AC 2007-2729: ADVANCED MODELING IN BIOLOGICAL ENGINEERING USING SOFT-COMPUTING METHODS

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Advanced Modeling in Biological Engineering Using Soft-computing Methods

Abstract

A new engineering graduate course on advanced modeling techniques and applications provides both basic and practical understanding of techniques for simulating biological and environmental processes to future scientists and research engineers. Of particular importance are those models that benefit with soft computing methods. Simulation of biological and environmental systems involves the treatment of vagueness, uncertainty, and incomplete information usually associated with these systems. A primary course emphasis was the inclusion of fuzzy set theory and the positioning of fuzzy set theory (FST) within a broader topic of soft computing. At the conclusion of the course, students had developed their own paradigms and semester projects related to their particular research interest. Students made use of current literature for theory formation and hypothesis building related to biological and environmental systems. Future researchers must effectively use methods to simulate ambiguous systems for directing limited resources toward the solution of these problems. Principle course topics included fuzzy variables, inference systems, neural networks, signal processing, controls, visual simulation, machine vision, and genetic algorithms in support of modeling. Students were expected to read and critique related journal articles each week. To enhance communication skills, students lead selected class sessions by discussing and critiquing refereed articles related to soft computing and modeling, especially within their chosen research areas. Students learned practical modeling skills using MATLAB® , MATHCAD®, and LabVIEW® programming exercises. This paper discusses the course content and topics presented, and how the course continues to evolve. A summary of student projects and results are also presented.

Keywords: Courseware, biological systems, modeling, fuzzy systems, optimization

Course Concept

A new 3-credit graduate level course addressing advanced modeling in biological engineering was approved in 2006 and is now being offered at the University of Nebraska over a 15-week semester. Preliminary versions of this course had been offered for three years prior as a special problems class, for only a handful of selected graduate students. This past fall, eleven students from four discipline areas took the class. Three were masters, while nine were doctoral students. Ten students completed the class while one took an incomplete. The objective of this course is to provide students with a basic and practical understanding of the use of modeling techniques for simulating biological, environmental, and associated engineering systems.

Primary emphasis included the application of fuzzy set theory and the positioning of fuzzy set theory (FST) within a broader topic of soft computing. At the conclusion of the course, students were to be able to (a) develop and test FST and apply selected FST models to their particular research interest, (b) use current modeling literature related to biological and environmental systems for theory formation and hypothesis building, and (c) effectively use these methods to simulate systems for understanding and solving new research problems. Supporting topics included neural networks, machine vision, and genetic algorithms. Table 1 shows the syllabus of course topics by number. Appendix A gives the university catalog description. Of particular concern is the treatment of uncertainty and incomplete information associated with biological and environmental systems.

Fuzzy Logic Modeling

The universe of discourse of available information in the biological world includes both precise and ambiguous information. An approach is the use of FST. The concept of FST is attributed to Zadeh[1,2], who developed this theory to address uncertainty, ambiguity, and vagueness for pattern recognition and classification problems. Fuzzy sets are defined with degrees of membership for linguistic variables. FST is in contrast to crisp or binary memberships in classical set theory where no uncertainty is taken into account. Fuzzy logic (FL) for solving problems through modeling uses either a rule-based or fuzzy arithmetic inference systems to map fuzzy antecedents to fuzzy consequents as *modus ponens* logic. FL has been demonstrated in many physical applications to be good enough to simulate or mimic the human decision-making processes based on imprecise criteria[3]. For example, machine vision which mimics human vision and reasoning would certainly fit into this category.

The class begins by actually demonstrating existing fuzzy models. The traditional means of data representation are usually treated as probabilistic in nature. Research has developed the means to use FST an alternative to (and in some cases complementary to) a probabilistic approach. The basis of FL is the concept of a fuzzy set. A fuzzy set is defined as a set without a clearly defined boundary. Sets may overlap. Such a set can contain elements with only a partial degree of membership. Zadeh[1] noted that the concept of fuzzy sets parallels ordinary set theory in many ways, but fuzzy sets are more general and potentially have wider applicability, particularly in the fields of pattern classification and information processing. Ross's book[4] and classes 2-10 were used to cover the fundamentals.

From the agricultural and biological literature, fuzzy logic has been demonstrated for crop management and environmental control in greenhouses[5,6,7]. Schmoldt[8] described the simulation of plant physiological processes using fuzzy logic. Center and Verma[9] developed a fuzzy photosynthesis model for tomato plants. Fuzzy results compared favorably to traditional modeling techniques. Gottimukkala[10] developed a fuzzy logic classifier to detect weeds. Fuzzy rules for each weed species were established using spectral response data collected using a spectrometer. The membership functions were derived using a genetic optimization algorithm (GA). GA was covered in classes 19-21. Tizhoosh[11] provided a fundamental overview of the application of fuzzy logic to image processing. Several modeling techniques were identified including fuzzy clustering, rule-based systems, fuzzy geometry and arithmetic, and fuzzy measure theory. Chi et al[12] also presented useful algorithms for fuzzy machine vision.

Bezdek[13] summarized various imaging methods using neural networks (NN). A neural network is a technique that seeks to develop an accurate response function or rules based on a model and input and output data. Ross[4] outlined methods for generating fuzzy membership functions from imprecise image data. Basak et al[14] described neural-fuzzy methods of unsupervised training for determining membership functions for various applications. El-Faki et al[15] used fuzzy color features to establish a simple weed detection method using a color machine vision system. Fuzzy rules have been shown to mimic complex mathematical functions very accurately[14].

Laviolette and Seaman[16] and Pal and Bezdek[17] presented a mathematical background for using FST as a means of describing uncertainty. They also indicated that the use of FST is only appropriate for certain types of data, and should not arbitrarily usurp the use of probabilistic measures. Furthermore there is a work that combines the use of FST and probabilistic measures[17, 18, 19]. A more aggressive approach to data representation is the use of fuzzy classifier systems, also described as fuzzy clustering. Geyer-Schulz[20] reviewed these systems and concluded that fuzzy genetic-based machine learning has an advantage over crisp representations. This is important when trying to extract information from highly ambiguous data[21, 22].

Why Fuzzy Set Theory?

Fuzzy logic provides several advantages over crisp mathematical methods:[3]

1. While fuzzy logic is based on the same theoretical concepts as classical sets, the theory adds two new laws: the law of excluded middle and the law of contradiction. Otherwise, mapping of fuzzy sets to functional relationships is similar to classical methods.
2. Fuzzy logic as a modeling tool is flexible. Fuzzy reasoning can be simple or complex to predict a unique numerical value for the consequence or predict a classification category of a fuzzy consequence.
3. Fuzzy logic inference can be developed from the experience of a human expert. If the relationships between input and output data are well understood, rules can be readily developed to reflect this a priori knowledge. FL can mimic the human thought process to process and predict imprecise results.
4. While fuzzy logic is tolerant of imprecise data, its precepts allow convergence to classical sets. Fuzzy logic can model nonlinear functions of arbitrary complexity. Fuzzy systems can be created to address any set of input/output data. The ability to deal with nonlinear

relationships is enhanced through use of adaptive techniques such as neural networks (NN).

5. Fuzzy logic can be blended with conventional control techniques. In many control applications, fuzzy logic may be used to enhance existing systems and simplify their implementation. Fuzzy logic is based on natural language and fundamental logic. Because fuzzy reasoning is based on imprecision in the data, rules can be generated in linguistic terms that are more readily comprehended.

Membership Functions

A membership function (MBF) is a mathematical relationship that defines how each data point within an input space is mapped to a membership value μ or degree of membership $(0 \le \mu \le 1)$. The input space (X) is referred to as the universe of discourse. Membership functions can take on various forms of the distribution of the input data, including piecewise linear, Gaussian, sigmoid, or polynomial curves. In the case of a classical Boolean set, the membership function μ would be a constant value (either zero or one) for a given input.

Logical Operations

Fuzzy logic can be considered a superset of conventional Boolean logic, rather than a simple binary truth table based on intersection (AND) and union (OR) functions. Mathematical operations are described using variables or membership values between zero and one. One means of implementing this method is the redefinition of the AND operator as a minimum and the OR operator as a maximum of two membership values. In the case of a fuzzy system, the NOT operator becomes the additive complement of the input membership value.

Classical Versus Fuzzy Sets and Mapping

Assume X and Y are two separate universes of discourse, with X representing input information for the model and Y the output classification information. A model will define a mapping function between an element x within universe X and a corresponding element y within universe Y, or

$$f : X \rightarrow Y \tag{1}$$

Define two sets A and B on the input universe X. For a classical Boolean model, characteristic (indicator) functions for the input data are defined by

$$\chi_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases} \tag{2}$$

$$\chi_B(x) = \begin{cases} 1 & x \in B \\ 0 & x \notin B \end{cases} \tag{3}$$

These functions describe "membership" in the respective sets A and B, for each element x within universe X. The values 1 and 0 represent the possible values for y within the output universe Y to which the input x can be mapped. Classical set operations can now be defined in terms of these characteristic functions as follows:

Union: $A \cup B = \{x \mid x \in A \text{ or } x \in B\}$

$$\rightarrow \chi_{A \cup B}(x) = \chi_A(x) \vee \chi_B(x) = \max(\chi_A(x), \chi_B(x)) \tag{4}$$

Intersection: $\mathrm{A} \cap \mathrm{B} = \{\mathrm{x} \mid \mathrm{x} \in \mathrm{A} \text{ and } \mathrm{x} \in \mathrm{B}\}$

$$\rightarrow \chi_{A \cap B}(x) = \chi_A(x) \wedge \chi_B(x) = \min(\chi_A(x), \chi_B(x)) \qquad (5)$$

Complement: $\overline{\mathrm{A}} = \{x \mid x \notin \mathrm{A}\} \rightarrow \chi_{\overline{A}}(x) = 1 - \chi_A(x)$ (6)

Containment: $\mathrm{A} \subseteq \mathrm{B} \rightarrow \chi_A(x) \leq \chi_B(x)$ (7)

Next, two fuzzy sets $\underset{\sim}{A}$ and $\underset{\sim}{B}$ are defined on the same universe X. Membership functions are defined for the two sets as continuous functions:

$$\mu_{\underset{\sim}{A}}(x) = f_1(x) \qquad 0 \leq f_1(x) \leq 1 \qquad (8)$$

$$\mu_{\underset{\sim}{B}}(x) = f_2(x) \qquad 0 \leq f_2(x) \leq 1 \qquad (9)$$

Set operations can be defined as for classical sets:

Union: $\mu_{\underset{\sim}{A} \cup \underset{\sim}{B}}(x) = \mu_{\underset{\sim}{A}}(x) \vee \mu_{\underset{\sim}{B}}(x) = \max\left(\mu_{\underset{\sim}{A}}(x), \mu_{\underset{\sim}{B}}(x)\right)$ (10)

Intersection: $\mu_{\underset{\sim}{A} \cap \underset{\sim}{B}}(x) = \mu_{\underset{\sim}{A}}(x) \wedge \mu_{\underset{\sim}{B}}(x) = \min\left(\mu_{\underset{\sim}{A}}(x), \mu_{\underset{\sim}{B}}(x)\right)$ (11)

Complement: $\mu_{\overline{\underset{\sim}{A}}}(x) = 1 - \mu_{\underset{\sim}{A}}(x)$ (12)

Containment: $\underset{\sim}{A} \subset \underset{\sim}{B} \rightarrow \mu_{\underset{\sim}{A}}(x) \leq \mu_{\underset{\sim}{B}}(x)$ (13)

If-Then Inference Rules

If-then rule definitions apply to fuzzy logic as for Boolean logic, with the exception that the crisp mathematical values are replaced with linguistic notation that reflect the imprecision of the data. Interpretation of fuzzy rules is a three-part process:

1. First, fuzzify the inputs. Resolve all fuzzy statements in the antecedent to a degree of membership between zero and one. If there is only one part to the antecedent, this is a degree of support for the rule.
2. Apply a fuzzy operator to multiple part antecedents. If there are multiple parts to the antecedent, apply fuzzy logic operators and resolve the antecedent to a single number between zero and one. This is a degree of support for the rule.
3. Apply the implication method. Use the degree of support for the entire rule to shape the output fuzzy set. The consequent of a fuzzy rule assigns an entire fuzzy set to that output. This fuzzy set is represented by a membership function that is chosen to indicate the qualities of the consequent. If the antecedent is only partially true (i.e., is assigned a value less than one), then the output fuzzy set is truncated according to the implication method.

In general, a fuzzy logic inference system is composed of two or more rules that define the relationships between input and output variables. The output of each rule is a fuzzy set. The output fuzzy sets for each rule are then aggregated into a single output fuzzy set, which is then defuzzified to resolve the output into a single value.

Fuzzy inference maps a given input to an output using fuzzy logic. Mapping provides a basis from which decisions can be made or patterns discerned. There are two basic types of fuzzy inference systems in common use, Mamdani and Sugeno. Mamdani-type inference expects the output membership functions to be fuzzy sets[23]. After aggregation, there is a fuzzy set for each output variable. The output membership function can be defined as a singleton spike (single value) or as a centroid of a two-dimensional function. Sugeno-type systems can be used to model any system in which the output membership functions are either linear or constant values. The Mamdani method is highly intuitive, has widespread acceptance, and is well suited to human input. The Sugeno is computationally efficient and works well with linear techniques, optimization, and adaptive techniques. It has a guaranteed continuity of the output surface. Fuzzy arithmetic can be used to develop useful models. Fuzzy inference for practical controls was implemented with a hands-on session with the LabVIEW® controls toolkit (National Instruments, Inc, Austin, TX).

Fuzzy Arithmetic

Fuzzy arithmetic was covered in classes 8 and 9 and Ross, chapter 12. Problems assigned were usually computed by hand. The instructors found very few existing software examples to implement the approximate methods of the extension principle: vertex, Dong, Shah and Wong (DSW) and modified DSW algorithms[24,25], so MATHCAD® (Mathsoft, Inc., Needham, MA) versions were written, with the future expectation of converting them later to MATLAB script.

Fuzzy Clustering

During pattern recognition, the volume of raw data is often prohibitive for development of an efficient fuzzy inference system[26]. Therefore, it is necessary to identify natural groupings of data to produce more efficient representations of the data. This is often accomplished through the use of clustering. Clustering refers to the identification of distinct subclasses within a data set and the partitioning of these data into subclasses. Data are assigned to a given cluster based on a minimum distance from the cluster center in the feature space. The clustering method can be either hard (crisp classification partitions) or fuzzy (cluster membership is determined by a membership function). Fuzzy C-means (FCM) clustering has been suggested as a method for obtaining segmented object membership functions from color images. FCM and the Gustafsen-Kessel (GK)[26] clustering algorithms were covered in classes 7, 11, and 12. Various cluster validity methods were also discussed and demonstrated[28].

Machine vision systems with imaging and fuzzy clustering for example can distinguish grasses from broadleaf weed plants especially those are 7-21 days old. A machine vision with a plant species classification system by Camargo Neto and Meyer[29], Camargo Neto et al[30,31] was demonstrated in classes 17 and 20. Improved and automated systematic inventorying and assessment of plants, their condition, competitiveness, and growth stages from images across natural vegetation could be very important for remote sensing applications.

Neural Networks and Controls

A Neural Network (NN) is an information-processing system with analytical characteristics that mimic biological neural processes[32]. A NN adjusts parameters of the membership functions using either a backpropagation algorithm or in combination with a least squares method. The goal of a NN is to accurately map input variables to the corresponding output value, while minimizing the predictive error rate. Bezdek[13] summarized the use of neural networks in fuzzy pattern recognition for generating membership functions, performing fuzzy logic operations, and derivation of optimal rule sets. NN's were covered and demonstrated in classes 22 and 23. Fuzzy control systems utilize rules that are developed or defined arbitrarily, or based on accepted relationships between input and output variables[32]. For many applications, especially data classification, rules often can not be readily defined based on observations of the variables alone. Moreover, membership functions for data classification often cannot be predefined. In these instances, an adaptive learning technique such as a neural network approach is used to train or discover potential membership functions and rules, based on input data[33]. Ross[4] described methods for generating membership functions using neural networks. This class focused in the Adaptive Neural Fuzzy Inference System software (ANFIS) as part of the MATLAB Fuzzy Logic Toolbox® (MathWorks, Inc., Natick, MA).

Students Projects

Ten independent student projects were developed and presented as posters at an annual Department open house which invited other students, alumni, faculty, administrators and potential employers (class 29). The final written term paper was graded according to the instrument shown in Appendix B. A brief summary description is given for each project below**.**

<u>Project 1: Fuzzy Model for Predicting the Microbial Growth in Shell Eggs</u>
Microbial contamination in eggs is a major cause of concern for the poultry industry. *Salmonella* species, in particular is of interest as it causes the widely spread infection- Salmonellosis. It is estimated that nearly 1.3 million people are affected by salmonellosis every year. *Salmonella* Enteritidis is considered to be the main pathogen responsible for causing salmonellosis. One of the important contributing factors for the growth of this pathogen is temperature. Improper temperature conditions can lead to the growth of this pathogen in the eggs, causing the infection. Hence it is very important for the poultry industry to constantly monitor the temperature to keep a check on the growth of the microorganism. Periodic/random microbial tests on the eggs are conducted to ascertain the growth of the microorganism. The traditional tests are time consuming (takes nearly 48 hrs) to get the results. It is difficult for a large poultry industry to hold the stocks for long duration before they are cleared microbiologically. Hence a need was felt to develop a quicker and accurate method to predict the growth of the microorganisms. A predictive model will be very useful for the industry to make decisions regarding the microbiological safety of eggs. The predictive model will also take into account the fluctuations in the temperature in the real conditions. Thus a Fuzzy predictive model will enable to predict the growth of the microorganism at a given temperature and time there by saving time and money of the industry.

<u>Project 2: ANFIS Model for Predicting the Error in Air Temperature Measurement in MMTS</u>
Fuzzy Inference is the process of formulating the mapping from a given input to an output using the concept of fuzzy set theory. This mapping forms the basis from which rules can be developed and the contribution of an input against the output can be drawn. In this study the error in air temperature measurement was predicted through ANFIS and the results were correlated with that of the actual error in air temperature measurement obtained from the experimental site. By using ANFIS, the error in air temperature measurement was predicted and was correlated with the actual error obtained in experimental site. The correlation factor was obtained as 0.97 for training

data set and 0.84 for testing data set. The effect of each input variable on the output variable is shown graphically with correlation coefficient. The contribution of each input variable on the output in the ascending order of the contribution was wind speed, solar radiation, clear index, solar time according to the values of correlation coefficient.

Project 3: Fuzzy and Neural Network Modeling Of Near-Infrared Reflectance Data For Beef Tenderness Prediction

Beef tenderness is an important quality attribute for consumer satisfaction. The objective of this study was to implement Adaptive Neuro-Fuzzy Inference System (ANFIS) modelling of Near-Infrared (NIR) reflectance spectra for beef tenderness prediction. A spectrometer (λ : 1000 – 1800 nm) was used to record the NIR reflectance spectra of beef ribeye steaks (n=294). Slice shear force (SSF) values were used as tenderness reference. Based on SSF values, three beef tenderness categories namely tender (SSF=< 21 kg), intermediate (SSF=21.1 to 25.9 kg), and tough (SSF>=26 kg) were defined. Two canonical variables were derived from reflectance values using PROC STEPDISC in SAS. A Sugeno Fuzzy Inference System (FIS) with two inputs (canonical variable 1 and 2) and one output (tenderness category) was developed. To handle the non-integral nature of the FIS output, Gaussian membership functions were developed using the mean and standard deviation of training results and solved with maximum membership criteria. A ten-fold cross validation procedure was followed. Cross-validation and true validation classification accuracies were 92.6% and 69.4%, respectively. ANFIS models of NIR reflectance spectra shows promise in predicting beef tenderness.

Project 4: Fuzzy Logic Modeling of Tapioca Starch-polylactic acid-based Nanocomposite Foams as Affected by Type of Organoclay

Polymer melt-intercalation or exfoliation is a promising approach for the preparation of nanocomposites since they exhibit greatly improved mechanical, thermal and barrier properties. The structure of nanoclay platelets in the nanocomposites depends not only on the properties of polymer matrix and nanoclay, but also on the extrusion conditions. The objective of the present work is to investigate the effects of different types of nanoclays and extrusion conditions upon the nanoclay structure in nanocomposites prepared with a twin screw extruder. Tapioca starch containing 10% polylactic acid (PLA) and 3% nanoclay at 16% moisture content were extruded. Feed rate, screw configuration, screw speed, barrel temperature, die opening were maintained constant. Three different types of clay were used to determine the effect on nanoclay dispersion. Wide-angle X-ray diffraction (WAXD) was used to examine the gallery height or *d*-spacing in clay particles to determine nanoclay interaction and exfoliation in the foam. The *d*-spacing can be determined by the diffraction peak in the XRD patterns. Although data had not been completed collected, a fuzzy inference model was prototyped and presented.

Project 5. Physical Activity Detection using Fuzzy C Means Clustering and a Mamdani FIS.

A system for monitoring and classifying physical activity that a person performs daily for physical therapists and trainer was developed using fuzzy methods. Biaxial accelerometer data was used to classify different activities, using Fast Fourier Transform (FFT) data from ten young individuals (5 males and 5 females, age 23.1$\pm$3.1 years). Activities included over ground walking, over ground running, reaching activity, star climbing, stair negotiation, table activity, treadmill walking, treadmill running, vita glide, and wheel chair propulsion. Amplitude and frequency parameters were derived from the FFT's. Model output however, was correct only 42 % of the time.

Project 6. Optimal Distribution of Electrical Power using a Genetic Algorithm.

A genetic algorithm method[34] was used to discover a distributed grid (DG) electrical power system for a standard IEEE 30-bus transmission system. The DG on each bus with a possibility of seven buses was derived by two genes. Each set of genes formed a chromosome. The Loss of Load Probability Index (LOLP) was calculated for a possible 16,384 potential systems. The fitness function was a reliability factor time LOLP) plus Cost. A crossover rate of 0.8 and mutation rate of 0.05 were used. Less desirable systems were removed, and best systems were found by observing a LOLP versus Cost cluster diagram.

Project 7. Using Fuzzy Logic to Manage the Harvest of Wildlife Populations in the Face of Uncertainty.

Decisions about the magnitude and frequency of wildlife harvest are made by wildlife managers. Population dynamics are poorly understood. Two fuzzy modeling approaches were compared. A fuzzy knowledge-based model (FKM) was compared to a rule-based fuzzy cluster (FCM) model. A third model (MSY) harvested the population with a constant rate set at the theoretical maximum sustainable yield. Each model was tested and compared on whether they held the population at a specified target size, maintained a predictable average yield, and whether their use would cause the population to drop below a minimum threshold. This was done for a 50 year sequence. Both the FKM and FCM models met the specified criteria, while MYS model failed to meet any.

Project 8. In-line Viscosity Control in an Extrusion Process using a Fuzzy Controller.

In an extrusion process, the end product quality will depend on a number of process parameters, such as screw speed, quality of the feed material, melt temperature, melt pressure, and melt viscosity. The quality of the feed material and screw speed can be set manually. Melt temperature, viscosity, and pressure can be measured by in-line transducers. A prototype fuzzy controller to automatically adjust screw speed was based on two inputs of viscosity -viscosity set point difference and the change in viscosity with time. Each was divided into seven linguistic sets of membership values, resulting in 49 rules. Preliminary test on the fuzzy inference systems suggest an R^2=0.78 and optimization might be required to shorten the response time of the controller.

Project 9. Predicting Drying Requirements with Fuzzy Logic.

A data driven fuzzy logic model was created to portray the characteristics of variability might occur during extrusion and manufacturing of breakfast cereal at a local company affects the drying requirement of the process. Several ANFIS models were trained and tested for predicting moisture content of the cereal from six proprietary measured extruder inputs. Correlation results (R^2) of predicted versus actual output ranged from 0.64 to 0.98.

Project 10. Fuzzy Logic Modeling of Extrusion Expansion of Starch-Based Foams

Biodegradable starch-based packaging foams were extruded with a single screw laboratory scale extruder. Extrusions were carried out with 18% moisture starch and three polystyrene levels of 15, 20, and 25%. Talc was added at 0, 1,2, and 5 percent. The size of foam pellets was measured. Fuzzy logic methods including FCM clustering ANFIS rule-generation were used to map torque and pressure to radial expansion, and torque, pressure, and talc to radial expansion. The models training and validation were able predict expansion very well with correlation factors around 0.94.

Student Acceptance

Student reaction to this class was very good. The overall class score was (3.38 ± 0.54 /4.0). The overall instructor score was (3.67 ± 0.35 /4.0). Students were quite complimentary about the course. They felt both instructors did a good job. The material was considered very relevant. Examinations were fair, but long. A common complaint was knowledge of the software used, and a request to make it a prerequisite or provide some elementary training may be considered for future offerings. Improvements could be made on the homework. Posters at the open house were well-done. Term papers were well-written. A couple of the student papers are being considered for publication.

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Table 1. Advanced modeling in biological engineering. Schedule of Topics.

Class	Topic
1	Course Introduction: Modeling, Challenges, Ambiguity and Uncertainty
2	Introduction to soft computing. Introduction to Fuzzy Set Theory (FST) Classical Set Theory v FST
3	Probability and Statistics v FST
4	Membership Functions, Development and Conversions
5	*MATLAB laboratory:* Introduction to MATLAB and Toolboxes for Modeling
6	Fuzzy Modeling Applications: MATLAB Fuzzy Toolbox and Mamdani and Sugeno type models
7	Clustering Strategies for data organization and model development
8,9	Arithmetic with fuzzy numbers (Hand calculations and MATHCAD functions)
9,10	Classical and Fuzzy Relations Fuzzy Logic and Inference Systems
11,12	*MATLAB laboratory*: Model development and cluster analysis
13,14	*MATLAB laboratory*: Cluster analysis and model optimization
15,16	Fuzzy decision making
17	*MATLAB laboratory*: Fuzzy Image Enhancement and Fuzzy Segmentation
18	Image Shape and Texture Analysis- Classical, Elliptic Fourier, Haralick, and Gabor Filters
19	Introduction to Genetic Algorithms, Fitness Functions, and Optimization
20	Genetic Algorithms, Fitness Functions, and Optimization Applications; Machine vision – Plant Species Identification Example
21	Genetic Algorithms, Fitness Functions, and Optimization Applications; Machine vision – Applications
22,23	Neural Network Systems
24	Introduction to Process Control Models: Comparing PID with Fuzzy Logic Control
25	*Laboratory*: Applications of Process Control Models with Fuzzy Logic (integration of fuzzy controllers with LabVIEW instrumentation systems)
26	Adaptive Modeling: Integration of Instrumentation (LabVIEW) with Real-time Process Script Models – Controlled Environment Turf water use and fuzzy irrigation control example.
27,28	Student Progress reports
29	Student Poster Presentations

Appendix A

Catalog Description: 951. Advanced Modeling in Biological Engineering (3 cr) Lec 3. Prereq: Graduate student status in Engineering or permission. Advanced modeling techniques and applications. Topics are extracted from the current literature and research areas. Specific topics vary depending on research interest and current literature. Credit**:**3 hours

Text Book: **Fuzzy Logic with Engineering Applications 2nd Edition**
Timothy J. Ross
John Wiley and Sons, Ltd.
ISBN: 0-470-86075-8
…and selected excerpts and recent papers from the literature.

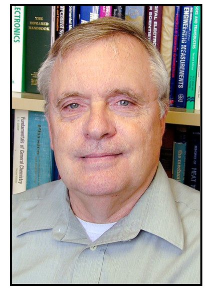
Format: The class meets 1.5 hours on each of two week days to be announced. Class material will be presented via lectures, class discussions, directed readings, homework, quizzes, and reviews of research papers. The students are expected (with guidance from the instructors) to access the research literature (mostly published journal articles) and lead the class in discussions of assigned research papers related to modeling, soft computing, and their individual research areas. Of particular importance are those works that use modeling and can apply soft computing in the students' research area. Students will be expected to read 1-3 related journal articles each week. Examinations include only bi-weekly quizzes consisting of 1 or 2 problems or conceptional responses. Students will also have hands-on activities with MATLAB, LABVIEW, and MATHCAD (no previous programming experience is expected, but student must have a basic knowledge of the Windows operating system). More details will be discussed in class, but the course grade depends on the completion and execution of the paper reviews, student-led class discussions, and a final term project.

Appendix B. **FINAL REPORT - SCORE SHEET - 100 Points**

CATEGORIES	POSSIBLE POINTS	POINTS GIVEN	COMMENTS
REPORT CONTENT AND FORMAT			
Summary - Single descriptive paragraph or abstract.	**5**		
Background and Literature Review - Cites useful literature, previous instrumentation approaches, and describes purpose and impact of the project.	**5**		
Objectives - Overall objective, and 1-2 sub objectives.	**5**		
Procedure/ Methods - Methods used. Source of data and/or knowledge. Appropriate equations, algorithms, units, numbered, and cited. Support with pictures, figures and/or tables, as appropriate.	**20**		
Results and Discussion - Reports details and results of development efforts, methods, testing, with table and figure support.	**25**		
Conclusions - Appropriate conclusions that match objectives. Suggestions for future work.	**10**		
References (Complete citations - ASAE method).	**5**		
Figures and Tables - Appropriate use of significant digits, information displayed, correctly justified, labeled, footnotes, and captions in the correct position. Landscapes attached correctly to the report. Stands by themselves.	**5**		
Appendices - Appropriate supporting material. Examples: computer code used, sample calculations, samples of raw data, etc.	**5**		
OVERALL REPORT APPEARANCE			
Neatness and Writing Quality - Proper spacing, justification, proper grammar, correct spelling, and page numbers. Drawings and sketches are neat and properly labeled.	**5**		
Overall Creativity – Demonstrates mastery of modeling and the use and interpretation of soft computing techniques.	**10**		
FINAL TOTAL SCORE	**100**		

Biographical Information

GEORGE MEYER, Professor, has taught graduate and undergraduate classes that involve plant and animal growth and environmental factors, modeling, and instrumentation and controls for both agricultural and biological systems engineering students for 28 years. He has received national paper awards and recognition for his work in distance education and has received university teaching awards. His current research include measurement and modeling of crop water stress, fuzzy logic controls for turf irrigation management, and machine vision detection, enumeration, and plant species identification for spot spraying control and precision agriculture.



DAVID JONES, Professor, has taught graduate and undergraduate classes that involve fuzzy set theory and soft computing techniques, risk assessment of complex systems, and mathematical modeling of physical and biological systems for the past 18 years. He also teaches a Heat and Mass Transfer course to engineering juniors and the senior design classes. He has received numerous university and national awards for his teaching excellence.