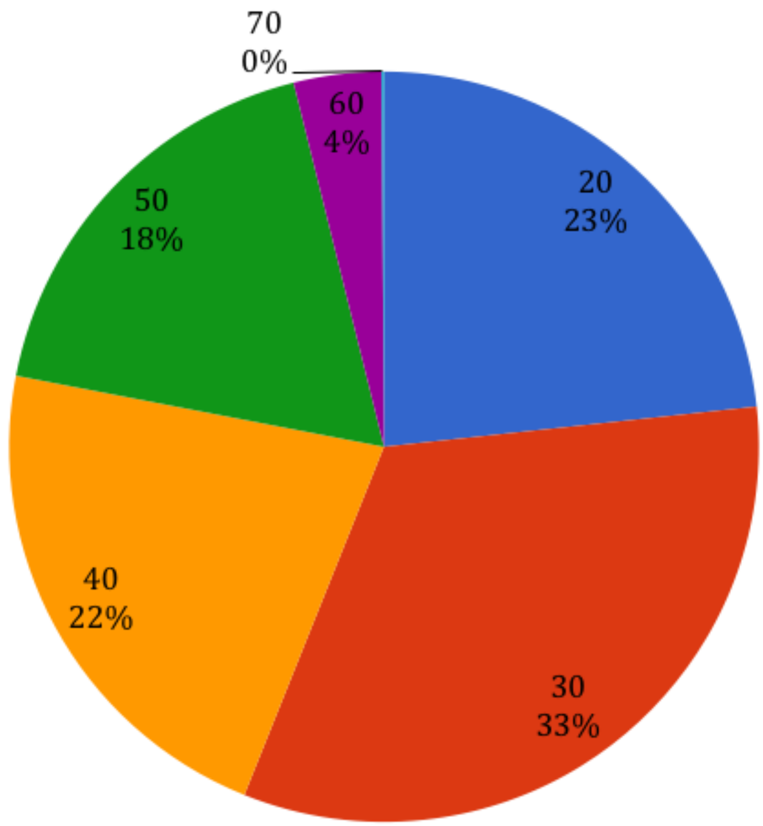

Fig. 1. Distribution of MIT program participants by decade of age.

Education details from survey

Participants indicate their highest level of education and enrollment rationale in the survey. These education details may reveal information about participant roles, responsibilities, and subject matter interests. For example, participants with advanced degrees may have more knowledge about modeling techniques in their organizations than others, while enrollment might provide insight into individual knowledge gaps or organizational priorities.

Fig. 2 indicates the highest degree attained by participants. Over 90 percent of course participants reported attaining a four-year college degree or higher. In this subset of participants, 57 percent reported a graduate degree and 43 percent reported a bachelor's degree.

Accepted for publication in IEEE Transactions in Engineering Management.

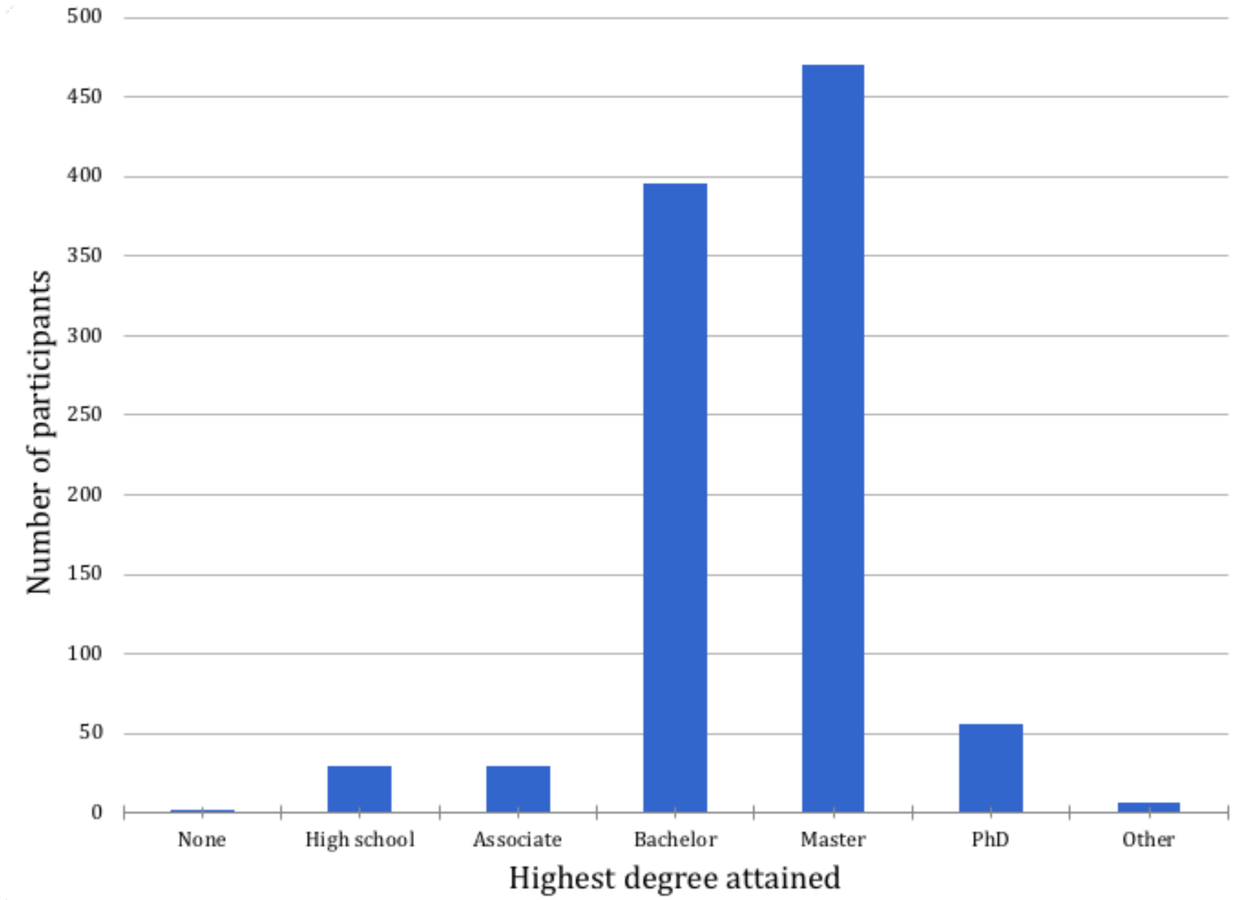

Fig. 2. Education of MIT program participants by highest degree attained.

Participants reported enrollment reasons in the survey using five qualitative levels ranging from "Extremely Important" to "Not Important." Fig. 3 reflects the top enrollment reasons reported by course participants. The reasons "Learn course content" and "Lifelong learning" received the highest number of top reasons (849 and 680, respectively), based on the number of participants who selected "Extremely Important" or "Very Important" levels. These responses suggest that participants are interested in models, aspire to stay current about emerging model topics, and may consider models as an opportunity for themselves or their organizations.

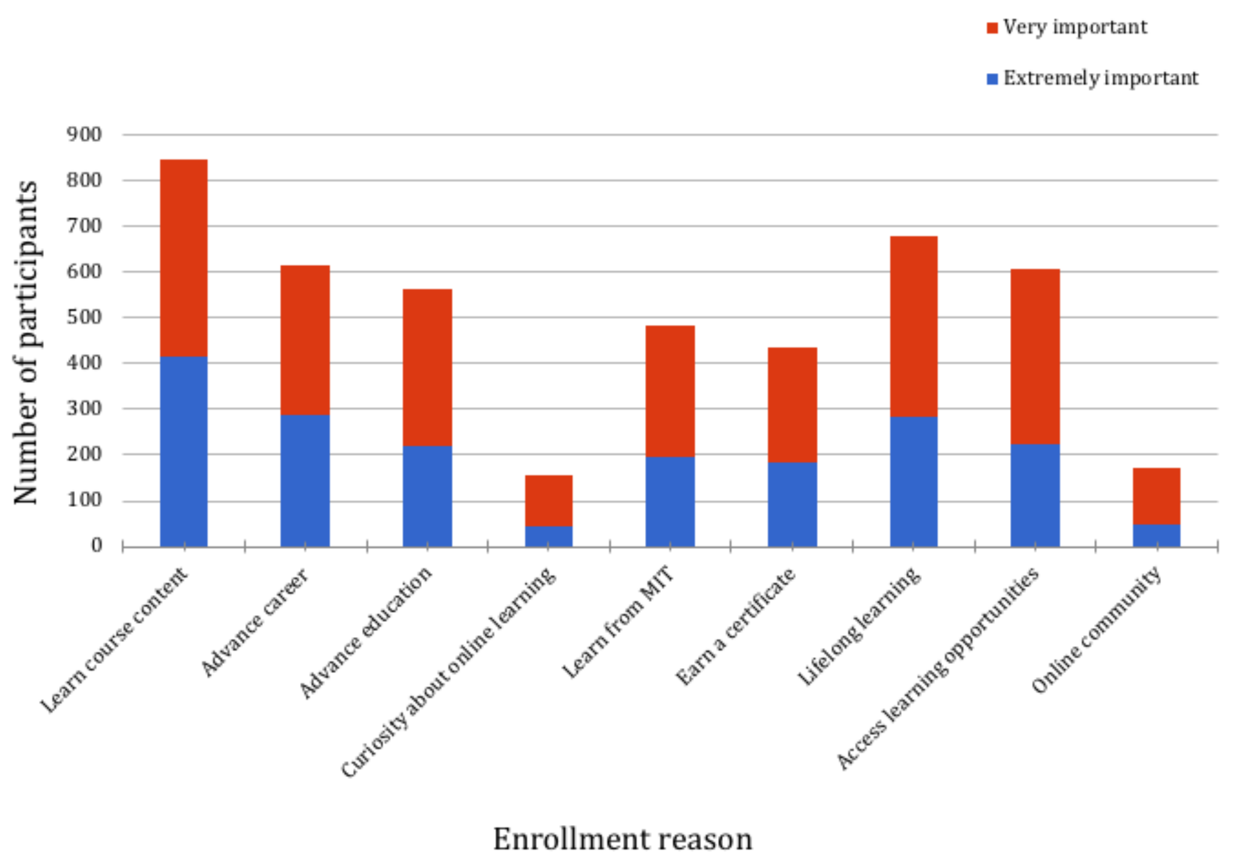

Fig. 3. Top enrollment reasons for MIT program participants.

Therefore, we argue that highly educated participants with a strong interest in models are appropriate to provide insight about modeling practices in their organizations through the polls questions.

Career details from survey

Participants provide their industry and number of years of experience in the survey. These career details may indicate whether participants are in engineering-driven firms, and whether participants are experienced engineers themselves.

Fig. 4 indicates participants by industry. While participants reported affiliation with fifteen different industries, the "Manufacturing," "Professional and Technical Services," and "Other Services" industries accounted for 85 percent of enrollment. Whereas "Other Services" is very broad, the other top industries are highly likely to include engineering-driven firms.

Accepted for publication in IEEE Transactions in Engineering Management.

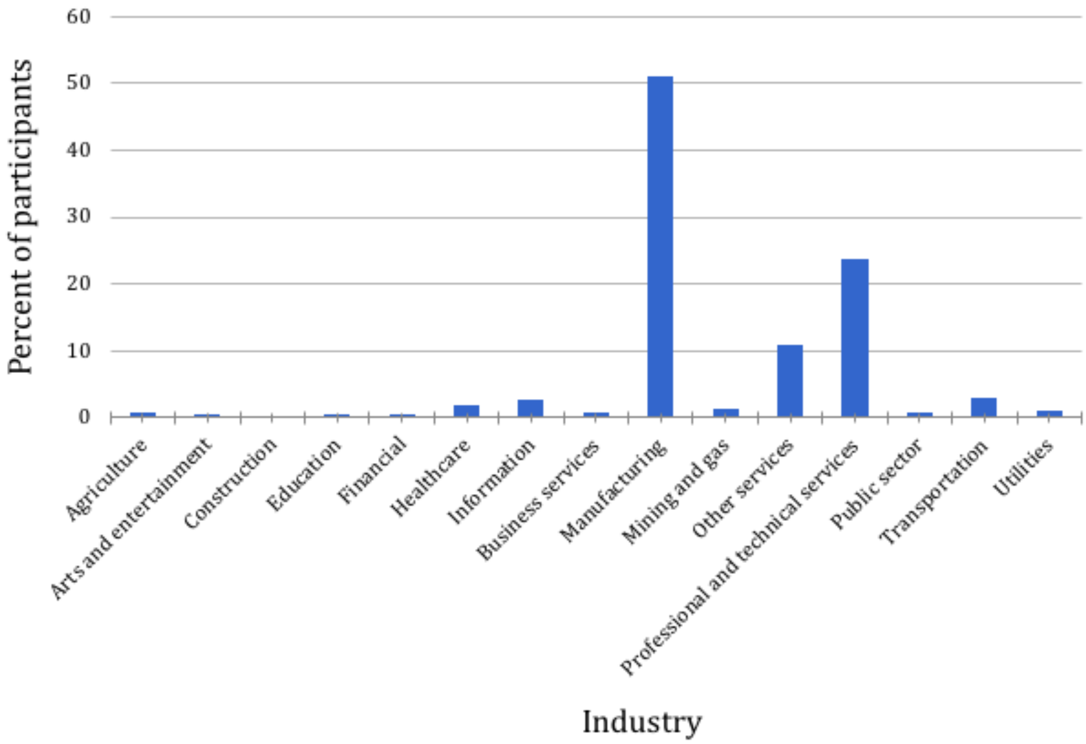

Fig. 4. MIT program participants by industry.

Participants reported number of years of professional and engineering experience across six classifications ranging from “zero years” to “more than 15 years.” Fig. 5 indicates general professional and engineering years of experience for participants. Overall, participants reported higher years of general professional experience and lower years of engineering experience. Almost 60 percent of participants reported more than ten years of professional experience, whereas over 50 percent of participants had three years or less of engineering experience.

Accepted for publication in IEEE Transactions in Engineering Management.

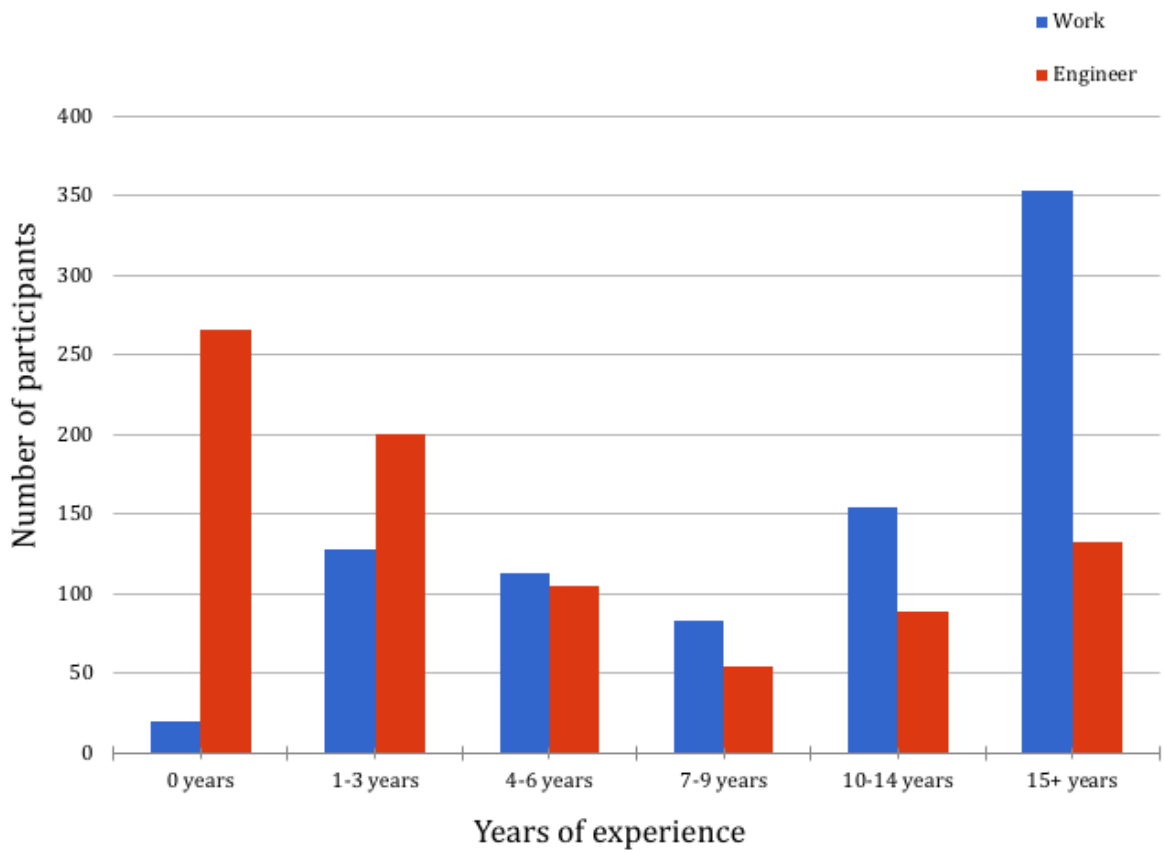

Fig. 5. MIT program participant years of experience.

Whereas not all participants are experienced engineers, we argue that this industry and experience distribution reflects sufficient association by participants with engineering-driven firms. Additionally, over 40 percent of participants received corporate sponsorship, which demonstrates commitment to develop engineering competence within organizations.

Results: Modeling use and sophistication from polls questions

This section analyzes polls responses about Model-Based Systems Engineering (MBSE), documentation, languages, programs, and queries. These responses provide insight into respondents' modeling use and user sophistication in engineering-driven firms.

Model-Based Systems Engineering practices from polls

In the polls, participants provide details about organizational and individual MBSE approaches. Even though MBSE is a specific term, it is possible for participants to interpret the

Accepted for publication in IEEE Transactions in Engineering Management.

scope as modeling in general. We propose that these questions are an effective measurement for modeling practices using the polls data.

First, participants are asked “Does your organization use an MBSE approach?” Second, participants are asked “Have you ever been asked to formally evaluate or critique an MBSE approach?” Fig. 6 indicates the participant responses about MBSE. Based on the answers submitted, 35 percent of respondents reported an organization with an MBSE approach, whereas only nine percent of respondents reported being asked to perform or evaluate a critique. The latter seems very low.

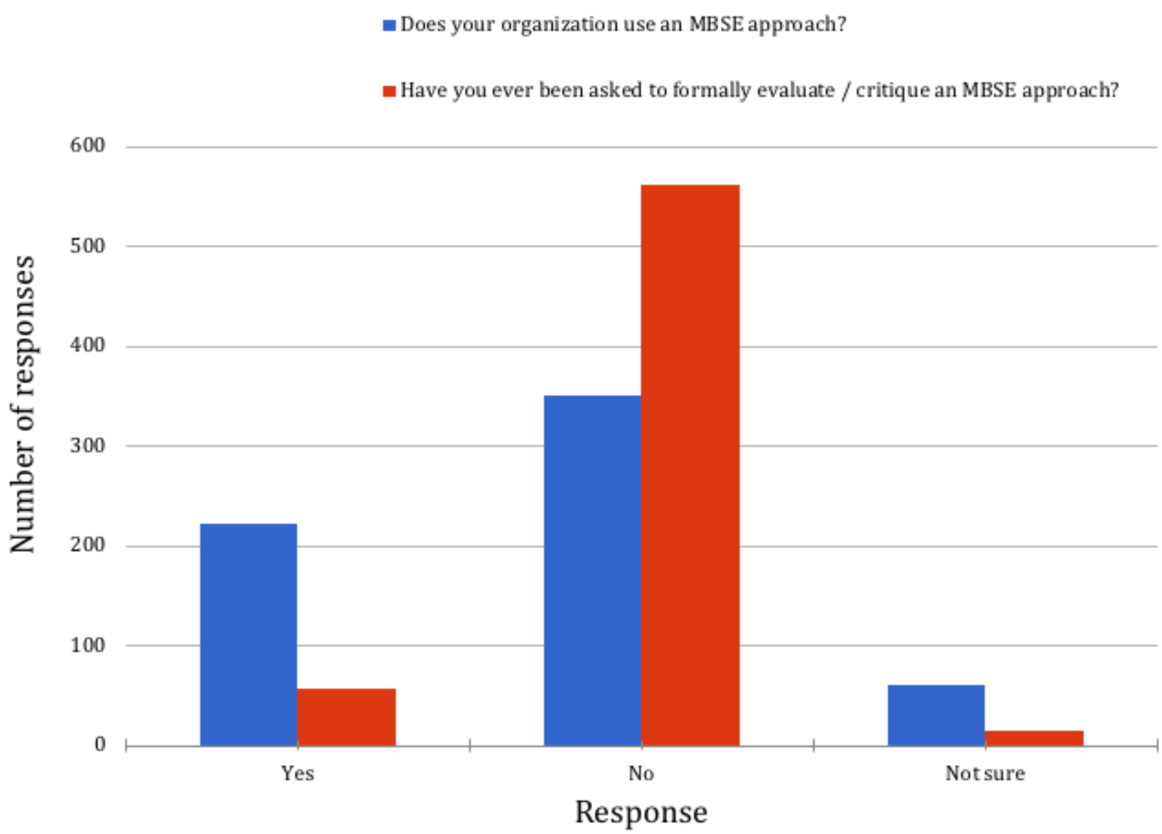

Fig. 6. Responses to polls about MBSE.

According to these results, approximately one quarter of respondents who reported that their organizations used an MBSE approach had been asked to evaluate an MBSE approach. This difference is surprising considering that these questions are asked at the same time and received nearly identical numbers of total responses. If program participants are highly educated and experienced professionals in their organizations, it is logical to assume that they would be involved with models at a review level if their organizations had adopted MBSE approaches because effective implementations require collaboration. We propose that this discrepancy may indicate a disconnect between perceived and actual behaviors.

Accepted for publication in IEEE Transactions in Engineering Management.

Documentation and data practices from polls

In the polls, participants provide details about individual and organizational documentation and data methods. While not necessarily models, these methods are crucial indicators about modeling practices. In particular, structured and interconnected data enable modeling because they can be quantitatively analyzed. Furthermore, ease of documentation was identified as a potential use case for MBSE in the literature review.

Participants are asked about "documentation methods have you used." Fig. 7 indicates the documentation methods used by respondents. The choices were not intended to be an exhaustive enumeration. Microsoft Word and PowerPoint based methods were most commonly selected. This result is not particularly useful because having used them at some point in the past does not indicate persistent or systematic use. However, many least used methods are the most closely associated with modeling, including Systems Modeling Language (SysML), Unified Modeling Language (UML), and Design Structure Matrix (DSM). We argue that lower use of these methods is interesting for the research objective.

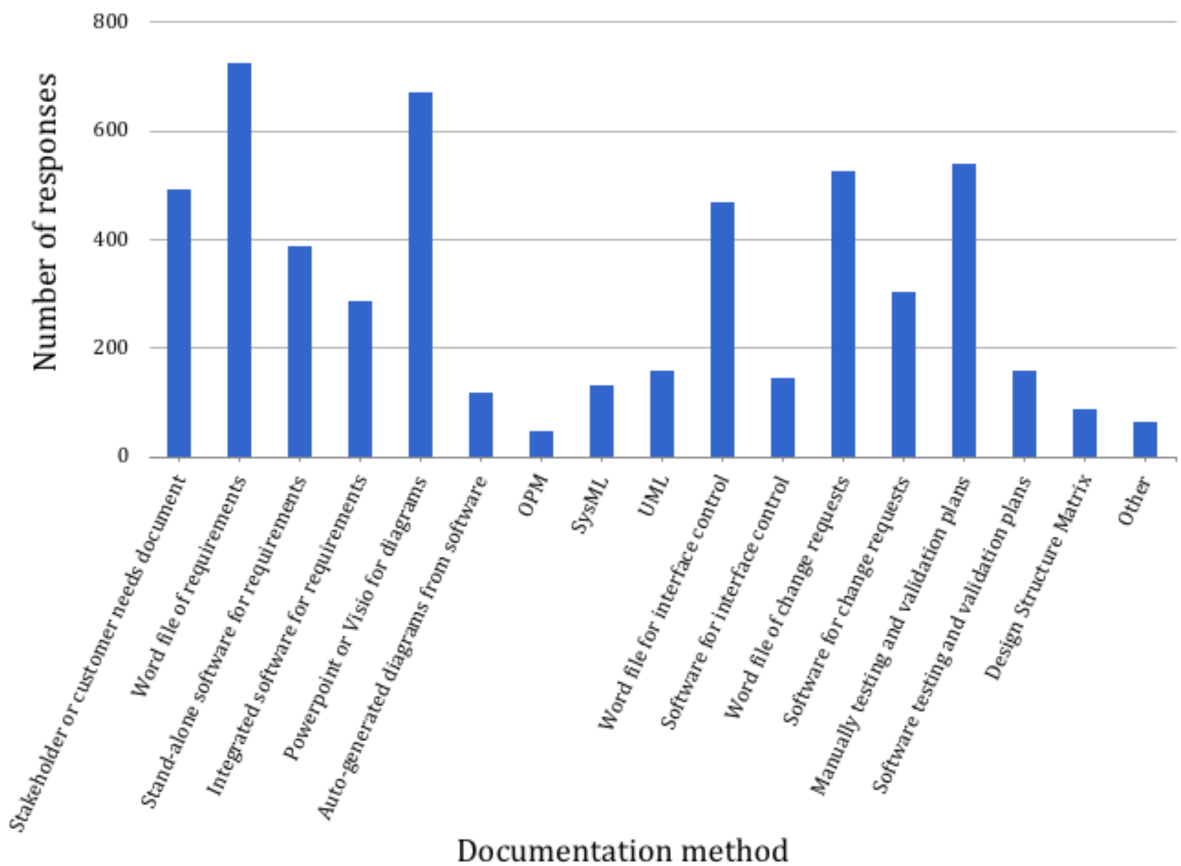

Fig. 7. Documentation methods used by respondents.

Accepted for publication in IEEE Transactions in Engineering Management.

Regarding data, participants are asked about the "primary mode of capturing system data" in their organization. In contrast to the previous question about individual awareness, this question asks about organizational behavior. Fig. 8 indicates the primary modes of data capture. Almost 90 percent of respondents reported documents or predominantly documents as the primary mode to capture system data. Approximately 11 percent of respondents chose models or predominantly models. The number of respondents that selected models appears surprisingly low, especially considering that it is roughly one third of the fraction of respondents who indicated that their organization uses an MBSE approach.

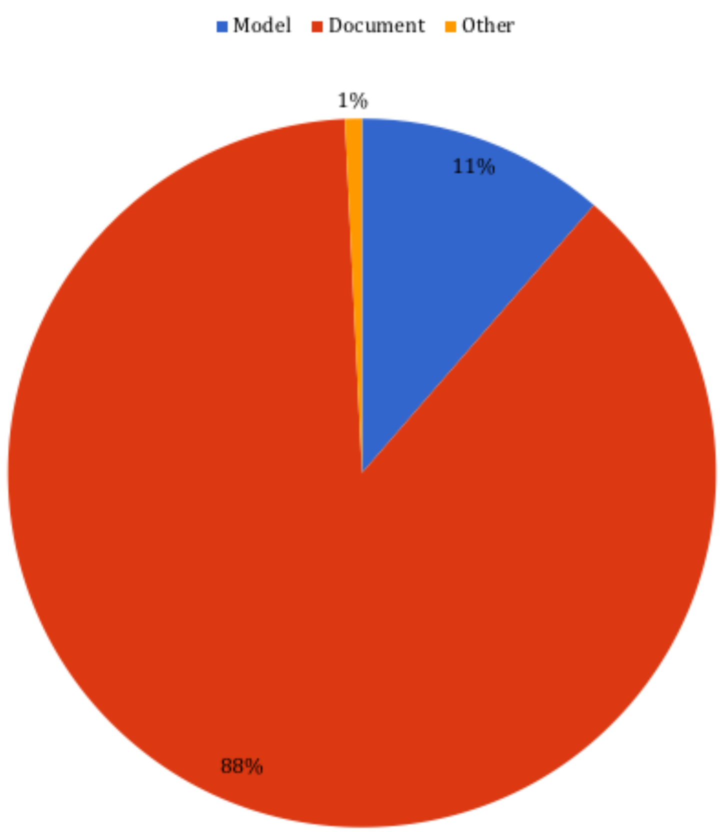

Fig. 8. Primary mode of capturing system data by respondents.

Whereas the documentation and data are not the same as modeling, they are closely related. We argue that the low familiarity with documentation methods related to models combined with document dominance further indicates low use of modeling.

Accepted for publication in IEEE Transactions in Engineering Management.

Language, program, and query practices from polls

In the polls, participants provide details about the use of languages, programs, and queries that are related to modeling. As with documents and data, these are not models themselves. However, language, program, and query use may reveal modeling practices.

Regarding modeling languages and programs, participants are asked about "the extent to which you have used" any of 20 specific languages frequently associated with MBSE on a qualitative scale ranging from "No Use" to "High Use." Fig. 9 indicates the use of languages and programs by respondents. Almost 93 percent of responses indicated "No Use" of any program or language, whereas over 96 percent indicated either "No Use" or "Low Use." For a highly educated, mid-career participant profile reflected by the enrollment survey, we propose that the effective use among this population sample is very close to zero. However, it is important to note that the population of participants in this course may well skew to those who have not yet learned which languages may benefit them, and the course may attract fewer users who already consider themselves proficient in one or more modeling languages.

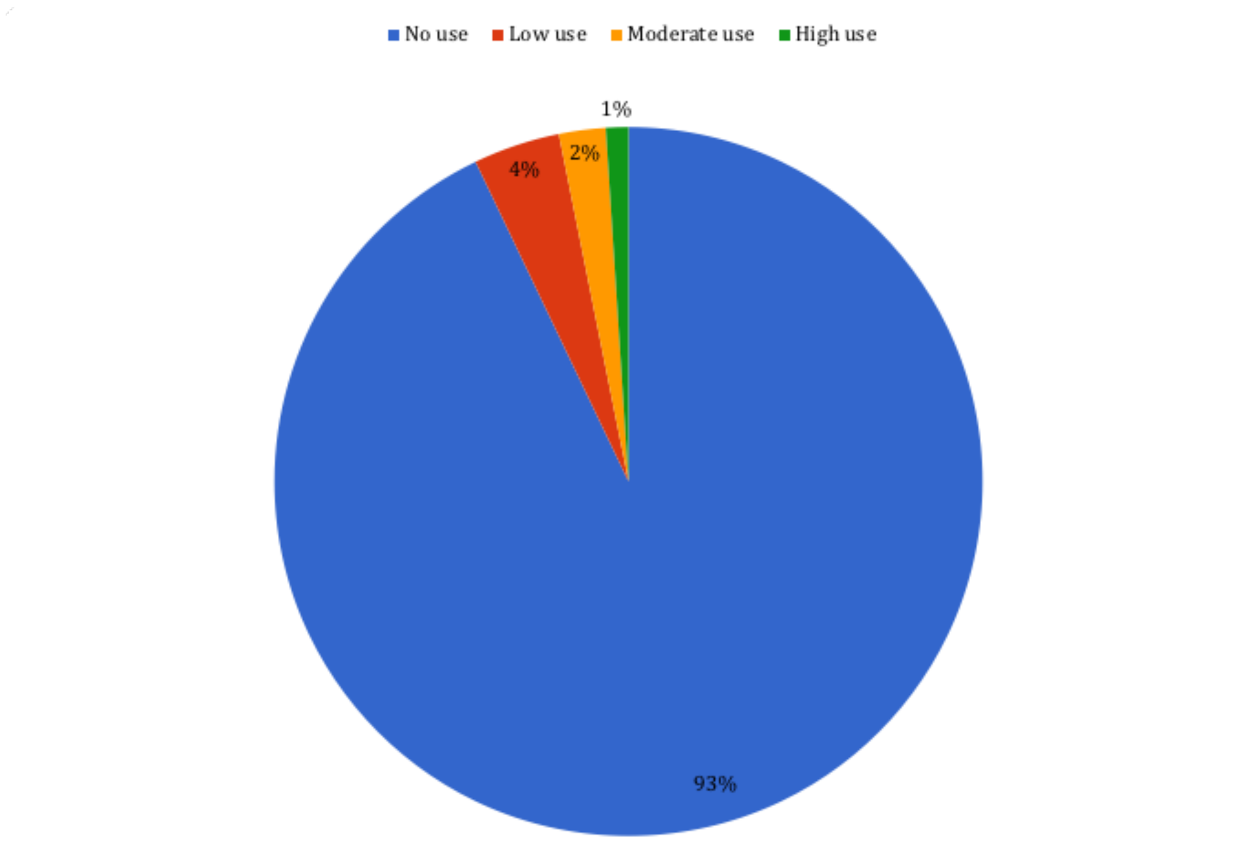

Fig. 9. Use of 20 modeling languages and programs by respondents.

Accepted for publication in IEEE Transactions in Engineering Management.

Additionally, participants are asked "the most sophisticated query type" they had written. Fig. 10 indicates the most sophisticated query types reported. Over 60% of respondents reported Microsoft Access databases, spreadsheets, or less sophisticated queries. Whereas Access is a database, it is a basic application distributed with the Microsoft Office suite that includes Word and PowerPoint. However, the level of SQL usage reported indicates higher penetration of sophisticated techniques than the language and program results.

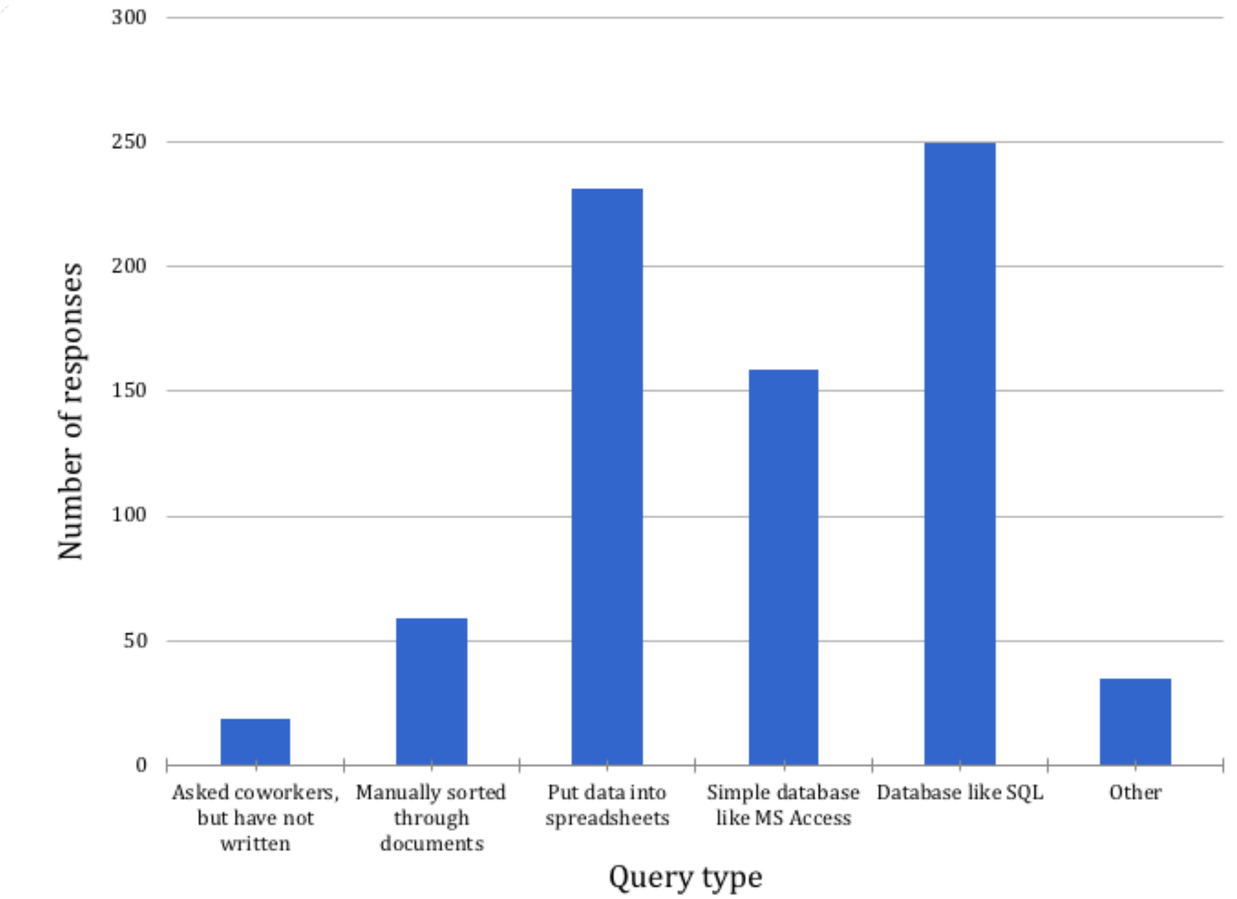

Fig. 10. Most sophisticated query written by respondents.

Languages and tools provide an indication of modeling practices. We argue that low penetration of languages and tools and unsophisticated use of queries indicates underdeveloped modeling practices by course participants and within their organizations.

V. Discussion

The results of this research are based on analysis of enrollment survey and polls question data from the "Architecture and Systems Engineering" program at MIT. Based on the enrollment surveys, many participants in the program are highly educated, mid-career professionals with

Accepted for publication in IEEE Transactions in Engineering Management.

interest in the course content. Whereas modeling and MBSE represent important interests, polls data indicates that model use is relatively low and unsophisticated by this population sample and the engineering-driven firms that it represents.

Of course, it seems logical that individuals or organizations who perceive themselves as unsophisticated modelers would enroll in a course to improve knowledge about modeling. If the program enrollment favors participants who perceive themselves or their organizations as unsophisticated modelers, then that could explain the lack of effective modeling practices observed in the data. However, there is an apparent deficiency in self-awareness about modeling practices based on contradictions between different polls results. Therefore, whereas this course may be attractive to individuals who perceive themselves as unsophisticated modelers, enrollment in the courses is broader.

We also acknowledge that this analysis is imperfect. In particular, the analyzed data covers a limited scope and relies on details that are self-reported by participants. Observation may provide a more accurate means to uncover actual behavior. Additionally, course participants might not be equipped or empowered to reveal practices that this research seeks. For example, participants who respond to polls might interpret the questions differently, might not be familiar enough with the modeling or MBSE approaches, or might not have full knowledge of their organizations. There are few, if any, approaches that could mitigate these challenges using the existing data.

Whereas custom questions or data collection methods could have been designed from scratch, we argue that the existing data is sufficient to reveal useful insights about model use and user sophistication in engineering-driven firms per the research objective. Whereas it is entirely possible that modeling or MBSE initiatives are underway inside organizations without course participant knowledge, this seems unlikely based on the highly educated mid-career profile uncovered in the enrollment surveys. We argue that participants who enroll in this program are very likely to be familiar with modeling initiatives in their own organizations. Furthermore, any misinterpretation by different participants, such as the technical differences between MBSE and modeling in engineering, is inconsequential to this particular analysis because ultimately the results demonstrate very unsophisticated overall practices.

Therefore, we propose that this research is a useful step to understand and diagnose modeling practices within organizations. In particular, while prescriptive engineering studies may suggest theoretical frameworks or methods to enhance modeling [6], [22], [10], [16], this research reveals what happens in the current state. We intend this as a descriptive rather than prescriptive study because we seek to describe this current state based upon our observations using the data rather than to recommend any specific action. Sophisticated prescriptive methods are inconsequential if there is no path to adoption by engineering-driven firms. There are several relevant outcomes from this research, including the relatively unsophisticated use of models among engineers and the lack of self-awareness about this usage. At a secondary level, this paper also demonstrates in a novel way how data from online courses for professionals may be applied to specific questions in industry.

Based on the results, there is no evidence that documentation, language, and program practices are the reason for low model use or unsophisticated modeling practices. However, inertia bias and the status quo are potential challenges to any organization. Even if many people are trained in modeling practices, it could be difficult to transition an entire organization away from established practices and dominant software programs if every person who is involved or requires access to information depends on those tools. This might be especially challenging for non-technical stakeholders. Therefore, in addition to studies about advanced modeling methods and tools, we argue that value exists in further descriptive research about modeling practices within engineering-driven firms.

VI. Conclusions

The analysis of participant profiles and polls responses demonstrates an effective use of online course data to assess model use and user sophistication in engineering-driven firms. While the research exhibits some challenges with the underlying data, it is notable as a descriptive research paper in engineering that inspires further research into practices and behaviors in industry. The results yield three primary conclusions about modeling that are relevant to the highly educated, mid-career professional participants and organizations represented by the population sample.

First, MBSE penetration is low. Less than ten percent of respondents reported being asked to evaluate an MBSE approach, and only 11 percent of respondents selected predominantly models as the primary mode of capturing systems data. Considering that these participants are likely among the most familiar with models within their organizations, these results indicate that MBSE is not broadly used in organizations. Future research should include more descriptive studies to identify reasons why MBSE adoption is so low.

Second, modeling is used less or in a less sophisticated way than claimed or presented externally. In particular, many more participants claimed an MBSE approach in their organizations than was corroborated through other questions about documentation, languages, programs, and queries. Whereas there are many potential explanations, including misunderstanding or ignorance of actual practice within their organizations, this effect is still notable because it represents a disconnect in self-awareness. Furthermore, simple use of modeling tools or techniques does not necessarily imply effective use. Results about documentation, languages, programs, and queries suggests that participants only scratch the surface, model informally or rely on suboptimal resources such as general-purpose office software. Besides more sophisticated modeling techniques, future research should examine the organizational reasons that inhibit the adoption of effective modeling practices.

Third, the analysis is a step towards initial assessment of modeling practices that reflects a novel use of data from online courses. The ability to reach participants with a specific profile using online courses enabled this research. Other researchers could also use online course data to answer questions unrelated to modeling.

There are multiple ways that the results could be used by the authors or the readers. For example, there is broad potential for future research in this area including observational studies, choice of different survey questions, and studies that rely on MOOC course performance instead of surveys. Additionally, while we do not propose any specific course of action to advance MBSE or modeling, certain readers might use the conclusions in this research to create their own action plans.

Accepted for publication in IEEE Transactions in Engineering Management.

References

[1] A. M. Madni and M. Sievers, "Model-Based Systems Engineering: Motivation, Current Status, and Needed Advances," in *Disciplinary Convergence in Systems Engineering Research*, A. M. Madni, B. Boehm, R. G. Ghanem, D. Erwin, and M. J. Wheaton, Eds. Cham: Springer International Publishing, 2018, pp. 311–325.

[2] R. S. Sharma, D. W. Conrath, and D. M. Dilts, "A socio-technical model for deploying expert systems. I. The general theory," *IEEE Transactions on Engineering Management*, vol. 38, no. 1, pp. 14–23, 1991.

[3] A. T. Bahill and R. Botta, "Fundamental Principles of Good System Design," *Engineering Management Journal*, vol. 20, no. 4, pp. 9–17, Dec. 2008.

[4] A. Albers and C. Zingel, "Challenges of Model-Based Systems Engineering: A Study towards Unified Term Understanding and the State of Usage of SysML," in *Smart Product Engineering*, M. Abramovici and R. Stark, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 83–92.

[5] P. Derler, E. A. Lee, and A. S. Vincentelli, "Modeling Cyber–Physical Systems," *Proceedings of the IEEE*, vol. 100, no. 1, pp. 13–28, Jan. 2012.

[6] V. Ramadesigan, P. W. C. Northrop, S. De, S. Santhanagopalan, R. D. Braatz, and V. R. Subramanian, "Modeling and Simulation of Lithium-Ion Batteries from a Systems Engineering Perspective," *Journal of the Electrochemical Society*, vol. 159, no. 3, pp. R31–R45, Jan. 2012.

[7] J. A. Estefan, "Survey of Model-Based Systems Engineering (MBSE) Methodologies," p. 70, 2008.

[8] G. P. Moynihan and D. Triantafillu, "Energy Savings for a Manufacturing Facility Using Building Simulation Modeling: A Case Study," *Engineering Management Journal*, vol. 24, no. 4, pp. 73–84, Dec. 2012.

[9] R. Cloutier, "Current Modeling Trends in Systems Engineering," *INSIGHT*, vol. 18, no. 2, pp. 10–13, 2015.

[10] A. Rutle, K. I. F. Simonsen, H. G. Schaathun, and R. Kirchhoff, "Model-driven Software Engineering in Practice: A Content Analysis Software for Health Reform Agreements," *Procedia Computer Science*, vol. 63, pp. 545–552, 2015.

[11] R. F. Kizilcec, C. Piech, and E. Schneider, "Deconstructing disengagement: analyzing learner subpopulations in massive open online courses," 2013, p. 170.

[12] M. Vuolo, J. Staff, and J. T. Mortimer, "Weathering the great recession: Psychological and behavioral trajectories in the transition from school to work," *Developmental Psychology*, vol. 48, no. 6, pp. 1759–1773, 2012.

[13] H. Altabbakh, S. Murray, K. Grantham, and S. Damle, "Variations in Risk Management Models: A Comparative Study of the Space Shuttle Challenger Disaster," *Engineering Management Journal*, vol. 25, no. 2, p. 13, 2013.

[14] N. M. Scala and J. A. Pazour, "A Value Model for Asset Tracking Technology to Support Naval Sea-Based Resupply," *Engineering Management Journal*, vol. 28, no. 2, pp. 120–130, Apr. 2016.

Accepted for publication in IEEE Transactions in Engineering Management.

[15] M. Fathian, M. Saei-Shahi, and A. Makui, "A New Optimization Model for Reliable Team Formation Problem Considering Experts' Collaboration Network," *IEEE Transactions on Engineering Management*, vol. 64, no. 4, pp. 586–593, Nov. 2017.
[16] C. E. Dickerson and D. Mavris, "A Brief History of Models and Model Based Systems Engineering and the Case for Relational Orientation," *IEEE Systems Journal*, vol. 7, no. 4, pp. 581–592, Dec. 2013.
[17] A. L. Ramos, J. V. Ferreira, and J. Barcelo, "Model-Based Systems Engineering: An Emerging Approach for Modern Systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 42, no. 1, pp. 101–111, Jan. 2012.
[18] K. Tsilipanos, I. Neokosmidis, and D. Varoutas, "Modeling Complex Telecom Investments: A System of Systems Approach," *IEEE Transactions on Engineering Management*, vol. 62, no. 4, pp. 631–642, Nov. 2015.
[19] S. Son, J. Kim, and J. Ahn, "Design Structure Matrix Modeling of a Supply Chain Management System Using Biperspective Group Decision," *IEEE Transactions on Engineering Management*, vol. 64, no. 2, pp. 220–233, May 2017.
[20] B. Selic, "The pragmatics of model-driven development," *IEEE Software*, vol. 20, no. 5, pp. 19–25, Sep. 2003.
[21] H.-B. Jun and H.-W. Suh, "A Modeling Framework for Product Development Process Considering its Characteristics," *IEEE Transactions on Engineering Management*, vol. 55, no. 1, pp. 103–119, Feb. 2008.
[22] S. AbouRizk, D. Halpin, Y. Mohamed, and U. Hermann, "Research in Modeling and Simulation for Improving Construction Engineering Operations," *Journal of Construction Engineering and Management*, vol. 137, no. 10, pp. 843–852, Oct. 2011.
[23] E. A. Bjorkman, S. Sarkani, and T. A. Mazzuchi, "Using model-based systems engineering as a framework for improving test and evaluation activities," *Systems Engineering*, vol. 16, no. 3, pp. 346–362, Sep. 2013.
[24] C. Keating *et al.*, "System of systems engineering," *Engineering Management Journal*, vol. 15, no. 3, pp. 36–45, 2003.
[25] M. DiMario, R. Cloutier, and D. Verma, "Applying Frameworks to Manage SoS Architecture," *Engineering Management Journal*, vol. 20, no. 4, pp. 18–23, Dec. 2008.
[26] C. Romero and S. Ventura, "Data mining in education: Data mining in education," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 3, no. 1, pp. 12–27, Jan. 2013.
[27] L. Breslow, D. E. Pritchard, J. DeBoer, G. S. Stump, A. D. Ho, and D. T. Seaton, "Studying learning in the worldwide classroom: Research into edX's first MOOC," *Research & Practice in Assessment*, vol. 8, 2013.
[28] Z. Papamitsiou and A. A. Economides, "Learning Analytics and Educational Data Mining in Practice: A Systematic Literature Review of Empirical Evidence," p. 17, 2014.
[29] R. S. Baker, "Educational Data Mining: An Advance for Intelligent Systems in Education," *IEEE Intelligent Systems*, vol. 29, no. 3, pp. 78–82, May 2014.

Accepted for publication in IEEE Transactions in Engineering Management.

Author profiles

Bruce Cameron is the Director of the System Architecture Lab at MIT and a co-founder of Technology Strategy Partners (TSP), a boutique consulting firm. His research interests at MIT include technology strategy, system architecture, and the management of product platforms. Prior to MIT, Dr. Cameron worked as an engagement manager at a management consultancy and as a system engineer. Dr. Cameron received his undergraduate degree from the University of Toronto and graduate degrees from MIT.

Daniel Mark Adsit is a consultant specializing in content and data strategy. His interests in educational technology platforms include learning optimization, collaboration between industries, and knowledge retention within teams. During his career, he has completed projects in over 15 countries for organizations that include Eaton Corporation, Intel (formerly Altera), HubSpot certified marketing agencies, and MIT. He received his undergraduate degree from the College of Engineering at Cornell University and a graduate degree from MIT.

Accepted for publication in IEEE Transactions in Engineering Management.