Bifocal Modeling: Mixing Real and Virtual Labs for Advanced Science Learning

Paulo Blikstein, Tamar Fuhrmann, Daniel Greene, Shima Salehi
Transformative Learning Technologies Lab (TLTL), Stanford University
{paulob, dgreene}@stanford.edu {tamarrf, shimasalehi87}@gmail.com

ABSTRACT
In this paper, we describe a set of user studies within the Bifocal Modeling (BM) framework. BM juxtaposes physical and computer models using sensor-based and computer modeling technologies, highlighting the discrepancies between ideal and real systems. When creating bifocal models, students build both a physical model with sensors of a given scientific phenomenon, and a computer model of the same phenomenon, connecting the two in real time with a special hardware interface. In this paper, we describe four formats for using BM in the classroom, as well as its affordances and characteristics.

Categories and Subject Descriptors
K.3.1 [**Computers and Education**]: Computers Uses in Education

General Terms
Design, Experimentation.

Keywords
Computer modeling, sensing, constructivism, physical computing.

1. INTRODUCTION
Scientists increasingly use computer models as important tools to think about, explain, and predict phenomena in the world, and many studies emphasize the importance of children building, manipulating, and understanding computational models for understanding scientific phenomena [7, 8, 11]. At the same time, hands-on, sensor-based science has also been shown to improve students' understanding of challenging scientific topics [9]. However, theoretical modeling and sensor-based data-collection activities are not often found *together* in science classrooms. Not only they are done separately, but they fail to introduce students to computational tools as powerful cognitive instruments to enhance our capacity to interpret real world data. Bifocal Modeling (BM) [1, 3] is an approach to science pedagogy that challenges students to build and compare physical and virtual models in real time. A core component of the Bifocal Modeling framework is that students engage in not only building physical and computer models, but connecting them and investigating their commonalities and differences.

In previous work, Blikstein [2] classified modeling activities into two categories: Interaction-Based Modeling (IBM) and Construction-Based Modeling (CBM). In Interaction-Based Modeling activities, students are presented with a pre-assembled sequence of models embedded in a curriculum, and they interact with the models by changing parameters and running experiments, but with no access to the code itself. Examples of such activities are Biologica [5], Molecular Workbench [7], and Connected Chemistry [8]. Construction-Based Modeling present students with open-ended tasks and require them to design their own models [10, 11]. In this paper, we describe four pilot studies applying IBM and CBM with high school students learning scientific phenomena in biology, chemistry, and physics. Our goal was to demonstrate proof-of-concept examples for implementing the Bifocal Modeling framework in a variety of high school settings. The emphasis and resources allocated to each BM activity varied according to the study context.

2. RESEARCH SETTING
Students have three main tasks when building a Bifocal Model (Figure 1). First, they design a physical model to explore a scientific phenomenon (1), using electronic sensors and data logging board (typically the GoGo Board [4]). Second, students design a virtual computer model of the same phenomenon using computer modeling software (2). Finally, students run both models connected in real time to compare and debug the physical and virtual models (3), using special hardware interfaces or camera-based sensing. They can see side by side the results of both models, easily comparing the results (Figure 1). In Figure 2, we present two examples of prototypical Bifocal Models, the first examining heat transfer, and the second the gas laws.

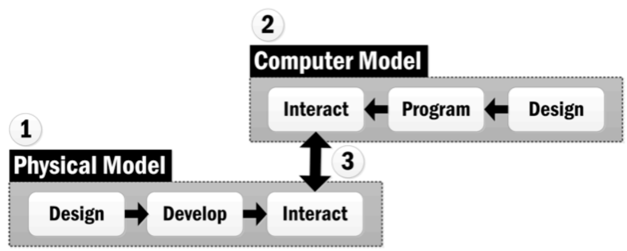

Figure 1: A general structure of the Bifocal Modeling process

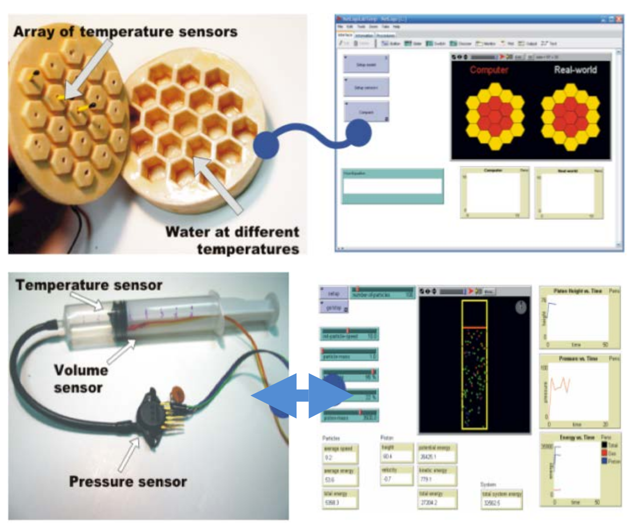

Figure 2: Examples of Bifocal Models: heat transfer and gas laws.

Given that BM comprises many different tools, techniques, and classroom facilitation, there are multiple possible formats and phases for implementation. In order to structure our user studies, we divided the physical and the virtual modeling assignments into a sequence of smaller activities:

A. Research - In each study, students were encouraged to use external learning resources, such as the web or books, to gather initial information about the phenomenon. The format of this phase was dependent on the context of the study and students' previous knowledge about the phenomenon. The general goal of this phase was to give students baseline information about the normative representations of the phenomenon under scrutiny.

B. Design - Within a guiding theme (e.g., gas laws), students select variables that they want to explore, make hypotheses about what they will observe, and design physical and virtual models that can potentially answer those hypotheses. In designing the virtual model, students typically define the possible variables, and conceptualize micro-rules or equations to describe the phenomenon.

C. Build - Students construct physical models (e.g. a ball and ramp, a Petri dish filled with agar and bacteria, a system with interconnected beakers with different substances) and virtual models (e.g. a physics model of gravity and friction, an agent-based model of bacteria growth, or a computer model of diffusion) that will capture the phenomena under study. The most common software to develop virtual models for BM has been NetLogo [12], a free and open-source environment for agent-based modeling.

D. Interact - Students interact with their physical models by direct observation and collecting data using embedded sensors. Similarly, they interact with the virtual model by changing parameters, running the model, observing the results, and recording data.

In each of the studies described in the paper, we attempted to fit the BM framework within a format that would be realistic within different types of school implementations. Therefore, in all studies, our design decisions were based on previous cycles of iterative design (Design-Based Research, [6]), grounded on different challenges we had in this specific school context. For example, we had to take into account how much time it takes to collect sensor data, students' familiarity with scientific inquiry methods, and their programing skills. The activities in the current studies will vary from implementations in which we focused on *interaction* with pre-made models (IBM, see [2]), to activities which highlighted *model-building* (CBM). In all of the studies, the overall goal was to have students reflect about the different between real and ideal systems, following the general structure of the BM activity (Figure 1), and evaluating different implementation models.

3. METHOD

Three of the studies took place in an after-school workshop session for high school students ranging from 9th to 11th grade, in the United States. These workshops and studies were all conducted in the same laboratory setting, with students who had not previously learned the topics of inquiry in their classes. The fourth workshop was an after school program in a high school in Moscow, Russia.

1. Biology: The first study was conducted with four female high school students and lasted for a total of about five hours, split across three afternoon sessions. The researchers tasked students with collecting a sample of bacteria from the environment and preparing it in a Petri dish. When finished, they used a provided time-lapse camera that captured images of the dishes every 30 minutes for five days. The images were automatically compiled into a video that showed the students the growth pattern of the bacteria. Because of the long time required to assemble a long-enough movie (1 week), we also provided students with a movie previously made by the research team. Students were grouped into two pairs and each pair used a computer to do internet research on the bacterial growth curve. In the final session, the students conducted a variation of "paper modeling" [2] in which they collectively designed an agent-based model of bacterial growth on a whiteboard with staff providing verbal scaffolding.

2. Physics: In the second study, 11 high school students (4 females and 7 males) studied Newton's laws by investigating the time it takes for a ball to travel down a ramp. The study lasted for 6 hours. Students were first asked to build a physical model to investigate the variables affecting the time it took for a ball to roll down a ramp. In groups of two or three, they built ramps and attached light and infrared sensors to detect the position of the balls. For this pilot study, we shortened the activity of designing a virtual model and let students investigate and interact with a pre-made NetLogo model made by one of the authors. It enabled students to simulate a ball rolling down a ramp and vary parameters such as ball mass and ramp angle without them having to program the model from scratch. Finally, the staff led the students in comparing the behavior of the virtual and real models – particularly, to observe that the virtual model predicted that ball's mass had no effect, while the empirical data suggested otherwise.

3. Chemistry: In the third study, students investigated the relationship between gas volume and pressure in a closed system. This study was conducted with the same group of school students as the previous study, and for the same amount of time (6 hours). Students were asked to interact with a pre-built syringe system with pressure sensors, and collected data about the relationship between pressure and volume. Next, we provided a NetLogo computer model of the gas laws, with which students could interact and see the behavior of gas particles in a container with a moving piston. As the volume of the physical syringe changed, the computer model varied accordingly, and the students compared the match between the pressure sensor values and the results supplied by their virtual model.

In studies 1-3, all students were given two open-ended questionnaires about the content before and after the session. They were also videotaped during all activities, their computer usage was documented with screen-capture software, and researchers asked questions and kept field notes. Students' notes and sketches were scanned and stored.

4. Open-ended: In this study, students could freely choose their topic of interest. Over three days (24 hours total), they were supposed to build a physical model, a computer model in NetLogo, and write a report about the comparison about them. The entire workshop was videotaped and students answered pre- and post-questionnaires. Figure 3 shows one typical project, a model investigating liquid diffusion, with the physical model on the left and the computer model on the right.

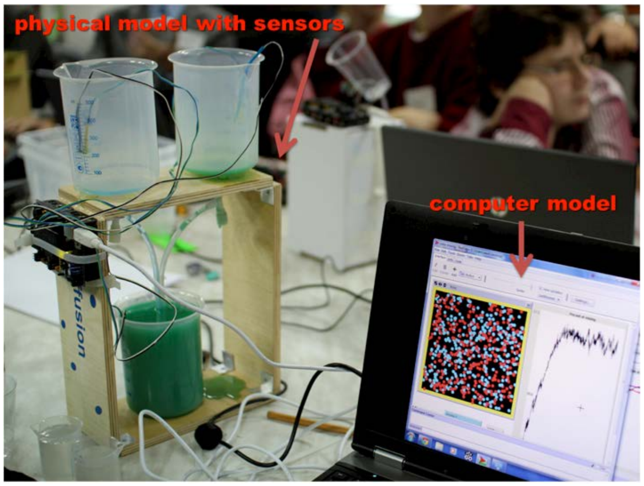

Figure 3: One of the projects in the 'open-ended' workshop. Note the physical model of diffusion on the left, with sensors, and the computer model in NetLogo on the right, connected in real time.

All four implementation modes are summarized in Figure 4, with the rectangles in black indicating the design elements used.

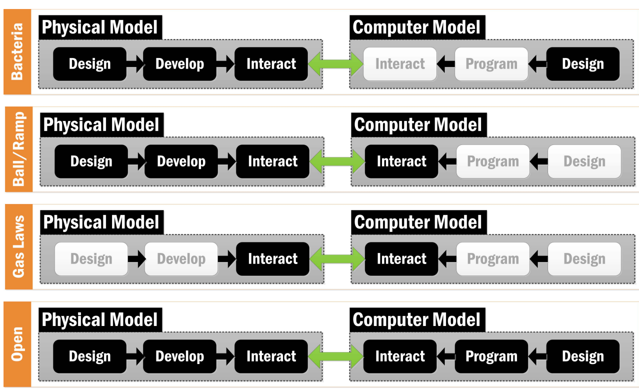

Figure 4: Different Bifocal Design implementation modes, showing the blocks we used in the four studies (in black).

4. DATA AND DISCUSSION

In this paper, for space considerations, we will focus mainly on one dimension of the data: the way students resolve the mismatches between the real and virtual models, within the main goal of evaluating the different implementation models.

In the first study (bacterial growth, see Figure 5), we designed the activities so that we mostly had students focused on creating a conceptual agent-based model to match the imagined emergent behaviors to the real time-lapse video data. Students were actively constructing a model on the whiteboard, even though they were not writing the code. Overall, the group's method was to "run" a few steps of their whiteboard virtual model in order to see how the bacteria grew, and compare the results to their goal – the growth curve calculated from the physical model. Then, they would resolve the perceived differences between the two by adding rules and variables to the virtual model. For example, a student observed at one point after "running" the virtual model that their growth curve was increasing exponentially from the start. She noted that this was not correct, because the real growth curve had an initial flat "lag phase" before the beginning of the more pronounced growth phase. After a moment's reflection, she remembered that this was because real bacteria have an initial phase of settling into a new environment before multiplying. So she went on to add a rule which determined that the bacteria would "wait" some time before starting to grow. Most students went through a similar process to add new variables and rules to their initial model. In general, we observed the students in this study to be more engaged in investigating the behavior of the phenomena.

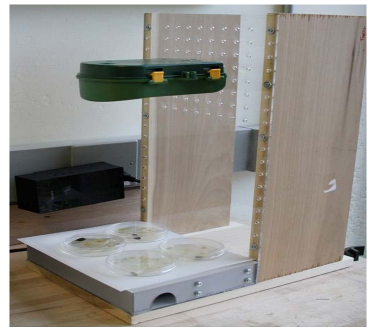

Figure 5: Physical model of the bacterial growth study, with a time-lapse camera and several petri dishes.

In the second study about the "ball on a ramp," we made different design decisions, given the size of the group (11) and the available time (6 hours). Students partially designed and developed their own physical model, but the virtual model was given to them, so the emphasis was just on interacting with the pre-made virtual model (interaction-based modeling). Interestingly, as students proceeded in the activity, they became more critical about their own observations rather than questioning the pre-made model and its assumptions. For example, in their physical experiment, heavier balls appeared to roll down faster, possibly due to air resistance, slipping, and friction. When the virtual model appeared to refute the idea that heavier balls would roll faster (as they experienced in their physical experiment), students were surprised, and ended up trusting the given computer model more than their own observations.

In the "Gas Laws" study, again, the emphasis was on interacting with pre-made models rather than creating them. In this case, students did not build any of the two models: they were given a physical and a virtual model. Students were tasked with collecting real-time data from the pressure sensor, and comparing with the "ideal" data generated by the pre-made virtual model. Student critically evaluated the scientific experiment with sensors and offered many ideas about how to improve it, trying to make sense of the discrepancies between the two datasets. For example, when asked about the discrepancies between the P-V graph which resulted from their own physical measurement, compared to the one demonstrated by the virtual model, the causes that students mentioned were the accuracy of the sensor and data-logging software. Again, they never mentioned that the virtual models could have been wrong.

In the last study, students had not only to come up with their own idea for a project, but design both the physical and virtual models from scratch. Despite having more time (24 hours), the building of the physical model ended up being a significant time commitment for most, and left relatively little time for the conceptual and computational model. Therefore, a formal post-facto comparison of the two models was not properly completed in some cases. However, during the construction itself of the physical model, many dissimilarities were foregrounded. For example, one group decided to build a bridge to investigate how much vibration it would withstand, together with the accompanying computer model (Figure 6).

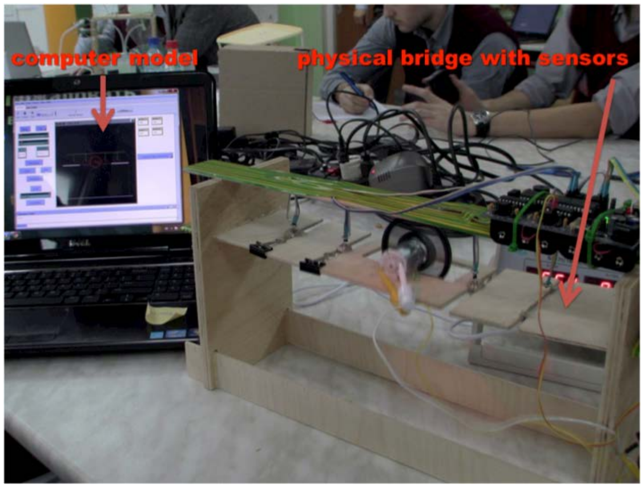

Figure 6: A Bifocal Model for bridge harmonics

During the construction of the bridge, the facilitators encouraged students to run systematic experiments with different frequencies of vibration, comparing them with the canonical formula. Even though they were able to construct a plot that approximated the canonical formula, evidently it was not a perfect match, which was a crushing disappointment for the group. However, through multiple cycles of measurement and rebuilding the system, students acquired a much more refined understanding of the phenomena and of the scientific method itself.

5. CONCLUSION

Our goal in this paper was to offer some initial data on the comparison of many different implementation models for Bifocal Modeling. From the four studies, we observed at least one overall pattern: the epistemological resource most valued by the majority of the students were the ones “given” to them by authority, and the only ‘mode’ to achieve the same validity, it seemed, was to perfectly match the given data. Many students, indeed, believe that a perfect experiment would generate a perfectly smooth graph. A second pattern was that in the studies in which there was no virtual model-building (gas laws and ball/ramp), students’ level of sophistication in comparing real and virtual models was lower, and their epistemological stance was even more radical: they would critique their work and their own observations but rarely question the computational models that were given to them.

Finally, we observed that the benefits of model-building appear even if students are not coding, but creating ‘white board’ agent-based models, but only if they indeed use it as a ‘computational surface’ that can enact the imagined agent-rules. Within this context, the use of the physical model as a reference pattern for the creation and refinement of the virtual model was generally effective. When students were instructed to design a virtual model that recreated the bacterial growth curve, they used their previously-learned knowledge about the curve and the physical appearance of the bacteria as a reference patterns for what their model should generate. When the model data did not match the observed data, they went back and made changes.

One key conclusion from these four implementations is that the full model building experience (both physical and virtual) was indeed a richer learning experience. However, with the proper facilitation and a careful choice of which modeling phase to abbreviate (e.g., bacteria study), similar learning goals can be achieved in a dramatically reduced time-frame. However, these studies have shown that model-building, rather than simply having access to sensors and tangible learning tools, was the determinant factor in generating deep engagement with the phenomenon.

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