CEE

chemical engineering education

VOLUME 47 • NUMBER 3 • SUMMER 2013

Chemical Engineering Division, American Society for Engineering Education

American Institute of Chemical Engineers

Feature Articles . . .

and ChE at . . .

Iowa State University

Chemical Engineering Education

Volume 47 Number 3 Summer 2013

▶ *DEPARTMENT*

▶ *CLASS AND HOME PROBLEMS*

▶ *SURVEY*

▶ *CLASSROOM*

▶ *LABORATORY*

▶ *RANDOM THOUGHTS*

▶ *OTHER CONTENTS*

CHEMICAL ENGINEERING EDUCATION[ISSN 0009-2479 (print); ISSN 2165-6428 (online)] is published quarterly by the Chemical Engineering Division, American Society for Engineering Education, and is edited at the University of Florida. Correspondence regarding editorial matter, circulation, and changes of address should be sent to CEE, 5200 NW 43rd St., Suite 102-239, Gainesville, FL 32606. *Defective copies replaced if notified within 90 days of publication. Write for information on subscription costs and for back copy costs and availability. POSTMASTER: Send address changes to Chemical Engineering Education, 5200 NW 43rd St., Suite 102-239, Gainesville, FL 32606. Periodicals Postage Paid at Gainesville, Florida, and additional post offices (USPS 101900). www.che.ufl.edu/CEE*

Chemical Engineering at . . .

Iowa State University

Chris Neary,
Surya Mallapragada
and George Burnet

Sweeney Hall is home to the Department of Chemical and Biological Engineering at Iowa State University.

In many ways, Iowa State chemical engineering epitomizes the land-grant philosophy its university lives by—Iowa State University was the nation's first land-grant university. It is the birthplace of the first digital computer and is one of the few universities to host a Department of Energy national laboratory, Ames Laboratory, on its campus. Iowa State ranks second among universities in R&D 100 awards, given by *R&D* magazine for top technologies. The College of Engineering is the 10th largest in the nation. It is home to many interdisciplinary research centers of excellence including a National Science Foundation Engineering Research Center (NSF-ERC) focused on Biorenewable Chemicals. This research center, commonly referred to as CBiRC, is led by Iowa State chemical engineering faculty members.

This year, the Department of Chemical and Biological Engineering at Iowa State University, currently the ninth largest in the nation, celebrates its centennial—2013 marks 100 years of education and research excellence in chemical and biological engineering at Iowa State University. This is a key milestone for the department as it looks forward to continuing the long tradition of excellence and building on its successes for the next 100 years.

CENTENNIAL HISTORY*

Chemical engineering courses at Iowa State were originally offered in the Department of Mining Engineering, Ceramics, and Chemical Engineering in 1913. Dr. **O.R. Sweeney** led the Iowa State chemical engineering program and began pioneering work on utilization of agricultural wastes. Sweeney became "Iowa's Edison" as he served on national panels with the likes of General Motors Chairman **Alfred Sloan**, FBI Director **J. Edgar Hoover**, and Canadian Prime Minister **W.L. McKenzie**. Today, Iowa is home to a wealth of agricultural raw materials that would otherwise be wasted. With the

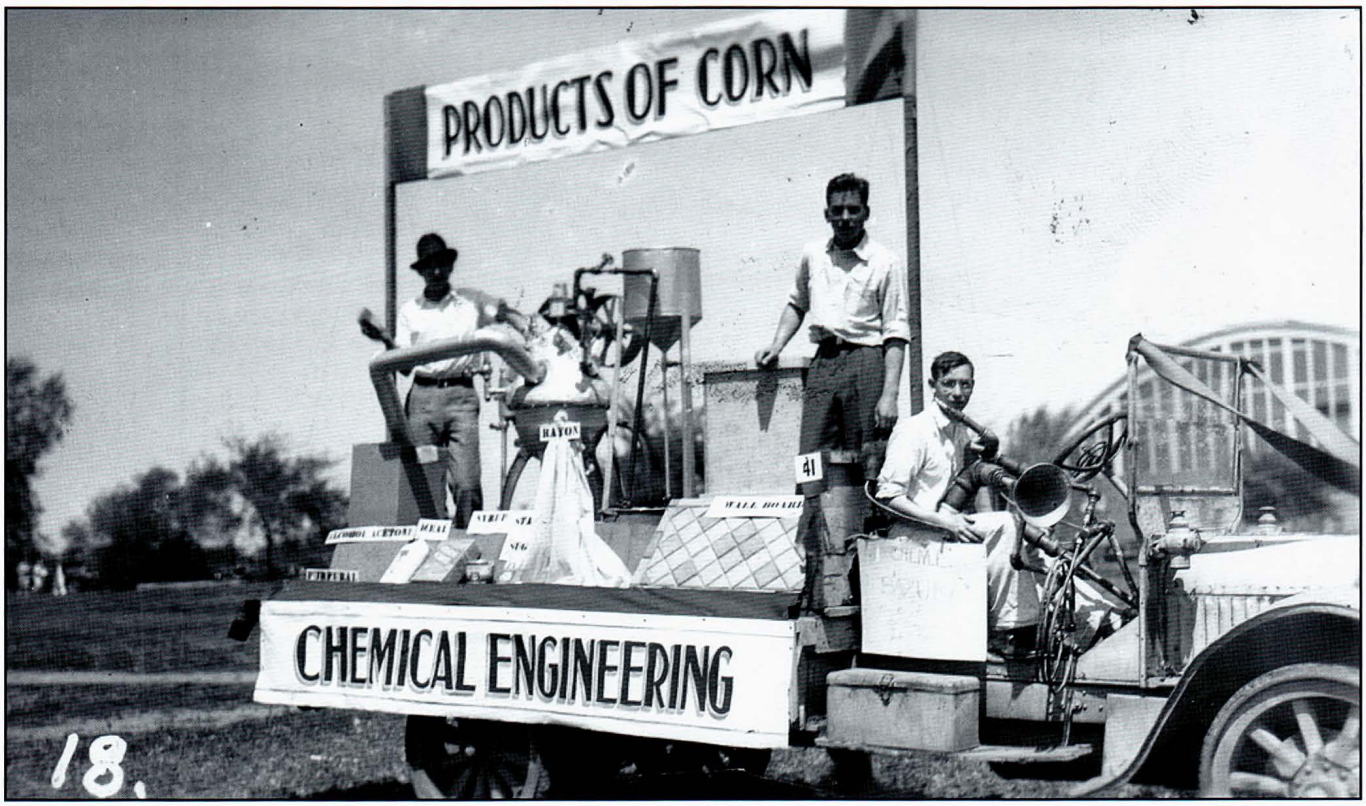
* *Some parts of this text are summarized from "100 Years of Chemical and Biological Engineering at Iowa State University," by George Burnet and Steve Sullivan, set to be published in summer 2013. All copyrights reserved.*

CELEBRATING 100 YEARS

field of biorenewables experiencing resurgence, it is worth looking at our departmental history for some of the earliest successes that have shaped this field. For example, research on furfural from agricultural byproducts took place at Iowa State from the 1920s to 1940s. In the book, *Creation of the Modern Land-Grant University: Chemical Engineering, Agricultural By-Products and the Reconceptualization of Iowa State College*, **Alan Marcus** notes that "the destructive distillation of corncobs liberated substantial quantities of (furfural). Ames engineers not only refined furfural production techniques and designed the blueprints for commercial facilities, but also set about to determine furfural's potential industrial uses."

In 1936, the Engineers' Council for Professional Development (ECPD, now ABET) first accredited the Iowa State chemical engineering program. The American Institute of Chemical Engineers (AIChE), a founding society of ECPD, recognized the Iowa State University chemical engineering program in 1925. Because Iowa State was one of the first schools to be recognized by AIChE, many schools around the country patterned their courses after Iowa State. In fact, the Iowa State program was the first to offer chemical engineering plant design as a course. In 1926, **Juanito Mina** was the first female graduate of the Iowa State chemical engineering program. One year later, the department moved into its own building complete with a large unit operations laboratory, classrooms, offices, and research labs. The U.S. Department of Agriculture built its By-Products Laboratory west of the Chemical Engineering Building in 1935, further strengthening work on the utilization of agricultural wastes. In 1964, Sweeney received the ultimate honor (six years after his passing) when a second chemical engineering building was constructed and named Sweeney Hall. The new three-floor building added dozens of faculty and graduate student offices and new spaces for research. By the time Sweeney stepped down as department head in 1947, Iowa State's chemical engineering program was one of the largest and most highly respected in the United States.

In 1947, chemical engineering research was significantly enhanced with the creation on campus of the Ames Laboratory, an interdisciplinary research laboratory of the Atomic Energy Commission (now the U.S. Department of Energy). The Ames Laboratory became a "clearinghouse for nuclear research on campus, a public resource for atomic energy consultation, a liaison between Iowa State, the Argonne National Laboratory, and its associated 25 Midwestern universities, a mecca for graduate students, and an administrative hub for processing federal and private funds as they become available," according to **Joanna Abel Goodman**'s *National Science in the Nation's Heartland: The Ames Laboratory and Iowa State University, 1942-1965*. Through a chemical



Chemical engineering students build a "Products of Corn" float for 1937 VEISHEA, the country's longest student-run festival. Items displayed on this float include syrup, starch, rayon, and wallboard—all made in Iowa State labs from corn. This demonstrated various ways chemical engineering was commercialized in the 1930s.

engineering division at the Ames Laboratory, chemical engineering faculty and graduate students were very involved in the development of processes for the recovery of thorium, rare earth minerals, and uranium from monazite sands, all high-priority needs at that time.

In 1957, the department name changed from the Department of Chemical and Mining Engineering to simply the Department of Chemical Engineering. In 1959, the Iowa State College of Agriculture and Mechanic Arts was renamed Iowa State University of Science and Technology.

From 1961 to 1978, **George Burnet** led Iowa State chemical engineering with engineering education as the significant focus. Burnet held many positions nationally including as president of American Society for Engineering Education (ASEE); national president of Omega Chi Epsilon; U.S. representative to the United Nations Committee on Education and Training; member of the NSF Commission on Precollege Education in Mathematics, Science, and Technology; and many more.

Ray Fahien, a faculty member in the department, also echoed Burnet's passion for engineering education. From 1967 to 1995, he served as the editor of *Chemical Engineering Education*. The journal created an award after him, which honors an educator who has shown evidence of vision and contribution to chemical engineering education.

In 1968, Iowa State chemical engineering's first female doctoral candidate, **Idelle Peterson**, graduated.

Maurice Larson became department chair of chemical engineering in 1978. Larson and his crystallization work put Iowa State University on the world map. In a 1988 letter, Professor **John Garside** from The University of Manchester said, "(Iowa State's) work on crystallization has enabled crystallizer design methods to be put on a rational, quantitative basis.... Virtually all chemical engineering crystallization research groups throughout the world now base their developments on these methods." Professor **Richard Seagrave** became department chair after Larson stepped down in 1983. Seagrave picked up on Larson's vision to expand Sweeney Hall facilities to accommodate the new research areas such as biotechnology. Larson's vision for expanded facilities, and the continued work of Seagrave and **Terry King**, who became chair in 1990, culminated in the dedication of the Sweeney Hall addition in 1994. The $8 million addition expanded Sweeney Hall by 35,000 square feet. In 2005, the department changed from the Department of Chemical Engineering to the Department of Chemical and Biological Engineering to better reflect the bio-based research and teaching under way.

L.K. Doraiswamy joined Iowa State faculty as Glenn Murphy Visiting Professor in Engineering in 1989. At Iowa State he helped create a research program in catalysis and reaction engineering. In 1998, Iowa State and the National Chemical Laboratory in India established the L.K. Doraiswamy Honor Lectureship, a dual-lecture series where a distinguished leader in chemical engineering lectures at both Iowa State in Ames, Iowa, and at NCL in Pune, India. Among the highest honors Doraiswamy received was election to the National Academy of Engineering in 2010. Doraiswamy passed away in 2012.

Professor **Charles "Chuck" Glatz** was chair of chemical engineering from 1997 to 2005. During this time the department pursued further interests in biological engineering, and several faculty were hired, mainly at the associate and full professor levels. These included **Brent Shanks**, **Jackie Shanks**, **Rodney Fox**, **Andrew Hillier**, and Vlasta Klima Balloun Professor **Balaji Narasimhan**. In 1999, former chair Seagrave served as interim provost of Iowa State University, and later as interim president of the university from 2000 to 2001. Seagrave stepped into the national curriculum spotlight as chairman of ABET from 1996 to 1997, then as ABET president from 2005 to 2006.

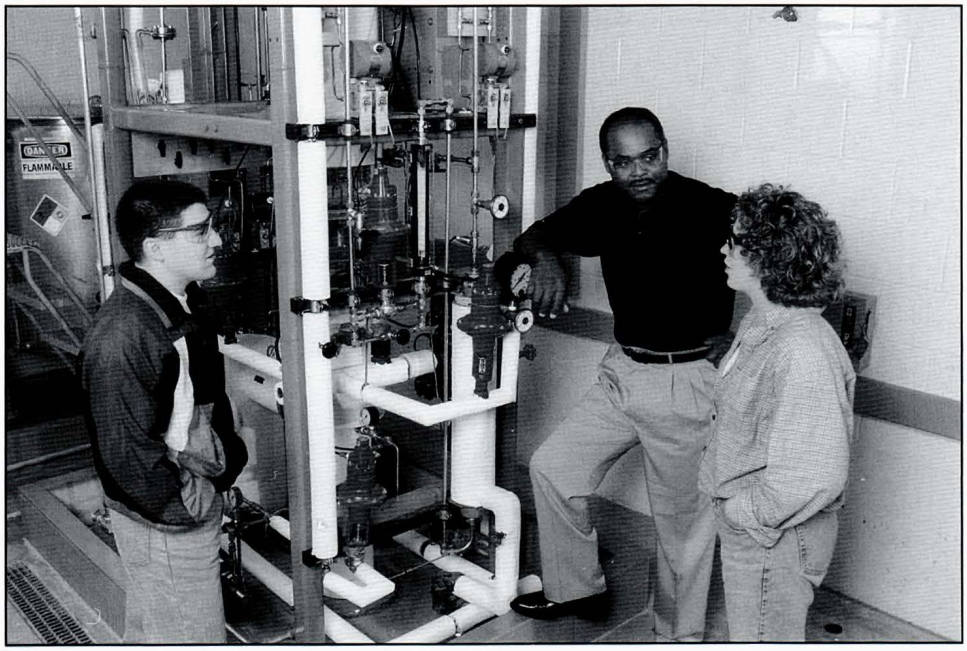
Professor **James Hill** became chair of the department in July 2005. For the next four years, the Iowa State chemical engineering program expanded research in biological and biomedical areas. Six professors joined the faculty during this time. In 2007, ConocoPhillips established an eight-year, $22.5 million biofuels research program to develop technologies that produce biorenewable fuels, led by Professor **Robert Brown**.

In 2010, the biorenewables faculty and work found a new home at the Biorenewables Research Laboratory, built directly west of Sweeney Hall. The $32 million Phase I of Iowa State's $107 million Biorenewables Complex serves as a "front door" to the university's diverse and broad-reaching programs in biorenewables.

In 2009, Professor and Stanley Chair in Interdisciplinary Engineering **Surya Mallapragada**—an Iowa State faculty member since 1996—was named the first female chair of the Department of Chemical and Biological Engineering. Mallapragada's research in biomaterials and bioinspired materials has led to several awards including a TR100 award. Under her leadership, the CBE department has attracted consecutive record enrollment, consecutive record department research expenditures, and record diversity within the student population. To keep up with this rapid growth, the department renovated 20 laboratories in Sweeney Hall through a $1.75 million competitive grant from the National Science Foundation to grow research in biomedical engineering and nanomaterials. Several teaching spaces have also been renovated through funding from alumni as well as the Carver Charitable Trust.

FACULTY

The department currently has 20 tenure-track/tenured faculty members who are engaged in the research and educational mission of the department. Included among the faculty are four Iowa State B.S. chemical engineering graduates: Assistant Professor **Eric Cochran** (B.S.ChE '98; Ph.D., University



Prof. Derrick Rollins works with students in the undergraduate teaching labs.

of Minnesota), Assistant Professor **Ian Schneider** (B.S.ChE '00; Ph.D., North Carolina State University), Mike and Jean Steffenson Professor **Brent Shanks** (B.S.ChE '83; Ph.D., California Institute of Technology) and Manley Hoppe Professor **Jacqueline Shanks** (B.S.ChE '83; Ph.D., California Institute of Technology).

Current faculty of the Iowa State CBE department have garnered more than 35 national honors and awards, including NSF CAREER Awards (Cochran, Mallapragada, and Hillier), NSF Young Investigator Awards (**Rodney Fox** and Jacqueline Shanks), and several spots on national research committees and "top" lists. Such lists include MIT Technology Review's Top 100 Young Innovators (Mallapragada and Narasimhan) and Biofuels Digest's Top 100 People in Bioenergy (**Robert Brown**). The department has five professors with the Iowa State College of Engineering's highest faculty honor, Anson Marston Distinguished Professor: Brown, Fox, **Peter Reilly**, Burnet (emeritus), and Seagrave (emeritus). Three faculty members have the University Professor honor: **Charles Glatz**, **James Hill**, and **Thomas Wheelock** (emeritus).

The first female chemical engineering faculty member at Iowa State, **Carole Heath**, was hired in 1993. Today the Iowa State chemical and biological engineering department has one of the country's highest percentages of female tenured/tenure-track faculty. Since Heath, the department has hired eight tenured and three non-tenured female faculty members; today, the proportion is 42 percent female.

Professor **Derrick Rollins** was hired in 1990 as Iowa State chemical engineering's first African-American faculty member. He founded several Iowa State programs for recruitment and retention of underrepresented minority students. His passion for student success has been recognized nationally by several awards, including the American Association for the Advancement of Science Mentor Award and Tau Beta Pi McDonald Mentor Award.

In August 2007, Narasimhan was named associate dean for Research and Economic Development in the College of Engineering. Among many other successes in this role, Narasimhan has overseen development of the interdisciplinary Dean's Research Initiatives, which are designed to lead to the creation of large center-scale grants.

Iowa State biorenewables research received a major boost in 2008 with the creation of the National Science Foundation Engineering Center for Biorenewable Chemicals (CBiRC). NSF contributed $18.5 million for the first five years of development. Headed by Brent Shanks, CBiRC is Iowa State's first NSF Engineering Research Center and serves to transform the chemical industry into a renewable resource-based industry. In 2012, CBiRC was awarded an additional $12 million, three-year, NSF grant to continue research and educational activities. Professors Jacqueline Shanks (who also serves as a Thrust Leader in CBiRC), **Laura Jarboe**, Rollins, and Reilly have contributed to the development of CBiRC research and education. Two new departmental hires, **Jean-Philippe Tessonier** and **Zengyi Shao**, are also associated with CBiRC.

Chemical engineering facilities at Iowa State continue to meet the department's leading research and teaching demands. The W.M. Keck Laboratory for High Throughput Atom-Scale Analysis opened in Sweeney Hall in 2007. The 1,600-square-foot space houses leading combinatorial science and atom-scale materials research. A state-of-the-art local electrode atom probe microscope, along with complementary instrumentation, provides the most advanced analysis to date of compositional mapping of materials. Professors Hillier and Narasimhan from CBE led the development of the Keck Laboratory.

UNDERGRADUATE PROGRAM

Over the past 100 years, Iowa State's chemical engineering curriculum has transformed along with the many advancements and diversifications that chemical engineering industries have experienced. Today students can take

Prof. Jacqueline Shanks, the microbial metabolic engineering thrust leader for CBiRC, is pictured here with current students and research staff.

either the general chemical engineering track or biological engineering track. As juniors, undergraduates enroll in a CHE 325 (chemical engineering laboratory I) / ENGL 314 (technical communication) hybrid course that teaches students both how to operate a laboratory and how to develop communication materials that accompany chemical engineering practices. The program also provides a freshmen learning community, which introduces students to the chemical engineering profession, and provides career planning and academic course support. Undergraduates learn in a state-of-the-art two-story unit operations laboratory, named the Herbert L. Stiles Teaching Laboratory after 1929 alumnus **Herbert Stiles**.

Enriching undergraduate experiences extend beyond the Ames, Iowa, campus. In summer 2001, Reilly helped start the International Summer Course in Chemical Engineering, held every summer at the University of Oviedo, Spain. Select undergraduate students participate in an intense, five-week unit operations laboratory course. Iowa State partners in the course with the University of Wisconsin-Madison and the University of Oviedo. Professor Emeritus **Ken Jolls** has coordinated the program since 2002. Students also take advantage of summer, semester, and mini-term internships and co-op experiences at companies in Iowa and throughout the United States. Since its beginning, the Iowa State chemical engineering program has awarded more than 4,700 baccalaureate degrees. More than 250 companies attract interns at the Engineering Career Fair every semester at Iowa State University—site of one of the country's largest collegiate career fairs in engineering—leading to very high placement rates (90%+) for graduates of the college.

In 2006, Iowa State first received NSF funding for the Biological Materials and Processes Research Experience for Undergraduates (BioMaP REU). Every summer since, a dozen or so undergraduate students from around the United States have been matched with Iowa State CBE faculty to conduct 11 weeks of research and present their work at a public symposium on campus.

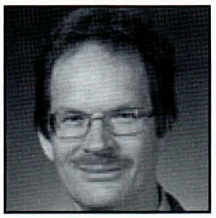
In addition to coursework and research, Iowa State chemical engineering faculty members have contributed to major literature in the field. Doraiswamy published six top chemical reaction engineering books: *Chemical Reaction Engineering: Beyond the Fundamentals* (2013); *Organic Synthesis Engineering* (2001); *Catalytic Reactions and Reactors* (1991); *Analysis of Chemically Reacting Systems: A Stochastic Approach* (1987); *Across Millenia: Some Thoughts on Ancient and Contemporary Science and Engineering* (1987); and *Heterogeneous Reactions: Analysis, Examples and Reactor Design* (1984). Brown has published three books contributing to biofuels and biorenewable resources: *Why Are We Producing Biofuels?* (2012); *Thermochemical Processing of Biomass: Conversion into Fuels, Chemicals, and Power* (2011); and *Biorenewable Resources: Engineering New Products from Agriculture* (2003). Fox published three books on computational fluid dynamics: *Computational Models for Polydisperse Particulate and Multiphase Systems* (2013); *Multiphase Reacting Flows: Modeling and Simulation* (2007); and *Computational Models for Turbulent Reacting Flows* (2003). Mallapragada and Narasimhan have co-published three books: *Combinatorial Materials Science* (2007); *Handbook of Biodegradable Polymers and Their Applications* (2006); and *Biomaterials for Drug Delivery and Tissue Engineering* (2001). These and other current Iowa State chemical engineering faculty members have served on many journal editorial boards: *AIChE Journal*, *Industrial & Engineering Chemistry Research*, *International Journal of Multiphase Flow*, *Annual Review of Fluid Mechanics*, *The Electrochemical Society's INTERFACE*, *Fluid Dynamics Research*, *Journal of Nanoparticle Research*, *ISRN Nanotechnology*, *Biotechnology Progress*, *Metabolic Engineering*,

FACULTY GALLERY (In alphabetical order with Ph.D. institution and research area)

Kaitlin Bratlie, University of California-Berkeley. *Biomaterials, tissue engineering, imaging*

Rebecca Cademartiri, University of Potsdam. *Interactions of biological entities with materials*

Eric Cochran, University of Minnesota-Twin Cities. *Self-assembled polymers*



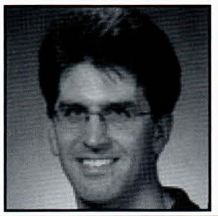
Rodney Fox, Kansas State University. *Computational fluid dynamics, reaction engineering*

Charles Glatz, University of Wisconsin-Madison. *Bioprocessing, bioseparations*

Kurt Hebert, University of Illinois at Urbana-Champaign. *Corrosion, electrochemical engineering*

Jennifer Heinen, University of Delaware. *Mechanism and kinetics of controlled polymerizations in heterogeneous media*

James Hill, University of Washington. *Turbulence, computational fluid dynamics*



Andrew Hillier, University of Minnesota. *Interfacial engineering, electrochemistry*

Laura Jarboe, University of California Los Angeles. *Biorenewables production by metabolic engineering*

Monica Lamm, North Carolina State University. *Molecular simulation of advanced materials*

Stephanie Loveland, Iowa State University. *Senior lecturer*

Surya Mallapragada, Purdue University. (Department Chair) *Tissue engineering, gene delivery*

Balaji Narasimhan, Purdue University. *associate dean for research for College of Engineering; Biomaterials, drug and vaccine delivery*

Peter Reilly, University of Pennsylvania. *Molecular mechanics, molecular dynamics, quantum mechanics*

Derrick Rollins, The Ohio State University. *Statistical process control*

Ian Schneider, North Carolina State University. *Cell migration, mechanotransduction*

Brent Shanks, California Institute of Technology. *Heterogeneous catalysis, biorenewables*

Jacqueline Shanks, California Institute of Technology. *Metabolic engineering, plant biotechnology*

Zengyi Shao, University of Illinois at Urbana-Champaign. *Biorenewables production by metabolic engineering*

Cory Stiehl, University of Massachusetts. *Senior lecturer*

Jean-Philippe Tessonnier, Universite de Strasbourg. *Heterogeneous catalysis, biorenewables*

R. Dennis Vigil, University of Michigan. *Transport phenomena, reaction engineering in multiphase systems*

Qun Wang, University of Kansas. *Drug delivery, nanotechnology, biomaterials and stem cells*

Current Opinion in Biotechnology, *Electrochemical Society*, *Biotechnology Letters*, *Starch*, ASME *Journal of Nanotechnology in Engineering and Medicine,* and ASME *Journal of Fluids Engineering*.

Several alumni from the department have had notable and distinguished careers and received national/international recognition. Iowa State University B.S. graduates such as **Allen Jacobson** (retired CEO of 3M), **James Katzer** (retired from Exxon), **Paul Willhite** (University of Kansas), **Jerry Schnoor** (University of Iowa), and **Lanny Robbins** (retired from Dow Chemical) have been elected to the National Academy of Engineering. Several alumni with undergraduate degrees from Iowa State University have established successful careers in academia: Alumnus **Tim Anderson** is currently dean of Engineering at the University of Massachusetts; other successful alumni in academia include **Mark Saltzman** at Yale and **Edward McGinn** at the University of Notre Dame.

Distinguished recognitions have come to recent graduates as well. For instance, in 2010, chemical engineering junior **Meredith Gibson** was a guest speaker (the only college student speaker) at the *Fortune* magazine Most Powerful Women summit, held in Washington, D.C. There she shared her Iowa State engineering experiences and involvement with the National Math and Science Young Leaders Program. Gibson graduated with a Bachelor's in chemical engineering in December 2012.

On campus, undergraduate students are very active in chapters of AIChE, Omega Chi Epsilon (chemical engineering honor society), and the National Organization for the Professional Advancement of Black Chemists and Chemical Engineers. In 2010, the AIChE Iowa State student chapter hosted the Mid-America AIChE Student Regional Conference.

GRADUATE PROGRAM

Iowa State offers the Doctor of Philosophy (Ph.D.), Master of Science (M.S.) and Master of Engineering (M.Engr.) degrees in chemical engineering. While Ph.D. and M.S. require a thesis, M.Engr. requires only coursework. M.S. students take an average of two years to graduate, while Ph.D. candidates complete their degrees in 4.5 years, on average. The Iowa State Chemical Engineering Graduate Student Organization (CEGSO) provides a venue for all Iowa State ChE graduate students for special professional development opportunities as well as for volunteering and social activities.

Graduate students become heavily involved in research endeavors in chemical engineering concepts and technology used in today's and tomorrow's energy, sustainability, and health industries. Research areas include advanced and nanostructured materials, biorenewables, catalysis and reaction engineering, computational fluid dynamics, health care technology and biomedical engineering, and renewable energy. Biorenewables research is quite popular given Iowa's abundance of biomass as a biorenewables resource. Doctoral graduate **Catie Brewer** (2012) received the 2011 George Washington Carver Award Scholarship Prize for Outstanding Student Achievement in Biorenewables at the World Congress on Industrial Biotechnology & Bioprocessing. Substantial funding has recently been attributed to health care technology and biomedical engineering, particularly in nanovaccine gene delivery and neuroregenerative strategies. Research has been published in high-impact journals such as *Nature Materials* and *Nature*. Since the Iowa State program was founded, 624 Master's degrees and 450 doctoral degrees have been awarded.

Graduate alumni have established successful careers. Recent alumni in academia include **Ganesh Sriram** at the University of Maryland; **Matthew Kipper** at Colorado State University; **Russell Gorga** at North Carolina State University; **Erin Jablonski** and **Brandon Vogel** at Bucknell; and **Venkat Raman** at University of Texas at Austin, among others. **Umit Ozkan**, now a distinguished professor at The Ohio State University, has received many national honors and awards for her teaching and research in heterogeneous catalysis. **Deniz Uner** is the professor and chair of chemical engineering at Middle East Technical University in Ankara, Turkey, and recently co-authored a book with the late Doraiswamy called *Chemical Reaction Engineering: Beyond the Fundamentals* (2013). Our alumni advance their Iowa State chemical engineering research through such academic, industrial, and entrepreneurial endeavors.

SUMMARY

The first century of Iowa State chemical engineering research and education excellence culminates in 2013. The department is proud of the academic, research, and professional networks it identifies with, and will continue to serve as a premier resource for chemical engineering teaching and development. Teaching and research facilities will expand to meet the demands of chemical engineering excellence. Faculty and students will continue to push the frontiers of interdisciplinary research to improve the theory and practice of chemical engineering. In 2013 Iowa State chemical and biological engineering starts an exciting new chapter—its second century. ❐

CHEMICAL ENGINEERING STUDENTS: A DISTINCT GROUP AMONG ENGINEERS

Allison Godwin, Geoff Potvin
Clemson University • Clemson, S.C. 29634

In traditional analyses of students' career choice, students in engineering majors are often treated as a monolithic population rather than belonging to a constellation of related disciplines. A few studies have documented different types of students and cultures within engineering disciplines,[1–3] but there is little discussion about how students' attitudes and perceptions of engineering disciplines affect their choice of major upon entrance into college and the characterization of these students. Studies that have been published have compared personality types through tests like Myers-Briggs, which have validity problems, especially due to the lack of relevant context.[4] Additionally, much of this work was conducted more than 30 years ago, and there is little current work on articulating students and cultures of different engineering disciplines. One study that does illustrate the differences between engineering groups examined the different attitudes between industrial engineering students and more traditional mechanical and electrical students at a single institution.[5] The conclusions from this study provide motivation to further explore this under-researched area: "Instead of examining the characteristics of persons gravitating toward engineering, we should inquire into what types of persons select which types of engineering."[5] Another study examined the differences between chemical engineers and other engineering students, science students, and non-science students. The data from this study were limited to transcript information from the Southeastern University and College Coalition for Engineering Education (SUCCEED). The authors did find differences in chemical engineering students with higher SAT Math and Verbal scores, higher high school GPAs, longer time to graduation, higher cumulative college GPAs, fewer changes in declared major, and more semester hours than other students.[6] Because of its design, however, this study did not explore students' career interests and attitudes, which is the focus of our study. Further study of students' interests and attitudes about engineering disciplines is vital to the recruitment and retention of engineering students.

It has been shown that students will develop a strong attachment to their chosen major when the perceived identity of a practitioner agrees with a student's self-defined identity.[7–12] Additionally, students who are more familiar with specific engineering disciplines express a greater confidence in their choice of major.[13] These findings have important implications for how students are recruited into particular programs as well

Allison Godwin *is a Ph.D. student and NSF graduate research fellow in engineering and science education at Clemson University. She completed her B.S. in chemical and biomolecular engineering at Clemson University. Her thesis focuses on identifying predictive factors for increasing female enrollment in engineering.*

Geoff Potvin *has been an assistant professor in the Department of Engineering & Science Education at Clemson University since 2008. He has a background in theoretical physics and STEM education and teaches undergraduate mathematics and physics courses, as well as graduate courses in STEM education research. His research is focused on sociocultural issues in the preparation of physical scientists and representation issues in the physical sciences.*

as how these students are instructed. With little literature on the differences between students who choose the spectrum of engineering disciplines, there is a missed opportunity to improve the recruitment, retention, and teaching practices for the students who enter chemical engineering classrooms, as well as other engineering majors.

Since high school students have not yet been fully exposed to science practice, let alone engineering practice, the choice of an engineering discipline upon entrance to college is only a partly informed decision. Many students enter college knowing they want to pursue engineering with particular career outcomes in mind, but they do not know which engineering discipline fits those career aspirations. Additionally, the coursework to prepare for a specific STEM career is often undifferentiated in high school. Some studies have attempted to classify different types of engineers by their career roles of research, development, production, and sales through using students' Strong Vocational Interest Blank (SVIB) scores. [14] These roles in industry are outdated and do not directly address the question of student attitudes and interest upon entrance into college, but these findings do add to the body of evidence that there are differences in engineers' specific interests and, more importantly, a specialization within the designation of a specific engineering career choice (*e.g.*, chemical, mechanical, electrical, etc.). Students just entering college may not be prepared to make a specialty choice in engineering. Instead, students choose an engineering discipline based on the perceived fit with their intentions and several irrational factors.[13] These findings add to the motivation to explore the underlying differences in students who choose different engineering disciplines.

Performance in math and science are not the primary reason that students either leave engineering studies or do not enter them in the first place.[15,16] Students reported that a loss of interest in their original major, pedagogical and curricular issues, disenchantment with perceived future careers, inadequate advising, lost confidence due to low grades or poor preparation, and—for females—covert or overt gender bias within the discipline, caused them to leave their originally declared major. In general, gaps between students' expectations and the perceived "fit" of a major result in students leaving. In *Talking About Leaving*, 10.5 percent of students initially declaring an engineering discipline as a major resettled within engineering, while 51.4 percent remained in the originally declared major, with the remaining group of students (38.1 percent), leaving engineering altogether.[15] A recent study of students switching from other engineering majors into industrial engineering found that the same pushes highlighted by Seymour and Hewitt continue to affect current engineering students.[16] From transcript databases, research has shown that engineering as a group does have one of the highest rates of persistence in STEM and the lowest rate of inward migration. Engineering students are also more likely to graduate in their declared major.[17] Additionally, testimony before the Subcommittee on Research of the Committee on Science for the U.S. House of Representatives in 2006 indicated that little, if anything, has changed since Seymour and Hewitt's findings almost 10 years prior. Current numbers show that 50 to 60 percent of students initially declaring a major in STEM eventually leave those studies. In view of the current situation in STEM attrition, the President's Council of Advisors in Science and Technology (PCAST) recently called for 1 million new STEM graduates over the next 10 years.[18] One way to address the need for more STEM graduates is through understanding which types of students choose engineering and how to more effectively recruit them upon entrance into college.

Understanding what factors (beliefs, attitudes, and goals) lead students to choose specific engineering disciplines can help address the need for new STEM graduates. By more thoroughly understanding students in chemical engineering departments, chemical engineering educators can better address their particular interests and needs. If, as expected, these students are different from non-engineering students, but are also different from their peers in other engineering disciplines, departments will reap many benefits from an improved understanding of their students.

In this paper, an exploration was conducted of pre-college factors (including academic backgrounds, classroom experiences, out-of-class experiences, attitudes, family influences, and demographic backgrounds) that impact students' chemical engineering career intentions, as measured by their self-identified likelihood of choosing a career in a specific engineering discipline. The results illustrate the specific differences in chemical engineering students identified in a nationally representative sample of college freshmen, and provide emphasis for the statement that "engineers should not be lumped together into a single category."[14]

METHODS

The data used in this study were drawn from a subsection of the Sustainability and Gender in Engineering (SaGE) survey (<http://www.clemson.edu/~gpotvin/SaGE.pdf>), a large- scale study of students in introductory English courses enrolled in colleges across the United States (NSF GSE 1036617). This methodology uses a cross-sectional approach relying on the natural variation in students' experiences and backgrounds across the United States. The SaGE project used a representative, stratified, random sample taken from a comprehensive list of four-year and two- year institutions. A list of all colleges and universities in the United States was obtained from the National Center for Education Statistics (NCES) and was divided by institution type (two-year or four-year) and by institution size (small, medium, or large) into six lists. Each list was randomized and then recruiters contacted schools on each list. The stratification accounted

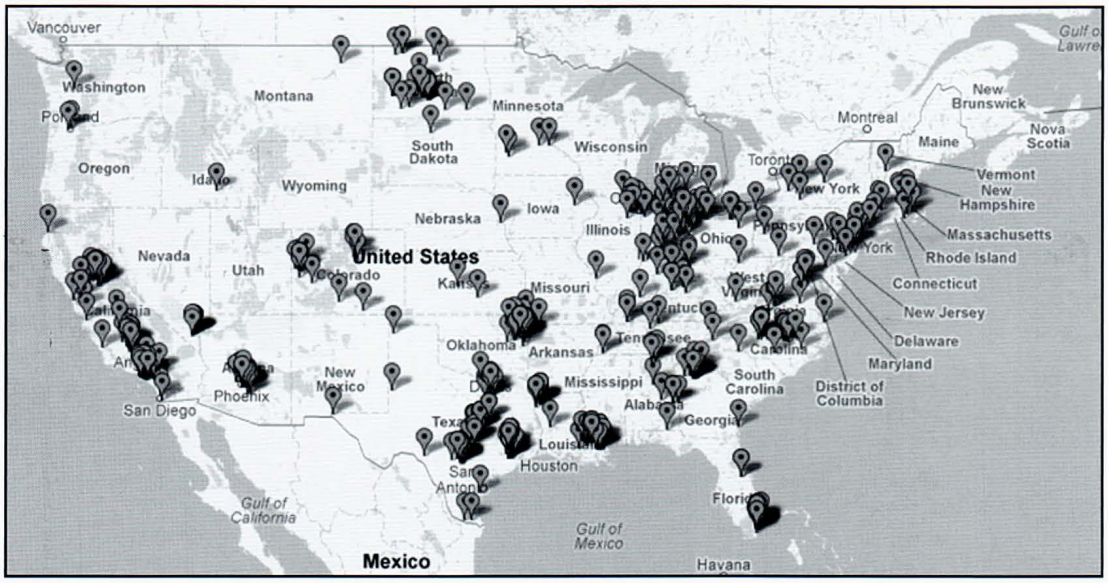


Figure 1. *Engineering students' hometowns in the contiguous United States created with BatchGeo.*[21]

for the size of the institution and prevented over-sampling of the smaller, but numerous, liberal arts colleges. In total, 50 schools agreed to participate in the survey. The survey was administered in required freshman English courses to capture a sample representative of both STEM and non-STEM majors. In all, 6,772 students completed the survey during the administration period in the Fall of 2011. The survey instrument focused on student backgrounds, pedagogical factors in physical science classrooms, classroom achievement, and student attitudes toward STEM and sustainability. Sustainability is most commonly and broadly defined as meeting the "needs of the present without compromising the ability of future generations to meet their own needs."[19] The intent of the study was to focus on factors that increased enrollment in engineering majors and to explore the connections between engineering and sustainability-related topics in students' experiences.

Using this retrospective cohort methodology, substantial natural variability in students' background and prior experiences can be captured. Students reported that they came from homes in at least 2,533 different ZIP codes across the United States. A map of the engineering students' home ZIP codes in the contiguous United States can be seen in Figure 1. This map is included to illustrate the geographic representativeness of the population which is reflective of the population of the United States.[20] International students are included in the study as a part of the cross- sectional sample gathered from the 50 institutions surveyed. Of the total student population that completed the demographic portion of the survey, 54.7% were female. Of the 814 students who indicated the choice of any intended engineering career, 19.8% of respondents were female.

The final version of the survey included 47 questions about student career goals, high school science experiences, earlier math, and science enrollment and achievement (including types of courses taken, the level of courses, the year courses were taken in high school, final grades, and AP test scores), student attitudes about sustainability, and demographic information. These questions consist of primarily Likert, Likert-type, multiple-choice, and categorical items.

Multiple aspects of validity and reliability of the instrument were assessed. An open-ended hypothesis-generation survey was collected from 82 first-year engineering and 41 non-engineering students, as well as 83 high school science teachers (recruited via the listserv of the National Science Teachers' Association). Lending to content validity, these hypotheses were included in the survey. Questions were further refined based on feedback from assessors and the results of pilot testing in a first-year freshman engineering course. In-person pilots of the survey and focus groups were conducted with first-year freshmen engineering students. Thus, each item of the survey was further examined for face and content validity.

One question used in this analysis asked students to "Please rate the current likelihood of your choosing a career in the following:". The various career options were "Mathematics," "Science/math teacher," "Environmental science," "Biology," "Chemistry," "Physics," "Bioengineering," "Chemical engineering," "Materials engineering," "Civil engineering," "Industrial/systems engineering," "Mechanical engineering," "Environmental engineering," and "Electrical/computer engineering." Students were asked to rate the likelihood of choosing a career in each discipline on a Likert-type scale from 0 ("not at all likely") to 4 ("extremely likely"). In the current analysis, students that responded as "extremely likely" to choose a career in chemical engineering were grouped together, and all other students that responded "extremely likely" to choose at least one other engineering discipline were grouped together for a comparative analysis. The reason for this choice was to identify students with the most unambiguous intentions of majoring in chemical engineering on the one hand and all other engineering disciplines on the other.

TABLE 1
T-test outcomes for linearized variables.

Variable	ChE Students (Mean ± Std. Error) N=123	Other Engineering Students (Mean ± Std. Error) N=691	Level of Significance§ (*: p< 0.05, **: p< 0.01, ***: p<0.001)
Career goals: solving societal problems (scale: 0-not at all important; 4-very important)	**2.50 ± 0.02**	2.22 ± 0.27	*
Career goals: making use of my talents and abilities	**3.63 ± 0.01**	3.48 ± 0.14	*
Career goals: applying math and science	**3.20 ± 0.09**	2.80 ± 0.32	***
In biology asked questions, answered questions, or made comments (scale: 0-never; 4-daily)	**3.22 ± 0.08**	2.85 ± 0.30	***
In chemistry asked questions, answered questions, or made comments (scale: 0-never; 4-daily)	**3.39 ± 0.23**	2.74 ± 0.43	***
In physics asked questions, answered questions, or made comments (scale: 0-never; 4-daily)	**3.19 ± 0.04**	2.84 ± 0.33	*
Interest in understanding natural phenomena (scale: 0-not at all interested; 4-very interested)	**2.94 ± 0.09**	2.50 ± 0.36	**
Interest in understanding science in everyday life (scale: 0-not at all interested; 4-very interested)	**3.11 ± 0.12**	2.67 ± 0.34	***
Interest in explaining things with facts (scale: 0-not at all interested; 4-very interested)	**3.24 ± 0.08**	2.88 ± 0.29	***
Interest in telling others about science concepts (scale: 0-not at all interested; 4-very interested)	**3.04 ± 0.21**	2.39 ± 0.45	***
Interest in making scientific observations (scale: 0-not at all interested; 4-very interested)	**3.04 ± 0.12**	2.55 ± 0.38	***
Confidence in designing an experiment to answer a scientific question (scale: 0-not at all confident; 4-very confident)	**2.81 ± 0.06**	2.44 ± 0.32	**
Confidence in conducting an experiment on your own (scale: 0-not at all confident; 4-very confident)	**3.03 ± 0.10**	2.62 ± 0.32	***
Confidence in interpreting experimental results (scale: 0-not at all confident; 4-very confident)	**2.99 ± 0.10**	2.59 ± 0.32	***
Confidence in writing a lab report/scientific paper (scale: 0-not at all confident; 4-very confident)	**2.90 ± 0.18**	2.30 ± 0.43	***
Confidence in applying science knowledge to an assignment or test (scale: 0-not at all confident; 4-very confident)	**3.04 ± 0.09**	2.63 ± 0.33	***
Confidence in explaining a science topic to someone else (scale: 0-not at all confident; 4-very confident)	**3.24 ± 0.24**	2.58 ± 0.44	***
Confidence in getting good grades in science (scale: 0-not at all confident; 4-very confident)	**3.50 ± 0.17**	2.98 ± 0.36	***
Learning science will improve career prospects (scale: 0-strongly disagree; 4-strongly agree)	**3.45 ± 0.11**	3.04 ± 0.30	***
Science is helpful in my everyday life (scale: 0-strongly disagree; 4-strongly agree)	**3.23 ± 0.08**	2.87 ± 0.29	***
Science has helped me see opportunities for positive change (scale: 0-strongly disagree; 4-strongly agree)	**3.27 ± 0.13**	2.84 ± 0.32	***
Learning science has made me more critical in general (scale: 0-strongly disagree; 4-strongly agree)	**3.14 ± 0.08**	2.77 ± 0.30	**
I see myself as a physics person (scale: 0-strongly disagree; 4-strongly agree)	**2.74 ± 0.10**	2.25 ± 0.41	**
Chemistry topics are relevant to my life (scale: 0-never; 4-daily)	**2.69 ± 0.14**	2.15 ± 0.41	***
Highest Chemistry Course Taken (scale: 0-none; 1-one course; 2-two courses)	**0.84 ± 0.01**	0.65 ± 0.18	*
Last chemistry grade (scale: GPA)	**3.62 ± 0.05**	3.29 ± 0.28	**

§ *The level of statistical significance is coded in the final column: * represents a statistical significance less than 0.05 but greater than or equal to 0.01, ** represents a statistical significance less than 0.01 but greater than or equal to 0.001, and *** represents a statistical significance less than 0.001.*

According to the classification outlined above, 123 students in the sample were categorized as chemical engineering students (29.3% of which were female) and 691 students were categorized as "other" engineering students (18.1% of which were female). The chemical engineering students were composed of 72% freshman, 21% sophomores, and 7% upperclassman. Similarly, the "other" engineering students were composed of 73% freshman, 20% sophomores, and 7% upperclassman.

For the questions with linear responses, Welch's t-test was used to compare the mean responses of chemical engineering with other engineering students.[22] A chi-square test was used for dichotomous variables to assess whether there is a statistically significant difference in the responses of the two groups.[23] For all tests performed in this analysis, the maximum probability of Type-I error (*e.g.*, a false positive result) that was permitted was 5%. Note that only survey items pertaining to student preparation, background, and attitudes were analyzed in this paper. All analyses were conducted using the statistical software system R.[24]

RESULTS

The results of the various t-test and chi-square tests are summarized in Tables 1 and 2. Only tests relating to the research question that were statistically significant are reported; in total, 26 linear and seven dichotomous variables showed significant differences.

For each variable in Table 1, the mean and standard error are given for both groups of students. The larger mean is listed in bold. Similarly, Table 2 gives the results from the chi-square tests. The percentages of each group answering affirmatively to each factor are listed, followed by the statistical significance. The higher percentage is listed in bold. Tests for related variables are grouped together in Table 1: first, career goals (in gray); second, science identity variables (in white); third, high school chemistry experiences (in gray). In Table 2 the questions are also grouped together: first, sustainability factors for career goals (in gray); second, family involvement (in white); third, type of high school (in gray).

As indicated in Tables 1 and 2, chemical engineering students show several substantial differences from students in other engineering disciplines. To understand the uniqueness of chemical engineering students and consider how to specifically design pedagogy for these students, it is instructive to consider the meaning of the related blocks of factors that were found to be significant.

In considering the demographic and prior educational experiences of chemical engineering students, there were several factors that were found to be not significantly different from other engineers including: SAT/ACT scores, high school physical science classroom experiences, family background, number of AP credits, and math and science preparation factors. This finding is perhaps not surprising since prior literature has shown that engineering students in general who persist are well prepared for their college courses.[15] The only overlap between the current work and the study by Zhang and colleagues is students' SAT scores and high school GPA. This earlier work found that chemical engineering students had higher SAT scores and GPAs than other engineering students.[6] Some reasons for the differences in these findings are that the transcript data collected by Zhang and colleagues range from 1988 to 2003, while the data in this study were collected from students enrolled in the Fall of 2011. In 2005, between these studies, the SAT assessment changed significantly.[25] In addition, Zhang and colleagues' sample is limited to Southeastern schools with several listed as research universities with "high" or "very high" research activity, which may have limited the earlier sample to exceptional engineering students.[26] There are a few indicators that students in chemical engineering come from a somewhat higher socioeconomic background than other engineering majors: students are more likely to come from a foreign high school ($p<0.05$) and these students' families are more likely to have arranged a tutor in math or science in the past ($p<0.01$). Many of the high school classroom practices and student attitudes were not found to be different, as well as a number of variables related to students' high school science course length, class sizes, frequency of meetings and activities. Similarly, students were questioned

TABLE 2
Chi-square test outcomes for dichotomous variables.

Variable	Percent of ChE Students Indicating (N=123)	Percent of Other Engineering Students Indicating (N=691)	Level of Significance (*: $p < 0.05$, **: $p < 0.01$, ***: $p<0.001$)
Want to address energy in career	**60%**	47%	*
Want to address disease in career	**39%**	18%	***
Want to address climate change in career	**20%**	11%	*
Want to address water supply in career	**34%**	19%	***
Science was a diversion or hobby in my family	**37%**	26%	*
My family arranged for tutoring in science	**20%**	10%	**
Attended a foreign high school	**10%**	4%	*

about their out-of-school science activities such as hobbies, exposure to science-related media, and possible engineering influences. These results suggest that, while such factors may have a significant impact on the recruitment of students into engineering, no differential effects could be found for chemical engineering majors.

Students' prior experiences in chemistry courses differed between chemical engineers and other engineering majors. Chemical engineering students more often take a higher-level chemistry course ($p<0.05$) and have higher chemistry grades than other engineering students ($p<0.01$). Additionally, these students report higher levels of engagement with the material, positive interactions with other students, and highly rated chemistry teachers. Student engagement was measured by how often the student asked questions, answered questions, or made comments in his/her classes ($p<0.001$) as well as measuring how interested the student was in his/her high school chemistry classes ($p<0.01$). Students identified chemistry topics as more relevant to their everyday lives ($p<0.001$).

Chemical engineers listed some career outcome expectations that were different from other engineering students. A surprising finding was that chemical engineers reported a stronger desire to apply math and science in their future career over other engineers ($p<0.001$). Chemical engineers also reported a stronger interest in solving societal problems ($p<0.05$) and making use of their talents and abilities ($p<0.05$). Some specific ideas related to sustainability were also highlighted as concerns that chemical engineers specifically hoped to address in their careers including: energy ($p<0.05$), disease ($p<0.001$), climate change ($p<0.05$), and water supply ($p<0.001$).

Chemical engineering students showed a strong interest in science and understanding the world around them. They indicated higher scores on their interest in understanding natural phenomena ($p<0.01$), understanding science and everyday life ($p<0.001$), explaining things with facts ($p<0.001$), telling others about science concepts ($p<0.001$), and making scientific observations ($p<0.001$). Another set of questions measures students' confidence in their scientific and mathematical abilities. Chemical engineers reported significantly higher differences on their abilities to design an experiment to answer a scientific question ($p<0.01$), conduct an experiment on their own ($p<0.001$), interpret experimental results ($p<0.001$), write a lab report or scientific paper ($p<0.001$), apply science knowledge to an assignment or test ($p<0.001$), explain a science topic to someone else ($p<0.001$), and get good grades in science ($p<0.001$).

Identity

To clarify the questions addressing students' interest and confidence discussed above, a composite measure of "science identity" was constructed using several of these items. As a construct, identity has been conceptualized as inherently related to individuals' self-beliefs.[10] In this study the particular context of interest is that of an engineering discipline. The importance of understanding identity is highlighted by Brickhouse and colleagues: If more students are to enter science and engineering, they need to see themselves as the "kind of people who would want to understand the world scientifically."[11] The construct of identity is based on four measurable dimensions of students' beliefs about their performance, competence, recognition by others, and interest.[8] These four dimensions richly capture an individual's self-perceptions and can be used to study the development of an engineering identity specifically in relation to critical events in students' experiences, their perceptions of the world around them, and the development of agency (*i.e.*, beliefs about the ability to act and enact change in one's world) in their lives and careers. The study of identity has proven useful in understanding college persistence.[12] This framework for measuring identity has been previously used in large-scale studies of physics and mathematics.[8]

Of the four sub-constructs of identity, the recognition component consists of beliefs about external recognition by parents, teachers, other students, etc., of an individual person as a good science student. Interest in the subject material also plays a key role in the choice of an engineering major. In this analysis, the questions used to construct an identity composite are the interest and confidence questions in Table 1 (which include students' perceptions of their performance and competence together) and the questions about family recognition and involvement in Table 2, all of which were found to be highly correlated with one another for each of the four sub-constructs measured.[8] These questions were averaged for each of the sub-constructs of identity (interest, recognition, performance, and competence) and used to compare chemical engineering students with other engineering students. Performing a t-test to compare chemical engineers and other engineers on this composite shows that the former have a higher overall science identity than the latter ($p<0.001$). Thus, chemical engineers appear to be responsive in ways that are somewhat more akin to traditional physical scientists than other engineers.

DISCUSSION

To a certain extent, these findings agree with prior work investigating the differences between engineering disciplines. Namely, this analysis found that there are, in fact, notable differences between chemical engineering undergraduates in career aspirations, perceived identities, and approaches to learning. This work is a step towards clarifying some of the differences between students who choose chemical engineering in college and others.

In utilizing a cross-sectional study design, the data gathered have some strengths: large statistical power, national representativeness in the sample, and the ability to test hypotheses surrounding events that were introduced to students naturally

rather than through an intervention. This study design also has certain weaknesses, notably including the inability to draw causal conclusions. Rather, results are correlational in nature. The results do indicate substantial correlations between student responses and students' choice of major, but further work is necessary to indicate a causal direction to these relationships. For example, students may see chemistry topics as relevant to their everyday lives because of their choice of chemical engineering as a major, or they may choose chemical engineering because of their prior view of chemistry as relevant to their lives.

Students' experiences in their high school chemistry classrooms tell us how students engaged in chemistry classes may develop a particular connection to the material and see a future in chemical engineering. Chemical engineering students usually take a second course in chemistry and do better than other future engineering students. The particular reasons why these students choose chemical engineering over chemistry are not yet clear, but may be rooted in better or more extensive math preparation, a stronger connection to hands-on applications of science, or other factors. The differences between chemists and chemical engineers upon entrance into college are an interesting topic that will be explored in the future.

A stronger interest in solving societal problems and addressing issues such as disease may point to chemical engineering students being interested in industries such as pharmaceuticals or possibly going on to a career in medicine. Connecting curriculum to current issues facing our global community may help to harness chemical engineering students' concerns related to the sustainability-related issues that were highlighted in this analysis. The inclusion of emerging fields such as nanotechnology and biomolecular engineering within traditional chemical engineering instruction is also suggested by these findings; these topics have direct connections to future solutions in human health and environmental applications. Also, in engineering, the perceived lack of a connection to societal problems is a substantial barrier to women entering the field,[27] and the subject of sustainability can overcome this barrier by explicitly connecting engineers' contributions to solving problems such as resource depletion, catastrophic climate destabilization, and social inequity. As STEM educators move toward the recruitment and education of 1 million extra STEM graduates in the next 10 years, attracting more women and students from other traditionally marginalized groups into engineering is vital.[18] By reducing some of the barriers to women relating to engineering through curricular choices, some of these hindrances may be addressed by our current chemical engineering faculty.

Perhaps unsurprisingly, chemical engineers have more positive experiences in their high school chemistry courses than other engineering students. Such findings could be expected due to typical college admissions requirements and the motivations of students who traditionally intend to

Students' experiences in their high school chemistry classrooms tell us how students engaged in chemistry classes may develop a particular connection to the material and see a future in chemical engineering

enter chemical engineering. These positive experiences may partially explain why students have a significantly stronger science identity than their peers. Zhang and colleagues found that chemical engineering students transferred more frequently to physical science majors than other engineering students and that students leaving physical science and entering engineering chose chemical engineering over other engineering disciplines more frequently.[6] These results triangulate the current paper's finding of a higher science identity among chemical engineering students. These students may also have a stronger connection with chemistry as it relates to their everyday lives and see chemical engineering as a way to positively affect the world around them, desires to solve societal problems, and apply mathematics and science in their careers. A strong science identity coupled with the desire to apply math and science also has implications for educators' curricular choices. Traditionally, students spend much of their time in the first two years of college learning basic theory (*e.g.*, fluid dynamics, heat and mass transfer, thermodynamics). This practice may hinder students' ability to connect their choice of major with their career goals and may reduce student persistence in the field or lead to a loss of motivation and perceived relevance of their chosen field. Additionally, students may be more engaged with the material if the connections to "real-world applications" are made explicit throughout their college studies rather than simply giving a perfunctory nod to the importance of the material for use in activities which may not appear until much later. For example, students may be told that thermodynamics is important because it allows them to predict system properties that will be used later in their design courses and often are expected to simply learn the principles first. However, the lack of a connection in the present course may negatively influence their perception of the material and its usefulness for their future career. Additionally, students may have difficulty applying abstract concepts and ideas to practical applications. Being able to understand the physical meaning of equations and manipulate those equations is an important engineering skill. Many students have difficulty grasping and understanding the abstract concepts of thermodynamics, making it one of the most difficult courses in the undergraduate career.[28,29] Creating connections to real-world scenarios that chemical

engineering students will implement in their careers may help students see the importance of the material and grasp concepts before the final year in senior design.

In previous work, engineering majors have been found to have marginally lower socio-economic status, stronger math skills, and less parental and teacher encouragement towards science than science majors.[30] From the current work, it can be seen that chemical engineering students are a demonstrably different group from other engineers. Further investigation of the specific pre-college influences and experiences that cause students to choose chemical engineering over other career choices is a topic for future study. The implications of the current findings, however, are that students' experiences in high school chemistry and a desire for deep understanding of natural phenomena may predict entrance into chemical engineering, and it may be possible to target students for recruitment into chemical engineering through specific support and encouragement. Additionally, a pedagogy that reflects students' deep interest in why things work and the premise behind particular chemical engineering theories may increase student interest in chemical engineering coursework.

CONCLUSIONS

The findings in this work have implications for student recruitment and/or matriculation into chemical engineering and how to improve the relevance and effectiveness of college instruction for these students.

To summarize the results of this paper in a useful way, we have prepared a list of possible considerations that may lend guidance to the recruitment, retention, and effective instruction of chemical engineering students:

- *Given the number of differences in the attitudes of chemical engineering students identified in this study, it may be less than optimal to the retention of these majors to make over-generalizations about "engineering students" when designing curricula or pedagogy in general.*
- *As chemical engineering students have been found to have particularly high expectations towards solving societal problems in their careers including a more frequent desire to address sustainability-related issues (disease, climate change, energy and water supply), it is likely to be beneficial (to their motivation, engagement, and ultimate performance) to regularly address, as part of the normal classroom activities, how and why the content students are learning can be used to address specific social issues.*
- *Similarly, since chemical engineering students have been found to put more weight on developing a deep understanding (of natural phenomena, in everyday life, using scientific questioning and evidence), attention should be paid in the classroom to explaining physical phenomena in more detail and to connecting these topics explicitly to students' everyday lives.*
- *It appears that chemical engineering majors would benefit particularly from having increased opportunities to examine scientific evidence and gain experiences providing explanations/argumentation towards its interpretation. This recommendation is consistent with the broad movement in STEM towards "active" learning environments and the emphasis on inquiry in the classroom; our work indicates that chemical engineering students would respond especially well to increased opportunities for this type of learning.*
- *As we found that chemical engineering students were particularly confident in their abilities to perform tasks related to their scientific and course activities (write a lab report, interpret experimental results, apply knowledge to an assignment/test, get good grades), it may be a waste of time to spend inordinate amounts of class or laboratory time having students develop these metacognitive skills; rather, putting more emphasis on other things (as discussed above) may be more beneficial.*
- *Lastly, our results indicate that students who choose chemical engineering are from slightly higher socioeconomic backgrounds. In order to increase enrollment and encourage diverse engineering perspectives, less traditional students that may prove to be highly competent engineers should be recruited.*

While chemical engineering students do have clear differences in their career aspirations, understanding of engineering, science identity, chemistry background, and family support than other engineering students, it is important to keep in mind that this group is nonetheless not homogeneous; there are a variety of students that may choose to pursue chemical engineering as a major. Thus, these results should not be over-interpreted to suggest that there is a "one-size-fits-all" solution to the successful recruitment and preparation of the next generation of chemical engineers.

ACKNOWLEDGMENTS

This work has been supported by a National Science Foundation Graduate Research Fellowship (Grant No. 0751278) and a Research on Gender in Science & Engineering Grant (No. 1036617).

REFERENCES

1. Johnson, H., and A. Singh, "The Personality of Civil Engineers," *J. Manag. Eng.*, **14**(4), 45 (1998)
2. Dee, K.C., E. Nauman, G. Livesay, and J. Rice, "Research Report: Learning Styles of Biomedical Engineering Students," *Annals Biomed. Eng.*, **30**(8), 1100 (2002)
3. Godfrey, E., and L. Parker, "Mapping the Cultural Landscape in Engineering Education," *J. Eng. Ed.*, **99**(1), 5 (2010)
4. Hunsley, J., C.M. Lee, and J.M. Wood, "Controversial and Questionable Assessment Techniques," in *Science and Pseudoscience in Contemporary Clinical Psychology*, Lilienfeld, S.O., J.M. Lohr, and S.J. Lynn, eds., New York, Guilford Press (2004)
5. Izraeli, D., M. Krausz, and R. Garber, "Student Self-Selection for Specializations in Engineering," *J. Vocat. Behav.*, **15**(1), 107 (1979)
6. Zhang, G., B. Thorndyke, and M. Ohland, "Demographic Factors and

Academic Performance: How Do Chemical Engineering Students Compare with Others?" in American Society for Engineering Education Proceedings, Nashville, TN (2003)
7. Witt, P., and P. Handal, "Person-Environment Fit: Is Satisfaction Predicted by Congruency, Environment, or Personality?" *J. College Student Personnel*, **25**(6), 503 (1984)
8. Hazari, Z., G. Sonnert, P.M. Sadler, and M.C. Shanahan, "Connecting High School Physics Experiences, Outcome Expectations, Physics identity, and Physics Career Choice: A Gender Study," *J. Res. Sci. Teach.*, **47**(8), 978 (2010)
9. France, M.K., O. Pierrakos, J. Russell, and R.D. Anderson, "Measuring Achievement Goal Orientations of Freshman Engineering Students," in ASEE Southeastern Section Conference Proceedings, Blacksburg, VA (2010)
10. Johnson, A., J. Brown, H. Carlone, and A. Cuevas, "Authoring Identity Amid the Treacherous Terrain of Science: A Multiracial Feminist Examination of the Journeys of Three Women of Color in Science," *J. Res. Sci. Teach.*, **48**(4), 339 (2011)
11. Brickhouse, N.W., P. Lowery, and K. Schultz, "What Kind of a Girl Does Science? The Construction of School Science Identities," *J. Res. Sci. Teach.*, **37**(5), 441 (2000)
12. Carlone, H.B., and A. Johnson, "Understanding the Science Experiences of Successful Women of Color : Science Identity as an Analytic Lens," *J. Res. Sci. Teach.*, **44**(8), 1187 (2007)
13. Shivy, V., and T. Sullivan, "Engineering Students' Perceptions of Engineering Specialties," *J. Vocat. Behav.*, **67**(1), 87 (2005)
14. Dunnette, M.D., P. Wernimont, and N. Abrahams, "Further Research on Vocational Interest Differences Among Several Types of Engineers," *Pers. Guid. J.*, **42**(5), 484 (1964)
15. Seymour, E., and N. Hewitt, *Talking About Leaving: Why Undergraduates Leave the Sciences*, Boulder, CO, Westview Press (1997)
16. Walden, S., and C. Foor, " 'What's To Keep You From Dropping Out?' Student Immigration into and within Engineering," *J. Eng. Ed.*, **97**(2), 191 (2008)
17. Ohland, M.W., S.D. Sheppard, G. Lichtenstein, O. Eris, D. Chachra, and R.A. Layton, "Persistence Engagement and Migration in Engineering Programs," *J. Eng. Ed.*, **97**(3), 259 (2008)
18. President's Council of Advisors on Science and Technology, *Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics* (2012)
19. Bruntland, G.H., *Our Common Future*, New York, Oxford University Press (1987)
20. Mackun, P., and S. Wilson, United States Census Bureau, (2010), <http://www.census.gov/prod/cen2010/briefs/> (accessed Nov. 10, 2012)
21. BatchGeo, (2012), <http://www.batchgeo.com/> (accessed Oct. 25, 2012)
22. Welch, B.L., "The Significance of the Difference Between Two Means When the Population Variances are Unequal," *Biometrika*, **29**(3/4), 350 (1938)
23. Ott, L.R., and M.T. Longnecker, *An Introduction to Statistical Methods and Data Analysis*, 6th ed., Belmont, CA, Brooks/Cole Press (2008)
24. The Core Development Team. R: A language and environment for statistical computing (accessed Aug. 21, 2012) <http://www.r-project.org>
25. College Board History of SAT Assessment, <http://sat.collegeboard.org/about-tests/history-of- the-tests>, (accessed Oct. 22, 2012)
26. Carnegie Foundation Institution Classification, <http://classifications.carnegiefoundation.org/lookup_listings/standard.php> (accessed Nov. 2, 2012)
27. Widnall, S., "Digits of Pi: Barriers and Enablers for Women in Engineering," in SE Regional NAE Meeting Proceedings, Atlanta (2000)
28. Hadfield, L.C., and C.E. Wieman, "Student Interpretations of Equations Related to the First Law of Thermodynamics," *J. Chem. Ed.*, **87**(7), 750 (2010)
29. Thomas, P.L., and R.W. Schwenz, "College Physical Chemistry Students' Conceptions of Equilibrium and Fundamental Thermodynamics," *J. Res. Sci. Teach.*, **35**(10), 1151 (1998)
30. Potvin, G., R. Tai, and P. Sadler, "The Difference Between Engineering and Science Students: Comparing Backgrounds and High School Experiences," in American Society for Engineering Education Proceedings, Austin, TX (2009) ❐

ACTIVE LEARNING AND JUST-IN-TIME TEACHING

In a Material and Energy Balances Course

MATTHEW W. LIBERATORE
Colorado School of Mines • Golden, CO 80401

Material and energy balances are used daily by most practicing chemical engineers across a wide range of job duties and industries. Due to the foundational nature, the material and energy balances course is usually delivered first in the chemical engineering curriculum. The literature includes numerous papers on the importance of the course, the difficulty of the course and its concepts, and high fail rate (*i.e.*, reputation as a "weed out" course).[1-7] Here, 21st century tools and techniques add to the established learning tools and have led to improved outcomes for the course.

Felder and Rousseau's textbook[8] is widely adopted for the course and defines the structure and course topics covered. While the concepts covered in the course have not dramatically changed recently, how the course is delivered has been altered by the availability of technology. A very recent survey[4] on how the course is taught elucidates numerous trends for the course. One clear evolution of the course delivery is the widespread use of software tools such as Excel (spreadsheets), Matlab (advanced mathematics), and many others. Although not covered in the survey, course-specific tools have also been developed.

Online homework from Sapling Learning has supplemented or replaced traditional problem sets out of the textbook for some instructors of a material and energy balances course.[6,9] Features of this tool include personalized problems (*i.e.*, same problem statement with different numbers), multiple attempts for the students to work until the problem is completed correctly, hints and tutorials available in real time, and real-time grading and class statistics. In addition, the rolling numbers on each problem make creating a solutions manual for all variations difficult. Therefore, the online homework dramatically decreases a common concern about the course, namely cheating through the availability of downloadable solutions manuals.[4,10] Another tool designed to improve students' problem-solving skills is open source educational software called ChemProV.[4,11] ChemProV is a chemical process visualizer that helps students learn material balances through the construction of process flow diagrams. This scaffolded software tool led to statistically significant improvement in problem-solving accuracy when dynamic feedback was built into the tool. Overall, a critical aspect of the Sapling homework and ChemProV are the immediate feedback mechanisms.

Leveraging technology to provide real-time feedback to students, both inside and outside of class, has spurred an instructional approach called just-in-time teaching (JITT).[12-14] The most widely used form of JITT centers on the use of clickers.[13,15-17] More than a decade ago, a group of physics faculty created assignments due before every class to minimize the ebb and flow or cramming throughout a semester. Not only did the faculty have a large amount of data on the students' learning and misconceptions, the faculty could improvise within the current class period and address the students' knowledge gaps. A more recent treatise covering JITT across disciplines[12] presents a number of techniques and settings to collect learning information from students' responses. The common theme is to stop regularly (within a class period or several times per week) so students and the instructor can assess what has been learned. Numerous platforms to interact and collect learning data exist (*e.g.*, clickers, pen-based technologies, course-management systems, and concept warehouses and inventories).

Matthew W. Liberatore *is an associate professor of chemical and biological engineering at the Colorado School of Mines. He earned a B.S. degree from the University of Illinois at Chicago and M.S. and Ph.D. degrees from the University of Illinois at Urbana-Champaign, all in chemical engineering. His current research involves the rheology of complex fluids as well as active and self-directed learning.*

Overall, delivering courses to students who are digital natives (*e.g.*, References 18-20) can involve numerous active -learning techniques and technology[21] to keep the activity level in the room high, independent of class size. Three main sections of this work include teaching in a large class environment (>100 students), homework and JITT response, and assessment. Course surveys and grades provide two assessment tools in evaluating the effectiveness of these various techniques.

COURSE OVERVIEW

At the Colorado School of Mines (CSM), the chemical engineering curricula (*i.e.*, for accredited degrees in chemical engineering and chemical and biochemical engineering) begin with a course in material and energy balances, which is delivered in the spring of the sophomore semester. The placement in the curriculum is one term later than many schools.[4] About 80% of the students in the course have completed a core sophomore-level thermodynamics course that covers a number of energy balance concepts. The course format is three 50-minute class meetings per week at 8 a.m. in a single, large classroom, with an enrollment of more than 150 students in 2011 and 2012 (Table 1). The course had been taught with multiple sections and instructors (including the author) during 2009 and 2010. A number of reasons for moving to a single section are outlined in this manuscript (*e.g.*, technology such as online homework, creating a small class within a large class). Larger sections are becoming more common for this course in recent years,[4] and a number of different approaches can be employed without overwhelming the instructor or "weeding out" large numbers of students. While traditional graduate student teaching assistants have not been available for the single primary instructor setting, a group of three or four senior undergraduates assist the instructor in the classroom as well as in grading homework and quizzes. Grade point averages are on a 4.0 scale and are consistent with those reported earlier.[3]

The course's content follows the textbook by Felder and Rousseau,[8] which is used in ~85% of chemical engineering programs.[4] To mitigate the course's cost to the students, the textbook was a suggested resource in 2011 and 2012 (especially the ~$50 ebook version from Wiley compared to >$200 hard cover book at the university bookstore). Once the textbook's solutions manual is available, the utility of the book as a whole decreases dramatically, in the author's opinion. Most students, however, have access to a version of the textbook. While no formal handouts or alternative textbook are used, all notes written by the instructor during class are scanned and posted. The primary "textbook" cost is for the Sapling's online homework (~$35/student). The course can be divided into three main areas, namely the classroom environment, homework, and assessment of learning. All three components play a critical role in the delivery of the course.

TABLE 1
Class statistics of material and energy balances class at the Colorado School of Mines. Statistics do not include students withdrawing from the course.

Year	no. of students	Average GPA	%C or better	Sections	Primary Instructors
2012	142	2.39	80	1	1
2011	147	2.50	82	1	1
2010	156	2.38	79	3	3
2009	96	2.04	69	2	2

CLASSROOM ENVIRONMENT

An active-learning classroom is created using peer-to-peer instruction, YouTube videos with course-related problems,[22-24] and JITT feedback from the previous assignment. The majority of class time centers on activity by the students, applying learning-by-doing to the course. In addition, work implementing a small class within a large class was instituted to engage a larger number of students during each class period.

Providing structure in peer-to-peer instruction exercises improves focus and decreases the number of students "waiting to be taught" by a lecturing professor.[17,25] The teacher-centered instruction (*i.e.*, lecture) is limited to two or three 5-10 minute blocks per 50-minute class period. Groups of three students are formed at the beginning of the semester and usually maintained throughout the term. Students have self-selected their groups in recent years. Sitting in groups of three provides a format to randomly assign three roles when working on examples. The roles are leader, questioner, and scribe. The leader takes the lead, does the talking to initiate problem solving, and outlines the steps to complete the problem. The questioner listens to the leader and asks questions if something is unclear or seems incorrect. The scribe's role is to write key steps to the solution for the group and share the solution with the group during or after class. The group work time varies from 2 minutes for concept questions and simpler tasks such as drawing and labeling process flow diagrams to 10 minutes for writing and solving multiple balances. A timer is projected to keep students on task for these periods, however if student use of electronic devices with games or text messages starts to increase, the time is cut off and refocused on the next segment of the class. The roles are randomly rotated by a set of cards used by the instructor (*e.g.*, tallest-leader, shortest-scribe).

With groups working diligently during 40 to 75% of the class time, the instructors use this time to actively engage a number of groups. At least one instructor for every 40 to 50 students is needed to engage the groups in a large class setting. Faculty, graduate students, or senior undergraduate students can fill this role as secondary instructors during group activities. Having a diversity of instructors,

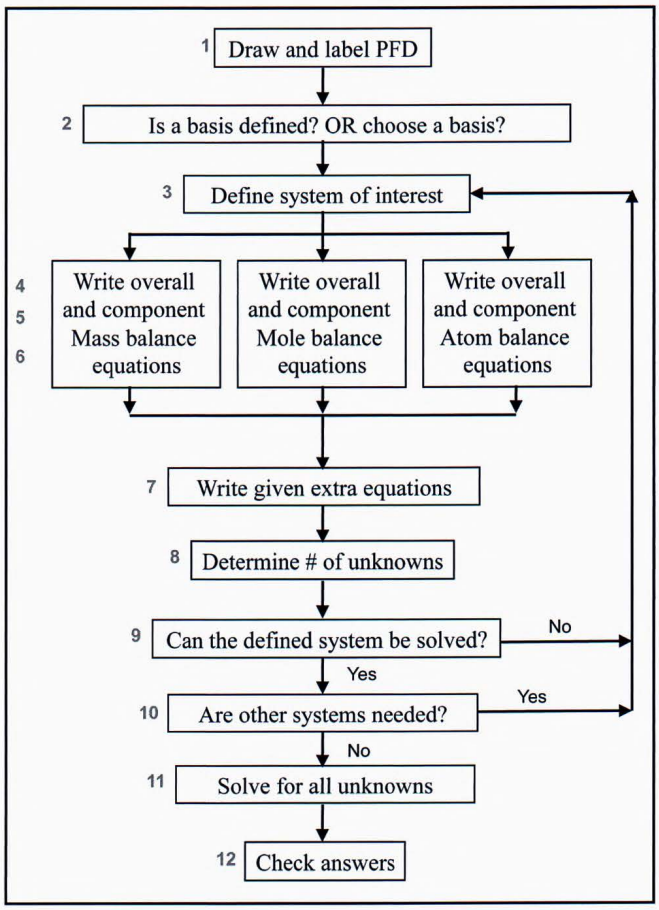


Figure 1. *A 12-step method for solving material balance problems.*

i.e., young/old, male/female, etc., can help build relationships with the students and appropriately represents the future work environment. The idea of using secondary instructors in large classes is not new and has been implemented successfully in 1,000 student sections with improved learning.[26] For the material and energy balances course in 2011 and 2012, three instructors alternated walking the front, middle, and back of the room depending on the day of the class (Monday, Wednesday, or Friday). Since students normally sit in the same general areas, each instructor had the opportunity to engage all of the students regularly.

The primary focus of the class is on providing basic tools for problem solving related to chemical engineering problems. A basic framework for problem solving in the course is summarized in a 12-step process (Figure 1). The utility of a 12-step method for energy and entropy problems (*i.e.*, first and second law) was recently summarized[27] and provided a linear problem-solving scheme. For more complex material balance problems, specifically multi-unit operations, required decisions and loops are added to the framework. The 12-step process is complementary to evaluating degrees of freedom, which is a point of emphasis in the Felder and Rousseau textbook. Feedback from students on the 12 steps (done with anonymous notecards near the middle of the semester) finds the steps useful but not critical to students learning the new material.

A final active-learning component used in the classroom is YouTube Fridays. Several papers have been published on this topic providing the details and feedback on this technique.[22-24] Briefly, students select videos from the Internet and write a course-related problem based on the events of the video (a collection of videos is available[28]). Most course topics have been covered by these problems over the past few years including multiple units, reaction-recycle systems, and vapor-liquid equilibrium. Therefore, selecting the most interesting and challenging YouTube problems to replace the "tried and true" textbook examples increases the energy level in the room. At this point, the examples are not restricted to Fridays since the database of problems has grown steadily in recent years. Groups of three students create one YouTube problem as a project during the semester. Overall, the integration of visuals is an established technique to increase learning, and the sense of personalization of the course engages a large number of digitally native students.[18-20]

HOMEWORK

Three homework assignments per week instill hard work and persistence. One assignment is due each Monday, Wednesday, or Friday class period except for exam days (*i.e.*, 13 assignments of each type of homework are due over the course of a semester). The delivery, length, and content of the assignments vary by assignment type. Short multiple-choice quizzes, personalized online homework, and a traditional "textbook" homework are the three types whose utility will be detailed here.

Instructor-written multiple-choice quizzes are delivered within the course management software (*i.e.*, Blackboard in this case). The content was developed over one semester with updating each semester to avoid the solutions being passed down from the previous year's students. The quizzes ask five to 10 questions per week covering vocabulary, basic calculations (*e.g.*, stoichiometric coefficients, vapor pressure), and concept questions. Adapting pieces of textbook examples or homework is one type of problem. For adding "bio" content, the BioEMB database[29] contains a wealth of full-length problems that can be simplified for this format (Figure 2). Performing atom balances on non-integer stoichiometry (*e.g.*, yeast in Figure 2) emphasizes the universality of the atom balance vs. balancing reaction stoichiometry by inspection. Overall, these quizzes primarily cover material at the remember and understand levels of Bloom's taxonomy.

For developing skills such as applying and analyzing (levels 3 and 4 of Bloom's taxonomy), personalized online homework and handwritten homework fill the role. The initial experiment with Sapling Learning's personalized online homework was published previously.[6] In summary, the students using Sapling earned consistently and statistically significant higher

quiz and exam scores, leading to a much lower fail rate for the course compared to students only completing textbook homework. The improved student achievement related to online homework led to adoption of this technology for the two more recent offerings of the course. Most of the online homework problems are as rigorous as the textbook (*e.g.*, multiple units, multiple-part problems). The personalization of the problems comes from rolling numbers within the problem statement. Thus, the concepts and problem-solving skills are the same from student to student but the numerical answers are different. Students were allowed to work in groups on the online homework, but each student needed to apply the correct balances to his or her set of numbers. No data was collected to quantify how many students worked in groups for any of the homework types. Most of the Sapling problems include hints to help students start or to correct errors. Also, some of the problems include full tutorial problems covering the similar concepts before attempting the problem for a grade.

A yeast ($CH_{1.66}N_{0.13}O_{0.40}$) is growing aerobically on arabinose ($C_5H_{10}O_5$) and ammonium hydroxide (NH_4OH) with a respiratory quotient (c/b) of 1.4. The reaction is:

$a\ C_5H_{10}O_5 + b\ O_2 + c\ NH_4OH \rightarrow d\ CH_{1.66}N_{0.13}O_{0.40} + e\ CO_2 + f\ H_2O$

Assume 1 mole of yeast as the basis. What is e?

- ○ 0.853
- ○ 0.299
- ○ 0.974
- ○ 0.411

Figure 2. *Example of a multiple-choice quiz problem based on content in the BioEMB.*

Problem sets done with paper and pencil are the third type of homework. Each year fewer problems are taken from the textbook to minimize the amount of rote copying of the solutions manual, which was discussed earlier. Alternate problems and solutions exist without a huge time commitment by the instructor or teaching assistants. Textbook problems with different numbers require work beyond copying the solutions manual. Rolling numbers is trivial in simpler cases (*e.g.*, non-reacting systems) and strongly constrained in others (*e.g.*, vapor-liquid equilibrium). Other sources include problems from other textbooks, the BioEMB database, and old quiz and exam questions. Doing some problems with pencil and paper each week is the best way to simulate quiz and exam situations for the students. While final numeric answers are given on some of the paper homework problems, focus in grading is placed on the problem-solving technique and correct balances, which is also how exams are graded.

While traditional textbook homework is graded within a week of completion (by undergraduate graders in this case), the short quizzes and online homework allow for just-in-time feedback. Both Blackboard's course management software and Sapling's online homework instantly tabulate individual and aggregate grades for evaluation. Both systems tabulate class averages for each problem while Sapling also produces a matrix with varying colors to represent the number of attempts the students needed on a specific problem. On Sapling, the average score is not always the best representation of the class's performance. Students who do not persist to the correct answer receive no credit for the problem (a very small fraction of the class). Distinguishing between the class needing several attempts on average to complete a problem and a low average skewed by a number of students giving up or not attempting a problem is data available for the instructor's professional judgment.

Two of the three class meetings begin by addressing one or more sticking points from the most recent homework assignment (due two hours before class begins). The JITT exercises last from 2 to 10 minutes. For example, a short lecture reviews and reinforces unclear concepts identified in the homework. Alternatively, active problem solving has included re-doing the most difficult problem in their groups, isolating one part of a problem for discussion and resolution, or assigning another problem covering the concept as the problem with the low score. Overall, online tools provide feedback to the instructor instantly that can help keep the students focused on the most important topics in the course. The JITT exercises need additional prep time for the instructor, which is not very difficult if the instructor has taught the course before. The assessment of the JITT exercises and homework is included in the next section.

ASSESSMENT

Homework, quizzes, and exams contribute to the grades earned by students in the class. In addition, formal and informal student surveys provide a second perspective on the multiple homework format and JITT. First, the grades for the three types of homework are aggregated into a single portion of the course graded (~15%). The average grades for homework are generally high (~90%) for the students who complete all of the problems. Next, in-class quizzes—approximately 10—given over the course of a semester provide a means to simulate the exam environment with a problem similar to exam problems. These quizzes take 10 minutes for vocabulary to 25 minutes for longer problems such as reaction with recycle problems. Some quizzes are announced while others are not, to encourage consistent studying of the course material (*i.e.*, avoid cramming before exams). On average, the students earn ~75% on the quizzes. While the majority of the students' effort for

the class is on homework and the 10 quizzes, exams make up the majority of the student's course grade.

The timing and frequency of major exams are especially important in the material and energy balances course. As pointed out previously,[2] the course starts out deceptively simple (*e.g.*, units, density) and quickly builds into multi-unit problems that do not always have an obvious place to start solving. During the previous four years, either two or three preliminary exams preceded a cumulative final exam. In years using the two-exam format, students covered the first four chapters of Felder and Rousseau before the first preliminary exam and the first eight chapters before the second preliminary exam. At the time, the logic of covering four chapters of material and then giving an exam seemed correct and in line with the previous deliveries of the course. In 2009, however, more than 75% of the class earned less than 60 out of 100 and a number of students dropped the course as a result. The main feedback from the students was that the difficulty of the material, specifically reaction-recycle problems, was greater than other sophomore-year courses (*e.g.*, math or chemistry). It was decided that overwhelming students in their first exam in their chosen major is not the best way to encourage students to enjoy the chemical engineering profession.

Further, the two-exam format with so many low scores required a curve, and students thought their grades were somewhat arbitrary. Thus, the next year (2010) the three-exam format was adopted and the distribution of material changed. The first preliminary exam covered the first three chapters (*i.e.*, no reacting systems), the second preliminary exam emphasized reaction systems and vapor liquid equilibrium (Chapters 4 through 6), and the final preliminary exam focused on energy balances (Chapters 7 through 9).

All exams are cumulative but emphasize the most recent material. In 2010, it turned out that the first exam provided a false sense of confidence, *i.e.*, an exam without reacting systems was trivial (over 91% average). The parsing of the second and third exam materials gave sensible averages (mid 60s to mid 70s). Therefore, as a further refinement in 2011 the additional material was covered before the first exam, namely single-unit reacting systems (the first part of Chapter 4). The results for 2011 and 2012 showed this new timing for the first exam as optimal with averages of 78 and 74, respectively. While a fraction of the class still earns a failing score on the first exam, the exam is representative of the rigor of the rest of the course and curriculum. As a side note, the ABET continuous improvement forms were used as a way to build this knowledge related to the exam scores.

Overall, course grades and the number of students earning a C or higher in the course have improved in recent years (Table 1). While the author's university teaching evaluations have fallen below the university average for the large course sections the last two years, student learning has improved by another metric. The number of students failing chemical engineering courses the next semester, namely thermodynamics and fluid mechanics, decreased to a four-year low after the Fall 2011 semester (the most recently available data). While course grades are not a standardized metric for engineering education researchers, trends can demonstrate the utility of the teaching strategies discussed earlier.

Online homework was shown to have a significant impact on student achievement when two control sections of the course were compared to one using online homework from Sapling Learning in addition to textbook homework.[6] The success of the online homework in 2010 led to its universal adoption during the past two offerings. Grades, although an incomplete metric, show a measurable improvement since the adoption of online homework for the course (Table 2). In addition to the dramatic shrinking of students earning an F grade in the course, the percentage of students withdrawing from the course also decreased (*i.e.*, from 7.5% to 6.5% of the total enrollment). The results are statistically significant ($p<0.0001$) and consistent with respect to a higher percentage of students earning the C or higher grade needed to enroll in the junior courses. In addition, student surveys beyond the university course evaluations provide insights into which techniques the students feel are helpful.

Three student surveys have been administered during the last two offerings of the course, *i.e.*, online homework, just-in-time teaching, and YouTube Fridays. YouTube survey results are covered elsewhere.[22-24] Surveys related to online homework show a number of interesting trends. During its first introduction in 2010, the students preferred the textbook homework (Table 3), with respect to their perception of gaining understanding and "liking." Online homework and Sapling Learning were unfamiliar to most of the students in 2010, outside of freshman physics (*i.e.*, LON-capa[30]); however,

TABLE 2
Grades earned when using online homework or not during the last four years.

Condition and Years[1]	% students earning grade					Average course GPA	no. of students	%C or better
	A	B	C	D	F			
With Online Homework	23	29	30	12	5.5	2.52	345	82
Without Online Homework	17	20	33	12	17	2.08	196	70

1 With Online Homework occurred for some students in 2010 and all students in 2011 and 2012. Without Online Homework occurred for all students in 2009 and some students in 2010.

TABLE 3
Student survey responses to four questions related to online homework.

% Strongly Agree/Agree	2010	2011	2012
Online homework helps me understand the course concepts and topics.	85	96	95
Textbook homework helps me understand the course concepts and topics.	92	84	92
I like doing Online homeworks.	50	75	60
I like doing Textbook homeworks.	65	42	52

Note: n=52 students for 2010, 134 students for 2011, and 123 students for 2012

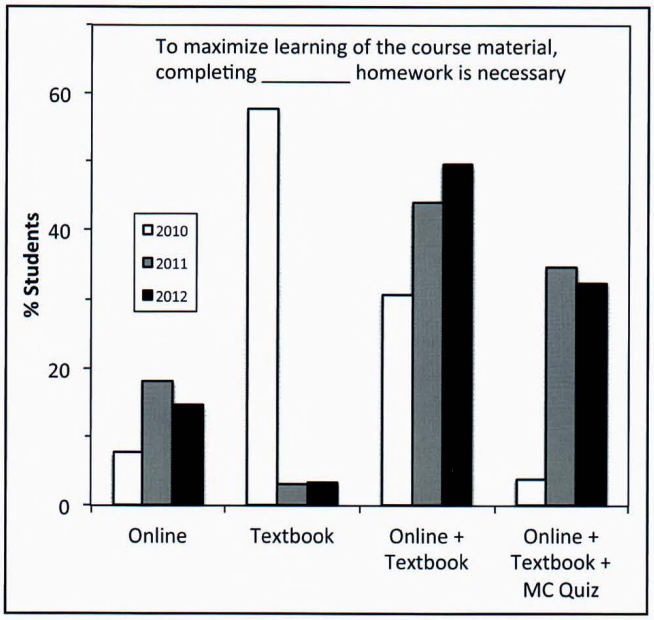


Figure 3. *Students' preferences on homework type(s) over the last three years. The n-values for each year are included with Table 3.*

online homework is becoming a more standard tool with use in organic chemistry, mechanics, and other courses across campus during the last few years. In the two subsequent years, students scored online homework higher than textbook homework on both questions. The category "understanding course concepts from online homework" received almost unanimous response during 2011 and 2012.

Another survey question probed the homework type or types that students perceived help them learn the course material. Textbook homework as a singular homework type received a majority of the responses in 2010, but has garnered only 3% of the response in the two most recent offerings.

To summarize, both familiarity with online homework and a smaller number of glitches with the online homework system likely led to the very favorable survey results over the last two years. Additionally, the vast majority (~80%) students in 2011 and 2012 believe that multiple types of homework help maximize their learning.

The final student survey probed the students' feedback on just-in-time teaching. As discussed earlier, multiple-choice quizzes and online homework provided immediate results to the instructor, which were acted upon to adjust the course content to the current group of students. Responses from 2011 and 2012 were averaged since the students responded with the same level of agreement (*i.e.*, within 3%). First, the immediate feedback from the homework resonated with the majority of the students (Figure 3). The students agreed that the JITT process gave them a means to be an active participant in class and was an effective use of class time. Students clearly understand that the instructor is aware of their strengths and weaknesses as well as not just delivering the same lecture as every previous year. The instructor taking class time to address students' concerns and deficiencies in real time (*i.e.*, not just in the exam review weeks later) is appreciated. Finally, more than 86% of students liked reexamining difficult course material during the JITT exercises (see Figure 4, next page). Focusing class time on the most important material has always been an instructor's prerogative, but now the instructor determines some of that important material from the responses of the students via online tools. The compromise on using class time for JITT exercises has been removing some introductory lecture material from class (*e.g.*, definitions). Overall, implementing JITT should become more common as more online tools are developed and available to faculty.

CONCLUSION

A number of techniques for delivery of a material and energy balances course have been explored and several items optimized over the last four years teaching the course. First, student engagement is achieved even at large class sizes by using multiple instructors—corroborating findings in other, non-engineering disciplines. Active-learning techniques, including short problem-solving periods in teams, problems based on YouTube videos, and JITT exercises, keep students' attention by varying the activity every 10 to 15 minutes. Next, a move away from textbook-based homework was necessary to avoid rote copying of the solutions manual that is available via a simple web search.

A combination of homework types has proven successful in engaging students several times per week in the course material. The implementation of Sapling Learning's online homework has allowed self-directed and personalized problem solving as well as the ability to deliver just-in-time feedback to the class (*i.e.*, only hours after students complete the assignment). Traditional paper and pencil homework and multiple-choice quizzes round out the homework assignments each week, and the quizzes also allow JITT feedback. Overall, JITT exercises received positive feedback from student surveys.

Individual exams and surveys provided assessment of the changes to the course. Timing of the first of three preliminary exams is critical to provide a fair assessment and minimize the students withdrawing from the course and likely changing majors. Student surveys show a strong preference (~80%) for multiple types of homework, especially online homework, to maximize their learning. In total, more active and self-directed tools with immediate feedback are needed to enhance the engineering education community in the near future.

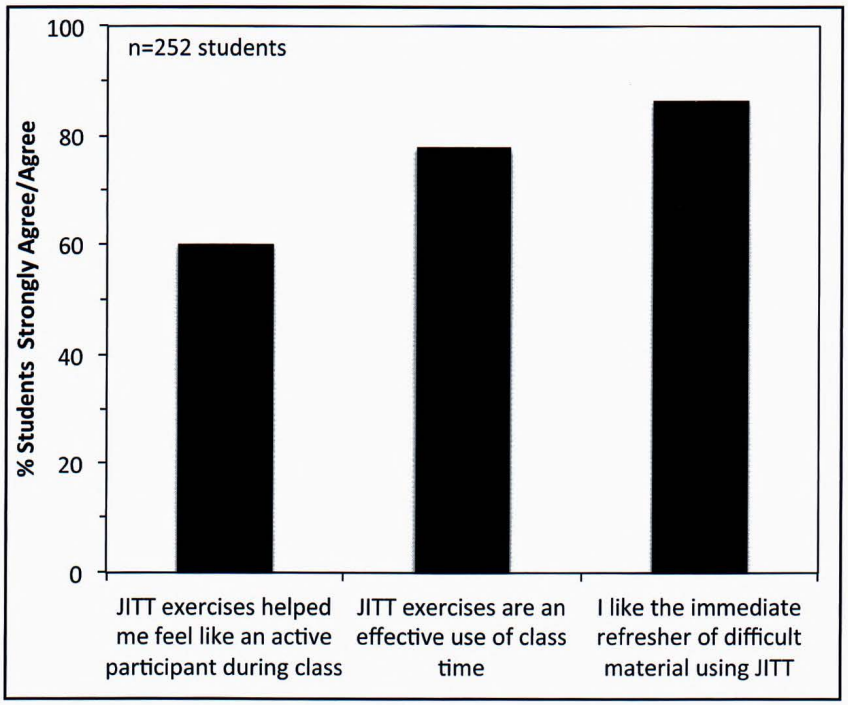


Figure 4. *Percentage of students who responded "agree" or "strongly agree" to three statements related to Just-In-Time Teaching exercises. Data are averages from 2011 and 2012.*

ACKNOWLEDGMENTS

The author thanks Theresa Nottoli for data entry from the paper surveys. Partial support from the National Science Foundation through CBET-0968042 is acknowledged.

REFERENCES

1. Felder, R.M., "Knowledge Structure of the Stoichiometry Course," *Chem. Eng. Ed.*, **27**, 92 (1993)
2. Felder, R.M., "Stoichiometry Without Tears," *Chem. Eng. Ed.*, **24**, 188 (1990)
3. Bullard, L.G., and R.M. Felder, "A Student-Centered Approach to Teaching Material and Energy Balances 2. Course Delivery and Assessment," *Chem. Eng. Ed.*, **41**, 167 (2007)
4. Silverstein, D.L., L.G. Bullard, and M.A. Vigeant, "How We Teach: Material and Energy Balances," Proceedings of the 2012 ASEE Conference 2012, AC 2012–3583
5. Keith, J.M., D.L. Silverstein, and D.P. Visco Jr., "Ideas to Consider for New Chemical Engineering Educators: Part 1 (Courses Offered Earlier in the Curriculum)," *Chem. Eng. Ed.*, **43**, 207 (2009)
6. Liberatore, M.W., "Improved Student Achievement Using Personalized Online Homework for a Course in Material and Energy Balances," *Chem. Eng. Ed.*, **45**, 184 (2011)
7. Faraji, S., "The Enhancement of Students' Learning in Both Lower Division and Upper Division Classes by a Quiz-Based Approach," *Chem. Eng. Ed.*, **46**, 213 (2012)
8. Felder, R.M., and R.W. Rousseau, *Elementary Principles of Chemical Processes*, 3rd Ed., Wiley (2005)
9. Walton, S.P., and A.P. Malefyt, "Increasing the Spirality of Material and Energy Balances," Proceedings of the 2012 ASEE Conference, AC2012–3359
10. Choi, C., "The Pull of Integrity," *Prism*, **18**, 28 (2009)
11. Hundhausen, C., P. Agarwal, R. Zollars, and A. Carter, "The Design and Experimental Evaluation of a Scaffolded Software Environment to Improve Engineering Students' Disciplinary Problem-Solving Skills," *J. Eng. Ed.*, **100**, 574 (2011)
12. *Just-In-Time Teaching: Across The Disciplines, Across The Academy*, Simkins, S. and M. Maier, eds. Stylus Publishing: Sterling, VA (2010)
13. Novak, G., A. Gavrin, W. Christian, and E. Patterson, *Just-In-Time Teaching: Blending Active Learning with Web Technology*, Prentice Hall, Upper Saddle River, NJ (1999)
14. Prince, M.J., and R.M. Felder, "Inductive Teaching and Learning Methods: Definitions, Comparisons, and Research Bases," *J. Eng. Ed.*, **95**, 123 (2006)
15. Falconer, J.L., "Use of ConcepTests and Instant Feedback in Thermodynamics," *Chem. Eng. Ed.*, **38**, 64 (2004)
16. Falconer, J.L., "Conceptests for a Chemical Engineering Thermodynamics Course," *Chem. Eng. Ed.*, **41**, 107 (2007)
17. Crouch, C.H., J. Watkins, A.P. Fagen, and E. Mazur, "Peer Instruction: Engaging Students One-on-One, All at Once," *Research-Based Reform of University Physics*, **1**, 40 (2007)
18. Digital Natives blog <http://www.digitalnative.org> (accessed July 12, 2010)
19. Palfrey, J., and U. Gasser, *Born Digital: Understand the First Generation of Digital Natives*, Basic Books (2008)
20. Tapscott, D., *Grown Up Digital: How the Net Generation Is Changing Your World*, McGraw-Hill (2009)
21. Koretsky, M. and B. Brooks, Student Attitudes in the Transition to an Active Learning Technology," *Chem. Eng. Ed.*, **46**, 289 (2012)
22. Liberatore, M.W., "YouTube Fridays: Engaging the Net Generation in 5 Minutes a Week," *Chem. Eng. Ed.*, **44**, 215 (2010)
23. Liberatore, M.W., C.R. Vestal, and A.M. Herring, "YouTube Fridays: Student-Led Development of Engineering Estimate Problems," *Advances in Eng. Ed.*, **3**, 1 (2012)
24. Liberatore, M.W., D. Marr, A.M. Herring, and J.D. Way, "Student-Created Homework Problems Based on YouTube Videos," *Chem. Eng. Ed.*, **46**(2), 122 (2013)
25. Prince, M., "Does Active Learning Work? A Review of the Research," *J. Eng. Ed.*, **93**, 223 (2004)
26. Prather, E., A. Rudolph, G. Brissenden, "Using Research to Bring Interactive Learning Strategies into General Education Mega-Courses," *Peer Review*, **13** (2011)
27. Liberatore, M.W., "Problem Solving in 12 Steps For Introductory Thermodynamics," *Chem. Eng. Ed.*, **45**, 0 (2011)
28. Liberatore, M.W., Rheology of Complex Fluids Laboratory Home Page, <http://rheology.mines.edu/> (accessed November 2012)
29. Komives, C., M. Prince, E. Fernandez, and R. Balcarcel, "Integration of Biological Applications into the Core Undergraduate Curriculum: A Practical Strategy," *Chem. Eng. Ed.*, **45**, 39 (2011)
30. Kortemeyer, G., E. Kashy, W. Benenson, and W. Bauer, "Experiences Using The Open-Source Learning Content Management and Assessment System LON-CAPA in Introductory Physics Courses," *Amer. J. Physics*, **76**, 438 (2008) ❐

COMPARISON BETWEEN LINEAR AND NONLINEAR REGRESSION

In a Laboratory Heat Transfer Experiment

Carine Messias Gonçalves,[1] Marcio Schwaab,[1] and José Carlos Pinto[2]
1 – Universidade Federal de Santa Maria, Cidade Universitária • Santa Maria, RS, 97105-900, Brazil
2 – Universidade Federal do Rio de Janeiro, Cidade Universitária • Rio de Janeiro, RJ, 21941-972, Brazil

The estimation of parameters from experimental data is a very common practice in teaching and research laboratories in chemical engineering and related fields. Data analysis and estimation of model parameters are usually performed without the required statistical accuracy, however, making the interpretation of obtained results more difficult and leading to erroneous and/or ambiguous parameter estimates.

As the mathematical models used to represent chemical processes are generally nonlinear, estimation of model parameters can only be performed with the help of numerical procedures. For this reason, a very common practice consists of rewriting the model in a linearized form through manipulation of the original measured values in order to facilitate the mathematical treatment of the data and allow for analytical analysis.

In a laboratory lesson about transport phenomena, interpretation of the data collected by students is usually performed through a linearized version of nonlinear models. Also, for the students this procedure had become the only way to perform this analysis. In some cases where linearization of the model is not possible, sometimes the students believe that it is not possible to perform the data analysis. In the educational literature there are some works where nonlinear regression is introduced to students, usually through the use of the commercial spreadsheet softwares.[1,2] In a paper by Fahidy,[3] the use of statistical-based procedures in an undergraduate course is presented. Its importance in many aspects and subjects of chemical engineering education and research is discussed. Also, the problem associated with the misuse of linearized models instead of nonlinear ones is briefly addressed.

Unfortunately, even in the scientific literature the use of linearized models is still very common. Although this type of manipulation of model equations is not necessary nowadays, given the impressive development and availability of computer resources, this procedure still finds widespread use for estimation of parameters of the Arrhenius[4-6] and Langmuir equations,[7,8] among many others. Linearization of the original nonlinear model leads to estimation of parameters that are different from those obtained when the original nonlinear nature of the model is preserved, however, as a consequence of the statistically biased parameters that are estimated, as pointed out by Fahidy.[3]

One of the criticisms concerning linearization of a nonlinear model is related to the change in the error structure of the dependent variable,[3,7] since if the variance of the original variable is constant along the experimental conditions, the variance transformed variable (usually the logarithm or reciprocal of the original variable) is not constant, invalidating the use of the least squares function. In fact, nonlinear models

Carine Messias Gonçalves *received her B.S. in chemical engineering in 2011 at the Federal University of Santa Maria, Brazil. Her interests are mathematical modeling and parameter estimation of chemical processes.*

Marcio Schwaab *earned chemical engineering degrees from State University of Maringá (B.S., 2002), and Federal University of Rio de Janeiro (M.Sc. 2005, D.Sc. 2007). He is a professor in the Chemical Engineering Department and Process Engineering Graduate Program of the Federal University of Santa Maria. His research interests are statistical analysis of experimental data, mathematical modeling, catalysis, and reaction kinetics.*

José Carlos Pinto *earned degrees in chemical engineering from the Federal University of Bahia (B.S., 1985) and the Federal University of Rio de Janeiro (M.Sc. 1987 and Ph.D. 1991). He is a professor in the Chemical Engineering Graduate Program of Federal University of Rio de Janeiro and is a permanent professor of the Graduate Program in Chemistry of the Military Engineering Institute. His focus is on general chemical reactors, with particular emphasis in the area of modeling, simulation, and control of polymerization systems.*

are linearized not because of the structure of the error, but to avoid difficulties in numerically obtaining nonlinear least-squares estimates, and to permit graphing a straight line, as pointed out by Harrison and Katti.[8]

Furthermore, it is not only the heteroscedasticity of the variance of the dependent variable that invalidates the use of the least squares function. According to Bard,[9] in the 19th Century Gauss had already observed that minimization of the least squares function leads to maximization of the probability of finding the experimental results, when the experimental errors are normally distributed around the values predicted by the mathematical model. That is, the least squares function should only be used when the experimental errors of the measured data are distributed normally. This observation is also in accordance with the maximum likelihood principle.[9,10] For this reason, it is important to determine the probability function distribution of the experimental errors, in order to guarantee the statistical basis of the parameter estimation procedure. Unfortunately, this does not constitute an easy task, as it is usually necessary to obtain a large number of replicates, making the experimentation time and cost very high.

In our opinion, in order to consolidate nonlinear regression in the scientific literature, it is necessary to begin with the insertion of statistically based procedures in the undergraduate courses of chemical engineering, as pointed out by Fahidy.[3] And as put forth by Harley,[11] chemical engineering and statistics are sufficiently successful professions that they can support further development of statistical procedures for experimental data analysis.

To analyze and illustrate this important parameter estimation problem, in this paper the estimation of the heat transfer coefficient is performed in a simple heat transfer laboratory experiment of the undergraduate course. The experiment analyzed in the present work is simple, fast, and can be performed without any significant costs, allowing for execution of the replicates and permitting a statistical evaluation of the proposed parameter estimation procedures, based on the linearized and nonlinear models. The estimation of the convective heat transfer coefficient was performed with and without the linearization of the original nonlinear mathematical model. Obtained results are analyzed and compared to each other with the help of statistical tools in order to show the very significant differences of final parameter estimates and respective confidence regions obtained with the two analyzed procedures.

METHODOLOGY

Experimental

In this section, the experimental procedure usually performed by undergraduate students in the sixth semester of chemical engineering is presented. The experimental procedure consists of placing a cylindrical aluminum piece, initially maintained at 33 °C, inside a water bath with a volume equal to 4 L, kept at 87 °C, through a heated jacket. The cylindrical piece has height of 5.0 cm and diameter of 3.0 cm. Some relevant physical properties of aluminum are[12]: thermal conductivity of 236 $W.m^{-1}.K^{-1}$; density of 2702 $kg.m^{-3}$; and heat capacity of 896 $J.kg^{-1}.K^{-1}$. After immersion in the water bath, the temperature of the metal piece is measured with a K-type thermocouple at its center. As time goes on, the test-piece temperature increases and eventually becomes equal to the bath temperature. A chronometer is used to register the time. The time length of the experiments was equal to 180 s, although only the first 100 s were considered for parameter estimation (which was sufficient for the test piece to reach the bath temperature). The procedure was repeated 16 times in order to provide enough data for the statistical analysis. Since it is a simple experiment and many more replications could be easily performed, the number of replications was kept as low as possible while still allowing observation of differences in the probability distributions of the nonlinear and linear procedures, since executing a very high number of replications is time and/or cost prohibitive in a general case.

Mathematical Development

Temperatures inside the test piece are assumed to be homogeneous. This assumption is supported by the fact that heat transfer by conduction in a small metal piece is much faster than heat transfer by convection from the liquid phase to the metal surface. The validity of this assumption can be formally verified with the Biot number, which represents the ratio between the external heat transfer resistance (fluid) and the internal heat transfer resistance (solid), as

$$Bi = \frac{h \cdot L}{k} \tag{1}$$

where Bi is the Biot number, h is the convective heat transfer coefficient (fluid), k is the thermal conductivity of the solid, and L is a characteristic dimension of the solid (for instance, the ratio between the volume and surface area of the cylindrical aluminum piece). According to the heat transfer textbook of Kreith and Bohn,[12] when Bi is smaller than 0.1, the convective heat transport can be regarded as very small, as compared to the thermal conduction in the solid, so that the heat transfer is controlled by convection. In these cases, it becomes reasonable to assume that the temperature profiles are homogeneous inside the solid, as the heat transported through the surface is quickly distributed throughout the solid volume. It is important to notice that for all estimated values of h the validity of this assumption was verified through Biot number computation.

Further, due to high water bath volume, compared with the volume of the cylindrical aluminum piece, the decrease in the temperature of the water bath due to the insertion of a cold piece inside it is lower than 0.1 °C, and can be clearly disregarded.

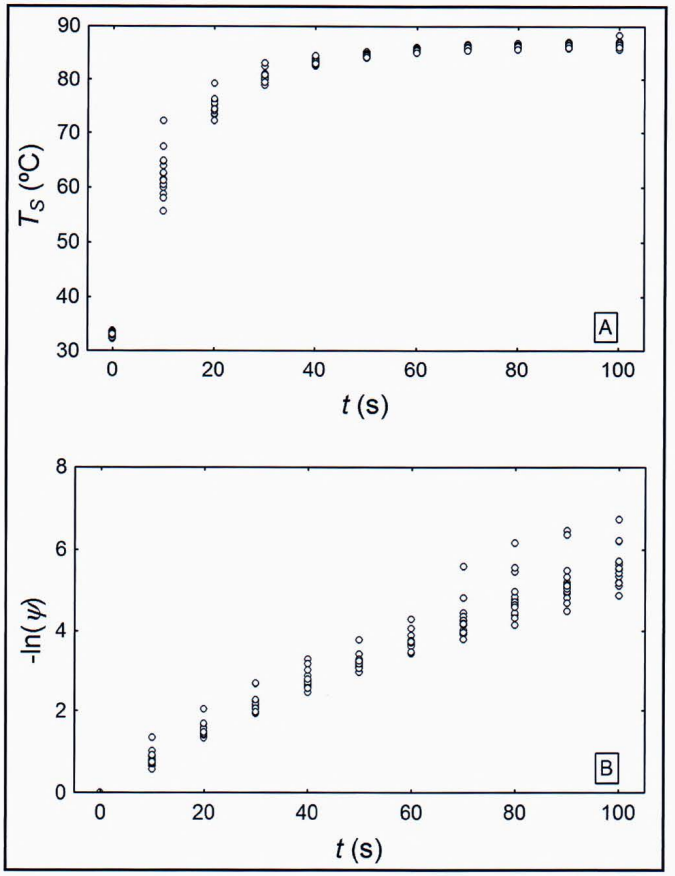


Figure 1. *Measured experimental T_S values (A) and computed "experimental" -ln(ψ) values (B) as a function of time.*

Based on the previous remarks, the energy balance of the solid can be described as:

$$\rho \cdot V \cdot C_p \cdot \frac{dT_s}{dt} = -h \cdot A \cdot (T_s - T_\infty) \tag{2}$$

where ρ is the solid density, V is the solid volume, C_p is the heat capacity and T_S is the solid temperature, h is the heat transfer coefficient, A is the external surface area of the solid piece, and T_∞ is the fluid temperature far from the solid piece.

Solution of Eq. (2) is presented in Eq. (3), where T_{S0} is the initial solid temperature and α is defined in Eq. (4).

$$T_s = T_\infty + (T_{S0} - T_\infty) \cdot \exp(-\alpha \cdot t) \tag{3}$$

$$\alpha = \frac{h \cdot A}{\rho \cdot V \cdot C_p} \tag{4}$$

Eq. (3) can be converted into a linear form presented in Eq. (5), where ψ is a dimensionless variable defined in Eq. (6).

$$-\ln(\psi) = \alpha \cdot t \tag{5}$$

$$\psi = (T_s - T_\infty)/(T_{S0} - T_\infty) \tag{6}$$

The mathematical models described by Eqs. (3) and (5) are exactly the same, but lead to different parameter estimation problems. For the mathematical model written in the linear form [Eq. (5)], the proposed parameter estimation procedure is based on a simple linear regression that minimizes the least squares function:

$$S = \sum_{i=1}^{N} \left[\ln(\psi_i^e) - \ln(\psi_i^m) \right]^2 \tag{7}$$

where i indicates the experimental measurement at time t_i, N is the number of measurements, "e" represents the experimental values and "m" represents the values predicted by the model. As the model is linear, minimization of Eq. (7) leads to an analytical solution, and the value of α can be calculated as:

$$\alpha = \frac{\sum_{i=1}^{N} -t_i \cdot \ln(\psi_i^e)}{\sum_{i=1}^{N} (t_i)^2} \tag{8}$$

This is the procedure commonly used to obtain the value of the parameter h [which is calculated from the value of α, using Eq. (4)]. Nevertheless, the minimization of the least squares function defined in Eq. (7) takes into consideration the square of the differences between the values of $-\ln(\psi)$, which is not the real experimental measurement. The goal of the parameter estimation procedure should be finding the parameter values that allow for good prediction of the observed experimental variables. In this problem the value observed experimentally is the solid temperature T_S and not $-\ln(\psi)$ So the least squares function should be written as:

$$S = \sum_{i=1}^{N} (T_{Si}^e - T_{Si}^m)^2 \tag{9}$$

and the nonlinear form of the model, as defined in Eq. (3), should be used. In this case, it is not possible to obtain an analytical solution for α (and consequently h) and the use of a numerical procedure becomes necessary if one intends to obtain the point of minimum of Eq. (9).

It must be noted that, as the relationship between T_S and $-\ln(\psi)$ is nonlinear, the minimization of the sum of the squares defined in Eq. (7) leads to a result that is different from the result obtained when minimization of the sum of the squares defined in Eq. (9) is performed. The selection between the mathematical form of the model, linearized or nonlinear, and thereafter, between the form of the least squares function, using Eq. (7) or Eq. (9), should be made on statistical grounds.

RESULTS

Statistical analysis of data

Figures 1A and 1B presents the experimental data obtained for 16 replicates.

These data were easily obtained by an undergraduate

student, following the experimental procedure usually employed during the laboratory lessons. As one can observe, experimental measurements are scattered to some extent, as always. Data points were collected every 10 seconds for statistical analyses.

An initial contradiction appears when comparing the experimental errors between the measured variable T_S and the transformed variable $-\ln(\psi)$, as shown in Figures 1A and 1B. The real experimental data T_S seem to be more scattered at the beginning of the experiment in Figure 1A; as time increases, data fluctuation decreases significantly, since the system achieves the thermal equilibrium and the only source of fluctuation is the thermocouple measurement noise, since fluctuations due the reproducibility of the heat transfer experiment are only important in the transient phase of the experiment. The more important error source in the beginning of the experiment is related to disturbance of the static bath due to insertion of the cylindrical body. Although the body was always inserted carefully into the static bath, it is virtually impossible to reproduce this procedure and it is for this reason that the experimental data is more scattered at low time values. Otherwise, the variable $-\ln(\psi)$ seems to be more scattered at the end of the experiment, even when the system achieves the thermal equilibrium, as shown in Figure 1B. The behavior of the experimental fluctuations can be explained with the help of standard error propagation analysis. When a variable y is calculated as a function of a second variable x, which is subject to measurement errors, the variance of y can be calculated as[3,9,10]:

$$\sigma_y^2(x) = \left(\frac{\partial y}{\partial x}\right)^2 \sigma_x^2 + \sigma_{ym}^2 \qquad (10)$$

where the first term on the right-hand side accounts for the variability of x and the second term accounts for the variability of the y measurement device. Considering the nonlinear model defined in Eq. (3), which describes how T_S changes as a function of time t, the total variance of T_S can be calculated as:

$$\sigma_{T_S}^2(t) = \left[(T_{S0} - T_\infty)\alpha \exp(-\alpha t)\right]^2 \sigma_t^2 + \sigma_{T_S m}^2 \qquad (11)$$

Eq. (11) makes clear that, as time increases, the variance of T_S diminishes exponentially and approaches the variance of the measurement device $\sigma_{T_S M}^2$, as shown in Figure 1A. On the other hand, in order to analyze the variance of $-\ln(\psi)$, it is necessary to acknowledge that:

$$-\ln(\psi) = -\ln\left[(T_S - T_\infty)/(T_{S0} - T_\infty)\right] \qquad (12)$$

so that:

$$\sigma_{-\ln(\psi)}(T_S) = \left(\frac{1}{T_S - T_\infty}\right)^2 \sigma_{T_S}^2 \qquad (13)$$

As $\sigma_{T_S}^2$ approaches a constant value (thermocouple noise) and T_S approaches T_∞ when the time increases, the total variance of $-\ln(\psi)$ increases continuously with time (and goes to infinity!), as shown in Figure 1B. Eqs. (11) and (13) are very interesting because they explain the behavior observed in Figure 1A and 1B and also prove that the original and the transformed variables can present completely distinct statistical behavior.

TABLE 1
Results of Shapiro-Wilk normality test.

Time (s)	p-value for $-\ln(\psi)$	p-value for Ts
0	0.0646	0.9190
10	0.0319	0.6729
20	0.0019	0.0786
30	0.0026	0.1234
40	0.0217	0.2854
50	0.0009	0.7872
60	0.0020	0.3442
70	0.0000	0.3384
80	0.1352	0.3741
90	0.0970	0.2232
100	0.5706	0.5606

The available experimental data were then analyzed to determine whether the normal distribution could be used to represent the fluctuations of experimental measurements. To do that, the normality test of Shapiro-Wilks[13] was used. This normality test was easily performed with the help of the Statitica® software,[14] which is available for students of the undergraduate course of the Federal University of Santa Maria, Brazil.

This normality test consists of determining if the normal distribution can be used to represent the distribution of data points in a particular data set, where measurement conditions are assumed to be the same and the data points represent the same experimental system. Sixteen replicates were carried out as similar experiments and both T_S and $-\ln(\psi)$ were submitted to the Shapiro-Wilks normality test. Obtained results are presented in Table 1 and Figures 2A to 2H. Table 1 reports the p-values obtained when the Shapiro-Wilks test is performed. When the p-value is lower than 0.05 (in the case of a 95% confidence level) the test indicates that the data cannot be represented by the normal distribution.

Figure 2, facing page. *Histograms and normal distribution fits for $-\ln(\psi)$ and T_S at: t =10 s for A and B; t =20 s for C and D; t =40 s for E and F; t =70 s for G and H.*

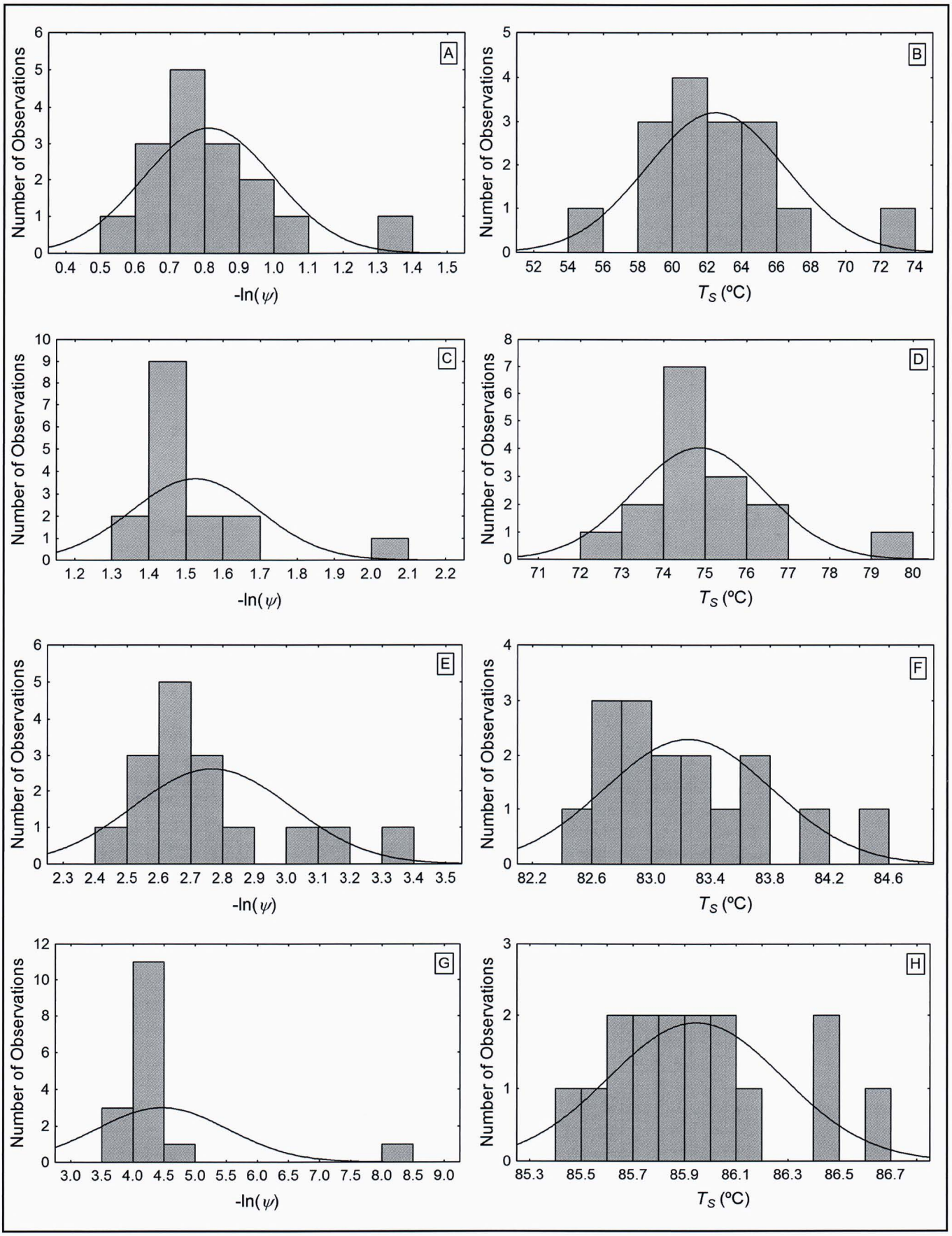

A
Number of Observations
-ln(ψ)
B
Number of Observations
T_S (ºC)
C
Number of Observations
-ln(ψ)
D
Number of Observations
T_S (ºC)
E
Number of Observations
-ln(ψ)
F
Number of Observations
T_S (ºC)
G
Number of Observations
-ln(ψ)
H
Number of Observations
T_S (ºC)

TABLE 2
Results of linear and nonlinear estimation of parameter h.

Experiment	Parameter Estimates h (kW/m².K)		Deviation (%)	Average Deviation of T_s	
	Linear	Non-linear		Linear	Non-linear
1	0.8031	1.2040	33.29	2.135	1.191
2	0.8641	1.1443	24.48	1.529	0.540
3	0.8227	0.9669	14.92	1.068	0.217
4	0.8077	1.1087	27.15	1.761	0.908
5	0.7696	1.0952	29.73	2.002	1.027
6	0.7423	0.9594	22.62	1.712	0.598
7	0.8302	1.0595	21.65	1.560	0.585
8	0.8275	1.1753	29.59	1.882	0.734
9	1.0671	1.6725	36.20	1.632	0.920
10	0.8359	1.0303	18.87	1.244	0.440
11	0.8629	0.9729	11.31	0.718	0.316
12	0.8620	0.9896	12.89	0.798	0.417
13	0.9187	1.0474	12.28	0.742	0.567
14	0.7856	0.9084	13.51	0.950	0.397
15	0.8203	0.9059	9.45	0.694	0.184
16	0.9696	0.9699	0.03	0.784	0.783
Mean	0.8493	1.0756	19.87	1.326	0.614

According to the p-values reported in Table 1 for variable $-\ln(\psi)$, only the data collected at sample times equal to 0, 80, 90, and 100 s could be represented by the normal distribution. In other words, the assumption of normal distribution of error measurements was not adequate for the majority of the observed data. It is important to note that the points where the normal assumption could be accepted were the ones placed in the beginning of the experiment (time equal to 0 s), when the heat transfer process had not started, and in the final part of the experiment (times equal to 80, 90, and 100 s), when the heat transfer process had reached the equilibrium condition. During most of the dynamic trajectory, the fluctuations of the variable $-\ln(\psi)$ could not be represented by the normal distribution, since the p-values were lower than 0.05. On the other hand, for variable T_s, fluctuations could be described by the normal distribution during the whole dynamic trajectories, since p-values of the Shapiro-Wilk test were always higher than 0.05. This clearly shows that the nonlinear transformation of T_s to $-\ln(\psi)$ changed the statistical significance of the analyzed measured data. Figures 2A to 2H show that the normal distribution fits to the obtained experimental replicates, used to perform the Shapiro-Wilk test. It can be seen that variable transformation caused magnification of some deviations from the average, also causing the formation of an asymmetric tailored distribution that cannot be well represented by the normal model.

Parameter estimation

According to the Shapiro-Wilk normality test, measurement fluctuations of variable T_s can be adequately described by the normal distribution, validating the use of the proposed nonlinear least squares function, as defined in Eq. (9). On the other hand, the Shapiro-Wilk normality test indicated that the least squares function should not be used for the linear fitting. Despite that, both linear and nonlinear approaches were used for estimation of parameter h in order to allow for comparison of final results. It must be emphasized that normality tests are almost never performed to support the use of least squares procedures in real problems, which can be regarded as a fundamental statistical weakness of most reported parameter estimation works. (As a matter of fact, as the variances of experimental measurements were not constant, more rigorous maximum-likelihood procedures should be used to perform the estimation of model parameters.[7,8,11] This was not done here in order to keep the presentation simple and because least-squares estimators are used more frequently to solve estimation problems.)

The linear parameter estimation procedure involved the use of the linear model defined in Eq. (5) and the objective function defined in Eq. (7). The nonlinear parameter estimation made use of the nonlinear model defined in Eq. (3) and the objective function defined in Eq. (9). Both linear and nonlinear regressions were performed with the help of the Statistica® software.[14] Table 2 shows the estimated parameters for each experiment for both linear and nonlinear procedures and also the relative deviations between the two obtained values (using the nonlinear result as reference). It can be observed that the average deviation between the two estimated parameters was close to 20 %, which can be regarded as a very significant difference. The highest difference was close to 36 % in Experiment 9, although in Experiment 16 the deviation between both parameter values was close to zero. In order to analyze why differences can be sometimes small and other times high, Figures 3A to 3D show linear and nonlinear fits for data obtained in Experiments 9 and 16. Table 2 also shows the average deviation between measured and calculated T_s values. In all experiments the average T_s deviations were smaller when the nonlinear procedure was adopted, showing the better prediction capability of the nonlinear procedure, as T_s was the real measured variable.

Comparing the fits presented in Figures 3A to 3D, it can be observed that for both linear and nonlinear approaches the quality of the fit is better when Experiment 16 is considered. To show this more clearly, Figures 4A and 4b show the residuals of the fits, obtained as the differences between the experimental and predicted solid temperatures. In Figure 4A, the fit obtained with the nonlinear procedure is much better

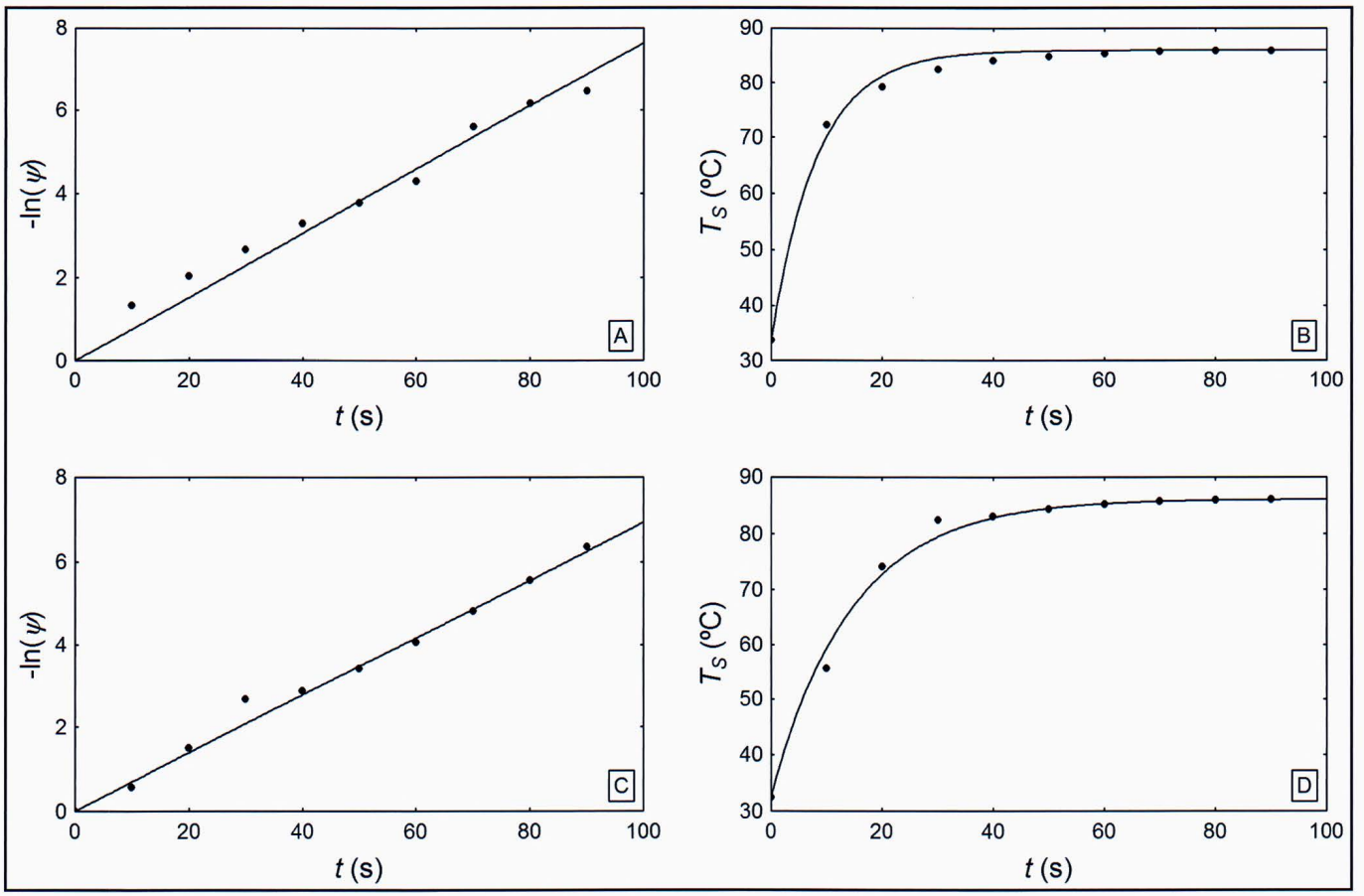


Figure 3. *Linear and nonlinear fits for Experiments 9 (A and B) and 16 (C and D).*

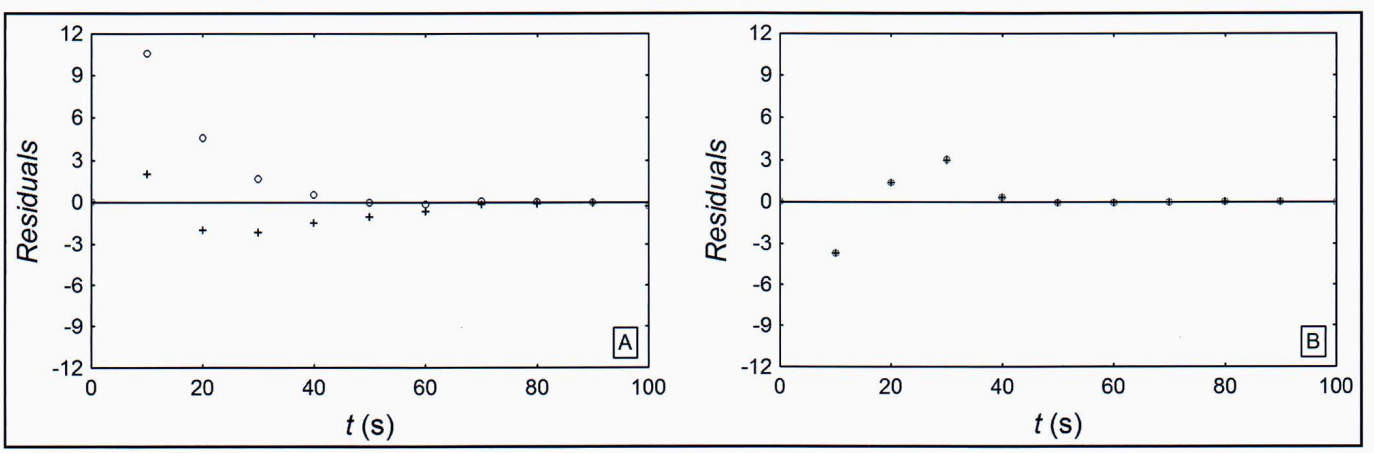


Figure 4. *Residuals between experimental and predicted temperatures for the linear fit (circles) and nonlinear fit (crosses) in Experiments 9 (A) and 16 (B).*

than the one obtained with the linear procedure. In Figure 4B, however, both fits are very similar, and the residuals are much smaller in Figure 4B than in Figure 4A. It can be concluded that both linear and nonlinear procedures lead to similar parameter estimates when the fits are very good; however, if the data presents some larger deviations that the model cannot predict with great precision, linear and nonlinear procedures can lead to very different parameter estimates.

It also must be pointed out that when undergraduate students encounter a result such as the one obtained in Experiment 16 they conclude that it does not matter if a linear or nonlinear regression is used, since the parameter estimate will be the same. And as the linear regression can be performed easily, it should be preferred. After showing the results for the sixteen runs and the normality tests, however, the undergraduate students can straightforwardly conclude that nonlinear regres-

sion must be used, avoiding model manipulation. At any rate, with the purpose of establishing the importance of a proper statistical analysis among undergraduate students, the following section is devoted to the computation of the parameter estimate deviations, showing students that together with its value, the parameter estimate must be always presented with its uncertainty, which assures the quality of the parameter estimate values.

Uncertainties of parameter estimates

Besides the analysis of the parameter values, it is also important to analyze the parameter uncertainties. As the experimental data are subject to measurement noise, the parameter values are also uncertain to some extent.[9,10] In order to calculate the confidence intervals of the obtained parameter estimates, the following equation can be used[10,15,16]:

$$S(h)=S(\hat{h})\left(1+\frac{NP}{N-NP}F^{\alpha}_{NP,N-NP}\right) \qquad (14)$$

where S is the objective function [Eqs. (7) or (9)], $\hat{h}$ is the estimated parameter value, NP is the number of estimated parameters (equal to 1 in this case), N is the number of experimental points (equal to 10 in this case), $F^{\alpha}_{NP,N-NP}$ is the Fisher probability distribution function with NP and N-NP degrees of freedom, and α is the confidence level. As a confidence level of 95% was assumed, $F^{\alpha}_{NP,N-NP}$ is equal to 4.9646 and Eq. (14) can be rewritten for the analyzed problem as:

$$S(h)=1.49646\cdot S(\hat{h}) \qquad (15)$$

Determination of the confidence intervals of parameter h requires determining the values of h that satisfy Eq. (15), remembering different objective function and h values were found for each particular data set. Table 3 presents the confidence limits of parameter h for each experiment.

It can be observed that the lower limit of parameter h estimated with the nonlinear procedure, except for Experiment 16, was always higher than the upper limit of parameter h estimated with the linear procedure, confirming that nonlinear and linear procedures generally lead to different parameter estimates. Further, although the estimated parameter values were similar for linear and nonlinear procedures in Experiment 16, the obtained confidence intervals were very different, showing that the results obtained with both procedures were not the same. It must also be noticed that the confidence intervals were not symmetric in the nonlinear case, meaning that the estimated parameter values were not placed at the center of the confidence interval and indicating that the uncertainties of the parameter estimates did not follow a normal distribution.

TABLE 3
Confidence limits of the parameter h for each experiment.

Exp	Linear		Nonlinear	
	h_{low}	h_{upp}	h_{low}	h_{upp}
1	0.7484	0.8579	1.0587	1.3835
2	0.8137	0.9145	1.0829	1.2112
3	0.7784	0.8669	0.9493	0.9851
4	0.7600	0.8553	1.0112	1.2217
5	0.7225	0.8167	0.9871	1.2228
6	0.6916	0.7932	0.9151	1.0070
7	0.7596	0.9007	1.0007	1.1237
8	0.7751	0.8800	1.0887	1.2732
9	1.0056	1.1284	1.4676	1.9306
10	0.7992	0.8727	0.9901	1.0731
11	0.8423	0.8835	0.9470	1.0001
12	0.8428	0.8814	0.9515	1.0298
13	0.8908	0.9468	0.9874	1.1132
14	0.7610	0.8103	0.8773	0.9412
15	0.7917	0.8490	0.8923	0.9198
16	0.9355	1.0036	0.8750	1.0810
Mean	0.8074	0.8913	1.0587	1.3835

CONCLUSION

In this paper a comparison was made between linear and nonlinear procedures used for regression of the convective heat transfer coefficient in a heat transfer problem, where a metal piece, initially at temperature T_{S0}, was placed in a thermostatic bath, kept at temperature T_{∞}. This procedure consists of an experiment usually found in many laboratory classes in the chemical engineering courses all over the world.

Application of the Shapiro-Wilk test showed that assumption of normal fluctuation was valid for the measured solid temperature values, T_S, but not for the transformed variable, $\ln(\psi)$, showing that variable transformation can change the statistical behavior of analyzed variables and make the use of least squares estimation procedures inappropriate. Analyses of 16 independent experiments showed that parameter values could present bias of up to 36%, when estimates obtained through regression of the transformed variable and of the originally measured temperatures were compared to each other. Further, analysis of model prediction residues showed that the nonlinear procedure could lead to much better representation of the measured T_S values. Particularly when the model deviations were small, fits obtained with the linear and nonlinear procedures were similar, although differences became evident when deviations increased because of the unavoidable measurement noise. Finally, it was also shown that the uncertainties of the obtained parameter estimates were sensitive to the adopted regression procedure, indicating that variable transformation should not be adopted when rigorous statistical analysis of obtained estimates is sought.

The proposed experiment, which can be easily performed in most chemical engineering laboratories, illustrates very

clearly the large number of problems that can arise when linearization of model structures is introduced into the quantitative analysis of measured data. It can be concluded that the use of linear regression procedures should be avoided when they are not supported by rigorous statistical arguments, since variable transformation can lead to biased and erroneous estimation of parameter values and respective parameter accuracies, as described by the confidence regions of the parameter estimates.

It is also important to report that this work has been used in the preparatory lessons for the laboratory experiment and assists new students in understanding the importance of the statistically based analysis of data. Most importantly, they can readily conclude that, despite the slightly higher computational effort, nonlinear regression must be preferred against the use linearized version of the nonlinear models.

Finally, besides learning the concepts regarding heat transfer process using a procedure described in this work, the undergraduate students become readily familiar with some statistical procedures and statistical software, which can help their future investigations as engineers or researchers.

ACKNOWLEDGMENT

The authors thank FIPE/UFSM for providing scholarships and for supporting this work.

REFERENCES

1. Machuca-Herrera, J.O., "Nonlinear curve fitting using spreadsheets," *J. Chem. Ed.*, **74**, 448 (1997)
2. Denton, P., "Analysis of first-order kinetics using Microsoft Excel Solver," *J. Chem. Ed.*, **77**, 1524 (2000)
3. Fahidy, T.Z., "An undergraduate course in applied probability and statistics," *Chem. Eng. Ed.*, **36**, 170 (2002)
4. Chen, N.H., and R. Aris, "Determination of Arrhenius constants by linear and nonlinear fitting," *AIChE J.*, **38,** 626 (1992)
5. Sundberg, R., "Statistical aspects on fitting the Arrhenius equation," *Chemom. Intell. Lab. Syst.*, **41,** 249 (1998)
6. Klicka, R., and L. Kubácek, "Statistical properties of linearization of the Arrhenius equation via the logarithmic transformation," *Chemom. Intell. Lab. Syst.*, **39,** 69 (1997)
7. Kumar, K.B., and S. Sivanisan, "Prediction of optimum sorption isotherm: Comparison of linear and non-linear method," *J. Hazard. Mater.*, **126,** 198 (2005)
8. Harrison, F., and S.K. Katti, "Hazards of linearization of Langmuir's model," *Chemom. Intell. Lab. Syst.*, **9,** 249 (1990)
9. Bard, Y., *Nonlinear Parameter Estimation,* Academic Press, New York (1974)
10. Schwaab, M., and J.C. Pinto, *Análise de Dados Experimentais. Vol 1: Fundamentos deEstatística e Estimação de Parâmetros*; e-Papers, Rio de Janeiro (2007)
11. Hartley, H.O., "Statistics as a science and as a profession," *J. Am. Stat. Assoc.*, **75** 1 (1980)
12. Kreith, F., and M.S. Bohn, *Principles of Heat Transfer*, 5th ed.; PWS Publishing Company; Boston (1997)
13. Thode Jr., H.C., *Testing for Normality*, Marcel Dekker Inc., New York, (2002)
14. StatSoft, Inc., STATISTICA (data analysis software system), version 8.0. <www.statsoft.com> (2007)
15. Bates, D.M., and D.G. Watts, *Nonlinear Regression Analysis and its Applications*, Wiley, New York (1988)
16. Schwaab, M., E.C. Biscaia Jr., J.L. Monteiro, and J.C. Pinto, "Nonlinear parameter estimation through particle swarm optimization," *Chem. Eng. Sci.*, **63** 1542 (2008) ❐

The object of this column is to enhance our readers' collections of interesting and novel problems in chemical engineering. We request problems that can be used to motivate student learning by presenting a particular principle in a new light, can be assigned as novel home problems, are suited for a collaborative learning environment, or demonstrate a cutting-edge application or principle. Manuscripts should not exceed 14 double-spaced pages and should be accompanied by the originals of any figures or photographs. Please submit them to Dr. Daina Briedis (e-mail: briedis@egr.msu.edu), Department of Chemical Engineering and Materials Science, Michigan State University, East Lansing, MI 48824-1226.

CONTINUOUS FEED AND BLEED ULTRAFILTRATION

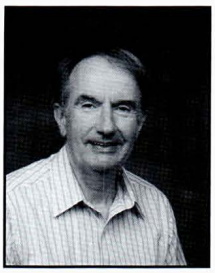
A Demonstration of the Advantages of the Modular Approach for Modeling Multi-Stage Processes

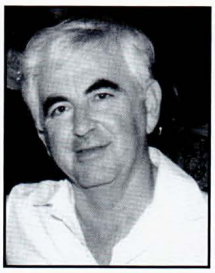
MICHAEL B. CUTLIP[1] AND MORDECHAI SHACHAM[2]
1 University of Connecticut • Storrs, CT 06269
2 Ben-Gurion University of the Negev • Beer-Sheva 84105, Israel

Multiple stage operations are widely used in separation processes. There are two commonly used approaches for modeling of multi-stage processes. The "simultaneous" approach involves modeling of the complete process (which includes all the stages) as one large set of equations. This approach is widely used for modeling of distillation columns and its main advantage is the high computational efficiency. In the "sequential modular" approach a model of a single stage (module) is prepared and tested separately. The complete multi-stage process is then constructed by tying together several modules by means of the material and energy flows between them. The advantages of this approach are that the model building is more straightforward; that the models are easier to construct, to follow, and to debug; and that the computer code can actually serve as problem documentation. Thus this approach is more adequate for educational use than the simultaneous approach.

An example presented by Foley[1] that concerns the design of a multi-stage ultrafiltration unit operated in a feed and bleed mode will be used to demonstrate the advantages of the "sequential modular" approach in the solution of various types of problems. This example is suitable for courses in separation processes, introduction to modeling and computation, and process and product design.

Michael B. Cutlip *is professor emeritus of the Chemical, Materials, and Biomolecular Engineering Department at the University of Connecticut and has served as department head and director of the university's Honors Program. He has B.Ch.E. and M.S. degrees from Ohio State and a Ph.D. from the University of Colorado. His current interests include the development of general software for numerical problem solving and application to chemical and biochemical engineering.*





Mordechai Shacham *is professor emeritus of the Department of Chemical Engineering at the Ben-Gurion University of the Negev in Israel. He received his B.Sc. and D.Sc. degrees from the Technion, Israel, Institute of Technology. His research interests include analysis, modeling and regression of data, applied numerical methods, and prediction and consistency analysis of physical properties.*

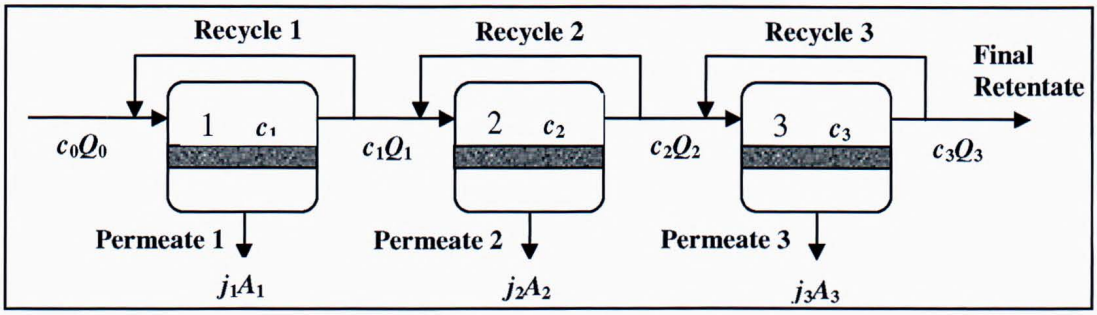


Figure 1. *Schematic plot of the Multi-stage Ultrafiltration System.*

PROBLEM BACKGROUND

Continuous concentration of a protein solution by multi-stage feed and bleed ultrafiltration

A typical 3-stage feed-and-bleed ultrafiltration process is shown in Figure 1. Fresh feed with a volumetric flow rate of Q_0 (m^3/s) and solute concentration of c_0 (g/L) is mixed with retentate (product stream) recycle from the first stage and enters the first membrane module. Some of the solvent (and possibly some of the solute) passes the membrane and exits the unit as permeate (filtrate). The concentrated product stream (with solid concentration of c_1 g/L) is partially recycled in order to increase the flow rate into the unit to ensure well-mixed conditions. The product (bleed) stream from the first unit is fed into the second stage with a volumetric flow rate of Q_1 (m^3/s).

Detailed discussion of the multi-stage ultrafiltration process, including the associated design equations, is provided, for example, by Seader and Henley.[2] Here the assumptions suggested by Foley[1] are used for simplification of the model. These assumptions are that 1) no solute passes the membrane (complete rejection), and 2) the gel polarization model applies. Thus the membrane is operating at the limiting flux (j, m/s) given by

$$j = k \ln \frac{c_g}{c_i} \tag{1}$$

where k is the mass transfer coefficient (m/s), c_g is the limiting or "gel" concentration (g/L), and c_i is the solute concentration in stage i. The solute balance on stage i (assuming complete rejection) yields

$$Q_i c_i = Q_{i-1} c_{i-1} \tag{2}$$

The total balance on the feed, retentate, and permeate streams of stage i can be written

$$f_i = Q_{i-1} - Q_i - jA_i \tag{3}$$

where A_i is the membrane area in stage i.

Eqs. (1), (2), and (3) represent a complete model of stage i. At the solution f_i must vanish ($f_i = 0$). One of the variables associated with stage i (say c_i, A_i, etc.) can be selected as unknown and values for the rest must be specified.

The sequential modular approach requires building the model of a single unit so that it can calculate the "output" variables (Q_i, c_i, and the permeate flow rate) if the input variables (Q_{i-1} and c_{i-1}) and the design parameters (k, c_g, and A_i) are specified. One possibility to carry out this calculation is to solve Eq. (2) for Q_i yielding

$$Q_i = Q_{i-1} c_{i-1} / c_i \tag{2A}$$

Introducing Eqs. (1) and (2A) into Eq. 3, and replacing the input variables and design parameters by their numerical values, yields a single nonlinear algebraic equation that can be solved for the unknown output variable c_i. The other output variable Q_i can be consequently calculated directly by solving Eq. (2A).

If all the input variables and design parameters are specified and the output variables need to be calculated, the problem is categorized as a "simulation problem." In a "design problem" some of the output variables are specified and the same number of input variables and/or design parameters need to be determined, so that the specification regarding the output variables is met. Adding an objective function that contains input variables and/or design parameters that need to be minimized to meet an economic objective, subject to constraints related to the output variables, constitutes an "optimization problem."

The different parts of the following problem statement are related to these three types of problems.

PROBLEM STATEMENT

The assignments and numerical data presented by Foley[1] are considered. A multistage feed-and-bleed ultrafiltration unit is used for concentrating a protein solution. Fresh feed enters the first stage at the rate of Q_0 = 1 L/min with solute (protein) concentration of c_0 = 10 g/L. Complete rejection can be assumed for the protein. The membrane is operating at the limiting flux with the mass transfer coefficient: k = $3.5 \cdot 10^{-6}$ m/s and the gel concentration c_g = 300 g/L.

a) Given that the membrane area in the first stage is A_1 = 2.7 m^2, calculate the product's outlet concentration: c_1 and flow rate: Q_1 from this stage.

b) A 3-stage system with equal membrane areas of A_i =0.9 m^2 is used to separate the protein solution. Calculate the

product's outlet concentrations and flow rates for the three stages (a simulation problem).

c) *Find the total membrane area of a three-stage ultrafiltration system that yields retentate concentration leaving the third stage of 100 g/L assuming equal membrane areas for the three stages (a design problem).*

d) *Repeat question (c) but this time allow for different membrane areas for the different stages so as to obtain the same final concentration but minimizing the total membrane area (an optimization problem).*

PROBLEM SOLUTION

Modeling a single stage using the sequential modular approach

Modeling a single stage can proceed following the algorithm outlined in the problem background section. Several available software packages can be used for solving the nonlinear algebraic equation of the single-stage model. The POLYMATH[3] software package was used for this purpose.

The input of part (a) of the problem into the POLYMATH software package is shown in Table 1. The POLYMATH program includes the code and comments (text that starts with the "#" sign and ends with the end of the line). The row numbers shown in Table 1 are not part of the program; they were added as references for the explanations that follow.

In the POLYMATH program, the equations and data are grouped into "model equations" [lines 1-4, Eqs. (1), (3), and (2A)], problem-specific data, including units (lines 6-11, including the input variable and design parameter values), and initial estimates for the unknown exit concentration. The POLYMATH software automatically orders the equations prior to solution. The solution with POLYMATH using this equation set was c_1 = 66.93 g/L and Q_1 = 0.15 L/min.

The program shown in Table 1 provides a clear, precise, and complete documentation of the problem and its mathematical model. Observe that there is actually no need to combine the three basic equations into one equation and this provides an easier-to-follow problem documentation. Combining the equations can also be a source of errors.

TABLE 1
POLYMATH program for the solution of Part (a) of the assignment

No.	Equation/ # Comment
1	#Model equations
2	j=k*ln(cg/c1) #Membrane Flux
3	Q1=c0*Q0/c1 #Complete Rejection of Protein
4	f(c1) = Q0-Q1-j*A #Overall Material Balance
5	
6	# Problem specific data
7	Q0=1/(60*1000) #m^3/s
8	k=3.5e-6 #m/s
9	c0=10 # g/L
10	A=2.7 # m^2
11	cg =300 # g/L
12	
13	# Initial estimates
14	c1(min)=20
15	c1(max)=100

Modeling the three-stage system using the sequential modular approach

The model used for the first stage can be used for the subsequent stages except that the outlet variables of the earlier stage become the inlet variables of the subsequent one and the design parameters need to be updated, if necessary. Thus, modeling the operation of three consecutive stages of the ultrafiltration system [Part (b) of the problem statement] involves writing the model equations that were used for the first stage,

TABLE 2
POLYMATH program for the solution of Part (b) of the assignment

No.	Equation/ # Comment
1	#Model equations
2	#First Stage
3	j1=k*ln(cg/c1) #Membrane Flux
4	Q1=c0*Q0/c1 #Complete Rejection of Protein
5	f(c1) = Q0-Q1-j1*A #Overall Material Balance
6	#Second Stage
7	j2=k*ln(cg/c2) #Membrane Flux
8	Q2=c1*Q1/c2 #Complete Rejection of Protein
9	f(c2)=Q1-Q2-j2*A #Overall Material Balance
10	#Third Stage
11	j3=k*ln(cg/c3) #Membrane Flux
12	Q3=c2*Q2/c3 #Complete Rejection of Protein
13	f(c3)=Q2-Q3-j3*A #Overall Material Balance
14	
15	#Problem specific data
16	Q0=1/(60*1000) #m^3/s
17	k=3.5e-6 #m/s
18	A=0.9 # m^2
19	c0=10 # g/L
20	cg =300 # g/L
21	
22	# Initial estimates
23	c1(0)=20
24	c2(0)=50
25	c3(0)=170

TABLE 3
Results summary for Parts (b), (c), and (d) of the multi-stage ultrafiltration problem

	Part (b)		Part (c)			Part (d)		
Stage No.	c_i (g/L)	Q_i (m^3/s)	A_i (m^2)	c_i (g/L)	Q_i (m^3/s)	A_i (m^2)	c_i (g/L)	Q_i (m^3/s)
1	20.34	0.492	0.712	17.4	0.575	0.947	22.14	0.452
2	56.07	0.178	0.712	37.7	0.265	0.505	49.73	0.201
3	163.45	0.061	0.712	100	0.100	0.567	100	0.100
Total			2.136			2.019		

	A	B	C	D	E	F
1	**POLYMATH NLE Migration Document**					
2		**Variable**	**Value**		***Polymath Equation***	***Comments***
3	Explicit Eqs	j1	9.1218E-06		*j1=k*ln(cg/c1)*	*Membrane Flux*
4		Q1	7.5266E-06		*Q1=c0*Q0/c1*	*Complete Rejection of Protein*
5		j2	6.2903E-06		*j2=k*ln(cg/c2)*	*Membrane Flux*
6		Q2	3.3516E-06		*Q2=c1*Q1/c2*	*Complete Rejection of Protein*
7		j3	3.8451E-06		*j3=k*ln(cg/c3)*	*Membrane Flux*
8		Q3	1.6667E-06		*Q3=c2*Q2/c3*	*Complete Rejection of Protein*
9		**At**	**2.01539045**		***At=A1+A2+A3***	***Objective function***
10		Q0	1.6667E-05		*Q0=1/(60*1000)*	*m^3/s*
11		k	0.0000035		*k=3.5e-6*	*m/s*
12		c0	10		*c0=10*	*g/L*
13		c3	100		*c3=100*	*g/L*
14		cg	300		*cg=300*	*g/L*
15		**A1**	**0.94676198**		*A1=0.7*	
16		**A2**	**0.50474175**		*A2=0.7*	
17	Implicit Vars	c1	22.1436941		*c1(0)=20*	*Overall Material Balance*
18		c2	49.7272272		*c2(0)=50*	*Overall Material Balance*
19		**A3**	**0.56388672**		*A3(0)=1*	*Overall Material Balance*
20	Implicit Eqs	f(c1)	5.0389E-07		*f(c1)=Q0-Q1-j1*A1*	
21		f(c2)	1E-06		*f(c2)=Q1-Q2-j2*A2*	
22		f(A3)	-4.833E-07		*f(A3)=Q2-Q3-j3*A3*	
23	**Sum of Squares:**		**1.4875E-12**		*F = f(c1)^2+f(c2)^2+f(A3)^2*	

Figure 2. *Excel Worksheet for the solution of Part (d) of the multi-stage ultrafiltration problem.*

for the second and third stage while changing the indices of the inlet and outlet streams and introducing equal $A_i = 0.9$ m^2 membrane areas as design parameters. The POLYMATH program prepared according to these principles is shown in Table 2 and the results are presented in Table 3. Observe that (as was pointed out by Foley[1]) the final concentrate in this case is $c_3 = 163.45$ g/L, which is much higher than the concentration reached by a single stage unit of the same total membrane area [in Part (a), $c_1 = 66.93$ g/L].

The model shown in Table 2 can be easily modified to solve Part (c) of the assignment. In this part the exit concentration of the protein from the third stage (c_3) is specified and it is required to calculate the membrane areas in the three stages, assuming equal areas (A_i). There is no need to modify the model equations in Table 2 except to change the status of c_3 to a specified design parameter (instead of unknown) and to include the unique A value as one of the unknowns. The results of the computation for Part (c) are shown also in Table 3. Observe that the total area required to reach $c_3 = 100$ g/L is $A_t = 2.136$ m^2.

These examples demonstrate the flexibility provided by the sequential-modular approach to investigate various design alternatives.

Minimizing the total membrane area of the ultrafiltration system

In part (d), it is requested to minimize the total area of the multi-stage system with a pre-specified c_3 value while allowing different areas A_1, A_2, and A_3 for the three stages. This problem can be formulated as a constrained minimization problem to minimize $A_t = A_1 + A_2 + A_3$ subject to the constraints $f(c_1) = 0$, $f(c_2) = 0$, and $f(A_3) = 0$. The variables are A_1, A_2, A_3, c_1, and c_2.

Only minor changes need to be introduced in the program shown in Table 2 to accommodate this new problem formulation. As the POLYMATH package does not solve constrained nonlinear optimization problems, the program should be solved with a software package that includes tools for solving such problems. POLYMATH can automatically export programs to MATLAB[4] or Excel[5] that can solve a constrained minimization problem. The Excel solution will be shown here.

In Figure 2 the Excel worksheet—as obtained by exporting the POLYMATH program to Excel—is shown. Note that the Excel formulas of the various equations are in column C. The additional information, generated by the POLYMATH export routine, is textual and serves as documentation. The names of the variables, as defined in the POLYMATH program, are shown in column B. The original POLYMATH equations are displayed in column E and the associated comments are given in column F. The Excel "Solver" Add-In is used for finding the minimal area. The following information is used to specify the "Solver" parameters; the minimum is sought for "Target cell" C9 (A_t) by changing cells C15 through C19 (A_1, A_2, A_3, c_1, and c_2), subject to the constraints C20 = 0, C21 = 0, and C22 = 0

[which forces the residuals of the nonlinear equations given by $f(c_1)$, $f(c_2)$, and $f(A_3)$ to be zero]. The optimal solution found is shown in Table 3 and Figure 2. At the minimum, $A_t = 2.015$ m_2, which is slightly lower than the total area required ($A_t = 2.136$ m^2) when stages with equal areas are used to achieve the same final concentration.

Solution approach presented by Foley

To highlight the educational advantages of the "sequential modular" approach for solving problems that involve staged processes, the solutions provided here can be compared with the solution techniques used by Foley.[1] According to his approach, the equations representing a single stage [Eqs. (1), (2), and (3)] are brought into the form of a single nonlinear algebraic equation containing two unknowns, x_{i-1} and x_i, where $x_i = c_0/c_i$.

$$\frac{Q_0}{kA}(x_{i-1} - x_i) - \ln\frac{C_g}{C_0} - \ln x_i = 0 \qquad (4)$$

This model is inconsistent with the "sequential modular" approach as it includes the input variables of the first stage (c_0 and Q_0) in the models of all the subsequent stages. While the definition of the unknown x_i used in this equation was essential for graphical solution of the ultrafiltration problems, it is absolutely unnecessary for numerical solution. Keeping the original variables associated with a particular stage makes it much easier to understand, to interpret, and to modify the model in order to fit the various problem types (design, optimization, etc.). Furthermore, the model equations cannot provide full documentation of the problem as some of the original variables (Q_i and c_i) do not appear in them.

TABLE 4
MATLAB function (model) for the solution of part (d) of the ultrafiltration problem

No.	Command % Comment
1	function fx = MNLEfun(x);
2	c1 = x(1);
3	c2 = x(2);
4	A3 = x(3);
5	cg = 300; %g/L
6	c0 = 10; %g/L
7	k = .0000035; %m/s
8	Q0 = 1 / (60 * 1000); %m^3/s
9	j1 = k * log(cg / c1); %Membrane Flux
10	c3 = 100; %g/L
11	A2 = .7 %m^2
12	Q1 = c0 * Q0 / c1; %m^3/s, Complete Rejection of Protein
13	j2 = k * log(cg / c2); %Membrane Flux
14	Q2 = c1 * Q1 / c2; %m^3/s, Complete Rejection of Protein
15	Q3 = c2 * Q2 / c3; %m^3/s, Complete Rejection of Protein
16	j3 = k * log(cg / c3); %Membrane Flux
17	A1 = .7 %m^2
18	fx(1,1) = Q0 - Q1 - (j1 * A1); %Overall Material Balance
19	fx(2,1) = Q1 - Q2 - (j2 * A2); %Overall Material Balance
20	fx(3,1) = Q2 - Q3 - (j3 * A3); %Overall Material Balance

USING THE EXAMPLE TO DEMONSTRATE GOOD PROGRAMMING PRACTICES

Software packages such as POLYMATH and Excel are very convenient tools for problem solving, but there are more complex tasks that may require programming. One such complex assignment can be optimization of the membrane areas of the multi-stage system for different final concentration: c_3 values (parametric runs). In this section the membrane area optimization assignment (d) is carried out for various c_3 values: c_3 = 50, 60 ... 150 g/L and the resultant optimal areas are plotted vs. c_3. Such parametric optimization runs can be carried out with Excel by manually changing the parameter values. This approach is inefficient and cumbersome, however, particularly for problems where there are many parameters and a wide range of parameter values to be considered. In such cases, programming is required for repetitive solution of the problem with the various parameter values. One option is to carry out the parametric runs efficiently using MATLAB. The development of the MATLAB program can serve for demonstration of good programming practices.

The MATLAB function representing the operation of the multistage ultrafiltration unit can be automatically and efficiently generated by POLYMATH (Table 4). The function is named *MNLEfun*. It accepts c_1, c_2, and A_3 as input parameters and returns the values of $f(c_1)$, $f(c_2)$, and $f(A_3)$ to the calling program. Note that MATLAB requires input of the variable values into the function in a single array (x, in this case), and return of the function values in a single array (fx, lines 18-20 in Table 4). The variable values are put back into variables with the same names as used in the POLYMATH model (lines 2-5) to make the MATLAB code more meaningful. POLYMATH orders the equations sequentially as required by MATLAB and converts any needed intrinsic functions and logical expressions.

The function in Table 4 contains several variables (c_g, c_0, c_3, Q_0, A_1, and A_2) to which constant numerical values are assigned. Assigning numerical values to variables inside functions is considered poor programming practice as it limits the use of the function to one particular problem with just one set of parameter values. To enable general use of the function the numerical values of these variables must be passed to the function by the program that calls this function. One possibility to pass variable values to a

function is by defining these variables as "global" variables. Unlike "local" variables, which are separate for the different functions and the main program, a single copy of a "global" variable is shared by all of them. The use of "global" variables is not considered good programming practice, however, as it overrides the hierarchical structure of the program. This means that change of a global variable in a lower-hierarchy-level function may cause unforeseen changes in higher-level functions or in the main program. Good programming practice requires the passing of the numerical values of constants as input parameters to the function.

In Table 5 the revised form of the *MNLEfun* is shown. Observe that in this version all the numerical values of the variables are passed through one array, named *parm*. Good programming practice requires introducing the numerical values into the original variables (see lines 5 to 11 in Table 5) so that the original forms of the equations (lines 12 through 20) can serve as clear documentation of the ultafiltration system model.

The MATLAB multiple variable minimization function: *fminsearch* combined with the nonlinear equation solver function: *fsolve* can be used to find the minimal membrane area configuration for various c_3 values. The *fminsearch* function is called with the following parameters:

[Aopt,TArea,exitflag] = fminsearch(@minA,A1A2,[],parm);

The input parameters are: *minA* is the name of the function that calculates the objective function At = A1+ A2 + A3 value, *A1A2* is an array containing the current values of A_1 and A_2, and *parm* is the same array of the parameter values that is used in the *MNLEfun* function (Table 5). The output parameters are: *Aopt* is an array that contains the optimal values of A_1 and A_2, *TArea* contains the optimal value of the total membrane area, and *exitflag* indicates whether a minimum has been found (*exitflag* = 1) or the search has been terminated for other reasons (*exitflag* ≠ 1).

The function *minA* is shown in Table 6. This function obtains the values of *A1A2* and *parm* from the *fminsearch* function and returns *Asum* (A_t). The *minA* function passes the current A1 and A2 values to the *MNLEfun* function (through the *parm* array) and uses the nonlinear equation solver function *fsolve* to solve the system of nonlinear equations: $f(c_1) = 0$, $f(c_2) = 0$, and $f(A_3) = 0$. This is necessary in order to find the A3 value that satisfies the constraints with the current set of A1 and A2 values.

The complete MATLAB program can be downloaded from the ftp site: <ftp://ftp.bgu.ac.il/shacham/Ultrafiltration/>. The calculated optimal areas are plotted vs. the exit concentration c_3 in Figure 3 (next page). As expected, higher outlet concentrations require larger membrane areas.

A similar example involving development of a MATLAB program for modeling of imperfect mixing in a Chemostat that involves the use of minimization and nonlinear equation solver functions can be found in Cutlip, et. al.[6] The example presented there can also be used for demonstration of good programming practices.

TABLE 5
Generalized form of the MATLAB function (model) of the ultrafiltration system

No.	Command % Comment
1	function fx = MNLEfun(x,parm);
2	c1 = x(1);
3	c2 = x(2);
4	A3 = x(3);
5	cg = parm(1); %g/L
6	c0 = parm(2); %g/L
7	k = parm(3); % m/s
8	Q0 = parm(4); %m^3/s
9	c3 = parm(5); % m/s
10	A1 = parm(9);% m^3
11	A2 = parm(10);% m^3
12	j1 = k * log(cg / c1); %Membrane Flux
13	Q1 = c0 * Q0 / c1; %m^3/s, Complete Rejection of Protein
14	j2 = k * log(cg / c2); %Membrane Flux
15	Q2 = c1 * Q1 / c2;%m^3/s, Complete Rejection of Protein
16	Q3 = c2 * Q2 / c3; %m^3/s, Complete Rejection of Protein
17	j3 = k * log(cg / c3); %Membrane Flux
18	fx(1,1) = (Q0 - Q1 - (j1 * A1)); %Overall Material Balance
19	fx(2,1) = Q1 - Q2 - (j2 * A2); %Overall Material Balance
20	fx(3,1) = Q2 - Q3 - (j3 * A3); %Overall Material Balance

TABLE 6
MATLAB Function for calculating the total membrane area

No.	Command % Comment
1	function Asum=minA(A1A2,parm)
2	c1=parm(6); c2=parm(7); A3= parm(8);
3	xguess = [c1 c2 A3];
4	A1= A1A2(1); A2 = A1A2(2);
5	parm(9)=A1; parm(10)=A2;
6	options = optimset('Display',['off'],'TolFun',[1e-14],'TolX',[1e-14]);
7	xsolv=fsolve(@MNLEfun,xguess,options,parm);
8	A3=xsolv(3);
9	Asum=A1+A2+A3;

CONCLUSIONS

The example presented here provides an opportunity to practice several aspects of modeling and design of multi-stage processes

- *Using a consistent "sequential modular" approach for modeling the single units.*
- *Solving problems of increasing levels of difficulty—simulation, design, and optimization—while selecting the most effective software tool for numerical solution of the problem at hand.*
- *Building the model and the computer input so that they can serve as clear and complete documentation of the problem and its solution.*
- *Using advanced tools available for solving nonlinear algebraic equations and optimization problems.*

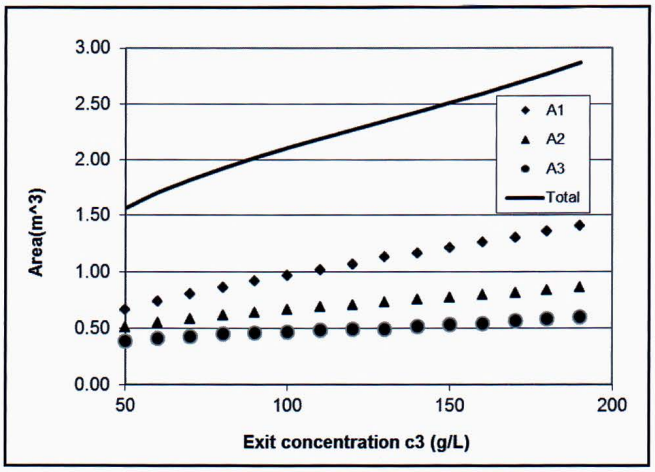


Figure 3. *Plot of membrane areas vs. required exit concentration.*

REFERENCES

1. Foley, G., "Solution of Nonlinear Algebraic Equations in the Analysis, Design, and Optimization of Continuous Ultrafiltration," *Chem. Eng. Ed.*, **45**(1), 59 (2011)
2. Seader, J.D., and E.J. Henley, *Separation Process Principles*, 2nd Ed, New York, Wiley (2006)
3. POLYMATH is a product of Polymath Software, <http://www.polymath-software.com>
4. MATLAB is a product of MathWorks, Inc., <http://www.mathworks.com>
5. Excel is a registered trademark of the Microsoft Corporation, <http://www.microsoft.com>
6. Cutlip, M.B., N. Brauner, and M. Shacham, "Biokinetic Modeling of Imperfect Mixing in a Chemostat—an Example of Multiscale Modeling," *Chem. Eng. Ed.*, **43**(3), 243 (2009) ❐

IN MEMORIAM

Donald Robert Woods

(April 17, 1935 - April 26, 2013)

Don Woods, Professor Emeritus at McMaster University and former member of *CEE*'s Publications Board, died April 26, 2013. He was 78 years old. Don's beloved family includes his wife of 52 years, Diane; his children, Russell Glen (predeceased), Suzanna Lynn Peters (Denis Dallaire), and Cynthia Jane Veals (Scott); and five grandsons, Caleb, Marcus, and Andrew Veals and Nicholas and Benjamin Peters.

Don was a chemical engineering professor at McMaster University from 1964-2000 where he used innovative teaching methods and won many teaching awards (and three honorary doctorates, from Queens, Guelph, and McMaster). In the words of Phil Wood, Associate Vice President (Student Affairs) & Dean of Students, "Don was the greatest educator in McMaster's history."

In 1986, Don was named to the inaugural cohort of 3M National Teaching Fellows. He is perhaps most widely known as a pioneer of McMaster's distinctive learning strategies: inquiry and problem-based learning, as well as a recognized expert on teaching and learning within the engineering academic community. He was author/coauthor of more than a dozen books including *Problem-based Learning* and was on the editorial board of *The International Journal of PBL* and *The Journal of General Education*. He edited the newsletter *Problem Solving News* for 20 years and wrote a column, Developing Problem Solving Skills, in the *Journal of College Science Teaching* for 10 years.

During his career and well into retirement, Don gave more than 500 workshops on effective teaching and process skill development, problem-based learning, and motivating and rewarding teachers to improve student learning. Befitting his research focus, he was a regular and valued contributor to *Chemical Engineering Education*.

This report was compiled from obituary notices prepared by the Canadian Society for Teaching and Learning in Higher Education and by the family.

A remembrance from CEE Associate Editor Phil Wankat . . .

Don Woods, one of the great originals of engineering education, has passed on. My first impression of Don was of energy—he was a force of nature. But I learned that he was much more than that. Underneath the energy Don was a very caring person who believed in his students. Everyone who attended one of Don's workshops was a student, and Don did his absolute best to reach and teach every student whether there were four or four hundred. Because Don believed I was a better, more capable, teacher than I thought I was, I was able to become that teacher. He had the power to improve people by believing in them—great teachers do that. He was interested in everyone—student, professor, and janitor. Probably because he was so helpful Don was able to graciously accept help and that oxymoron, constructive criticism, from others. Don received honors during his career, but not others that he should have received. When I asked about one, it was clear that Don was hurt by this lack of recognition, but I never heard him say a mean or cruel word about anyone.

The morning I heard that Don had died I cried and did not want to have to withstand the pain. But Don's enduring message is that the pain of reaching out, caring, and teaching is worth it.

Random Thoughts . . .

SPEAKING OF EVERYTHING — III

RICHARD M. FELDER
North Carolina State University

The intuitive mind is a sacred gift and the rational mind is a faithful servant. We have created a society that honors the servant and has forgotten the gift. • *Albert Einstein*

Man is rated the highest animal, at least among all animals that returned the questionnaire. • *Robert Brault*

The only man I know who behaves sensibly is my tailor: he takes my measurements anew each time he sees me. The rest go on with their old measurements and expect me to fit them. • *George Bernard Shaw*

Fanaticism consists in redoubling your effort when you have forgotten your aim. • *George Santayana*

The cardiologist's diet: If it tastes good, spit it out. • *Source unknown*

I am, and ever will be, a white-socks, pocket-protector, nerdy engineer, born under the second law of thermodynamics, steeped in steam tables, in love with free-body diagrams, transformed by Laplace and propelled by compressible flow. • *Neil Armstrong*

A conference is a gathering of important people who singly can do nothing but together can decide that nothing can be done. • *Fred Allen*

Find a job you love and you'll never have to work a day in your life. • *Confucius*

Never ruin an apology with an excuse. • *Kimberly Johnson*

Why do they put Braille on the drive-through bank machines? • *George Carlin*

It is a tremendous act of violence to begin anything. I am not able to begin. I simply skip what should be the beginning. • *Rainer Maria Rilke*

A conclusion is the place where you got tired of thinking. • *Steven Wright*

As to the Seven Deadly Sins, I deplore Pride, Wrath, Lust, Envy, and Greed. Gluttony and Sloth I pretty much plan my day around. • *Robert Brault*

Your assumptions are your windows on the world. Scrub them off every once in a while, or the light won't come in. • *Isaac Asimov*

You cannot truly listen to anyone and do anything else at the same time. • *M. Scott Peck*

Thank you for sending me a copy of your book; I'll waste no time reading it. • *Moses Hadas*

It's hard to be religious when certain people are never incinerated by bolts of lightning. • *Bill Watterson*

One does not discover new lands without consenting to lose sight of the shore for a very long time. • *Andre' Gide*

I cannot see how to refute the arguments for the subjectivity of ethical values, but I find myself incapable of believing that all that is wrong with wanton cruelty is that I don't like it. • *Bertrand Russell*

We should be careful to get out of an experience only the wisdom that is in it—and stop there—lest we be like the cat that sits down on a hot stove-lid. She will never sit down on a hot stove-lid again—and that is well; but she will also never sit down on a cold one anymore. • *Mark Twain*

Seek simplicity, and distrust it. • *Alfred North Whitehead*

How we spend our days is, of course, how we spend our lives. • *Annie Dillard*

I have only three enemies. My favorite enemy, the one most easily influenced for the better, is the British nation. My second enemy, the Indian people, is far more difficult. But my most formidable opponent is a man named Mohandas K. Gandhi. With him, I seem to have very little influence. • *Mohandas Gandhi*

Whether you think you can or think you can't, you're right. • *Henry Ford*

Protons have mass? I didn't even know they were Catholic. • *Source unknown*

Life is like driving a car at night. You never see further than your headlights, but you can make the whole trip that way. • *E.L. Doctorow*

No snowflake in an avalanche ever feels responsible. • *Stanislaus Jerzy Lee*

His mother should have thrown him away and kept the stork. • *Mae West*

I look back on my life like a good day's work. It was done and I am satisfied with it. • *Grandma Moses*

I knew if I stayed around long enough, something like this would happen. • *George Bernard Shaw's epitaph*

REMOTE LABS AND GAME-BASED LEARNING FOR PROCESS CONTROL

Imran A. Zualkernan, Ghaleb A. Husseini, Kevin F. Loughlin, Jamshaid G. Mohebzada, and Moataz El Gaml
American University of Sharjah • Sharjah, UAE

Remote laboratories appeared in higher education almost two decades ago. Since then, the infrastructure for building remote laboratories has come a long way and stand-alone and commercial tools such as MATLAB and LabVIEW are easily integrated with off-the-shelf learning management systems (LMS) to build comprehensive remote-laboratory learning environments.[1-3] Shared social networking platforms such as Facebook have a potential to take remote laboratories to yet another level. A recent survey shows that a significant amount of research in remote laboratories has focused on comparing remote laboratories against hands-on and virtual laboratories.[4] For example, Tzafestas et al.[5] show a comparison between students trained in a traditional way on robots as opposed to using a virtual laboratory or a remote laboratory, and observed no statistical differences in performance due to the modality of delivery. Each modality tends to emphasize different educational objectives.[4] In addition to conceptual understanding, hands-on laboratories have historically emphasized design, professional, and social skills. Virtual laboratories, on the other hand, have focused primarily on professional and conceptual skills while remote laboratories have mostly addressed professional skills and conceptual understanding.

In some sense, prior research on remote laboratories has centered on the amplification and attenuation effects of introducing the remote laboratory technology.[6] The amplification effect is represented by positive impacts of this technology such as round-the-clock remote access. For example, surveys in specific fields such as RF have been conducted recently to identify scarce laboratory equipment most suited for such amplification.[7] The attenuation effects, on the other hand, represent negative impacts of introducing this technology. For example, the slow response time is one such attenuation effect mediated by using high-speed Internet to provide real-time video from a remote laboratory.[8] The predominance of these two factors is also reflected in assessments models. For example, Nickerson et al.[9] present a detailed model for comparing hands-on laboratories, remote laboratories, and simulated laboratories. This model contains criteria such as purpose of the experiment, the experimental and the coordination interface, and laboratory frame and technology. The only pedagogically related criterion in this model, however, is the individual differences between learners. This paper takes the view that remote laboratories are more than simple surrogates for real or virtual laboratories and can be used to explore forward-looking learning designs such as game-based learning. The rest of the paper is organized as follows. First, a brief introduction to game-based and mobile learning (m-learning) is presented. This is followed by a description of a learning problem in chemical engineering. A game-based remote laboratory to address this learning problem is presented next. This is followed by a pilot study to validate the learning design.

Imran A. Zualkernan *is with the Department of Computer Science and Engineering at the American University of Sharjah, Sharjah, UAE. Prof. Zualkernan received a B.S. in 1983 and a Ph.D. in 1991 from the University of Minnesota, Minneapolis. Research interests include advanced learning technologies, IT services management, agile processes, and Six Sigma.*

Ghaleb A. Husseini *is with the Department of Chemical Engineering at the American University of Sharjah, Sharjah, UAE. Prof. Husseini received a B.S. in1995, an M. Eng. Mgmt. in 1997, and a Ph.D. in 2001, all from Brigham Young University in Provo, UT. Research Interests include drug delivery and biomaterials and modeling of biological processes.*

Kevin F. Loughlin *is with the Department of Chemical Engineering, American University of Sharjah, Sharjah, UAE. He received his B.E. in 1965 and M.Eng.Sc. in 1970, both from the National University of Ireland and his Ph.D. in 1978 from the University of New Brunswick, Fredericton, Canada. His research interests include adsorption equilibria, kinetics technology, and modeling of processes.*

Jamshaid G. Mohebzada *is with the Department of Computer Science and Engineering, American University of Sharjah, Sharjah, UAE.*

Moataz El Gaml *is with the Department of Computer Science and Engineering, American University of Sharjah, Sharjah, UAE.*

GAME-BASED LEARNING

What constitutes a game has many definitions. For example, Prensky[10] defines game as organized play. After analyzing many definitions of a game, Salen and Zimmerman[11] define a game to be "a system in which players engage in artificial conflict, defined by rules, that results in a quantifiable outcome," (pp. 80). We extend this definition to define instructional games to be a system where learners engage in artificial conflict, defined by rules, that results in quantifiable outcome and enhances learning.

While Aldrich[12] and Gibson et al.[13] have outlined various principles of digital game-based learning, recent studies[14] have shown that game-based learning actually improved student motivation as well as performance. There is also emerging evidence[15] that when using game-based learning as opposed to self-learning, the students not only thought that the game was the preferred method and was more enjoyable, but also they showed willingness to continue to use this method of learning. Tuzun et al.[16] show that not only did children do better while using game-based learning, but playing games also developed them as independent learners. Game-based learning has also been used successfully in higher education. For example, Ebner and Holzinger[17] show that performance of students using game-based learning was better than the control group in the context of civil engineering.

M-learning has also received much attention recently.[18,19] For example, Akkerman et al.[20] show that students learned history by walking around with their mobile phones and by sharing information about what they saw in the city. There are also efforts to move existing gaming platforms to m-learning platforms[21] Mobile game-based learning has also been used in the context of providing mass learning in developing countries.[22] M-learning, to extend a traditional LMS, also received a positive response from college students.[23] Podcasting was also found to be more effective for revision of lectures than notes or other conventional means.[24] M-learning has also been shown to significantly increase environmental awareness.[25] A framework for designing m-learning games has been proposed.[26] Specific criteria for assessing the quality of learning games have also been proposed.[27] Issues addressing the quality of m-learning are also outlined in Gafni.[28]

Alternative pedagogical approaches including using competition games have been recently used to teach robotics in remote laboratories.[29] Using a gaming engine as an interface to a remote laboratory in a conventional pedagogical context has also been explored.[30] Such studies are more an exception than a rule, however. The relative absence of game-

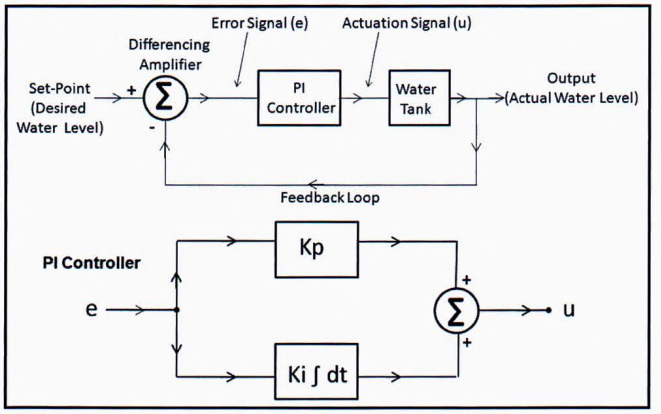


Figure 1. *Block diagram for PI controller for a water tank.*

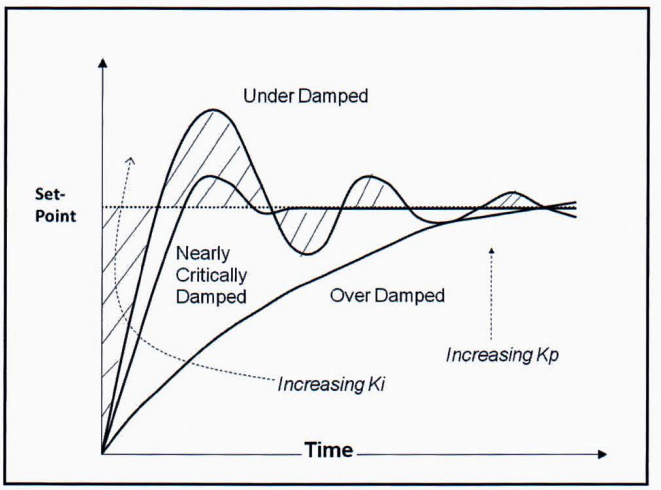


Figure 2. *General effect of K_p and K_i on the setpoint.*

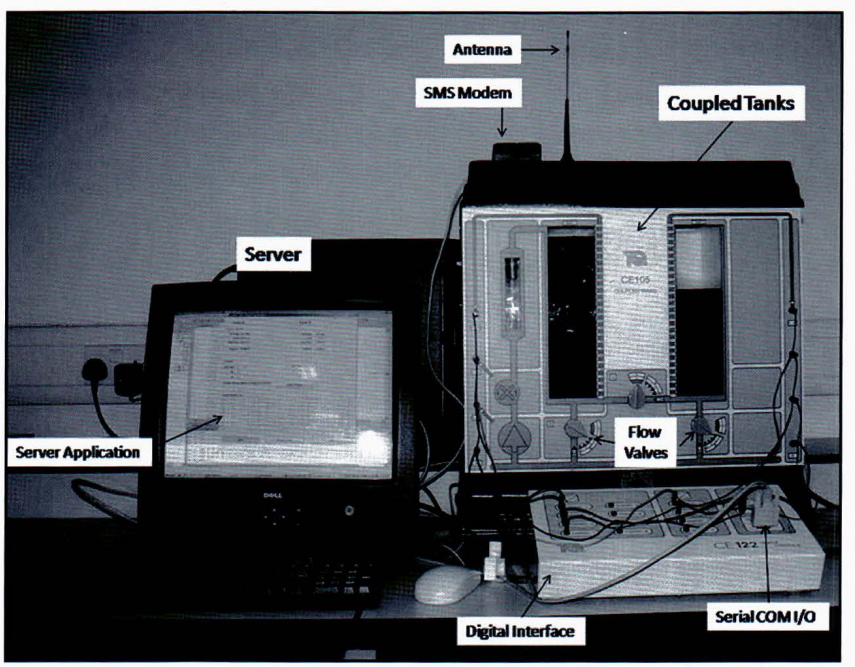


Figure 3. *Physical setup for the remote lab game.*

based learning in remote laboratories can be attributed to the fact that infrastructure is a pre-requisite for experimentation with novel pedagogical paradigms like game-based learning. Since such infrastructure is now widely available or easy to build, another explanation can perhaps be that most teachers and researchers are digital immigrants who did not grow up with the Internet and gaming technologies and consequently hold a completely different viewpoint, while most students are digital natives of the gaming generation.[10]

THE LEARNING PROBLEM

The learning problem being addressed in this paper is how to teach proportional integral (PI) controllers in an undergraduate chemical engineering course on control systems. Using remote laboratories to teach control applications is not new.[31,32] The water tank equipment has been typically used to demonstrate a PI controller. This equipment consists of a tank of water that is connected to a water reservoir. There is a constant drainage of water from the tank into the reservoir. The control problem is to maintain a constant water level in the tank by continuously pumping water back into the tank from the same reservoir. This is done by providing a square-wave input to a controller that sends a voltage signal to an electric pump to maintain a particular level of water. Figure 1 shows a PI controller for the water tank equipment. Setpoint represents a desired water level in the water tank. Actuator signal is the voltage applied to the water pump. The output process variable is the actual water level. Difference between the desired and actual water level is represented by an error signal. The error signal is fed into the PI controller to continuously calculate the voltage being applied to the pump. A PI controller does so by multiplying the error with a constant proportional constant (K_p) and with an integral term represented by the sum of error accumulated so far multiplied with an integral constant (K_I). The control loop in Figure 1 can be described by a transfer function, and a time-domain solution can be derived as shown in Eq. (1).

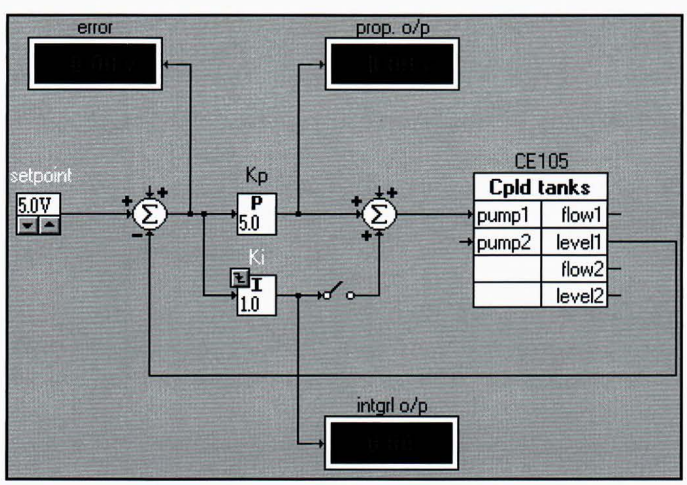


Figure 3a. *Schematic for Proportional + Integral Control.*

$$h'(t)=\frac{K_3}{\tau_3\sqrt{1-\zeta_3^2}}e^{\frac{-\zeta_3 t}{\tau_3}}\sin\left[\sqrt{1-\zeta_3^2}\,\frac{t}{\tau_3}\right]$$
$$*\left[\frac{C}{2}-C\,S(t-t_w)+C\,S(t-2t_w)-CS(T-3t_w)+\cdots\right] \quad (1)$$

C and t_w are the height and width of the input square wave, respectively. Also,

$$K_3=\frac{K_I}{K_pK_1} \quad (2)$$

$$\zeta_3=\frac{1}{2}\left(\frac{1+K_pK}{K_pK}\right)\sqrt{\frac{K_I}{\tau}} \quad (3)$$

$$\tau_3=\sqrt{\frac{K_I\tau}{KK_p}} \quad (4)$$

where K_p is the controller gain and K_I is the integral or reset time. K and K_1 are constants that include the process gain, the gain on the valve, and the gain on the measurement sensor. The values of K_p and K_I determine an appropriate behavior for the closed-loop system. As Figure 2 shows, an ideal behavior for the water level is represented by the near critically damped curve where the water level oscillates initially but settles down to the setpoint quickly. An under-damped behavior means that the water level will fluctuate around the desired level and take a long time to settle down. Finally, as Figure 2 shows, when the system is over-damped, it takes a long time to reach the desired water level. The area under each curve on both sides of the setpoint represents the total accumulated error. A smaller error typically corresponds to a better controller.

THE REMOTE LABORATORY GAME

A key consideration in the design of any control system is to quickly bring the system to the desired setpoint and to maintain it there. This remote laboratory game has two learning goals or objectives. The first goal is to learn how to throw a system into oscillations and the second goal is to stabilize or tune the system and bring it back to the setpoint.

Architecture

Figure 3 shows the physical setup for the remote laboratory game and Figure 3a shows the schematic of our process. The water tank equipment (CE105 from QT- Quasar Technologies, Oslo, Norway) consists of two identical water tanks with the corresponding water pumps and a reservoir. Each tank has a flow valve that can adjust the amount of water draining into the reservoir. The pump for each tank is controlled through a voltage provided through the digital interface. The digital interface is connected to a personal computer (PC) through a serial port. Figure 4 (next page) shows the software architecture. A java program (1180 lines of Java code) was written to communicate with the microcontroller in the digital interface

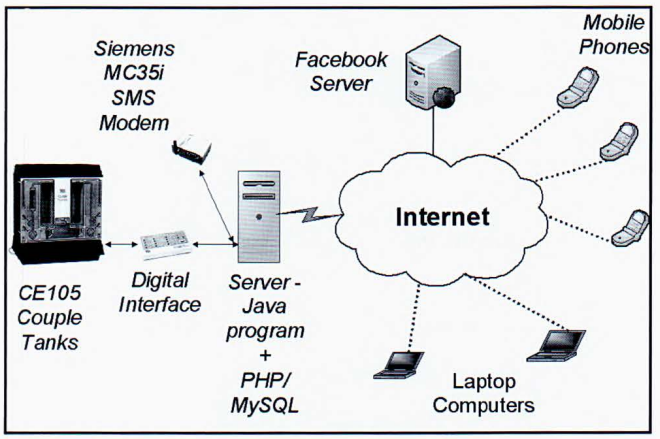


Figure 4. *Software architecture for the remote lab game.*

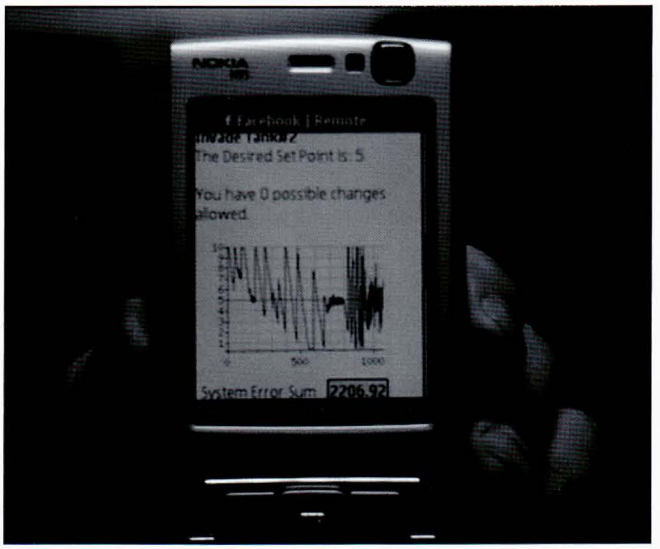


Figure 5. *The Mobile User Interface.*

through the serial port and to implement the PI-controller on the PC. In addition, the same Java program also communicates with an Apache server-based PHP/MySQL application (1487 lines of PHP code) that implements a game interface by communicating with the popular Facebook social networking site through the Internet. The Java application is also able to send SMS messages through a Siemens MC-35 SMS modem connected to another serial port on the PC. The Java server consists of various classes providing interfaces to each of the hardware components. For example, *CTHardwareInterface* class implements the binary communication protocol between the PC and the digital controller running over the serial port. Similarly, the *HTTPInterface* class is responsible for processing new inputs from Facebook that come through the Apache HTTP server and forwarding these control parameters to the equipment using an instance of the *CTHardwareInterface* class. The *HTTPInterface* class is also responsible for retrieving the current values of various tank parameters (such as the water level) using the *CTHardwareInterface* class and updating these in the MySQL database. The *SMSSender* class communicates with a Siemens MC35i SMS modem to send alerts to the game players. A *ControlPanel* class provides a user-friendly GUI for the server and allows a user to start and stop the server and to display the current readings of the equipment for diagnostic purposes. Instances of each class run concurrently using Java's native multi-threading capabilities. For example, instances of *SMSSender* and *HTTPInterface* class each run in their own thread. Since the architecture uses Apache server's native HTTP concurrency-handling mechanism in addition to Java threads, the number of concurrent players at one point is limited only by the memory and processing limitations of the Apache server and the Java virtual machine. The MySQL database records the complete history of all the changes made by each team along with time stamps.

A learner who wishes to play the remote laboratory game can access the game by logging into Facebook. It is possible to create a new game tied to a particular water tank or to join an existing game. Two roles are provided to a player. A player can either join as an invader or as a defender. The objective of a defender is to change the values of K_I and K_p to bring the water level in the tank to a particular setpoint. An invader, on the other hand, tries to destabilize the system by throwing the system into oscillations. The game continues until the person who created the game decides to stop it.

Typically, two teams play the game. One team is charged with defending one tank and attacking the other. Another team does the converse; attacking the tank being defended by the first team, and defending the tank being attacked by the first team. Each player is allocated a fixed number of changes to either of the two parameters (K_I and K_p) after which they are not able to make any changes until the end of the game. Within these limitations, each player is allowed to make changes at any time. This means that players can request changes to the parameters of any tank in a concurrent fashion; the requested changes are queued and are actually applied to the system in a first-come-first-served fashion. Each player can view the behavior of the system the player is attacking or defending in the form of a visual display. In addition, each player sees the total error the player has accumulated on a particular system indicating whether the player is winning or losing the game.

The computer connected to the water-column instrument runs a customized Java-based web-server (using server sockets) that allows the Facebook web application to connect as a socket client. This server uses Java's native multi-threading and synchronizing mechanism to ensure that only one client has access to one water column at a time. A single thread is spawned for each socket connection from the Facebook application, and the request to make changes to each water column is queued on the semaphore being used to access each water column. The change request is automatically processed once the water column is released by another client's request (if any).

Each player can access the game using his or her mobile phone or through a normal browser on the Internet. The user interface (UI) for the game is specifically designed using the Facebook mobile interface to accommodate small mobile devices. The UI has been deliberately kept simple and functional. For example, as Figure 5 shows, in addition to showing that the team is supposed to invade Tank #1 as opposed to defending it, the UI also details the desired setpoint, the number of changes allowed, a graphical representation of how the water level has changed over time and the total system error accumulated so far. Figure 5 shows how another team can use the simple UI to change the K_p and the K_I of a tank they are defending or invading; they are only allowed to change one parameter at a time. A team member can quickly scroll up and down to view the same information about each tank the team is either attacking or defending in a consistent manner.

If the user leaves the game and significant changes appear in the behavior of either tank, they receive an SMS warning that a change has occurred. One important aspect of the system is its ability to capture and show the actions of any player in real time. Such information can also be used in the post-analysis of any game to pinpoint conceptual gaps of the students.

Finally, it should be noted that some parameter changes can take a long time to manifest in the behavior of the system. This is part of learning how a PI controller may behave in the real world. Consequently, the game is designed to be played over a few hours. A limited number of changes force the players to be deliberate about their choices, however.

Game rule design

The main objective of the game is to teach chemical engineering seniors the principles of proportional integral control including the objective of feedback, the basic equations of proportional and integral controllers, the key concepts behind both proportional and integral control, the general purpose behind the two controllers, how K_p and K_I respond to a process disturbance, and in addition the disadvantages of proportional and integral control.

The game rules and regulations were:

1) *The period of the contest was 3 hours.*
2) *Each team consisted of 2 members.*
3) *12 students constituted the "control" group.*
4) *12 students constituted the "gaming" group.*
5) *The "control" group consisted of the students who did not play the game but ran a simple level-control experiment with one tank. The "control" group was then asked to take the quiz before and after they ran their experiment.*
6) *The "gaming" group was divided into 6 teams (two members in each group). The teams were randomly selected and named (Team A, Team B, Team C, Team D, Team E, and Team F).*
7) *The teams were randomized to see who played who.*
8) *Each team member needed a mobile phone with SMS capability.*
9) *The objective of the game was to minimize the Standard Square of Error (SSE) between the setpoint and the control variable over a 3-hour period.*
10) *The offensive and defensive teams had different objectives. The offensive teams were trying to maximize the SSE in their opponents' tank. The defensive teams were trying to minimize the SSE for their own tanks.*
11) *The teams could control the level by changing K_p or K_I.*
12) *Each team could change K_p or K_I 12 times in the 3-hour period (6 changes to fix their tank and 6 changes to disturb the other team's tank).*
13) *The 12 changes allowed the students to change either K_I or K_p.*
14) *The minimum and maximum values for K_p were 1 and 10, respectively.*
15) *The minimum and maximum values for K_I were 0 and 1.0, respectively.*
16) *The setpoint change was a square wave input.*

Typically any game contains three levels of rules.[11] Operational rules are rules that come with a game as a set of instructions. Constitutive rules define the underlying formal structure below the surface of a game. These structures can be mathematical or logical. Finally, implicit rules are unwritten rules of the game and are concerned with etiquette and good sportsmanship. These rules can change from game to game. For example, a child playing chess may be allowed to take back a move while an adult might not. Table 1 shows the three types of rules for this game.

TABLE 1
Three Levels of Game Rules

Nature of Rules	Rules
Operational Rules	• Each team acts as an invader for one tank and a defender for another. • Each member of the team gets a fixed number of tries at changing the parameters of a tank as a defender or an invader. • Only one parameter can be changed at a time. • The team whose total error for the tank they are invading is more than the one they are defending wins. • The game ends in fixed amount of time.
Constitutive Rules	These rules are governed by the transfer function of a PI system which determines the error that will be accumulated.
Implicit Rules	The players will not abandon the game; the players will not cheat or collaborate; etc.

TABLE 2 Effectiveness of Game Design	
Criteria	**Comment**
Challenge: There should be multiple ways to win the game, vary the difficulty of the game, sufficient randomness, and constant feedback about performance.	There are multiple ways to win the game by varying K_p and K_I differently. Constant feedback in the form of the total accumulated error and its profile is provided.
Curiosity: The activity should offer sensory stimulation and novelty to stay in the game.	Since the competing team is constantly reacting, there is enough novelty and the error curve provides sensory stimulation.
Control: The player should feel control over the activity and witness the effects of making choices.	This is clearly provided when every change to K_p or K_I results in an immediately different response from the system.
Fantasy: The player should feel involved in the game.	Although the game does not have a "surface story," since there is a real chemical process that needs attention, the players should feel involved.
Interpersonal Motivation: The players meet and play with others and earn respect among peers for performance.	This is a team-based game and in addition pits students' knowledge of control systems against each other.

Effectiveness

Malone and Lepper[34] define five criteria for evaluating the effectiveness of a game. Table 2 shows how each of these criteria is incorporated in the game design. For example, the curiosity criterion is satisfied in two ways. First, the team is left to wonder which parameter the opposite team changed to explain the current behavior. Secondly, the team is curious about what impact changing a particular parameter will have on the system. In either case, the response is novel because it depends on the current as well as previous states of the system. Similarly, Dondi and Moretti[27] define four classes of criteria to evaluate a learning game. Pedagogical and context criteria include target groups, learning objectives, context of usage, didactic strategy, communication and media, and evaluation activities. Each of these criteria has been considered in designing the game. For example, the target groups have been clearly identified as the chemical engineering students taking the control course. In addition, the two learning objectives have been formally specified. The instructions for playing the game are clear and the game is clearly related to the working context because both system tuning and trying to determine the causes of a system destabilization are important professional activities for control engineers. The didactic strategy has clearly defined roles for attackers and defenders; the rules are clear and there is a clear coherence between the rules and the consequences of actions that a learner makes. The user interface of the game has been kept minimal and simple and leads to a good quality of interaction between the user and the game. The evaluation is inherently built into the game in term of the accumulated error. In other words, if a student can minimize the error, this is a direct measure of their understanding of how to tune the system. Content criteria include properties of content such as obsolescence and balance for the target group. In this game, content only consists of game instructions and as such does not play a major role. Technical criteria include credits, conformance to standards, and technical quality issues. The game is robust because it has been tested for many hours without any errors. In addition, it conforms to the Internet standards which mean that any standard browser on a mobile phone or a laptop can be used to play the game. The user interface is minimal and functional and the images of the graph are clear even on small mobile screens. Finally, for the information-produced category, the game uses Facebook as the underlying platform, and all passwords and user information are safely maintained through Facebook. In addition, the game also saves all the activities including each action of each player as a history. These reports can easily be printed by the instructor as desired.

Game design and outcome criteria

It is also instructive to evaluate game design from a preparation for lifelong learning perspective. The ABET organization provides one set of criteria that graduating chemical engineering students must meet on their graduation day. Table 3 shows how each of these criteria is addressed by the game. As Table 3 shows, the game directly addresses criteria (a)-(e), (g), and (k).

EVALUATION

A pilot study was conducted to evaluate the remote laboratory game. The pilot study had two objectives. The first objective was to gain an insight into whether the students would like playing the game. A second objective was to see if playing the game would make a quantitative difference in student performance. Unlike previous remote laboratory studies that have compared a remote laboratory to a virtual or hands-on laboratory, the objective here was to compare game-based remote laboratories treatment against a control group represented by students who had no exposure to this game.

Pilot study design

Students currently taking the CHE 421 - Chemical Process Dynamics and Control class at the American University of Sharjah were recruited to evaluate the game. The students had been exposed to the proportional and integral control loop in classroom lectures before their participation. Twelve students were chosen at random as the control group while another 12 volunteered to play. There was no statistical difference between the mean GPA of the control and treatment groups. The control group had seven women while the treatment group had five women. The 12 volunteers were randomly divided into six teams of two students each. Each of the six teams was

TABLE 3 ABET Outcome Criteria and Game Design	
ABET Criteria	**Game Design**
(a) an ability to apply knowledge of mathematics, science, and engineering	The game requires a mathematical interpretation of the transfer functions.
(b) an ability to design and conduct experiments, as well as to analyze and interpret data	The students need to conduct mini-experiments to verify their assumptions about the parameters of the system being attacked or defended.
(c) an ability to design a system, component, or process to meet desired needs within realistic constraints such as economic, environmental, social, political, ethical, health and safety, manufacturability, and sustainability	Tuning or destabilizing the system is a parameter design problem.
(d) an ability to function on multidisciplinary teams	Since control is taught in many engineering disciplines, the game can be played by a multidisciplinary team.
(e) an ability to identify, formulate, and solve engineering problems in engineering practice.	System tuning is an engineering problem and is regularly practiced in many engineering contexts.
(f) an understanding of professional and ethical responsibility	Not directly addressed in the game.
(g) an ability to communicate effectively	Team members are playing from remote locations and therefore require an effective communication strategy.
(h) the broad education necessary to understand the impact of engineering solutions in a global, economic, environmental, and societal context	Not directly addressed in the game.
(i) a recognition of the need for, and an ability to engage in life-long learning	Not directly addressed in the game.
(j) a knowledge of contemporary issues	Not directly addressed in the game.
(k) an ability to use the techniques, skills, and modern engineering tools necessary for engineering practice.	To compete successfully, the students need to use the mathematical knowledge and tools often used in engineering practice for control engineers.

randomly assigned a competing team. This resulted in three gaming contests each consisting of two teams of two students each. Each contest was run for a total of three hours. All students took a pre-quiz on PI controllers before the contests. Similarly, all students took a post-quiz on PI control after the contests. One day before the contests, the students playing the game were invited to the laboratory where they were shown the laboratory equipment and given explanation of how it worked. Twelve hours before the game, each team was e-mailed a copy of game instructions that included a description of the operational rules of the game. The students were given the option of either playing the game on their mobile phone or on their laptop computers using wireless LAN. After playing the game, each student was asked to individually fill out a survey to evaluate various aspects of the game.

Results

Post-game survey

Table 4 shows the post-game survey questions. Table 5 (next page) shows the results from the survey including a weighted average (WA) for each question, where 1 means strongly agree and 5 means strongly disagree. Results in Table 5 indicate that more than 10 out of 12 students either agreed or strongly agreed that the game helped with the learning objectives (WA = 1.33). Most students enjoyed playing the game (WA = 1.13) and felt that the game was immersive (WA=1.27).

In addition, most students indicated that they would recommend this game to a friend (WA = 1.27). Half the students felt that the game motivated them to learn more about control systems while the other half were not so sure (WA = 1.6). None disagreed with the assertion, however. Out of 12 students, four were not sure if the game was addictive (WA = 1.67). In summary, the students generally thought that it helped them learn the material and was enjoyable.

None of the students noticed the unusual behavior caused by opening the flow valve. Many students carried the control textbook with them. In addition, in two out of three contests, students continued to play with the system even after they had won the game. When asked about the reason, they typically indicated that they were curious about how the system would behave under certain conditions.

Performance

Playing the game once did not have an impact on performance of the students. An analysis of variance to compare the test results from before and after the game for both control

TABLE 4 Post-Game Survey Questions	
No.	**Post-Game Survey Questions**
Q1.	Playing the game improved my understanding of how to tune proportional-integral control systems.
Q2.	Playing the game improved my understanding of how to destabilize proportional-integral control systems.
Q3.	I felt immersed in the game.
Q4.	I enjoyed playing the game.
Q5.	The game motivated me to learn about control systems.
Q6.	I would recommend this game to a friend.
Q7.	The game was addictive.

TABLE 5 Post-Game Survey Results						
No.	Strongly Agree	Agree	Neither	Disagree	Strongly Disagree	Weighed Average
Q1.	6	4	2	0	0	1.33
Q2.	4	7	1	0	0	1.40
Q3.	7	3	2	0	0	1.27
Q4.	9	2	0	1	0	1.13
Q5.	6	1	4	1	0	1.60
Q6.	7	3	2	0	0	1.27
Q7.	3	5	4	0	0	1.67

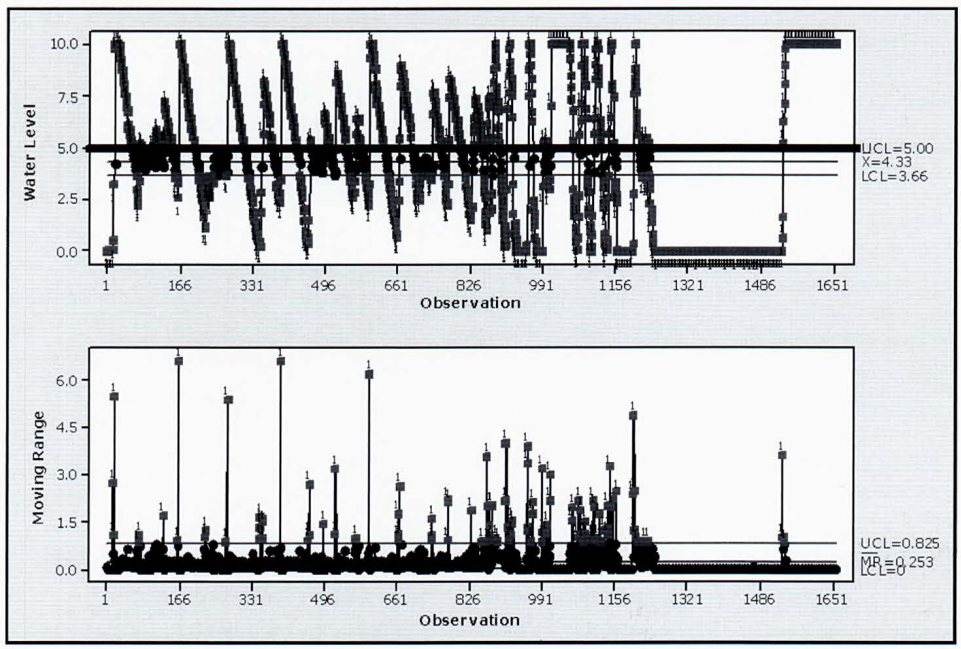


Figure 6. *Performance of Tank A in the second game.*

and treatment group showed no statistical difference F(3,44) = 0.55; p = 0.625. This means that playing the game once did not directly lead to improving the performance of the students.

Qualitative analysis

One important aspect of the remote laboratory game is the ability for post-game analysis to determine the gaps in student understanding. An illustrative analysis of the second game is presented next. The second game was played between Team-A and Team-B, both teams composed of two students. Team-A was defending Tank A while attacking Tank B and Team-B was defending Tank B and attacking Tank A.

Figure 6 shows the behavior of Tank A over the three-hour period of play. The top graph in Figure 6 shows the actual level of a tank as a function of time. The bottom graph in Figure 6 shows the moving range of the water level for the last two time intervals. The moving range shows the level of fluctuation over time; spikes in this graph represent drastic changes in the water level over short periods of time indicting turbulence or level instability. The first half of the game is characterized by the level going out of control and then coming back into control for brief periods of time before it is out of control again. Team-A was not very conscious of how they used up the limited amount of changes to K_p and K_i and hence ran out of changes about 70% into the game. This means that afterward Team-B had a free reign over changing the parameters as they liked. This is reflected in the uncontrolled variation seen after about two-thirds of the game. It is interesting to note that towards the end, Team-B had brought down the level of tank to zero, which means that the tank was accumulating maximum error. They chose to play with the tank, however, and made it saturate by pushing it to the other direction. This posed no advantage in terms of the game. A post-interview with the students indicated that they were just "playing around" with the opponent's system to see what would happen. The invaders' median K_p was 3 (with 95% confidence intervals of [2,5] using Wilcoxon signed rank test) while the defenders' median K_p was 5 (with a 95% interval of [4,6]). Though not statistically different, this means that invaders were trying lower-range K_p values to over-dampen the system and hence build up error while the defenders were trying the opposite strategy. An optimal strategy, however, would be to simply use a K_p of 1.0—indicating that the invaders perhaps did not fully comprehend what K_p does. Similarly, the invaders' estimated median for K_I was 0.75 (with 95% confidence interval of [0.5, 0.95]) while the estimated median for K_I for the defenders was 0.5 (with 95% confidence intervals of [0.45, 0.75]). Clearly, the invading team was trying to destabilize the system by using high values of K_I. Why the defending team was also using reasonably high values, however, tends to suggest a misunderstanding of how K_I works.

Figure 7 shows the behavior of Tank B. As the Figure shows, Team-B was eventually able to find the values of parameters to get the water level within control. Team-B was partially helped by the fact that the Team-A ran out of turns. The invaders' estimated median for K_p was 5.5 (with a 95% confidence interval of [5, 9.5]). The defenders' estimated median for K_p,

on the other hand, was 7 (with a 95% confidence interval of [5, 7]). The invader's estimated mean for K_I was 0.4 (with a 95% confidence interval of [0.2, 0.5]). The defender's estimated mean for K_I was 0.25 (with a 95% confidence interval of [0.15, 0.4]). In other words, the defending team kept trying the middle values for K_p while the invading team tried a range of higher values. Similarly, the defenders used a reasonably low K_I while the invaders also kept the K_I below 0.4. Again, this confirms Team-A's fundamental misunderstanding of how K_I impacts the system response.

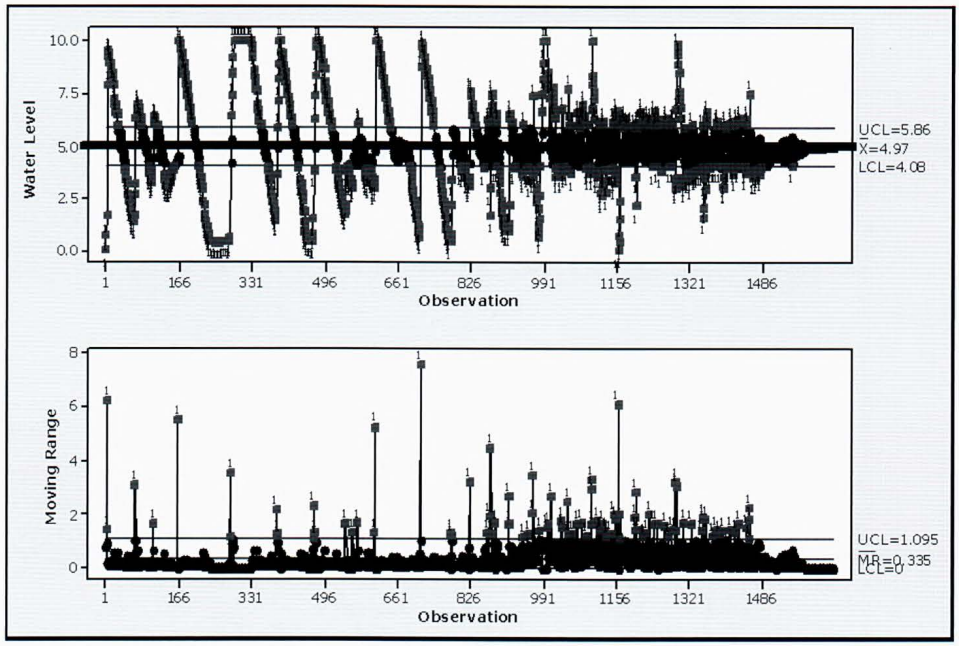


Figure 7. *Performance of Tank B in the second game.*

DISCUSSION

While playing the remote game did not show a statistical increase in the performance of students, this is perhaps expected since the students only had one chance to play the game. The performance could perhaps be improved if they were allowed to play the game many times. The post-game survey results, however, clearly indicated that they enjoyed the game and that they would recommend it to their friends. This was confirmed by the excitement shown by students while playing the game as well. It is interesting to note that half the students used the mobile phone to receive the SMS messages but chose to use the laptop to play the game. The other half were comfortable using a mobile device. The students also indicated that three hours was too long and thought that the time for the game should be reduced to one hour only.

A number of improvements can be made in the game. For example, since the game creator can view the performance of each team, he or she can easily use Facebook to communicate with the students to either mentor or ask them why they are using a particular strategy. Live video showing the tanks and turbulence of the water would also add to the gaming experience. Since Facebook mobile currently does not support video, however, this feature can be included only if the game is played on a laptop.

One final observation is that despite dealing with off-the-shelf hardware, currently available technology makes it very easy to put together a remote laboratory. The challenge lies in one's ability to utilize this technology in a pedagogically sound and interesting manner.

CONCLUSION

This paper has shown how remote laboratories can be used for game-based learning. A game specifically designed to teach a particular control topic was developed using a sound pedagogical foundation. In addition, the game design was evaluated against various criteria for what constitutes a good game. Finally, a pilot study was conducted to further validate the game design. The pilot study indicates that the game was well received by the students who enjoyed the game. Pre- and post-tests comparing this group to a control group, however, did not show any significant statistical differences.

REFERENCES

1. Rapuano, S., and F. Zoino, "A learning management system including laboratory experiments on measurement instrumentation," *IEEE Transactions on Instrumentation and Measurement*, **55**(5), 1757, (2006)
2. Cmuk, D., M. Borsic, T. Mutapcic, and S. Rapuano, "A novel approach to remote teaching: Multilanguage magnetic measurement experiment," *IEEE Transactions on Instrumentation and Measurement*, **57**(4), 724, (2008)
3. Gurkan, D., A. Mickelson, and D. Benhaddou, "Remote laboratories for optical circuits," *IEEE Transactions on Education*, **51**(1), 53, (2008)
4. Ma, J., and J.V. Nickerson, "Hands-on, simulated, and remote laboratories: A comparative literature review," *ACM Computing Surveys*, **38**(3), 1, (2006)
5. Tzafestas, C.S., N. Palaiologou, and M. Alifragis, "Virtual and remote robotic laboratory: Comparative experimental evaluation," *IEEE Transactions on Education*, **49**(3), 360, (2006)
6. Lindsay, E.D., and M.C. Good, "Effects of laboratory access modes upon learning outcomes," *IEEE Transactions on Education*, **48**(4), 619, (2005)
7. Cagiltay, N.E., E. Aydin, R. Oktem, A. Kara, M. Alexandru, and B. Reiner, "Requirements for remote RF laboratory applications: An educator's perspective," *IEEE Transactions on Education*, **52**(1), 75, (2009)
8. Kikuchi, T., S. Fukuda, A. Fukuzaki, K. Nagaoka, K. Tanaka, T. Kenjo, and D.A. Harris, "DVTS-based remote laboratory across the Pacific over the gigabit network," *IEEE Transactions on Education*, **47**(1), 26, (2004)
9. Nickerson, J.V., J.E. Corter, S.K. Esche, and C. Chassapis, "A model for evaluating the effectiveness of remote engineering laboratories

and simulations in education," *Computers & Education*, **49**, 708-725, (2007)
10. Prensky, M., *Digital Game-Based Learning*, McGraw-Hill, New York (2004)
11. Salen, K., and E. Zimmerman, *Games of Play: Game Design Fundamentals*, The MIT Press, Cambridge (2004)
12. Aldrich, C., *Learning by Doing: A Comprehensive Guide to Simulations, Computer Games, and Pedagogy in e-Learning and Other Educational Experiences*, Pfeiffer, San Francisco (2005)
13. Gibson, D., C. Aldrich, and M. Prensky, Eds., *Games and Simulations in Online Learning: Research & Development Frameworks*, IGI Global, (2006)
14. Papastergiou, M., "Digital Game-Based Learning in High School Computer Science Education: Impact on Educational Effectiveness and Student Motivation," *Computers & Education*, **52**(1), 1-12, (2009)
15. Sward, K.A., S. Richardson, J. Kendrick, and C. Maloney, "Use of a Web-Based Game to Teach Pediatric Content to Medical Students," *Ambulatory Pediatrics*, **8**(6), 354, (2008)
16. Tuzun, H., M. Yilmaz-Soylu, T. Karakus, Y. Inal, and G. Kizilkaya, "The effects of computer games on primary school students' achievement and motivation in geography learning," *Computers & Education*, **52**(1), 68, (2009)
17. Ebner, M., and A. Holzinger, "Successful implementation of user-centered game-based learning in higher education: An example from civil engineering," *Computers & Education*, **49**(3), 873, (2007)
18. Ryu, H., and D. Parsons, *Innovative Mobile Learning: Techniques and Technologies*, Information Science Reference, Hershey, PA (2009)
19. Guy, R., (Ed.), R. Gafni, *The Evolution of Mobile Teaching and Learning*, Informing Science Press, Santa Rosa, CA (2009)
20. Akkerman, S., W. Admiraal, and J. Huizenga, "Storification in History education: A mobile game in and about medieval Amsterdam," *Computers & Education*, **52**(2), 449, (2009)
21. Lavín-Mera, P., P. Moreno-Ger, and B. Fernández-Manjón, "Development of Educational Videogames in m-Learning Contexts," in *Proc. Second IEEE International Conference on Digital Game and Intelligent Toy Enhanced Learning*, pp. 44-51 (2008)
22. Kam, M., A. Agarwal, A. Kumar, S. Lal, A. Mathur, A. Tewari, and J. Canny, "Designing e-learning games for rural children in India: a format for balancing learning with fun," in *DIS '08: Proceedings of the 7th ACM conference on Designing interactive systems*. : ACM, New York (2008), pp. 58-67. [Online]. Available: <http://dx.doi.org/10.1145/1394445.1394452>
23. Motiwalla, L.F., "Mobile learning: A framework and evaluation," *Computers & Education*, **49**(3), 581, (2007)
24. Evans, C., "The effectiveness of m-learning in the form of podcast revision lectures in higher education," *Computers & Education*, **50**(2), 491 (2008)
25. Uzunboylu, H., "Using mobile learning to increase environmental awareness," *Computers & Education*, **52**(2), 381, (2009)
26. Parsons, D., H. Ryu, and M. Cranshaw, "A design requirements framework for mobile learning environments," *J. Computers*, **2**(4), 1-8, (2007)
27. Dondi, C., and M. Moretti, "A methodological proposal for learning games selection and quality assessment," *British J. Educational Technology*, **38**(3), 502, (2007)
28. Gafni, R., "Measuring Quality of m-Learning Information Systems," *The Evolution of Mobile Teaching and Learning*, R. Guy, Ed., Informing Science Press, Santa Rosa, CA (2009), pp. 211-247
29. Fernandez, J., R. Marin, and R. Wirz, "Online competitions: An open space to improve the learning process," *IEEE Transactions on Industrial Electronics*, **54**(6), 3086, (2007)
30. Arango, F., G. Altuger, E. Aziz, C. Chassapis, and S. Esche, "Piloting a game-based virtual learning environment," *Computers in Education J.*, 18(4), 82, (2008)
31. Casini, M., D. Prattichizzo, and A. Vicino, "The automatic control telelab: A user-friendly interface for distance learning," *IEEE Transactions on Education*, **46**(2), 252, (2003)
32. Hassan, H., C. Dominguez, J. Martinez, A. Perles, and J. Albaladejo, "Remote laboratory architecture for the validation of industrial control applications," *IEEE Transactions on Industrial Electronics*, 54(6), 3094, (2007)
33. Zualkernan, I., "A framework and a methodology for developing authentic constructivist e-Learning environments," *Educational Technology & Society*, **9**(2), 198, (2006)
34. Malone, T.W., and M.R. Lepper, "Making learning fun: A taxonomy of intrinsic motivations for learning," in R.E. Snow and M.J. Farr (Eds.), *Aptitude, learning and instruction: III. Congnitive and affective process analyses*, Erlbaum, Hillsdale, NJ (1987), vol. 3, pp. 223-253 ❐

Author Guidelines for the
LABORATORY
Feature

The laboratory experience in chemical engineering education has long been an integral part of our curricula. *CEE* encourages the submission of manuscripts describing innovations in the laboratory ranging from large-scale unit operations experiments to demonstrations appropriate for the classroom. The following guidelines are offered to assist authors in the preparation of manuscripts that are informative to our readership. These are only suggestions, based on the comments of previous reviewers; authors should use their own judgment in presenting their experiences. A set of general guidelines and advice to the author can be found at our Web site: <http://che.ufl.edu/~cee/>.

- Manuscripts should describe the results of original and laboratory-tested ideas. The ideas should be broadly applicable and described in sufficient detail to allow and motivate others to adapt the ideas to their own curricula. It is noted that the readership of *CEE* is largely faculty and instructors. Manuscripts must contain an abstract and often include an Introduction, Laboratory Description, Data Analysis, Summary of Experiences, Conclusions, and References.
    - An **Introduction** should establish the context of the laboratory experience (*e.g.*, relation to curriculum, review of literature), state the learning objectives, and describe the rationale and approach.
    - The **Laboratory Description** section should describe the experiment in sufficient detail to allow the reader to judge the scope of effort required to implement a similar experiment on his or her campus. Schematic diagrams or photos, cost information, and references to previous publications and Web sites, etc., are usually of benefit. Issues related to safety should be addressed as well as any special operating procedures.
    - If appropriate, a **Data Analysis** section should be included that concisely describes the method of data analysis. Recognizing that the audience is primarily faculty, the description of the underlying theory should be referenced or brief. The purpose of this section is to communicate to the reader specific student-learning opportunities (*e.g.*, treatment of reaction-rate data in a temperature range that includes two mechanisms).
    - The purpose of the **Summary of Experiences** section is to convey the results of laboratory or classroom testing. The section can enumerate, for example, best practices, pitfalls, student survey results, or anecdotal material.
    - A concise statement of the **Conclusions** (as opposed to a summary) of your experiences should be the last section of the paper prior to listing **References**.

Visit
us
on the
Web
at

http://che.ufl.edu/CEE