SIMULATING CLASSROOMS: EXPERIENCE WITH AGENT-BASED MODELS IN ENGINEERING EDUCATION

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Abstract – In this paper, we share our experiences applying agent-based modelling (ABM) to engineering education problems. ABM is a well-established modelling approach that has been successfully applied to a range of natural science, engineering science, and social science problems. However, its application to the scholarship of teaching and learning is in the early stages. The examples in this paper focus on two general areas: (1) teaching and learning, and (2) academic administration. We follow an established ABM framework to describe how each model was approached and how the models differ from each other. Our experience has been that ABM offers a promising tool for engineering education researchers, particularly as an early “prototyping” tool when designing an engineering education study.

Keywords: agent-based modelling : engineering education research : classroom assessment : COVID-19 response.

1. INTRODUCTION

Over the past two years, we have explored the application of agent-based modelling (ABM) to problems in engineering education. In particular, we have investigated the use of ABM as an engineering education research (EER) design tool [3, 13]. Given that EER studies involve considerable uncertainty, and typically require sufficiently large sample sizes and timeframes to validate the effects of the study, there is always the risk that the time and effort put into the study can be wasted if errors are made in the early design phase of the study. To mitigate this risk, we use ABM to perform preliminary studies to understand the behaviour of the system that will be used to inform the experimental design in a way that will result in well-designed, and successful EER studies.

In this paper, we build on our previous papers [3, 13] and share our experiences applying ABM to engineering education problems. Although ABM, a form computational modelling where a system’s behaviour is modelled by software agents and their interactions [22], has been successfully applied to a range of natural science, engineering science, and social science problems, its

application to the scholarship of teaching and learning is in the early stages. Our motivation is to provide researchers interested in this approach with insights into its application to engineering education studies, and particularly, the range of different engineering education systems that agent-based modelling can be used to model.

As summarised in Table 1, these models include our original homework and cheating behaviour models [3, 13], a model to explore summer camp parking logistics in the context of the COVID-19 restrictions, a set of models to explore COVID-19 transmission in the university environment [2, 12, 20], and models to explore student teams and student motivation [5]. Overall, these models provided us with test cases on the feasibility of using ABM to answer educational research questions. This paper will provide examples of the general structure of the models, and how these can be applied to the real classroom environments.

Table 1: Agent-based models.

ABM	Question	Refs.
Homework	How does the design of homework assignments impact student behaviour?	[3], [13]
Integrity	How does the design of homework assignments impact student behaviour?	-
Motivation	How can the design of homework assignments maximise student productivity and learning?	[5]
Teams	How do team dynamics influence team performance?	-
Parking	What parking lot drop-off process minimises wait time?	-
Scheduling	What timetabling and interventions minimise the spread of COVID-19 in the classroom?	[2]
Class Layout	What laboratory layouts minimise the spread of COVID-19?	[12], [20]

2. BACKGROUND

2.1. Agent-based Modelling

Agent-based modelling typically involves the study of the dynamics of complex systems, such as organizations, whose behaviour is the consequence of many different interdependent agents [19]. For example, early work in this area focused on understanding natural phenomena such as ant foraging, termite nesting, and bird flocking behaviour, as well as the behaviour of engineered systems such as freeways and computer networks [15]. In the past two decades interest has expanded to the study of social science systems [6], including studies of market economies, cooperation in groups, ethnocentrism, segregation, and language change [22].

In the area of higher education, agent-based modelling has found applications primarily in two areas: (1) the study of higher-education institutions as organizations, and (2) the teaching of ABM from a software engineering / computer science perspective [9]. More recently, there has been work on applying agent-based models to engineering education research questions; however, this is still a relatively new application of ABM [3, 13, 10, 17].

2.2. ABM Framework

The conceptual framework used for our work on agent-based modelling is the agent-based modelling cycle proposed by Grimm and Railsback [8]. This is a six-phase, iterative approach to agent-based modelling: (1) formulate the question, (2) assemble the hypothesis, (3) choose the model structure, (4) implement the model, (5) analyze the model, and (6) communicate the model. Our focus for this paper is on the initial three phases of this process, where the basic model structure is established.

As with a conventional engineering education research study, the process begins with the formulation of a clear research question. As noted by Grimm and Railsback, this “serves as the primary compass and filter for designing a model” [8]. It is important to note that, although formulating the research question is this first step in the process, it is still part of an iterative process: i.e., it is important to return to the research question to improve the clarity, ensure that it is not too simple or too complex.

During the second phase – assembling hypotheses for essential processes and structures – the focus is on identifying what will be ultimately tested with the model. This involves establishing the basic assumptions that will be made, as well as identifying the factors that will be considered (i.e., the model parameters and outputs). An important consideration during this phase is keeping the model as simple as possible. This relates directly to the number of factors that will be considered. A common mistake is to have too many factors, which makes it difficult to recognise the important from the trivial. Ideally, the model should allow one to understand the factors in the

model, their interactions, and their influence on the model’s behaviour.

Once the research question has been identified, and the simplifying assumptions and hypotheses to represent the system have been specified, the model structure can be considered. A common way to approach this with ABM is the ODD (Overview, Design concepts, and Details) protocol, popularised by [7] and [14]. The intention of the protocol is to describe the ABM in a generic (applicable to any field of application or discipline) and hierarchical (high level “overview” to implementation “details”) manner that facilitates replication of the model by other researchers. For this paper, we describe the basic model structure in terms of the “entities” (the agents) and the “design concepts” [7]. The identification of the model’s agents is central to agent-based modelling. This tends to be a fairly straight-forward process of identifying the key actors in the model (e.g., students, instructors, classrooms, etc.) – however, care must be taken with the choice of what is and what isn’t represented by an agent. For example, when considering communication between student agents, it is possible to represent student-to-student communications as link agents (i.e., these can be thought of agents that facilitate communication over a communication channel). Alternatively, student-to-student communication can be achieved using a standard ACL (agent communication language protocol) [16].

As part of the process of identifying the model’s agents, the agents’ and the model’s intended behaviours must be considered. This involves making decisions about the which ABM design concepts will be important to the model: e.g., stochasticity, interactions, emergence, adaptation, etc. Some of these concepts can be thought of as characteristics of the agents or modelling environment. For example, most engineering education research projects have stochastic elements that must be properly represented in the model (e.g., individual homework completion times). Other concepts are characteristics of the ABM that can be observed at run-time such as emergent behaviour. As DeAngelis et al. [4] note, ABM is “naïve” in that the ABM directly represents the agents and their behaviour: once the agents are created and placed in their simulated environment, we can then learn from it.

In the following section, we use examples from our EER models to illustrate fundamental concepts of agent-based modelling such as the naïve nature of this modelling approach, the ability of ABMs to help us refine research questions, and the importance of experimental design.

3. EXPERIENCE WITH ABMS FOR ENGINEERING EDUCATION

The agent-based models reported in this paper fall into two general areas: (1) teaching and learning, and (2) academic administration. The first group of models focus on how students respond to various homework assignment

strategies. In each of these models, we take the perspective of a faculty member making decisions concerning the design of homework assignments (e.g., number of assignments, level of difficulty, deadlines, etc.) and model the behaviour of students in response to these decisions (e.g., study group formation, academic misconduct, learning, etc.). The second set of models focus administrative decisions during the COVID-19 pandemic. More specifically, the focus of these models is on minimizing the spread of COVID-19 in the student population while performing regular university functions.

In this section, we provide a brief overview of each of the agent-based models with specific reference to the first three phases of the ABM framework noted previously (i.e., formulating the research question, assembling the hypotheses for essential processes and structures, and choosing the model structure).

3.1. Teaching and Learning Models

Our work using agent-based modelling for preliminary engineering education experimental design began with our interest in studying how students respond to different homework assignment strategies [3]. One of the key questions that all faculty face when preparing an undergraduate course is whether or not to assign homework, and if so, how this homework should be structured.

Once the decision has been taken to assign homework, various questions then follow relating to the number of assignments, relative weight of assignments, level of difficulty, deadlines, etc. As many faculty members discover, these decisions have a direct impact on student behaviour. For example, based on anecdotal evidence, the relative weight of assignments can impact if and how assignments are completed: if no grade is assigned, students may not attempt the assignment – if a high grade is assigned, some students may feel pressure to copy. In both cases, the intended benefit of assigning homework may be lost (e.g., to provide students with an opportunity to learn and practice techniques demonstrated in lectures).

To determine how the design of homework assignments impacts student behaviour, various homework strategies could be tested in the classroom. Arguably, this approach is informally performed by many faculty members as they fine-tune their courses over many offerings. However, a formal engineering education study would require a carefully designed set of experiments that span a sufficient period of time, involve a sufficient number of students, and explore an appropriate number of options. Unfortunately, what is good for the experimental design may not be good for students' learning experience. For example, exploring an appropriate number of options will likely involve testing homework assignment strategies that are not in the best interest of students' learning.

Our motivation for exploring the use of agent-based modelling for preliminary engineering education

experimental design was to provide a means of testing or “prototyping” the experimental design. Ideally, this would have the benefits of helping separate the important from the trivial in the design, and also minimizing the risk of inflicting a poorly designed experiment on faculty and students.

The models developed for the “homework” experiments started with the basic research question, how does the design of homework assignments impact student behaviour? An immediate challenge that we faced with these models related to the high number of factors. For example, our working hypothesis was that various factors such as number of homework assignments, weighting of the assignments, duration of the assignment etc. impact student behaviour in a variety of ways such homework completion, cheating, learning, etc.

To focus our work in this area, we began with three input factors (homework difficulty, homework deadline; extracurricular) and two output factors (homework completion, study groups). The results of this study are reported in the 2019 proceedings of this conference [3]. Interestingly, one of the output factors (study groups) manifested itself as a design feature that is particular to agent-based modelling: i.e., as the simulations ran, study groups would emerge in response to increased homework pressure (e.g., more difficult homework, shorter deadlines).

This observation led us to question whether increased homework pressure would lead to more instances of academic misconduct (e.g., copying), and our second version of the model published in the 2020 proceedings of this conference [13]. For this model, we added a “sociability” factor to the student agents that, in combination with the student factors in the original model, provided more insight into how student agents adapt to changing homework expectations.

Currently, we are exploring two specific aspects of the homework assignment question: (1) student motivation with respect to homework completion, and (2) team formation (more in-depth details and results can be found in [5]). An example of the user interface for the “motivation” model is shown in Figure 1. As can be seen in this figure, a relatively large number of input factors are considered (shown by the green input sliders). However, from a modelling perspective, it is possible to manage this increased complexity given the input factor's relationship to each other as described the Steel et al. [18] motivation framework.

The simulation view is shown by the larger window that is divided into “incomplete” and “complete”. This view is dynamically updated as the simulation runs, displaying the number of students (person shapes) who have either not yet completed or have completed the homework. Student completion of homework is also tracked using the graph shown in the lower left part of Figure 1 (i.e., number of

Fig. 1. User interface for the student motivation model.

students who have completed the homework vs. simulation time).

The user interface for the team formation model is shown in Figure 2. To develop this model, we used the Netlogo “Team Assembly” model by Bakshy and Wilensky [1] as a starting point. The original model demonstrates how the assembly of small teams based on certain selection parameters can affect long-term collaboration networks. Our adaptation is designed to explore team dynamics in an engineering study or project group, and ways in which different dynamics can maximise team performance.

The network shown in the background of Figure 2 is a dynamic display of team formation over time. This window shows high performing student groups (blue) and average performing student groups (green) and how their interactions evolve over time (shown by the grey links). Three model outputs are also shown in Figure 2, superimposed over the simulation view. The “Team Performance” plot shown the number of teams formed in each performance category over time. The “Extraversion Levels” plot is a histogram representing the number of collaborations at various extraversion levels. Finally, “Project Difficulty” compares actual and perceived project difficulty over time. As can be seen by comparing the “Team Performance” and “Project Difficulty” plots in this

figure, perceived and actual difficulties converge as students collaborate through team formation.

3.2. Models for Academic Administration

In mid-March 2020, universities across Canada discontinued in-person classes in response to provincial and national guidelines concerning the COVID-19 pandemic and shifted to emergency remote teaching. In the months that followed, faculty and students were required to quickly adapt to a new mode of course delivery while institutions struggled to provide the necessary supports for remote instruction and assessment.

In addition to course delivery challenges, questions relating to the logistics of “in-person” activities came to the forefront. For example, in the summer of 2020, the authors’ home institution continued its on-campus summer camp program for children; among other challenges, this decision required a safe drop-off and pick-up process for parents and campers.

Our first model asked the question, what parking lot drop-off process minimises wait time? A variety of drop off options were considered: factors included the number of parking spaces, parking rows, as well as the volume of cars and campers.

This model did not consider the transmission of COVID-19 as its primary intention was to explore different

Fig. 2. User interface for the team formation model.

drop-off and pick-up strategies. We assumed that outdoor social distancing measures were strictly enforced. For this model, we were primarily concerned with typical queueing metrics such as wait time, service time, and number of cars in the system for various drop-off and pick-up strategies.

In contrast, our second set of academic administration models explicitly addressed the spread of COVID-19 in the classroom environment. These models focused on how universities could transition to limited in-person teaching activities during the pandemic while minimizing the spread of COVID-19 in the student population.

Our first model in this area focused on course timetabling strategies [2]. It was assumed that lectures would continue online; however, smaller tutorials and/or laboratory sections could be scheduled, to a limited degree, in-person.

The second model in this area, shown in Figure 3, focused on the layout of laboratories. In this case, various laboratory layouts can be explored by specifying the number of lab stations and students per lab section (i.e., “seats”). The model includes both students (blue person shapes) and instructors/TAs (green person shapes). The model also allows various laboratory activities to be explored by scheduling laboratory group work times, demonstration times (at the main demonstration table

and/or at group tables), and instructor/TA interactions (i.e., spending time with student groups to answer questions). The purpose of this model is to investigate virus spread given various layout and activity options. More in-depth details and results for this model are reported in [20] in these proceedings.

One of the main challenges for both of these models was the modelling of the COVID-19 transmission model. During the time these models were developed, many studies and meta-studies were being published on the transmission model; however, there was still considerable uncertainty around how COVID-19 spreads in a classroom environment. To help with this, we developed a separate model to experiment with the parameters from the literature and validate the transmission model used in our ABMs [12].

It is interesting to note that the model structure followed for the two main COVID-19 models (i.e., timetabling and laboratory layout) differed considerably. For the timetabling model, the world view for the model is a “social space” representation where the distance between student agents is intended to represent the closeness of social relationships (e.g., friendships, shared timetable cohort). However, for the laboratory layout model, our world view followed a “physical space” representation

Fig. 3. User interface for the laboratory layout model.

where agents exist within a schematic representation of the physical space as shown in Figure 3.

The decision to take different “world view” perspectives for the two models related to constraints around timetabling. If a “physical space” representation was used for the timetabling model, a large portion of the university would have to be represented by the model to the proper scale and with multiple levels, corridors, stairways, etc. However, since we only need to model potential interactions between students when they are in class or between classes (as represented by the timetable), a detailed physical model was not necessary. Conversely, the “physical space” representation was necessary for the laboratory layout model since the model was fundamentally concerned with the physical space. As well, the focus on a single laboratory space made this representation feasible.

3.3. Comparing the Models

Table 2 provides a summary of the seven agent-based models described in this paper. The table is organised based on the first three phases of the ABM framework noted previously: the research question, the number of

factors, and the model structure. For the model structure we focused on the number of agent types in each model and the key ABM design features.

Table 2: Comparing the agent-based models.

ABM	Factors		Structure	
	In	Out	Agents	Design*
Homework	3	2	2	E, S
Integrity	7	5	2	E, S, A
Motivation	8	3	1	E, S
Teams	4	3	4	E, S, A
Parking	5	2	2	S
Scheduling	4	3	2	E, S, I
Class Layout	14	1	4	S, I

* E = emergence, S = stochasticity, A = adaptation, I = interaction

By starting with a relatively simple model to address homework design, we were able to extend to more complex models with more factors and expanded design features. However, despite there being more input factors in the extended models, we would primarily focus on the new

factors in the experiments with the models in order to keep the experimental design reasonable.

One outlier in the models described in this paper is the “parking” model. Although this model was developed using agent-based modelling given our familiarity with the approach, it could have easily been developed using discrete-event simulation [11]. Like discrete-event simulation, ABM allows for stochasticity in the design and provides facilities for experimentation with the model.

4. DISCUSSION

Our original motivation for our work in this area was to explore whether or not agent-based modelling could serve as a useful tool for preliminary EER experimental design. As noted in [3], this approach has considerable potential and is certainly worth pursuing for a broad range of EER studies. As well, the models described in Section 3.1 illustrate how a simple preliminary model can be extended to allow various aspects of a research question to be explored. In this case, we use a variety of models to explore the general question, “how does the design of homework assignments impact student behaviour?”, from a range of perspectives (i.e., homework completion, group formation, academic integrity, student motivation).

The choice of progressing from simple to more complex models was deliberate. This provided us with the opportunity to focus on a relatively small subset of the problem before progressing to more complex models. As well, we took advantage of existing models from the literature that could be used as a starting point for our models. This provided the benefits of reducing the amount of work required to build our models as well as simplifying the validation process. However, the use of existing models can result in some limitations to the model design. In particular, this can result in a less creative approach to the model design that may result from trying to fit a modelling approach that has been designed to solve a related, but different problem, to the new problem.

As illustrated in Section 3.2, our work on agent-based modelling has also expanded beyond our original interest in models for preliminary EER experimental design. In this case, we were inspired to apply ABM to administrative and logistical problems associated with the response to the COVID-19 pandemic. These models fall into a more common application of ABM [6, 22]. Our experience in this area has been positive from the perspective of developing the basic models. In particular, ABM allows models to be developed and tested very quickly: i.e., the preliminary versions of each of the models in Section 3.2 took to be developed in less than one month. These preliminary models were quite useful for initial exploration of the research question (e.g., how do timetabling policies impact the spread of COVID-19?), but required considerably more work to refine, validate, and experiment with. This was particularly problematic for the timetabling

and laboratory layout models where information on the COVID-19 transmission model was being updated on a weekly basis.

Our future work on agent-based modelling will focus primarily on our original area of ABMs for preliminary EER experimental design. However, we are also exploring the use of ABM as an interactive tool that can be used within engineering education studies. For example, we are currently exploring the use of ABM as a tool to conduct consensus methodology research. Although other approaches such as nominal group process, consensus development panel, or Delphi technique could be used for consensus methodology research, they are tailored for relatively small panels of 8 to 12 experts [21]: our intention is to engage a large and diverse group of stakeholders (students, faculty, engineering professionals) in consensus building by interacting with an online, distributed form of ABM.

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