Integrating Model-Based Approaches into a Neuroscience Curriculum—An Interdisciplinary Neuroscience Course in Engineering

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Abstract*—*Contribution: **This paper demonstrates curricular modules that incorporate engineering model-based approaches, including concepts related to circuits, systems, modeling, electrophysiology, programming, and software tutorials that enhance learning in undergraduate neuroscience courses. These modules can also be integrated into other neuroscience courses.**

Background: **Educators in biological and physical sciences urge incorporation of computation and engineering approaches into biology. Model-based approaches can provide insights into neural function; prior studies show these are increasingly being used in research in biology. Reports about their integration in undergraduate neuroscience curricula, however, are scarce. There is also a lack of suitable courses to satisfy engineering students' interest in the challenges in the growing area of neural sciences.**

Intended Outcomes: **(1) Improved student learning in interdisciplinary neuroscience; (2) enhanced teaching by neuroscience faculty; (3) research preparation of undergraduates; and 4) increased interdisciplinary interactions.**

Application Design: **An interdisciplinary undergraduate neuroscience course that incorporates computation and model-based approaches and has both software- and wet-lab components, was designed and co-taught by colleges of engineering and arts and science.**

Findings: **Model-based content improved learning in neuroscience for three distinct groups: 1) undergraduates; 2) Ph.D. students; and 3) post-doctoral researchers and faculty. Moreover, the importance of the content and the utility of the software in enhancing student learning was rated highly by all these groups, suggesting a critical role for engineering in shaping the neuroscience curriculum. The model for cross-training also helped facilitate interdisciplinary research collaborations.**

***Index Terms*—Biological neural networks, biomedical engineering, brain modeling, computational neuroscience, experiential learning, neural engineering.**

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I. Introduction

UNQUESTIONABLY, the field of biology has had a significant impact on the engineering curriculum over the past two decades. This is evident from the creation of new departments of biological or biomedical engineering in most universities (e.g., [1] and [2]), and by the electrical and computer engineering (ECE) departments, such as those at MIT, CalTech, and Duke, making biology a requirement at the undergraduate level (e.g., [3] and [4]). These developments were spurred by engineering students' growing interest in tackling the theoretical and technical challenges of the biological and medical sciences. This increasingly data- and problem-rich field is attractive for its promise to shed light on biological function and to improve human health.

In addition to collaborating on tackling technical challenges in life sciences, engineering faculty also have increasing opportunity to introduce model-based approaches into biology and medicine, areas whose research and curricula lack such content. Herein the terms '*model-based approach*' and '*engineering content*' are used interchangeably to denote engineering concepts such as computation, circuits, systems theory, modeling, electrophysiology, and programming skills.

This paper focuses on the role that engineers can play in implementing such model-based approaches into curricula in neuroscience, a sub-area within life sciences that has seen a 592% increase in PSAT major selections among 9-11th graders (2007-2013; [5]) and a 100% increase in Ph.D. degrees awarded (2003-13; [6]). This surge in interest has resulted in the initiation of undergraduate majors in neuroscience at four-year institutions and at universities such as MIT, Harvard, UCLA, and University of Chicago [7], [8]. Indeed, a National Research Council report, *Research at the Intersection of the Physical and Life Sciences* [9], identified 'Understanding the Brain' as one of the top five grand challenges for research that will significantly benefit society, and to this end recommended development of introductory undergraduate courses at the interface of the appropriate disciplines. This, together with the recognition of 'reverse engineer the brain' as one of the 14 Grand Challenges for Engineering in the 21st century [10] and the substantial funding investment by the federal BRAIN initiative [11], represents a tremendous opportunity for engineers to collaborate with neuroscientists to tackle some of the neuro-challenges for the next century at theoretical, computational, experimental, and workforce readiness levels.

TABLE I
SYLLABUS FOR UNDERGRADUATE SEMESTER-LONG COURSE ECE/BIOSCI 4590 COMPUTATIONAL NEUROSCIENCE

Focus of week	Monday (Lectures)	Wednesday (Labs; S-Software; B-Biology)	Friday
1: Introduction – Biology/ Engineering	Welcome & Introduction	Software Experiment 0: Getting started with Math	Lecture: Nernst Equation and GHK-Eqn.
2: Biology	Electrophysiology and data acquisition	Biology Experiment 0: Electrophysiology and DAQ setup in Lab	Lecture: Resting membrane potential and GHK-equation
3: Engineering	Holiday	S-Experiment 1: How do we model a passive cell membrane?	Review for week
4: Biology	Details related to electrophysiology setup	B-Experiment 1: How the electrophysiology setup work? (Virtual Lab)	Review for week
5: Engineering	Hodgkin-Huxley models	S-Experiment 2: What makes a neuron spike?	Review for week **QUIZ 1**
6: Biology	Action potential	B-Experiment 2: Resting membrane potential	Review for week
7: Engineering	Bursting neurons	B-Experiment 3: Action Potential	Review for week
8: Biology	Voltage gated channels & bursting neurons	S-Experiment 3: What are adaptation? Bursting?	Review for week
9: Engineering	Creating models using NEURON	Description of Modeling and Biology projects – due at end of course	**MIDTERM Exam**
10: Biology	Synaptic transmission and processing	B-Experiment 4: Synaptic transmission – Earthworm preparation	Review for week
11: Engineering	Modeling of synapses	S-Experiment 4: How do neurons communicate via synapses?	Review for week
12: Biology	Motor-networks	B-Experiment 5: Local field potentials using MEA (Virtual Lab)	Review for week
13: Engineering	Motor-networks	S-Experiment 5: How do tetrapods decide when to walk, trot or gallop?	Review for week **QUIZ 2**
14: Engineering	Simple neural networks	S-Experiment 6: Modeling simple neural networks	Biology Project presentations. Report due
15: Engineering	Review	Modeling Project presentations + Report due	*No class; Finals – next week*

Leaders in the field of neuroscience believe that the tools and ideas developed in the physical sciences will play a pivotal role in this undertaking [9]. They assert that a model-based approach, the hallmark of engineering, physics, and statistics, is critical to piecing together the numerous seemingly disjointed findings and the voluminous data being produced in neuroscience into a coherent portrait of function, including behavior [12]. Although courses and textbooks (e.g., [13]–[15]) related to computational neuroscience are being developed, they are typically at the graduate level. Also, they tend to lack significant model-based or engineering content, and/or biological realism, particularly at the undergraduate level [15].

Computational neuroscience refers to the study of brain function in terms of the information processing properties of the structures that make up the nervous system. It is an interdisciplinary science that links the diverse fields of neuroscience, cognitive science, and psychology with electrical engineering, computer science, mathematics, and physics [16]. This emerging computational toolkit is important for furthering understanding of the nervous system, as evidenced by the critical emphasis placed on incorporating computation into biology by educators and federal funding agencies [11], [17], [18]. While there is a surge in interest in neuroscience at both undergraduate and graduate levels, engineers and quantitative scientists lack the training in neuroscience necessary to adequately understand 'systems' in brains and facilitate improved interactions with neuroscientists. Similarly, biological and behavioral scientists lack adequate training in the quantitative sciences [18], and are thus interested in collaborations with engineering to jointly develop curricula. Such curricula and interactions are critical for effective interdisciplinary research, including the development of relevant computational and technological tools. National [11] and international [19] initiatives to accelerate research in neuroscience represent a unique convergence of interests, beneficial for electrical and other engineering departments at levels including curriculum development, research, and outreach.

A novel interdisciplinary undergraduate neuroscience course, 'ECE/BioSci 4590 Computational Neuroscience,' was developed in 2008 and has been co-taught since by a faculty team from the Colleges of Engineering and Arts & Science at the authors' university. The lab course includes neurophysiology, computation, systems and programming concepts, and is taught in alternating weeks of modeling/software and wet-labs, Table I. This paper focuses on the modeling/software part of the course, and specifically on the integration of model-based approaches (see Section II) in the course. To measure learning and the importance of model-based approaches to student learning and faculty teaching, three distinct groups were surveyed: (i) neuroscience faculty from four-year undergraduate institutions around the nation, who participated in a one-week on-campus course [20]; (ii) neuroscience researchers (Ph.D. students, postdoctoral fellows, and faculty), who as well as an in-depth one-week exposure had an additional week of research training [21]; and (iii) undergraduate alumni of the semester-long course.

The next section describes the specific model-based approaches incorporated into the course. Section III describes the results from the survey of each group that rated the importance of model-based approaches to student learning and to teaching neuroscience. Section IV summarizes the salient features of the course. It is noted that the model-based

engineering approaches can be integrated into other neuroscience courses.

II. Relevant Computation, Circuits & Systems, and Programming Concepts

A. Specific Need and a Solution

In a report from the National Academies that summarizes numerous past efforts to redefine undergraduate biology and science education, Labov *et al.* [22] highlighted that quantitative tools are increasingly important for biologists and should be part of undergraduate education. Two of the six core competencies proposed in the *Vision and Change* document [18] directly pertain to computation (i.e., the ability to use quantitative reasoning, modeling, and simulation), and two others pertain to interdisciplinarity (i.e., the ability to use, communicate, and collaborate with multiple disciplines). Specific recommendations from biology educators in this regard include [18]: (1) build a strong interdisciplinary curriculum that includes biological science, physical science, information technology, and mathematics; (2) design meaningful laboratory experiences; (3) provide teaching support and training to faculty; and (4) eliminate administrative and financial barriers to cross-departmental collaboration.

The collaboratively-developed interdisciplinary lab-based undergraduate neuroscience course, Table I, addresses some of these needs. The course incorporates computation, circuits & systems, modeling, and programming concepts into neuroscience, and uses a framework of 'biology to model and back again.' The course is designed for undergraduates from any department within the colleges of engineering or arts & science, and assumes only a background level of high school-level cell biology, mathematics, and programming. The elective course, with ∼25 students/section, has been offered annually at the university since 2008 and focuses on concepts at the cellular and systems level. The students have come from various departments such as (in order of decreasing numbers) bioengineering, electrical engineering, biology, psychology, biochemistry, physics, and mathematics.

The model-based theme of 'function-biology-model-math' enhances systems thinking by having students approach any neurobiological concept by determining what function is being implemented, then determining how biology implements it (in wet labs or biology labs), then modeling it in circuit terms, and finally writing down and simulating the mathematical representation of the model (in software labs). Each biology lab is followed by a virtual or software lab (with graphical user interface developed using the open-source package NEURON [23]) to illustrate the same neurobiological concepts and data as in the biology lab [24]. For example, students see an action potential in the biology lab using a crab neuron, and then in the software experiment they study how the currents in the crab neuron generate the action potential. The biology laboratory has six state-of-the-art electrophysiology workstations to support six wet labs, while the software lab has standard desktops that run the NEURON code. The mathematical and neuroscience topics are covered sequentially in this order: basics of math, circuits, systems modeling, programming, and electrophysiology (see Section III); Nernst and rest potentials (using a crayfish prep); action potential and bursting (using a crab cardiac ganglion prep); synaptic transmission (using an earthworm prep); and functioning of a simple network (using a crab stomatogastric ganglion prep). The course also has a ten-week modeling project that helps students appreciate the importance of the function-biology-model-math framework in understanding biological systems (see next section). Students learn programming formally using the package NEURON during this semester-long project, starting week 9, Table I. So programming is largely self-learned, starting with sample codes and carefully prepared but 'incomplete' templates. Supported by help-sessions conducted by the teaching assistant, students complete pacer-modules related to programming every week, which are graded and returned to provide immediate feedback. The final modeling project report and presentation is scheduled for week 15.

The course has six open-source software experiments (virtual labs; Table I) that have been disseminated to undergraduate neuroscience faculty since 2007 via annual summer workshops [24]. (The curricular contents of these workshops can be accessed via the Canvas site https://courses.missouri.edu/: scroll to bottom of page and click on 'Canvas Guest and Visitor Login,' and enter the site with username 'cns' and password 'workshop,' both without quotes.)

B. Integrating Model-Based Content

The model-based content has the following steps:

(i) Instruction begins with an introduction to high-school concepts of functions, differentiation, and integration.

(ii) The students then consider two first-order systems. The first is modeling the dynamics of a car from throttle angle to speed using a model-based framework, where the students first define the problem, then write down all the relevant laws (Newton's 2nd law for motion, linear drag force), and derive the differential equation describing the evolution of the system. They realize how speed would increase in a first order fashion when the throttle angle is kept constant, which is something they can relate to easily. The second example is a passive neuronal membrane, i.e., with only the leak channel, which has a first order response from injected current to membrane voltage, Fig. 1a. Then Kirchoff's laws, Ohm's law, and the Nernst equation (a balance between diffusion and electrostatic forces) are introduced, and the students derive the first order ODE for a passive membrane; this derivation approach is followed in all components of the course. Such an approach enables the students to understand the linkage of differentiation and integration to first order ODEs via laws that govern the dynamics of the system; this key connection is typically not sufficiently emphasized even in engineering undergraduate courses. Two other optional examples are provided—the increase in temperature of a cold house when the heating is turned on, and the filling of a tank of water when the drain faucet is open—in which students again see how the equations for all these different systems have the same first order dynamics.

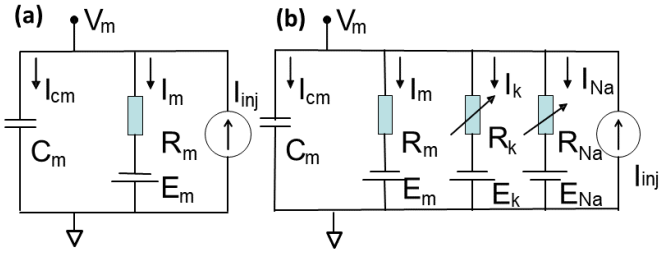

Fig. 1. Passive and active membrane models. Vm -voltage; Cm – capacitance; R – resistance; Em – reversal potential; m – membrane; Na- Sodium; K – Potassium. (a) Passive and (b) active membrane models.

TABLE II
SELF-EFFICACY ITEMS; RATING FROM 0 TO 100 0 = CANNOT DO AT ALL, 50 = MODERATELY CONFIDENT, 100 = HIGHLY CONFIDENT

0 = Cannot do at all, 50 = moderately confident, 100 = highly confident
1. Describe the basics of how neurons work to people outside the field
2. Use the NEURON software program
3. Compute a current using conductance and voltage
4. Describe how an action potential is generated
5. Explain how nervous systems use "binary information" (action potentials) to generate complex outputs
6. Explain the impact that computational approaches bring to biological questions

(iii) Once familiar with derivation of a first order ODE, the students solve it by hand using the Euler approximation for the derivative. Then they are shown how to solve it using packages such as Wolfram Alpha and MATLAB. This learning-by-doing also serves to provide valuable 'under the hood' insights related to numerical analysis packages.

(iv) The concept of time constant and gain for first order ODEs is introduced next, using two examples: car dynamics (cited above) and the passive membrane equation. To grasp this, the students have to understand how biology (membrane, channels, electrode for current injection in slice) can be viewed as a circuit model (capacitance, resistance, battery, and current injection source), and then how the biological system is converted into a first order ODE.

(v) The full neuron model is then considered. This begins with an introduction to probability concepts using single and multiple coin toss experiments. The joint probability concept is then tied to on/off positions of gates in channel proteins and to the concept of voltage-gated conductance. This enables students to extend the electrical circuit diagram of passive membrane to that of a spiking neuron (transition of membrane voltage from -65 mV to $+10$ mV in 1-2 ms) by adding parallel conductances for voltage-gated sodium and potassium channels. Students see how four first order ODEs can represent a spiking neuron in the form of a circuit, Fig. 1b. This step-by-step model-based introduction to the underlying mechanisms of what makes a neuron spike—typically difficult for neuroscience students to grasp—helps convey the concept logically.

(vi) The concepts of bursting (spikes followed by periods of quiescence) and of summation and attenuation of voltage in dendrites are easy to introduce once students understand how the circuit with voltage-based conductances causes spiking.

(vii) The alternating biology/software lab schedule, Table I, helps reinforce students' learning of the difficult neurobiological concepts. The hands-on and 'minds-on' format ensures that the students do not merely memorize facts, but have the opportunity to use programming concepts and high school calculus to better understand physiology and neuroscience principles.

(vii) Students are introduced to programming using the open-source software NEURON, starting with its use as a calculator, then progressing to loops, and then to modeling specific components of a neuron (such as membrane with capacitance, or various intrinsic and synaptic current channels with conductance and reversal potential). Students are then assigned a programming project that brings together all the components of the course over the remaining ten weeks of the semester. The students first study the literature on half-center oscillators, such as those that control blood flow in a leech heart. They then develop an electrical circuit model with all components, implement the model in NEURON, and then tune the parameters to reproduce the alternating oscillation pattern in the neurons.

(viii) Throughout the course, principles of electrophysiology are emphasized, including the functioning of the recording setup, buffering and amplification, and providing current injection using the electrode. Students perform a virtual lab experiment and analyze the circuit details such as the number of ions injected by the electrode for realizing a 1 pA current. This reinforces their learning related to electronics and instrumentation.

III. STUDENT RESPONSES TO THE COURSES

Surveys were developed and administered to three groups who participated in different courses at the university to determine gains in learning and in self efficacy, Table II, and how they rated the importance of engineering content, Table III.

A. Description of Participants

Three groups were studied:

(1) The *faculty group* ('faculty' in Table III) comprised 39 neuroscience faculty, from four-year institutions around the nation, interested in incorporating the contents into their own courses; during 2016 (n = 18) and 2017 (n = 21) they attended an in-depth one-week on-campus course focused on the model-based approaches [20]. This group had 22 females and 17 males, of whom 26 were White, one Native American, one African-American, three Latino, six Asian, and two other.

(2) The *researcher group* ('researchers' in Table III) included Ph.D. students, postdoctoral fellows, and faculty in neuroscience (from MIT, Stanford, UC-SF, USC, Brown, Tulane etc.) who were interested in model-based approaches for their research and so attended two-week research training courses offered during 2016 (n = 23) and 2017 (n = 23) [21]. The first week was the same as for the faculty group, and the second covered more advanced content. This group of

TABLE III
RATINGS OF IMPORTANCE AND USEFULNESS OF ENGINEERING CONTENT IN THE COURSE BY THREE NEUROSCIENCE GROUPS: (1) 4-YEAR COLLEGE FACULTY (FAC.; 2016& 2017; n = 26); (2) PH.D. STUDENTS, POST-DOCS, AND JUNIOR RESEARCH FACULTY (RES.; 2016&2017; n = 30); (3) UNDERGRADUATE ALUMNI OF OUR COURSE (UNDERGRADS; 2015&2016; n = 16). SCALE OF 1-5 (1-NOT IMPORTANT, 3-MODERATELY IMPORTANT, AND 5-VERY IMPORTANT)

Table IIIa. General items of model-based approach (arranged in order of increasing complexity)	**Importance - basics of model-based approaches** Mean (SD) Fac./Res./Undergrads		
1. Concepts of differentiation and integration in understanding neuroscience concepts such as time constant, spiking and bursting	4.00 (1.19)	4.43 (.88)	4.00 (1.03)
2. Circuit diagram of a general current channel as a resistance with a battery (from Nernst equation, also termed 'reversal potential for the ion')	4.12 (1.11)	4.43 (.79)	4.20 (.86)
3. Application of Ohm's Law to express the current through a leak channel as I_leak = G_leak*(V-E_leak)	4.08 (1.08)	4.50 (.84)	4.13 (1.15)
4. Understanding a passive membrane as a capacitance in parallel with a resistance (with battery), and developing an electrical circuit model for a passive membrane	4.15 (1.08)	4.57 (.69)	4.38 (.8)
5. Derivation of the capacitor charging equation from the definition of capacitance C = Q (charge)/V (voltage). Differentiating the equation and rearranging terms yields the capacitor current I_capacitor = C*dV/dt	3.04 (1.25)	4.14 (1.01)	3.50 (1.21)
6. Importance of putting it all together, i.e., draw circuit, derive a first order ODE for the voltage response of a neuronal membrane with only leak channels: I_inject=I_capacitor + I_leak	3.65 (1.20)	4.36 (.95)	4.13 (1.15)
7. Understanding how a first order ODE is solved by hand calculations. Leads to an understanding of how software packages such as Wolfram Alpha or NEURON automate the calculations.	2.92 (1.35)	3.96 (1.14)	3.00 (1.46)

Table IIIb. Model-based approach items integrated into neuroscience case studies with conceptual and software components (arranged in order of increasing complexity)	**Importance of model-based approaches in case studies**** Mean (SD) Faculty/Res.		**Usefulness of software for teaching** Mean (SD) Faculty/Res./Undergrads		
1. Nernst equation as a balance between diffusive and electrostatic forces relevant to a flow of ions across a semi-permeable membrane (no derivation)	4.42 (.95)	4.70 (.54)	3.96 (1.00)	3.89 (1.22)	3.88 (1.31)
2. Response of a passive membrane (with leak channels only) to current injection	4.36 (.76)	4.72 (.53)	4.20 (.87)	4.11 (1.10)	4.00 (1.10)
3. Role of Na+ and K+ channels in the generation of an action potential	4.84 (.37)	4.79 (.41)	4.40 (.71)	4.31 (1.07)	4.38 (.89)
4. Interactions of the various currents in generating the bursting output profile in a neuron	3.54 (1.10)	4.39 (.74)	3.96 (1.18)	4.21 (.92)	3.94 (1.44)
5. Mechanisms involved in generating synaptic responses, including excitatory/inhibitory synapses and summation	4.80 (.50)	4.68 (.55)	4.00 (1.13)	4.00 (1.05)	3.94 (1.00)
6. How changes in synaptic weights between four neurons (each connected to one of the legs) is sufficient to implement the walk/canter/trot/gallop gaits of a horse	3.42 (.97)	4.00 (1.07)	3.44 (1.00)	3.76 (1.22)	4.13 (1.15)
7. How simple neuronal networks might work to implement short term memory and winner-take-all functions	3.80 (1.06)	3.78 (1.01)	3.22 (1.22)	3.33 (1.30)	3.40 (1.18)

** Undergraduate students were not asked to rate this item

46 had 16 females and 30 males, of whom 28 were White, two African-American, eight Latino, seven Asian, and one other.

(3) The *undergraduates* ('undergrads' in Table III) included students from the semester-long undergraduate course on computational neuroscience. The 22 undergraduates surveyed for gain in learning (2017; described in Section III-B) were 13 males and 9 females, of whom one was African-American, three Asian American, and 18 White. Alumni of the course (2015-16) were surveyed on the importance of model-based approaches and utility of software (Section III; Table III); of the 16 respondents 6 were male and 10 female, of whom two were Asian American, 13 White, and one not reported.

B. Gains in Learning Neuroscience

Gains in learning in the course for the three groups were measured as described below. (Note that the number of participants for individual statistical tests varies due to fluctuation in participation).

Faculty group: Scores were compared on identical knowledge assessment tests, approximately one hour long, administered before and after the course, consisting of 15 items that measured concepts in math (two items) and in neuroscience (13 items). Items included topics such as the calculation of the time constant for membrane response with constant current injection, sketching an electrical circuit with linear and

nonlinear resistors and capacitors, Fig. 1, and writing the governing equations for a spiking neuron. The scores on the post-test were much higher than on pre-test (58 vs. 30; $p<.0001$, t-test; $n = 35$). Differences in gains between disciplines (Physical Sciences, Biological Sciences, and Psychology) were not significant (31 vs. 32 vs. 24; $p = 0.32$, one-way ANOVA).

Researcher group: The same approach was used as for the faculty group. The mean scores on the post-test were much higher than on the pre-test (64 vs 46; $p<.0001$, t-test; $n = 46$). Learning gains between disciplines (Physical Sciences, Biological Sciences, Medicine, and Psychology) did not differ significantly among these groups (14 vs. 16 vs. 32 vs. 23; $p = 0.08$, one-way ANOVA).

Undergraduates: Lacking similar pre- and post- tests for the undergraduate group, responses were examined ($n = 22$; 2017) on three questions that were identical to questions on the closed-book mid-term and final exams (for which students do not get to keep the question sheets), and pertained to model-based content: (i) parsing contributions of various nonlinear currents to the resting membrane potential, (ii) sketching and writing the ordinary differential equations (ODEs) for the circuit in Fig. 1, and (iii) writing the first order equation for a membrane with leak channels, sketching its response to a constant current injection, and finding the time constant. Scores on all questions were significantly higher on the final compared to the mid-term ($p<.01$, $n = 22$). Differences in gains between disciplines (Engineering or Biological Sciences) were not significant (8.78 vs. 7.35; $p = 0.63$).

C. Gains in Self-Efficacy

In addition to learning, self-efficacy was measured in researchers and faculty. Self-efficacy refers to confidence that one can carry out actions necessary to attain a desired performance; it is future oriented and refers to confidence for future behavior. Increases in self-efficacy have been linked by Bandura to enhanced learning and increases in test scores [25]. Self-efficacy is as important because learners with high efficacy tend to demonstrate increased interest, effort, persistence, and use of strategy. Several items in the study reported here were developed to measure self-efficacy, following suggestions in [25]; the neuroscience-related items are listed in Table II. On a scale of zero to 100 in ten-point increments (on an 11-point scale), participants indicated at the beginning of, and after the course, how confident they were that they could perform each behavior. The items in Table II were averaged to create a self-efficacy for neuroscience score. The efficacy scores increased significantly from pre- to post-course for both researchers (pre = 66, post = 85; $p<.001$; $n = 38$), and faculty (pre = 61, post = 80; $p<.001$; $n = 13$), indicating enhanced confidence in learning neuroscience for both groups. Taken together, the findings from the knowledge and self-efficacy assessments suggest that incorporation of model-based content increases learning in neuroscience.

D. Importance of Model-Based Approaches and Usefulness of Virtual Labs in Teaching Neuroscience

Surveys administered to the three groups (Table II) were used to examine the *importance* of model-based approaches described in Section II to student learning and the *utility* of the virtual (software) labs to enhance instruction. The undergraduates who responded to this survey were alumni of the 2016 and 2017 offerings of the course. Specifically, the groups were first asked to rate the importance of (i) introducing relevant math and systems content separately, and (ii) integrating math/systems content into neuroscience case studies, and then were asked to rate (iii) the *usefulness* of software tutorials to teach neuroscience concepts.

The rating of the importance of model-based approaches in general was very high, with an average of 4.02 out of 5.0 for the seven items in Table IIIa (the scale levels were 5=very important and 3=moderately important), indicating that all the topics were perceived as being important for undergraduate neuroscience. Between groups, the researchers rated the foundational model-based concepts higher on items 1–4 ($p<.2$) compared to four-year college faculty, and higher than both the other groups on items 5–7 ($p<.01$), Table IIIa. Furthermore, the average rating by undergraduates was higher on every item compared to those of faculty, although not significantly. Interestingly, all groups gave the highest rating to the item Understanding a passive membrane as a capacitance in parallel with a resistance (with battery), and developing an electrical circuit model for a passive membrane, Table III, a key model-based approach in engineering. All groups also gave their lowest rating (still a 3/5) to the same item, Understanding how a first order ODE is solved by hand calculations, with researchers rating it highest at 3.96/5. Research preparedness of undergraduates is evidenced only indirectly by the fact that two of the alumni of the undergraduate course secured funding to pursue advanced research in computational neuroscience (an NSF Graduate Fellowship to pursue a Ph.D. at the University of Washington, and a summer internship at MIT).

The *importance* of integrating model-based approaches directly into neuroscience case studies for instruction was again rated highly by all groups (undergrads were not asked to rate these items) with averages of 4.44 and 4.17 for researchers and faculty, respectively, with no appreciable differences on most items except the fourth ($p<.01$) in Table IIIb. For the section related to *usefulness* of software for teaching model-based approaches, the teacher ratings were higher than those of researchers for simpler tutorials (items 1–3 of Table IIIb) and vice versa or comparable for complex ones (items 4–7), although not significantly so. Interestingly, undergrads rated the usefulness of software lower than the other groups (although not significantly), except for the last one, which was linked to real-world applications. Implications of these findings are elaborated in Section IV. In summary, the importance of engineering content for student learning, of integrating that into concepts for teaching, and of the importance of software incorporating such content, were all consistently highly rated by faculty, researchers and undergraduates.

E. Standards of Expectations for Learning in Neuroscience

Based on input from the more than 150 faculty and researcher attendees so far in the summer programs, and a survey of the literature, one can see that neuroscience curricula lack even partial coverage of the model-based content reported here, although several programs require calculus and differential equations. An analysis of the topics in Table I shows that it is difficult to disentangle model-based concepts from those of neuroscience, highlighting the utility of such 'integrated' modules. The survey findings above, and the fact that model-based approaches are part of well-supported standards for expectations for learning in engineering [26], suggest that incorporation of such engineering content has the potential to improve learning and instruction in undergraduate neuroscience.

F. Limitations

Limitations of the study include: (i) Students in the summer workshops and undergraduate classes self-selected to be in the courses and probably represent unique groups, so results should not be generalized to all possible students. (ii) There was no random assignment to treatment and control groups, so attributing pre-test/post-test improvement to the courses is logical but not definite. (iii) Even though the undergraduate course has been offered since 2008, only one cohort of undergraduates participated in this data set, which limits generalizability.

IV. Discussion and Conclusion

An unprecedented surge of interest in neuroscience over the past decade has resulted in institutions, from liberal arts colleges to research universities, initiating new undergraduate majors in neuroscience [8], and NAE recognizing 'reverse engineer the brain' as one of 14 grand challenges for the 21st century [10]. This development ushers in tremendous opportunities for engineers to contribute to the exciting challenge of understanding the brain, and the course reported here provides a direction for engineering involvement in curricular development in neuroscience.

The field of neuroscience spans a wide range, including genetic, molecular, cellular, systems, and behavioral levels of study [27]. Engineering model-based approaches are critical to bridge these diverse levels and provide links to behavior [28]. The model-based content in the course, beyond basic modeling aspects, includes system theoretic concepts, starting with linkage of high school concepts of differentiation/integration to first order differential equations, basic electric circuit theory, derivation of passive membrane dynamics emphasizing laws to reveal first order dynamics (and elaboration using mechanical, hydraulic and thermal systems), illustration of the role of stochasticity in channel dynamics and spiking, highlighting the grouping of current modules to preserve function in bursting cells, instruction on electrophysiology fundamentals in a standalone virtual lab, and programming. Importantly, 'systems thinking' (using a function/biology/model/math framework) is emphasized throughout the course and reinforced using theory, open-source 'virtual' labs available on students' own laptops to facilitate self-paced learning, and by small group work. A survey of faculty, researchers, and undergraduates revealed that incorporation of engineering content into neuroscience enhances learning of the difficult neuroscience concepts, facilitates teaching, and is welcomed by each of the three groups.

Model-Based Approaches Enhance Student Learning and Facilitate Instruction: Gains in learning were quantified by pre- and post-tests, and by self-efficacy scores. Significant improvement in scores was found for all the groups. Also, the faculty from four-year colleges and researchers (Ph.D. students, postdocs and junior faculty) from around the nation who participated in the summer programs rated all components of the engineering content highly, attesting to the importance of such engineering content in teaching undergraduate neuroscience. Their enthusiasm is probably due to the fact that learning neuroscience is rated as a challenging and laborious task by undergraduate students [29]. One could argue that this is because most neuroscience courses are taught using the standard 'lecture-and-textbook' paradigm. It could also be that few neuroscience courses have sufficient quantitative content to explain the complex contents, and even if included, such content is unlikely to be woven into case studies in a tightly knit form as reported here. Once students began to comprehend the linkage between biology and models, they displayed tremendous interest. It was remarkable that the average rating of the importance of the general model-based contents, Table IIIa, was a high 3.69 among the faculty from four-year colleges that do not typically have strong research programs. This attests to the critical need for the utilization of such concepts to explain the intricate concepts in neuroscience. This observation is further strengthened by the fact that the perceived importance by trainees increases with research level: (i) undergraduates from the research university rated the same contents higher (although not significantly; Table IIIa) compared to faculty; and (ii) researchers from around the nation rated them the highest of all groups ($p<.2$; see Section III-D). Furthermore, all groups rated the usefulness of the open source software to learn these foundational concepts highly. The differential rating of the utility of software to illustrate the neuroscience case studies was along expected lines, with four-year college faculty focusing more on simpler case studies relevant to their students, Table IIIb, and the researchers desiring a deeper understanding of the more complex case studies. The importance of connecting to real-world application is highlighted by the fact that undergraduates rated items 6 (neuronal network and gaits in horses) and 7 (short-term memory and winner-take-all networks) of the software tutorials higher than the other two groups. Such interactive software tutorials improve learning and are particularly important for students from underrepresented groups [30], [31]. It is noted that model-based approaches can be taught with only the software tutorials (i.e., without the biology labs), as has been largely the case in the summer programs for faculty and researchers. Importantly, the engineering content can be distributed in more than one neuroscience course, as may happen eventually in this important and growing area of neural engineering.

An understanding of model-based approaches will be essential to "prepare the next generation of students to think critically, synthetically, and creatively as they confront the

problems facing humanity in the 21st century" [8, p. A34]. For instance, in the neurosciences, the disciplines of biology, psychology, and medicine would benefit from interactions with engineering to utilize model-based approaches for a fundamental understanding of neurons and circuits, the building blocks of the brain. Interestingly, biology and psychology faculty, and their administrators, are keen to incorporate computational skills and software tools in their curricula. This is evident from the fact that the annual summer workshops to disseminate such curricula have, since 2008, attracted 113 undergraduate neuroscience faculty from two- and four-year institutions from 27 US states, and continue to be popular [20]. It could also be argued that the voluminous data beginning to be generated at multiple neural levels in neuroscience make model-based approaches feasible, and perhaps imperative. At the authors' institution, the curricular collaboration between engineering and arts & science resulted in the institution of a popular interdisciplinary minor in computational neuroscience for undergraduates from both colleges; this has also benefited engineering with increased research collaborations. Indeed, neuroscience research challenges for engineering are numerous and include technological ones such as large scale monitoring of brain activity at fine temporal and spatial scales (e.g., [32] and [33]). Some challenges at the theoretical/systems level include novel hierarchical frameworks and big data analytics to bridge scales (genetic, molecular, cellular, systems, and behavior/clinical). These researchers are investigating how brains solve computational problems and what makes them unique, and how to enhance clinical decision-making by understanding neural mechanisms of dysfunction (e.g., [34]).

Finally, it is noted that although engineering departments have difficulty attracting female students [35], women are more likely to participate when biology is included in the program. One of the best demonstrated gender differences is that women are underrepresented in fields that are mathematics intensive, and are much better represented in fields such as the life sciences [36]. The course reported here bucked this trend, with a female/male ratio of 46% in a total enrollment of 29/year from 2015-17. This makes neuroscience an attractive area for recruiting women into engineering with its emphasis on model-based approaches to understanding the life sciences and human health.

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