A Sustainable Model for Integrating Current Topics in Machine Learning Research into the Undergraduate Curriculum

Michael Georgiopoulos[1], Ronald F. DeMara[1], Senior Member, IEEE, Avelino J. Gonzalez[1], Fellow, IEEE, Annie S. Wu[1], Mansooreh Mollaghasemi[1], Erol Gelenbe[2], Marcella Kysilka[1], Jimmy Secretan[1], Carthik A. Sharma[1], Member, IEEE, Ayman J. Alnsour[3], Member, IEEE

***Abstract*—This paper presents an integrated research and teaching model that has resulted from an NSF-funded effort to introduce results of current Machine Learning research into the engineering and computer science curriculum at the University of Central Florida (UCF). While in-depth exposure to current topics in Machine Learning has traditionally occurred at the graduate level, the model developed affords an innovative and feasible approach to expanding the depth of coverage in research topics to undergraduate students. The model has been self-sustaining as evidenced by its continued operation during the years after the NSF grant's expiration, and is transferable to other institutions due to its use of modular and faculty-specific technical content. This model offers a tightly-coupled teaching and research approach to introducing current topics in Machine Learning research to undergraduates, while also involving them in the research process itself. The approach has provided new mechanisms to increase faculty participation in undergraduate research, has exposed approximately 15 undergraduates annually to research at UCF, and has effectively prepared a number of these students for graduate study through active involvement in the research process and co-authoring of publications.**

***Index Terms*—Curriculum development, integrated research and teaching, machine learning, team teaching models, undergraduate research experiences**

I. INTRODUCTION

Current models of undergraduate research such as *Research Experiences for Undergraduate Students (REU)*, Honors Theses, and senior-year projects frequently

Manuscript received 28 September, 2007. This work was supported in part by the National Science Foundation grant #0203446.
Corresponding author: M. Georgiopoulos 407-823-5338; fax: 407-823-5835; e-mail: michaelg@mail.ucf.edu

[1] M. Georgiopoulos, R. F. DeMara, A. J. Gonzalez, A. S. Wu, M. Mollaghasemi, M. Kysilka, J. Secretan, and C. A. Sharma are with the University of Central Florida, Orlando, FL 32816 USA.

[2] E. Gelenbe is with the Imperial College, London SW7 2AZ, UK. [3] A. J. Alnsour is visiting faculty the University of Central Florida (on sabbatical leave from Al-Isra Private University, Amman, Jordan).

serve as effective means to introduce undergraduate students to research [1]. However, these interactions can reveal challenges with regards to sustaining undergraduate research over an extended period of time [2]. The *Sustainable Model for Assimilating Research and Teaching (SMART)* at UCF integrates current research into the undergraduate curriculum through a course sequence that has propagated beyond an NSF-funded *Combined Research and Curriculum Development (CRCD)* award [3], [4]. SMART reaches a wide audience of undergraduate students who may not otherwise have considered well-established research programs for undergraduates, such as the NSF-funded Research Experiences for Undergraduates (REUs). The effort described here is a structured approach with a focus on Machine Learning (ML), spanning multiple faculty members with various ML research interests. This approach has encouraged undergraduate students to pursue graduate education, while producing research results and outcomes which have advanced the professional development of students and faculty members involved. Furthermore, the approached presented here is designed to be a general one, applicable to almost any scientific or engineering discipline, where it is desired to combine graduate research with undergraduate education to the benefit of both. This approach provides a template for readers in different disciplines to follow and create similar programs.

Faculty members will frequently work individually with undergraduate students on topics that are related to their own research. However, the proposed SMART approach provides research-oriented, team-taught course offerings that span multiple topics. This approach exposes undergraduate students to a wider breadth of research experiences. The team-taught course offerings benefit the faculty involved in this effort by encouraging collaboration of faculty with similar research interests, and by providing a structured and sustainable mechanism for recruiting undergraduate students in their graduate research teams. Additionally, these provide a neutral, collaborative environment for senior faculty to mentor junior faculty in a non-intrusive fashion.

An overview of the SMART method is shown in Fig. 1. This framework was realized during the NSF CRCD grant's funding years of 2002 through 2005, and sustained thereafter. Part of the CRCD effort involved developing and teaching modules, such as appropriately chosen homework assignments, in required undergraduate courses to encourage students to register for the senior level courses called *Current Topics in Machine Learning I (CTML-I)* and *Current Topics in Machine Learning II (CTML-II).* In *CTML-I* the students learn the fundamentals of the current research topics from the faculty members who are co-teaching the course. In *CTML-II* those students who continue participate in a hands-on research project. Students work one-on-one with a SMART faculty member, either individually or in small groups, along with an appropriately-chosen graduate student mentor. During the NSF grant's funding period, an advisory board of faculty and industrial members acted as facilitators and evaluators of this effort, and provided valuable feedback leading to the *SMART* model. The *CTML-I* and *CTML-II* classes have been consistently taught since the Fall semester of 2003 facilitating exposure to a significant number of undergraduate engineering and computer science students.

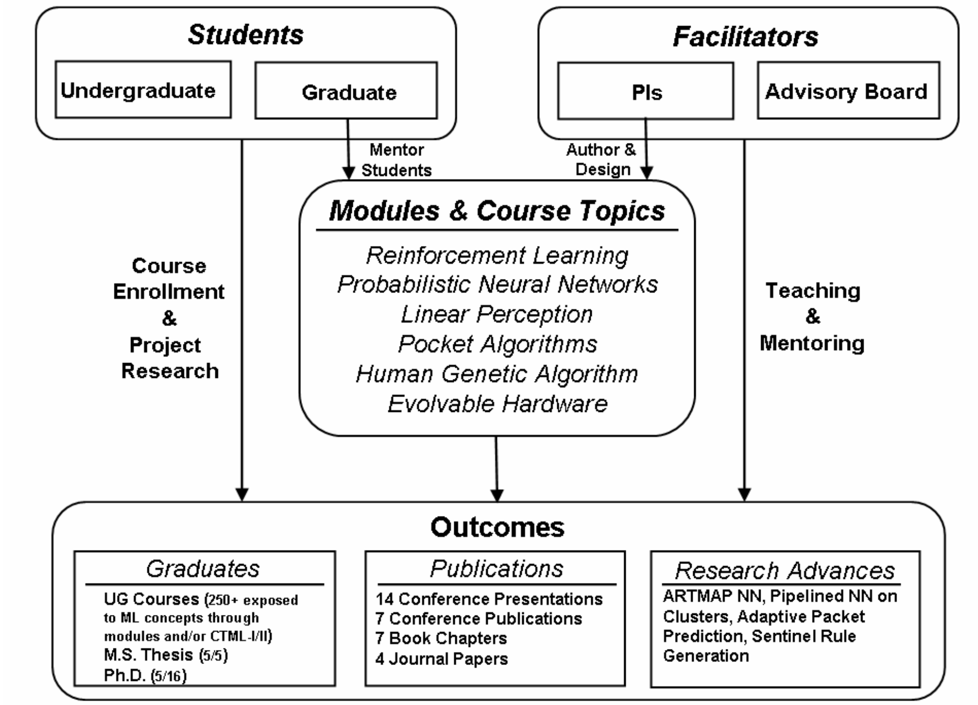


Fig. 1: SMART Project Framework

II. RELATED WORK

While many faculty members strive to integrate their research into undergraduate experiences either on an individual basis or a research team basis [5]-[7], the availability of a structured approach that spans multiple faculty and multiple semesters can be beneficial. The longer-term research relationships that are created between faculty members and undergraduate students through this long-term approach can be synergistic with other initiatives, such as summer internship programs [2] and the NSF REU under the direction of a research professor. Initial student perception of the value of REU programs has been overwhelmingly positive [1]. However, the REU program is mostly centered around performance of research, with little time devoted to classroom learning on the research topic or methods. Furthermore, some have found that the 10-week duration of a summer REU experience may be insufficient to fully convey the essence of technical research that leads to publishable results [2], [8].

Team-based teaching has previously been integrated into undergraduate curricula on a number of topics, but quite often with the goal of encouraging a multidisciplinary approach [10], [11] or redistributing faculty workload [9]. On the other hand, team-teaching in *CTML-I* introduces students to a range of current ML research topics, as well as to the research styles of a variety of faculty members. This exposure can assist students in their decision to consider a research apprenticeship with one of these faculty members. Several other CRCD projects have been funded by NSF, such as ones in particle technology at NJIT [12]; sensor materials at Ohio State [13]; optical sciences at NAT [14]; convex optimization for engineering analysis at Stanford [15] and smart materials at Texas A&M [16], but none of these projects have focused on the creation of a portable sustainable model. CRCD programs have the ability to immerse a student more fully because they avoid the time limitation of a summer term imposed by NSF REU programs. While the focus of SMART has been on ML, the model can be applied to other topics and at other institutions without the need for NSF funds to initiate it. This model requires only a small nucleus of faculty with similar research interests and the motivation to co-teach courses similar to the *CTML-I* and *CTML-II* courses described here.

III. RESEARCH AND CURRICULUM INTEGRATION APPROACH

The SMART initiative involves multiple mechanisms beyond those originally incubated by a CRCD award [17]–[22]. In the SMART approach, faculty members initiate the process via two alternative techniques. First, the availability of the program is publicized through seminars and workshops to students. Second, technical learning modules are delivered in select required undergraduate courses. Modules highlight current ML topics as application examples that students already learn, such as data structures. Both techniques attract undergraduate students to become involved in ML research, bootstrapping the integrated teaching and research method.

A. SMART Teaching and Research Methodology

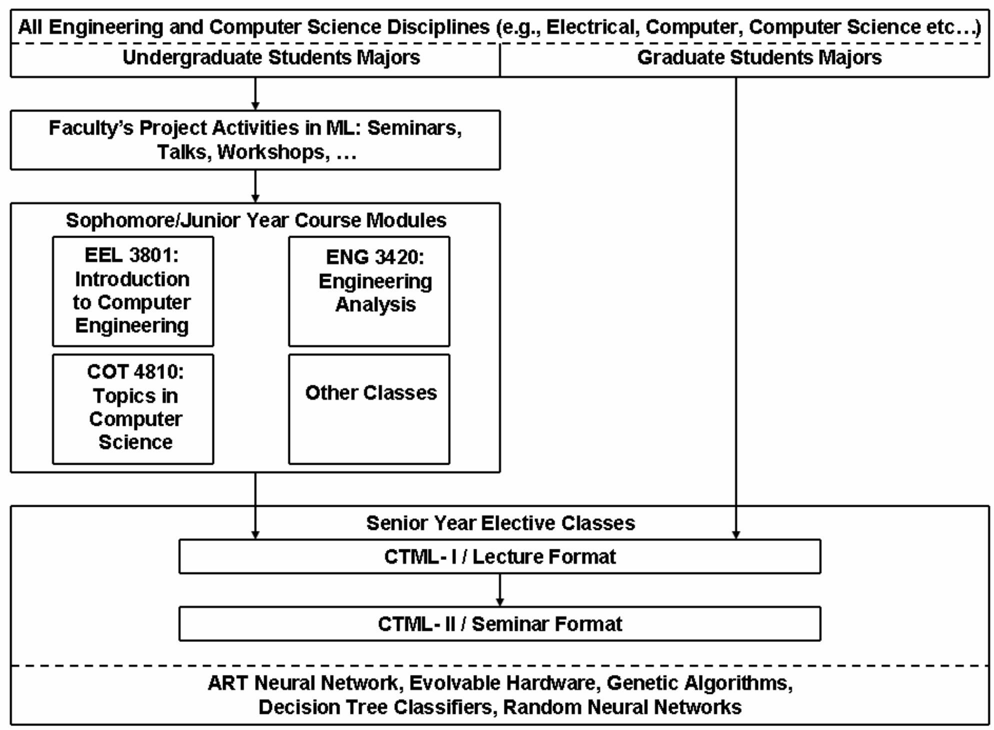


Fig. 2: SMART Activities to integrate ML research into Education.

As shown in Fig. 2, ML-related seminars, guest-lectures, one-on-one interactions with students, and ML modules, offered by SMART faculty members, are some of the many vehicles used by SMART faculty to encourage students to register for the CTML-I and CTML-II senior level courses. *CTML-I* introduces students to research faculty and topics, and leads to CTML-II, where students engage in research projects advised by a faculty member who co-taught in CTML-I. Both courses are electives in the degree program, and a number of disciplines in engineering and computer science allow their students to register for such technical electives. CTML-I emphasizes lecture-based instruction on current ML concepts of interest to the team of participating faculty, and CTML-II stresses hands-on research by undergraduate students working with a graduate student mentor while being actively advised by a faculty member. The course sequence helps to address challenges cited in alternate experiences with undergraduate research, especially recruitment of skilled students matched to faculty interests [23], [24].

The broad cross section of research interests in ML make it a suitable candidate for co-teaching of courses. In the School of Electrical Engineering and Computer Science at UCF, there are currently eight faculty members with significant interests in AI and ML, and at least three other faculty members who apply these techniques to applications. This grouping constitutes a sufficiently large nucleus of faculty expertise with diverse research interests to sustain the continual offering of *CTML-I* and *CTML-II*. Since initiation, two additional new faculty hires from the Computer Science program voluntarily enlisted in the SMART initiative. Furthermore, the initial proposal effort included a faculty member from the Education Department who helped in the design of the evaluation instruments, and in the assessment of the project’s accomplishments.

B. SMART People and Timeline

In order to achieve the goal of introducing undergraduate students to leading-edge research in ML, two objectives are pursued. The first objective is the creation and continuous offering of *CTML-I* and *CTML-II* that have now become permanent listings in the university catalog. The second objective is the task of making students aware of the CTML-I and CTML-II opportunities, the most noteworthy of which was the creation of *Machine Learning modules* that can be inserted in select sophomore- and junior-level undergraduate classes.

A three-year timeline required to establish a self-sustaining program is depicted in Fig. 3. Various semesters, since Fall 2002, have been devoted to course material development, project material development, as well as teaching, assessing and improving the course content and educational practices. CTML-I and CTML-II have consistently been offered to conduct teaching, assessing and improvement of both classes.

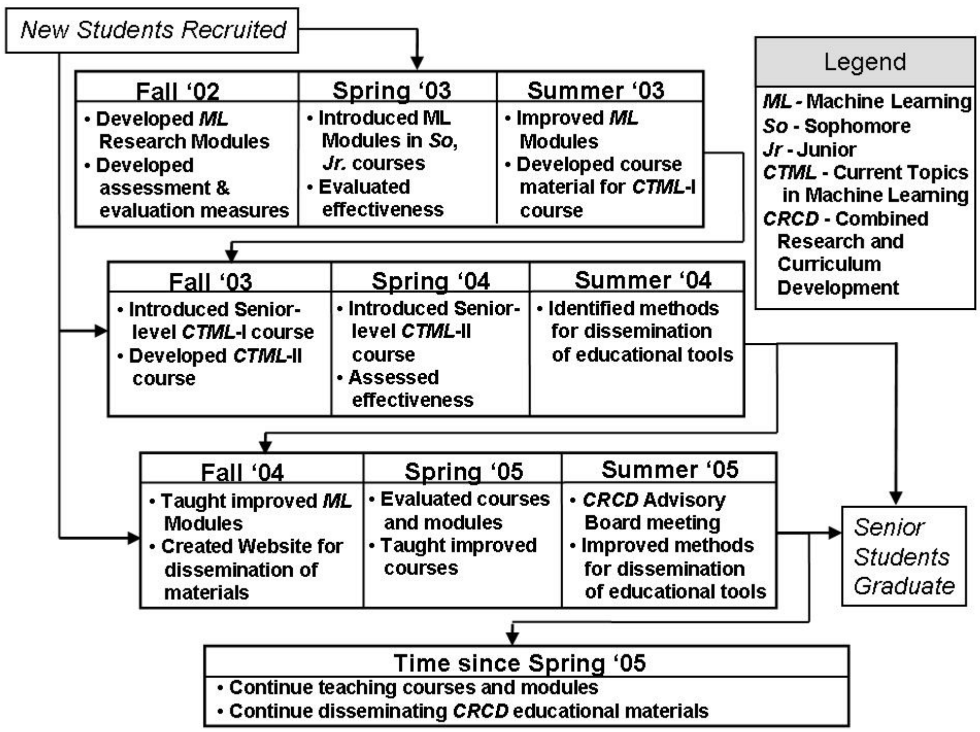


Fig. 3: SMART Timeline of Activities throughout the funding period to establish the model.

As shown, most of the initial effort was expended upon the design of the educational materials for the research modules and the CTML-I lecture notes, as well as on the advising of the students in research projects assigned in the CTML-II course. The CTML-I class is taught each Fall by a team of faculty, which allows each of them to provide students with the necessary background to join in that particular faculty member's current research efforts. The CTML-II class is taught each Spring by the same faculty who taught CTML-I in the previous Fall. Interested students from the

CTML-I class, as well as a few new students, work one-on-one with a faculty of their choice on an ML research project and may also receive mentoring from a faculty's graduate students.

C. Curricular Content and Student Projects

1) Machine Learning Modules

The ML course modules applied throughout the sophomore- and junior-year undergraduate courses can stimulate student interest in ML topics through application examples of elementary technical concepts required for the degree program. Modules developed as part of the project introduce students to some widely used algorithms for ML and their underlying principles. As an ongoing effort, these modules were refined and improved based on feedback from the students, such as the examples listed below:

- *EEL 3801 - Introduction to Computer Engineering* – Module: "Learning the Trick of the Game called Nim"
- *EGN 3420 - Engineering Analysis*– Module: "Perceptron-Based Learning Algorithms/The Pocket Algorithm"
- *EEL 4851 - Data Structures* – Modules: "Graph and Network Data Structures for Evolvable Hardware" and "Inductive Learning Algorithms"
- *COT 4810 - Topics in Computer Science*– Module: "Human GA: Learning Evolutionary Computation via Role Playing"

More details about the specifics of each of the aforementioned modules and student feedback are provided in [3]. Because of space limitations, this article focuses on the *CTML-I* and *CTML-II* classes. Advocacy of the SMART program by means of invited speakers, posters, and presentations to interested student groups such as senior design students and at graduate pre-recruitment seminars, have also had a positive impact on enrollment.

2) Current Topics in Machine Learning I

In any course, the tradeoff between breadth and depth must be considered. Traditional courses tend to focus on breadth, providing students with knowledge of many well-known and fundamental algorithms. The CTML-I class, on the other hand, emphasizes depth in specific research areas in order better to prepare students to actively join an ongoing research project through a bottom-up learning approach. Depending on the particular faculty involved in CTML-I, the topics covered in the course may not span all traditional machine learning algorithms. The philosophy adopted, which has been quite successful, is that involvement in an actual ML research effort will spark student interest to investigate the breadth of ML algorithms further in the future.

The CTML-I course features introductions to the research topics presented on a rolling basis by a group of faculty. Each faculty member presents five twice-weekly lectures on their topic of expertise. The teaching materials for CTML-I are derived almost exclusively from peer-reviewed publications of the SMART faculty and their other publications such as books or tutorials on *Adaptive Resonance Theory (ART*) neural networks [25] or decision trees [26]. For instance, the ART topic is elaborated below as an example.

a) Adaptive Resonance Theory (ART) Neural Networks

The students are first briefly introduced to neural networks because some may not yet have been exposed to this topic from the corresponding course module. Next, the students are exposed to the motivation behind ART neural network architectures and their specific parameters. The lectures are then devoted to discussing a benchmark ART neural network architecture, called *Fuzzy ARTMAP,* which is extensively used in solving classification problems. By understanding Fuzzy ARTMAP the student has the ability quickly to comprehend a number of other ART architectures. Furthermore, in the ART lectures, useful analogies are drawn between these basic ART architectures and other neural network architectures, such as multi-layer perceptrons and radial basis function neural networks. Finally, successful applications of ART neural network are discussed, and the students are encouraged to study additional ART-related papers.

b) Homework Assignments in CTML-I

Homework is assigned for every major topic discussed in the CTML-I class. This assignment is designed to reinforce some of the important concepts discussed in class, and ranges from paper and pencil assignments to running experimental simulations. For example, one such assignment involves walking through the process of a training cycle of a Fuzzy ARTMAP neural network for a simple example. Another assignment involves using existing Genetic Algorithm (GA) code to study the impact of parameter settings on GA performance.

3) Current Topics in Machine Learning II

The first two weeks are devoted to a discussion of the projects that the faculty advisors propose to the students as potential research projects. In each lecture, the challenges posed by, as well as techniques to complete, the proposed project are presented. After this two-week period, the students choose a research project of interest and work with the associated faculty member on a one-to-one basis. Examples of projects include various ML applications, experimentation on novel ML approaches, comparisons of two or more ML approaches on a class of application problems, and others. The research conducted in CTML-II always leads to a formal report, occasionally leads to an honors thesis, and frequently leads to a peer-reviewed publication.

a) Student Research Projects in the Current Topics in Machine Learning II

Students work on their chosen projects in groups of one to three. Each group of students is supervised by a faculty member and a graduate student mentor. Students are actively encouraged to form multi-disciplinary groups to emphasize collaborative work. Projects are completed over a 12-week period under weekly supervision by a faculty member and more frequent interaction with a graduate student mentor. Monthly course-wide meetings are conducted in which students report progress and receive feedback from all participating faculty and students about their research.

Students present their work incrementally at three presentation milestones. In the first presentation, students present a literature survey, requirements overview, proposed technical approach, and schedule. In the second presentation, held one month later, students present an overview of the design progress to date, and solicit advice for possible solutions to technical issues from other student groups and faculty mentors. In the third presentation, held during final exam week, students present results and conclusions. Students must submit a final project report on their work using the IEEE conference article format. The quality of the presentations, the technical report, and the interactions of faculty and graduate student mentors with the student contribute to the grade of the student in the CTML-II class.

Table I lists some examples of projects completed by students in CTML-II. Project 3 is an example of a joint effort by an undergraduate student and a graduate student mentor involving the parallelization of Fuzzy ARTMAP on a Beowulf cluster which improved the convergence speed of the training process on large databases. The undergraduate student implemented Fuzzy ARTMAP on the Beowulf cluster and generated experimental results that demonstrated its effectiveness. Results were published in two conference papers and two journal papers, all of which were co-authored by the undergraduate student. This student was later accepted into the Ph.D. program at UCF and received an NSF Graduate Research Fellowship, one of the most prestigious fellowships in the nation for recognition of student research potential.

Table I: Examples of Student Projects and Publications

Project Title	**No. of Students**	**Honors Thesis Produced**	**Conference Papers Published**	**Journal Papers Published**
1. *Comparison of ssFAM and sssFAM Classifiers*	3	0	1	0
2. *Comparison of GAM, micro-ARTMAP, ssFAM, ssEAM and ssGAM Classifiers*	1	0	2	1
3. *Pipelining of Fuzzy ARTMAP Neural Networks without Match-Tracking*	1	0	2	2
4. *Hilbert Space Filing Curve Nearest Neighbor*	1	1	1	0
5. *Experiments with the Probabilistic Neural Network: Implementation on Beowulf Cluster*	3	0	2	0
6. *Backward Adjustments with the C4.5 Decision Tree Algorithm*	1	1	1	0
. . .				
32. *Voting Schemes to Enhance Evolutionary Repair in Reconfigurable Logic Devices*	1	0	1	0

IV. Results and Assessment

Assessment of the SMART model for undergraduate research and curriculum begins with measuring the effectiveness of student recruitment and retention. Table II depicts the number of students who have registered for the CTML-I and CTML-II courses each semester. A total of 97 students have completed or are in the process of completing these courses. Since some of the students took both CTML-I and CTML-II, 77 distinct students have been introduced to research through the CTML-I and CTML-II sequence over this 5-year span.

The effectiveness of the CTML-I and CTML-II courses can be gauged by a number of indirect measures such as student survey questionnaires and direct measures, such as presentations and final reports. Furthermore, students' works have been judged as a direct measure by an independent group of evaluators who comprise the Advisory Board. Also, some of the students' work has been accepted for publication in peer-reviewed conference and journal venues, which provides another direct measure of their ability to perform research of publishable quality. Finally, information about the impact that SMART had on faculty culture is described below.

Table II: Number of students in the CTML-I and CTML-II courses.
*** denotes years of CRCD NSF funding**

Year Offered	Number of Students	
	CTML – I (Fall Semester)	CTML – II (Spring Semester)
2003 – 2004 *	11	12
2004 – 2005 *	10	8
2005 – 2006 *	13	6
2006 – 2007	14	8
2007 – 2008	10	5

A. CTML I Course Assessment and Evaluation

The learner outcomes for the CTML-I course are measured using a survey at the end of the course that probes students' understanding of the concepts and their confidence in applying the concepts learned. The CTML-I course lectures focus on ML topics such as ART Neural Networks, Genetic Algorithms, Decision Tree Classifiers, Inductive Learning, and Evolvable Hardware. At the end of each course topic, the students are quizzed with some questions gauging their understanding of the fundamental concepts, and others evaluating their ability to apply the concepts learned in class to solving problems, or extending the presented solutions. Students are able to respond with how well the objective was met through questions such as:

- I can explain the basic steps that occur in each generation of a GA
- I can discriminate between the one-classifier and the multiple classifier results within the application domain of the letters database

In the offerings of the CTML-I courses from Fall 03 to Fall 05, more than 60% of the students perceived that they understood the concepts. Cumulative results across the topics are presented in Fig. 4. Results show that 72% of the students stated an understanding of the concepts presented, with less than 6% of the students expressing failure to understand some of the concepts. These include responses from 33 students over the three-year period.

In order to measure the skills learned by the students and their confidence in applying these skills, as well as extending their understanding to real-life problems, questions included:

- I can apply the major steps of FAM’s performance phase to given examples
- I feel comfortable in writing code that implements the growing phase of a decision tree classifier

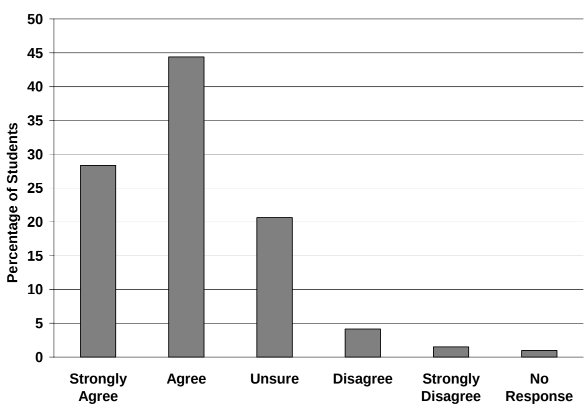


Fig. 4: Cumulative Learner Outcomes – Comprehension

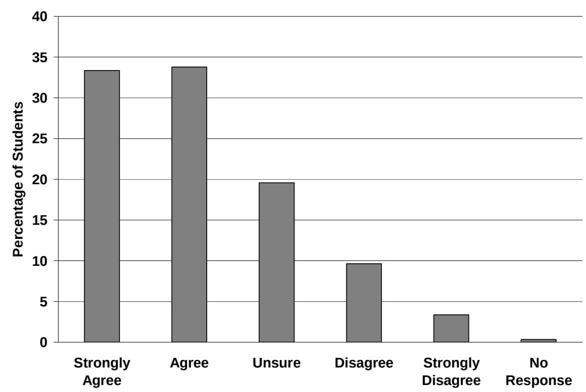


Fig. 5: Cumulative Learner Outcomes – Applying Techniques

The cumulative results of the survey questionnaire responses, over a three-year period are provided in Fig. 5, which shows that 67% of the students express confidence in applying their newly acquired skills, with 13% expressing concern in applying these skills.

B. CTML II Course Assessment and Evaluation

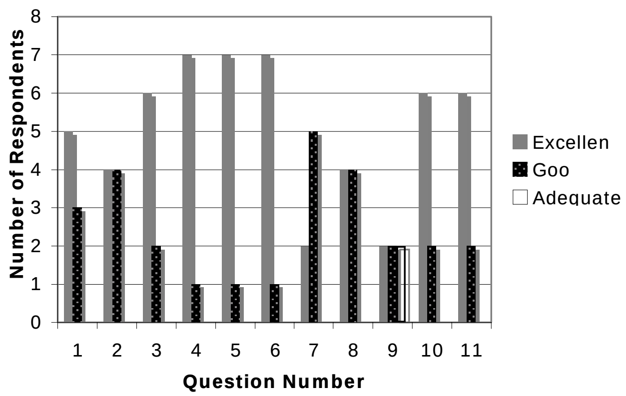
The performance of the students in the CTML-II course is assessed through their formal presentations, the one-to-one interaction with the faculty and the graduate student mentor, and through the technical reports that they produce for faculty review. The performance of the students in the CTML-II class was very encouraging. The participants in the SMART initiative have produced a total of four journal publications, 14 conference publications and presentations, and seven book chapters (see for example [27] – [31]). Journal papers co-authored by SMART undergraduate students include works on parallelization [32] and pipelining of Fuzzy ARTMAP [33], gap-based estimation [34] and experiments with micro-ARTMAP [35]. Three out of the four journal publications appeared in journal venues with a high impact factor. Neural Networks has impact factor of 2.0 and is ranked 16, while Neural Computation has impact factor of 2.6 with a rank of 14 in the list of highest impact factor AI journals (2006, Journal Citation Reports - Science Edition). Furthermore, the number of publications produced out of 35 CTML-II students is 18, with four journals, seven conference papers and seven book chapters. These publications represented 23 machine learning projects in the CTML-II classes of Spring 2004, 2005, 2006, and 2007. This 52% publication percentage is very high for undergraduate students, and is very competitive with the publication percentages of some of the most successful NSF REU programs in the nation. For example, the Computer Vision REU by Professor Mubarak Shah at UCF (http://server.cs.ucf.edu/~vision/) lists 60 publications in its 20 years of existence of that REU effort, involving 200 students, which results in a publication rate of 30% assuming that every student worked on a different project (see also [8]).

C. Advisory Board Assessment and Evaluation

The students' performance was also evaluated by the Advisory Board at a symposium, held in 2005, that brought together academics and government/industry professionals with expertise in ML and its applications. These participants included 13 faculty members from related departments at the Florida Institute of Technology, University of Nevada Reno, Florida State University, United States Military Academy, University of Puerto Rico, University of Hartford, University of New Mexico, and Technological Educational Institution of Kavala, Greece, as well as several professionals working for national research laboratories such as the NASA Ames Laboratory, and Los Alamos National Laboratories, and research and development organizations such as Soar Technology and SAIC, Inc.

The Board was requested to assess and evaluate the curriculum development efforts and their effect on the students' critical thinking, intellectual growth, and communication skills. Board members were provided in advance with a packet containing information about the ML modules, the CTML I and II courses, and the Assessment and Evaluation rubrics prepared by the SMART faculty from the Education Department[2]. The Advisory Board members assessed three elements of the SMART experience: (a) knowledge transfer in CTML-I, (b) knowledge transfer in CTML-II, and (c) potential for institutionalizing and disseminating SMART.

Eight of the student projects, conducted in the academic years 2003-2004 and 2004-2005, were presented during the symposium. Later, the faculty met with the Advisory Board to receive their comments regarding the SMART experience, based on a day-long interaction with the students. The responses of the Advisory Board to the Assessment and Evaluation rubric are listed in Fig. 6. The answers to each of the 11 questions were: *Excellent, Good, Adequate,* and *Poor* with Questions 1, 3, 4, 5, 6, 10, and 11 receiving predominantly *Excellent* responses. Questions 2, 7, and 8 received primarily *Good* responses and Question 9 had some *Adequate* responses.



1: Perception of knowledge acquisition based on student responses
2: Perception of knowledge transfer based on graded homeworks and examinations
3: Appropriateness of material
4: Quality of topics
5: Effectiveness of projects in knowledge transfer
6: Effectiveness of student presentations
7: Effectiveness of recruitment strategies
8: Effectiveness of 4 recruitment strategies
9: Interest in implementing similar program in evaluator's school
10: Efforts for evaluating of student learning
11: Efforts for evaluating project

Fig. 6: Responses of the CRCD Advisory Board Assessment and Evaluation rubric.

The board pointed out that some of the unique elements of the SMART initiative at UCF are that there is a well-tuned team-teaching process in CTML-I, and that SMART students are highly motivated to do the Machine Learning project work in CTML-II. They also mentioned that important aspects of administrative burden rest on a few faculty. These concerns have been managed, since the *CTML-I* and *CTML-II* courses have been successfully conducted for three consecutive years after funding expired.

D. Impact on Students

The impact of SMART exposure on the undergraduate students has been significant. A total of 77 distinct students have participated in the CTML-I and CTML-II classes from Fall 2002 to Spring 2008. These students have been exposed to the Machine Learning research from a number of professors. Out of the 77 distinct students, 40 students have participated in Machine Learning projects with individual professors registered for CTML-II. Thirty five of these students have completed CTML-II projects for a total of 23

[2] available at http://ml.cecs.ucf.edu/crcd/symposium/CRCD_Symposium_Evaluations/CRCD_Project_Evaluation_Rubric.doc

projects, some of which were group projects, and published their results at a rate of more than 50%. The specific numbers of students who took the CTML-II class from Spring 2004 to Spring 2008 and their current status are tabulated in Table III. Of the 40 students who completed the CTML-II class, 35 were undergraduates and 5 were graduate students. The proportion of participating undergraduates who continued to graduate school is 88%, which is much higher than the 60% of non-participating undergraduates who had even expressed a possible interest in pursuing a graduate degree after graduation, based on 2006-2007 graduating senior data from the UCF College of Engineering and Computer Science (CECS).

Two of the SMART program students have received the prestigious National Science Foundation Graduate Research Fellowship, while four other students who worked on a project in the Spring of 2007 placed first in the AAAI-07 Video Competition for their “Dance Evolution” project. This competition was organized by AAAI, a first-tier reputation conference, to encourage public promotion of AI. Furthermore, a number of graduate students (16 Ph.D.’s and 5 Master students) have developed professionally through SMART. Of the graduate students, all five Masters and six Ph.D. students have already graduated, while the remaining nine Ph.D. students are pursuing their degrees at UCF, and one is pursuing a Ph.D. at the University of Florida.

Table III: CTML-II students’ pursuits after graduation

Semester	# CTML-II Students	Grad School	Industry	Still an UG
Spring 2004	13 (4 G; 9 UG)	7 out of 9	2 out of 9	None
Spring 2005	8 (8 UG)	6 out of 8	2 out of 8	None
Spring 2006	6 (5 UG; 1 G)	5 out of 5	None	None
Spring 2007	8 (7 UG)	3 out of 8	1 out of 8	4 out of 8
Spring 2008	5 (5 UG)	None	None	5 out of 5

E. Impact on Faculty, Institutionalization and Dissemination

Since initiation of the effort, a total of six faculty have participated. Four of the six faculty have taught lectures in CTML-I and advised students in CTML-II during multiple semesters. This highlights the possibility for participating faculty to contribute based on their current availability. Furthermore, two new faculty hires have also voluntarily opted to teach CTML-I and advise students in CTML-II. Given the availability of eight ML faculty, and three additional faculty members who use machine learning algorithms for computer vision applications, in the School of EECS alone, the institutionalization of the SMART effort can continue despite faculty attrition or leaves of absence.

SMART has had a significant impact on the faculty members involved. For instance, one senior faculty member involved with the SMART initiative had not involved any undergraduate students in his research before CRCD's initiation. Six years later, this faculty has involved over 40 undergraduate students in Machine Learning research through the SMART initiative and other NSF-funded educational efforts. On a related note, one of the junior faculty was able to advise a team of five undergraduates to attain recognition at the AAAI 2007 conference for *Best AI video*. In general, SMART has provided an effective mechanism for new or senior faculty to staff their research laboratories with highly motivated and pre-trained students. The cumulative effect of SMART and its continued efforts to integrate research in education, cannot be understated, considering that only 20% of CECS faculty involve undergraduate students in their research through traditional methods, based on 2006-2007 data..

Finally, one of the members of the CRCD Advisory Board who is also a faculty member at the University of Hartford, has integrated some of the SMART techniques at her institution by incorporating ML modules in an undergraduate class. Additionally, two other undergraduate institutions, Central Connecticut State University and Gettysburg College, have adopted a variation of the SMART model through a CCLI Phase I effort funded by NSF in 2004. In 2007, University of Hartford received a second phase CCLI Phase II effort facilitating expansion of the model to a larger number of undergraduate institutions. For more details about those efforts, please consult http://uhaweb.hartford.edu/compsci/ccli.

V. Summary And Conclusion

An effort which began as a multiyear CRCD project funded by NSF at UCF in 2002 has led to the development and refinement of an innovative and feasible approach to integrating research into the curriculum. The resulting SMART framework has been sustainable and there are now two elective undergraduate courses, CTML-I and CTML-II. CTML-I is offered each Fall semester and CTML-II is offered each Spring semester. They have secured steady enrollments and research involvement, even after the CRCD grant's expiration. These classes are regularly populated by approximately 10-15 students in CTML-I and by 6-8 students in CTML-II. From a student perspective, this course series prepares undergraduate students for research, and then gives them an opportunity to experience the research process and a taste of what it means to be a graduate student. Through advocacy of these classes to undergraduate courses and students by SMART faculty it is expected that the interest in these classes will continue in future years. A total of eight faculty have already co-taught these classes, four of whom have taught these classes multiple times. Furthermore, there is a nucleus of eight faculty members with strong ML interests in the School of EECS at UCF. These attributes make the yearly offering of these classes possible.

The publication rate of students involved in the CTML-I and CTML-II courses is higher than that of the longest running REU program, a fact that makes this SMART effort appealing to both new students and new faculty. Furthermore, the percentage of SMART students who attend graduate school is high, which is an additional incentive of new faculty for getting involved with SMART. A key contribution of this work is the presentation of a model to introduce current topics of research in undergraduate education. This model can be disseminated to other research institutions that have a strong nucleus of faculty with common research interests. Moreover, the dissemination capability of this model to other institutions, like 4-year colleges, cannot be underestimated as Professor Russell's work at the University of Hartford has demonstrated[3].

REFERENCES

[1] E. Seymour , A.Hunter, S. L. Laursen, T. DeAntoni, "Establishing the benefits of research experiences for undergraduates in the sciences: First findings from a three-year study ," *Science Education,* vol. 88, no. 8, pp. 493-534, 2004

[2] G. Bebis. D. Egbert, and M. Shah, "Review of Computer Vision Education," *IEEE Transactions on Education*, vol. 46, no. 1, pp. 2-21, 2003.

[3] M. Georgiopoulos, J. Castro, E. Gelenbe, R. F. Demara, A. Gonzalez, M. Kysilka, M. Mollaghasemi, A. Wu, I. Russell, "CRCD Experiences at the University of Central Florida: An NSF Project," in *Proceedings of The 2004 American Society for Engineering Education Annual Conference & Exposition (ASEE 2004)*, June 20-23, 2004

[4] M. Georgiopoulos, "Machine Learning Advances for Engineering Education," *Annual Report for the CRCD NSF grant #0203446*, University of Central Florida, May 1, 2006

[5] J. Hemmes, D. Thain, C. Poellabauer, "Work in progress - integrating undergraduate research and education with the TeamTrak mobile computing system," *Frontiers in education conference - global engineering: knowledge without borders, opportunities without passports*, 2007, October 10-13, pp. F4J-6 - F4J-8

[6] C.F. Olson, "Encouraging the development of undergraduate researchers in computer vision," *ITICSE '06: Proceedings of the 11th annual SIGCSE conference on Innovation and technology in computer science education,* June 2006

[7] H.C. Davis, S. White, "A research-led curriculum in multimedia: learning about convergence," *ACM SIGCSE Bulletin*, vol. 37 no. 3, September 2005

[8] M. Shah, K. Bowyer, "Mentoring Undergraduates in Computer Vision Research," *IEEE Transactions on Education*, vol. 44, no. 3, pp. 252-257, August 2001.

[9] C.M. Maziar, J.C. Lee, "Team teaching a multisection introductory electronics course," *Proceedings of the Twenty-First Annual Conference*, *Frontiers in Education Conference,* 1991

[10] R. Newdick, "E4: the Drexel curriculum," *Engineering Science and Education Journal,* vol. 3, no. 5, Oct. 1994, pp. 223 - 228

[11] J.R. Rowland, "Interdisciplinary team teaching improvements," *Proceedings of the Frontiers in Education Conference*, vol. 3, pp. 5-8, Nov. 2003

[12] I. S. Fischer, R. Dave, J. Luke, A. Rosato, and R. Pfeiffer, "Particle Technology in the Engineering Curriculum at NJIT", *ASEE Annual Conference and Exposition*, Washington, DC, 1996.

[13] S. A. Akbar, and P. K. Dutta, "A Research Driven Multidisciplinary Curriculum in Sensor Materials", *ASEE Annual Conference and Exposition*, 2000, St. Louis, MO.

[3] Details of SMART methodology adoption and tailoring at University of Hartford are available at: http://uhaweb.hartford.edu/compsci/ccli

[14] J. F. Frederici, A. M. Johnson, H. Grebel, T. Chang and R. Barat, “CRCD Multi-Disciplinary Optical Science and Engineering Program at NAT”, *ASEE Annual Conference and exposition*, 1997, Milwaukee, WI.

[15] S.Boyd, and L. Vendenberghe, “CRCD Program: Convex Optimization for Engineering Analysis and Design”, *Proceedings of the 1995 American Controls Conference*, Seattle, WA, June, 1995.1995

[16] R.Caso, L. Jong-Hwan, J. Froid. and R. Kohli, “Development of Design Assessment Instruments and Discussion of Freshmen and Senior Design Assessment Results”, *Frontiers in Education*, vol., pp.1-8, 2002

[17] M. Georgiopoulos, I. Russell, J.Castro, A. Wu, M. Kysilka, R. DeMara, A.Gonzalez, E. Gelenbe, M. Mollaghasemi, "A CRCD Experience: Integrating ML Modules into Introductory Engineering and Science Programming Courses," in *Proceedings of the 2003 American Society for Engineering Education Annual Conference & Exposition (ASEE 2003)*, 2003, Session 2432.

[18] M. Georgiopoulos, J. Castro, A. Wu, R. DeMara, E. Gelenbe, A. Gonzalez, M. Kysilka, and M. Mollaghasemi, "CRCD in ML at the University of Central Florida: Preliminary Experiences," in *Proceedings of The 8th Annual Conference on Innovation and Technology in Computer Science Education (ITiCSE 2003)*, 2003, p. 249.

[19] M. Georgiopoulos, J. Castro, R. DeMara, E. Gelenbe, A. Gonzalez, M. Kysilka, M. Mollaghasemi, A. Wu, I. Russell, "ML advances for Engineering and Science Education: A CRCD experience at the University of Central Florida," in *Proceedings of The 13th International Conference on Neural Networks and 10th International Conference on Neural Information Processing ICANN/ICONIP 2003)*, 2003, pp. 465- 468.

[20] M. Georgiopoulos, E. Gelenbe, R. DeMara, A. Gonzalez, M. Kysilka, M. Mollaghasemi, A. Wu, I. Russell, G. Anagnostopoulos, J. Secretan, “Assessing and Evaluating our progress on the CRCD Experiences at the University of Central Florida: An NSF Project,” in *Proceedings of The 2006 American Society for Engineering Education Annual Conference & Exposition (ASEE 2006)*, 2006

[21] M. Georgiopoulos, E. Gelenbe, R. DeMara, A. Gonzalez, M. Kysilka, M. Mollghasemi, A. Wu, I, Russell, G. Anagnostopoulos, “Progress on the CRCD Experiences at the University of Central Florida: An NSF Project”, Proceedings of the ASEE 2005 Annual Conference and Exposition, Session 1332, Undergarduate Research and New Directions, June 12-15, 2005, Portland, Oregon, 2005.

[22] *Combined Research and Curriculum Development (CRCD) in Machine Learning at UCF Website*. Available: http://ml.cecs.ucf.edu/crcd , 2007

[23] M.A. Rahman, “Learning in computer science: assessment and evaluation of undergraduate research experience,” *Proceedings of the Frontiers in Education Conference*, 19-22 Oct. 2005, pp. F1F - 1-5

[24] J. S. Fairweather and K. Paulson, “Teaching and research in engineering education,” *Int. J. Eng. Educ*., vol. 8, no. 3, pp. 175–183, 1992

[25] J.G.Webster, Editor, Encyclopedia of Electrical and Electronics Engineering, Wiley Publishing company, February 1999.

[26] A.J. Gonzalez and D. D. Dankel, The Engineering of Knowledge-based Systems: Theory and Practice, 2nd Edition, Englewood Cliffs, NJ: Prentice Hall, 2004

[27] M. Zhong, J. Hecker, I. Maidhoff, P. Shibly, M. Georgiopoulos, G. Anagnostopoulos, M. Mollaghasemi, “Probabilistic Neural Network: Comparisons of the Cross-Validation Approach and a Fast Heuristic to choose the Smoothing Parameters,” *2005 Artificial Neural Networks in Engineering (ANNIE) conference*, November 7-9 2005, St. Louis, MI, pp. 131-140; also published as a chapter in a book entitled *Intelligent Engineering Systems Through Artificial Neural Networks*, vol. 15, Smart Engineering System Design: Neural Networks, Evolutionary Programming, and Artificial Life, editors: C. H. Dagli, A. L. Buczak, D. L. Enke, M. L. Embrechts, and O. Ersoy, ASME, 2005.

[28] M. Zhong, B. Rosander, M. Georgiopoulos, G. Anagnostopoulos, M. Mollaghasemi, and S. Richie, “Experiments with Micro-ARTMAP: Effect of the Network Parameters on the Network Performance,” *2005 Artificial Neural Networks in Engineering (ANNIE) conference*, November 7-9 2005, St. Louis, MI, pp. 51-60; also published as a chapter in a book entitled *Intelligent Engineering Systems Through Artificial Neural Networks*, vol. 15, Smart Engineering System Design: Neural Networks, Evolutionary Programming, and Artificial Life, editors: C. H. Dagli, A. L. Buczak, D. L. Enke, M. L. Embrechts, and O. Ersoy, ASME.

[29] J. Secretan, J. Castro, A. Chadha, B. Huber, J. Tapia, M. Georgiopoulos, G. Anagnostopoulos, and S. Richie, “Pipelining of ART architectures (FAM, EAM, GAM) without match-tracking (MT),” *2005 Artificial Neural Networks in Engineering (ANNIE conference)*, November 7-9 2005, St. Louis, MI, pp. 61-70; also published as a chapter in a book entitled *Intelligent Engineering Systems Through Artificial Neural Networks*, vol. 15, Smart Engineering System Design: Neural Networks, Evolutionary Programming, and Artificial Life, editors: C. H. Dagli, A. L. Buczak, D. L. Enke, M. L. Embrechts, and O. Ersoy, ASME, 2005.

[30] J. Castro, J. Secretan, M. Georgiopoulos, R. F. DeMara, G. Anagnostopoulos, and A. Gonzalez, “Pipelining of Fuzzy ARTMAP (FAM) without match-tracking,” *Intelligent Engineering Systems Through Artificial Neural Networks: Smart Engineering System Design: Neural Networks, Fuzzy Logic, Evolutionary Programming, Complex Systems and Artificial Life*, vol. 14, edited by C. H. Dagli, A. L. Buczak, D. L. Enke, M. Embrechts, and O. Ersoy, 2004, *ASME Press Series*, pp. 69-74; presented at the *ANNIE 2004* conference in St. Louis, MI, November 2004.

[31] K. Carr, K. Cannava, R. Pescatore, M. Georgiopoulos, and G. Anagnostopoulos, “Fast Stable and on-line training of Fuzzy ARTMAP using a novel, conservative, slow learning strategy,” *Intelligent Engineering Systems Through Artificial Neural Networks: Smart Engineering System Design: Neural Networks, Fuzzy Logic, Evolutionary Programming, Complex Systems and Artificial Life*, Volume 14, edited by C. H. Dagli, A. L. Buczak, D. L. Enke, M. Embrechts, and O. Ersoy, 2004, *ASME Press Series*, pp. 63-69; presented at the *ANNIE 2004* conference in St. Louis, MI, November 2004.

[32] J. Castro, M. Georgiopoulos, J. Secretan, R. DeMara, G. Anagnostopoulos, A. Gonzalez, "Parallelization of Fuzzy ARTMAP to improve its convergence speed: The network partitioning approach and the data partitioning approach," *Nonlinear Analysis*, vol. 63, no. 5-7, pp. e877-e889, 30 November 2005-15 December 2005.

[33] J. Castro, J. Secretan, M. Georgiopoulos, R. DeMara, G. Anagnostopoulos, and A. Gonzalez, “Pipelining of Fuzzy ARTMAP without Match-Tracking: Correctness, Performance Bound, and Beowulf Evaluation,” *Neural Networks*, to be published.

[34] M. Zhong, D. Goggeshall, E. Ghaneie, T. Pope, M. Rivera, M. Georgiopoulos, C. G. Anagnostopoulos, M. Mollaghasemi, "Gap-based estimation: Choosing the smoothing parameters for probabilistic and general regression neural networks,” *Neural Computation*, to be published.

[35] M. Zhong, B. Rosander, M. Georgiopoulos, G. Anagnostopoulos, M. Mollaghasemi, and S. Richie, “Experiments with micro-ARTMAP: Effect of the network parameters on the network performance,” *Neural Networks*; to be published.

A Sustainable Model for Integrating Current Topics in Machine Learning Research into the Undergraduate Curriculum

Michael Georgiopoulos[4], Ronald F. DeMara[1], Senior Member, IEEE, Avelino J. Gonzalez[1], Fellow, IEEE, Annie S. Wu[1], Mansooreh Mollaghasemi[1], Erol Gelenbe[2], Marcella Kysilka[1], Jimmy Secretan[1], Carthik A. Sharma[1], Member, IEEE, Ayman J. Alnsour[3], Member, IEEE

***Abstract*—This paper presents an integrated research and teaching model that has resulted from an NSF-funded effort to introduce results of current Machine Learning research into the engineering and computer science curriculum at the University of Central Florida (UCF). While in-depth exposure to current topics in Machine Learning has traditionally occurred at the graduate level, the model developed affords an innovative and feasible approach to expanding the depth of coverage in research topics to undergraduate students. The model has been self-sustaining as evidenced by its continued operation during the years after the NSF grant's expiration, and is transferable to other institutions due to its use of modular and faculty-specific technical content. This model offers a tightly-coupled teaching and research approach to introducing current topics in Machine Learning research to undergraduates, while also involving them in the research process itself. The approach has provided new mechanisms to increase faculty participation in undergraduate research, has exposed approximately 15 undergraduates annually to research at UCF, and has effectively prepared a number of these students for graduate study through active involvement in the research process and co-authoring of publications.**

***Index Terms*—Curriculum development, integrated research and teaching, machine learning, team teaching models, undergraduate research experiences**

Michael Georgiopoulos. Michael Georgiopoulos is a Professor in the School of Electrical Engineering and Computer Science at the University of Central Florida. His research interests include neural networks and their applications to pattern recognition, image processing, smart antennas, and data-mining.

Manuscript received 28 September, 2007. This work was supported in part by the National Science Foundation grant #0203446.
Corresponding author: M. Georgiopoulos 407-823-5338; fax: 407-823-5835; e-mail: michaelg@mail.ucf.edu
[1] M. Georgiopoulos, R. F. DeMara, A. J. Gonzalez, A. S. Wu, M. Mollaghasemi, M. Kysilka, J. Secretan, and C. A. Sharma are with the University of Central Florida, Orlando, FL 32816 USA.
[2] E. Gelenbe is with the Imperial College, London SW7 2AZ, UK. [3] A. J. Alnsour is visiting faculty the University of Central Florida (on sabbatical leave from Al-Isra Private University, Amman, Jordan).

Ronald F. DeMara (M'87–SM'03). Ronald F. DeMara is a Professor in the School of Electrical Engineering and Computer Science at the University of Central Florida. His research interests are in Computer Architecture with emphasis on Evolvable Hardware and Distributed Architectures for Intelligent Systems.

Avelino Gonzalez. (F'07) Avelino Gonzalez is a Professor of the School of Electrical Engineering and Computer Science at the University of Central Florida. He has co-authored a book entitled, *The Engineering of Knowledge-Based Systems: Theory and* Practice. His research interests focus on the areas of artificial intelligence, context based behavior and representation and learning tactical behavior through observation of human performance.

Annie S. Wu. Annie S. Wu is an Associate Professor at the School of Electrical Engineering and Computer Science at the University of Central Florida. Her research interests are in the areas of genetic algorithms, machine learning, biological modeling, and visualization.

Mansooreh Mollaghasemi is an Associate Professor at the department of Industrial Engineering and Management Systems at the University of Central Florida. Her research interests include simulation modeling and analysis, neural networks, and multiple criteria decision making.

Erol Gelenbe. Erol Gelenbe is a Dennis Gabor Chaired Professor and Head of Intelligent Systems/Networks at the Imperial College in London. He is a Fellow of IEEE and a Fellow of ACM. His research interests include packet network design, computer performance analysis, artificial neural networks and simulation with enhanced reality.

Marcella Kysilka. Marcella Kysilka is former Professor and Assistant Chair of the Education Foundations Department at the University of Central Florida. Her research interests are in curriculum studies.

Jimmy Secretan. Jimmy Secretan is a Ph.D. student in the Department of Electrical and Computer Engineering at the University of Central Florida. His research interests are in intelligent systems and cluster computing.

Carthik A. Sharma (M'02). Carthik A Sharma obtained his Ph.D. degree in Computer Engineering from the University of Central Florida, and his dissertation involved research in intelligent fault handling of reconfigurable systems. His research interests also include evolvable hardware and organic computation.

Ayman J. Alnsour (M'07). Ayman J. Alnsour is a full-time faculty member at Al-Isra Private University, Amman, Jordan where he is an Associate Professor in the Computer Science Department at the Faculty of Science and Information Technology. His research interests include neural networks and applications, distance learning, and simulation.