Artificial Intelligence Methods and Their Applications in Civil Engineering

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Handbook of Research on

Recent Developments in Materials Science and Corrosion Engineering Education

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Hwee Ling Lim

Handbook of Research on Recent Developments in Materials Science and Corrosion Engineering Education

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ABSTRACT

Simulation of material properties generally involves the development of a mathematical model derived from experimental data. In structural mechanics and construction materials contexts, recent experiments have reported that fuzzy logic (FL), artificial neural networks (ANNs), genetic algorithm (GA), and fuzzy genetic (FG) may offer a promising alternative. They are known as artificial intelligence (AI). In civil engineering, AI methods have been extensively used in the fields of civil engineering applications such as construction management, building materials, hydraulic, optimization, geotechnical and transportation engineering. Many studies have examined the applicability of AI methods to estimate concrete properties. This chapter described the principles of FL methods that can be taught to engineering students through MATLAB graphical user interface carried out in a postgraduate course on Applications of Artificial Intelligence in Engineering, discussed the application of Mamdani type in concrete technology and highlighted key studies related to the usability of FL in concrete technology.

INTRODUCTION

For many years, concrete has been known as one of the main materials in construction industry (Petcherdchoo, 2013). Concrete has a wide range of application in the area of construction and is considered a basic construction material that requires attention and diligence at every stage, from production to implementation. Concrete has an important place among all possible materials that form the basis of modern societies. In our environment, many civil infrastructures such as buildings,

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roads, bridges, dams, power plants, retaining walls, water tanks, ports, airports, etc. are made with concrete (Metha, 1986; Bİnİci, Durgun, Rızaoğlu, & Koluçolak, 2012). Concrete researchers know that it is not always easy to perform experiments to obtain data on the physical and mechanical properties of concrete. As a result, in the past two decades, different modeling methods based on soft computing have become popular and have been used by many researchers to obtain a variety of data on the properties of concrete.

This chapter focuses on the some approaches for solving the civil engineering problems by using computing techniques. It firstly describes the principles of FL methods that can be taught to engineering students through MATLAB graphical user interface carried out in a postgraduate course titled *Applications of Artificial Intelligence in Engineering*, then discusses the application of Mamdani type in concrete technology and finally highlights key studies related to the usability of FL in concrete technology.

Soft Computing is a combination of methodologies that were designed to model and identify solutions to real world problems. The main aim of soft computing is to devise methods of computation that lead to an acceptable solution at low cost in the shortest time possible. Unlike existing methods, it is tolerant of imprecision, uncertainty, partial truths, and approximations. Soft Computing is basically an optimization technique to find solutions to problems which tend to be complex (TheShodhganga@INFLIBNET Centre, 2014).

The definition of soft computing is not precise. Lotfi A. Zadeh, the inventor of the term soft computing, describes it as follows:

Soft computing is a collection of methodologies whose aim is to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost. Its principal constituents are FL, neuro computing, and probabilistic reasoning. Soft computing is likely to play an increasingly key role in many application areas, including software engineering. The model for soft computing is the human mind. (Zadeh, 1994 in Cevik, Göğüş, Güzelbey, & Filiz, 2010, p. 528).

Soft computing approaches in decision making have become increasingly popular in many disciplines. This is evident from vast number of technical papers appearing in journals and conference proceedings in all areas of engineering, manufacturing, science, medicine, and business. Soft computing is a rapidly evolving field that combines knowledge, techniques, and methodologies from various sources, using techniques from neural networks, fuzzy set theory, approximate reasoning, and using optimization methods such as genetic algorithms.

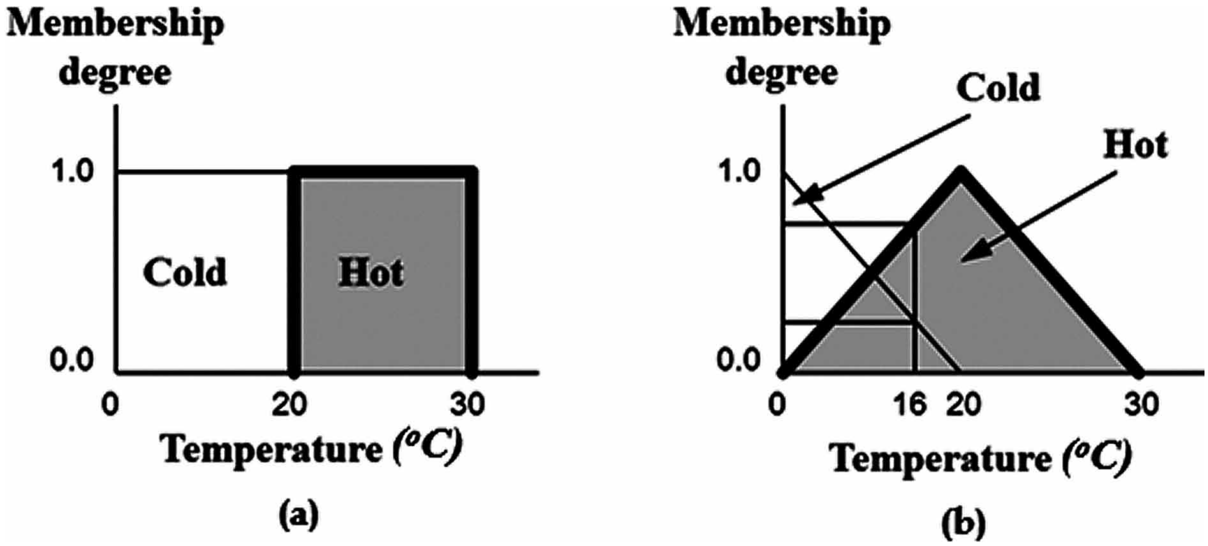
The integration of these and other methodologies forms the core of soft computing (Nguyen, Hung, Prasad, Walker, & Walker, 2003). One of the most popular soft computing techniques is fuzzy logic (FL). Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of different labels such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, FL controllers, and simply (and ambiguously) fuzzy systems (MATLAB, 2012). Fuzzy set theory that was proposed by Zadeh (1965) is a mathematical tool that allows work to be carried out in an uncertain environment. As opposed to classical logic, in which an element belongs (1) or does not belong (0) to a set, a fuzzy set is a set without a crisp, clearly defined boundary i.e., it can contain elements with only a partial degree of membership (a number between 0 and 1) (Garzón-Roca, Marco, & Adam, 2013).

BACKGROUND

Theory of Fuzzy Logic

Fuzzy Logic (FL) was used for the first time in 1965 by Zadeh (1965). He developed a new approach

Figure 1. An example for Aristotelian logic (a) and FL approaches (b)



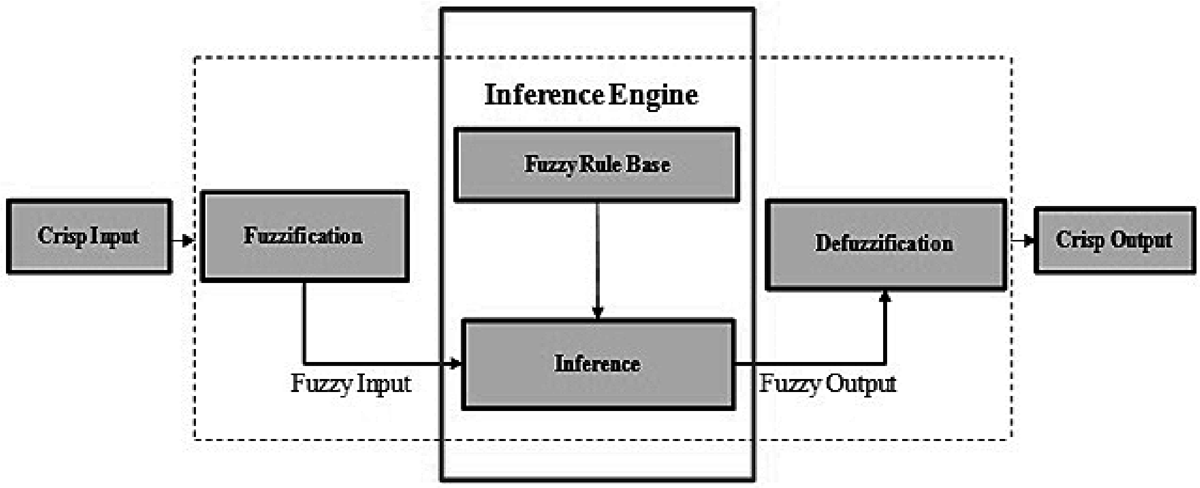
that was different from Aristotelian logic which contains only two definite possibilities (1 or 0). In contrast, FL provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria rather than the presence of random variables. In FL, an assertion can be more or less true. In classical logic, an assertion is either true or false - not something in between - and FL extends classical logic by allowing intermediate truth values between zero and one. FL enables a computer to interpret a linguistic statement such as: "If the washing machine is half full, then use less water". It adds intelligence to the washing machine since the computer infers an action from a set of such *if-then* rules. In other words, FL is computing with words, according to Zadeh.

The FL approach can be simply explained by an example: A temperature of 16°C is cold according to Aristotelian logic shown in Figure 1a. On the other hand, in the FL approach, it cannot be exactly said to be cold or hot at 16°C (as shown in Figure 1b) because the value of 16°C has a membership degree in both cold and hot levels. Thus the FL approach shown in Figure 1b is a structure accepted as plausible by the human brain.

In Aristotelian logic, all systems such as mathematic or stochastic have three components. These are input, system behavior, and output. The difference between the FL approach and Aristotelian logic is that the FL approach divides the system behavior into four parts as described below (Figure 2):

- **Fuzzification:** Converts each input data into degrees of membership by a lookup in one or more of several membership functions.
- **Fuzzy Rule Base:** Contains rules that include all possible fuzzy relationships between input and output using the *if-then* format.
- **Fuzzy Interference Engine:** Collects all fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to related outputs.
- **Defuzzification:** Converts the resulting fuzzy outputs from a fuzzy interference engine to a number (Zadeh, 1965; Topcu & Saridemir, 2008a; Beycioglu, 2008; Akkurt, Başyiğit, Kilincarslan, & Beycioğlu, 2010).

Figure 2. FL system behavior



Reasons for Using Fuzzy Logic

FL is one of the most popular artificial intelligent approaches with a large number of investigations focusing on the usability of rules based on Mamdani type FL systems. If the use of FL is questioned, the general responses are listed below according to the MATLAB FL Toolbox™ User's Guide (MathWorks, 2014):

- *FL is conceptually easy to understand.* The mathematical concepts behind fuzzy reasoning are very simple. FL is a more intuitive approach without far-reaching complexity.
- *FL is flexible.* With any given system, it is easy to layer on more functionality without starting again from the beginning.
- *FL is tolerant of imprecise data.* Most things are imprecise on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.
- *FL can model nonlinear functions of arbitrary complexity.* Fuzzy systems can be created to match any set of input-output data. This process is made particularly easy by adaptive techniques such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) that are available in the FL Toolbox in the MATLAB environment.
- *FL can be built on top of the experience of experts.* In direct contrast to neural networks that take training data and generate opaque, impenetrable models, FL allows users to rely on the experience of others who already understood a given system.
- *FL can be blended with conventional control techniques.* Fuzzy systems do not necessarily replace conventional control methods. In many cases, fuzzy systems augment them and simplify their implementation.
- *FL is based on natural language.* The basis for FL is also the basis of human communication. Since FL is built on the structures of qualitative description used in everyday language, FL is easier to use.

Types of Fuzzy Inference Systems and Their Comparisons

Fuzzy inference is a process of mapping from a given set of input variables to an output that relies on a set of fuzzy rules. There are two types of Fuzzy Inference Systems (FISs) that can be implemented in the MATLAB's FIS toolbox: Mamdani-type and Sugeno-type.

When the two methods are compared, the Mamdani's method is the most commonly used fuzzy methodology and it expects the output Membership Functions (MFs) to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification (Omid, 2011). Mamdani's method was one of the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani (Mamdani & Assilian, 1975) as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's works on fuzzy algorithms for complex systems and decision processes.

Another FIS is the Sugeno, or the Takagi-Sugeno-Kang method (Sugeno, 1985) of fuzzy inference introduced in 1985, which is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. For this reason, the Sugeno system is a more compact and computationally efficient representation than the Mamdani system. The Sugeno system allows the use of adaptive techniques for constructing fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system better models the data (Sugeno, 1985; Sugeno & Kang, 1988).

The Mamdani method is widely accepted for capturing expert knowledge. It allows us to describe the expertise in a more intuitive and human-like manner. However, Mamdani-type FIS entails a substantial computational burden. On the other hand, Sugeno method is computationally efficient and works well with optimization and adaptive techniques which makes it very attractive in control problems, particularly for dynamic nonlinear systems. The most fundamental difference between Mamdani-type FIS and Sugeno-type FIS is the way in which crisp output is generated from the fuzzy inputs.

While the Mamdani-type FIS uses the technique of defuzzification of a fuzzy output, Sugeno-type FIS uses weighted average to compute the crisp output. The expressive power and interpretability of Mamdani output is lost in Sugeno FIS since the consequences of the rules are not fuzzy. But the Sugeno has better processing time since the weighted average replaces the time consuming defuzzification process. Due to the interpretable and intuitive nature of the rule base, Mamdani-type FIS is widely used for decision support applications in particular. Other differences are that Mamdani FIS has output membership functions whereas Sugeno FIS has no output membership functions. The Mamdani FIS is less flexible in system design in comparison to Sugeno FIS as the latter can be integrated with an Adaptive Neuro-Fuzzy Inference System (ANFIS) tool to optimize the outputs (Kaur & Kaur, 2012).

APPLICATION OF FUZZY LOGIC BY USING MATLAB GRAPHICAL USER INTERFACE

In computing, Graphical User Interface (GUI) is a user interface that allows users to interact with electronic devices using images instead of text commands, a mouse and a keyboard can be used as input devices. Although it is possible to use the FL Toolbox by working strictly from the command line, it is easier to build the system using the graphical user interface. In the MATLAB environment, the graphical tools is used to build, edit, and view fuzzy inference systems.

There are five primary GUI tools for building, editing, and observing fuzzy inference systems in the FL Toolbox: the Fuzzy Inference System (FIS Editor), Membership Function Editor, Rule

Editor, Rule Viewer, and Surface Viewer. Their functions are briefly described below:

- **Fuzzy Inference System (FIS) Editor:** Displays general information about a fuzzy inference system.
- **Membership Function Editor:** Allows users to display and edit the membership functions associated with the input and output variables of the FIS.
- **Rule Editor:** Allows users to view and edit fuzzy rules using one of three formats - full English-like syntax, concise symbolic notation, or an indexed notation.
- **Rule Viewer:** Allows users to view detailed behavior of a FIS to help diagnose the behavior of specific rules or study the effect of changing input variables.
- **Surface Viewer:** Allows users to generate a 3-D surface from two input variables and the output of an FIS.

A MODEL DEVELOPMENT USING MAMDANI TYPE FIS THROUGH GUI

In this part of the chapter, a model development using Mamdani Type FIS through GUI is explained step by step with an example application. A flow diagram of the process showing the modeling phases of Mamdani-type modeling is given in Figure 3. All of the steps shown in the flow diagram will be explained in the following example. The five primary GUI tools for building, editing, and observing fuzzy inference systems in the FL Toolbox described earlier are shown in Figures 4a-d.

To examine the Mamdani-type FIS through GUI, an example study from the literature is used (Gencel, Brostow, del Coz-Diaz, Martínez-Barrera, & Beycioğlu, 2013). The title of the example study is "Effects of elevated temperatures on mechanical properties of concrete containing hematite evaluated using a FL model". The discussion here does not deal with the experimental details of the study.

Initially, by using the FIS editor (Figure 4) the general structure of the model is defined by carrying out the following steps:

- Select the type of FIS (Mamdani or Sugeno);
- Choose the defuzzification method;
- Define the number of input and output parameters and their names.

There are five built-in methods supported: centroid, bisector, middle of maximum (the average of the maximum values of the output set), largest of maximum, and smallest of maximum. In the sample study discussed here, the centroid technique was used in order to determine crisp values of outputs. The centroid defuzzification is also known as the center of gravity or the center of area defuzzification. It is most commonly used and regarded as a very accurate technique. The centroid defuzzification technique can be expressed with Equation 1.

$$x^* = \frac{\int \mu_i(x)\, x\, dx}{\int \mu_i(x)\, dx} \tag{1}$$

Here, x* is the defuzzified output, μi(x) is the aggregated membership function and x is the output variable.

In the second step, by using the Membership Function Editor (Figure 4), the input and output parameters are specified. The user can choose the number and types of membership functions for each inputs and outputs. There are many types of membership functions available as listed below:

- Difference of two sigmoids membership function.
- Gaussian membership function.

Figure 3. Flow diagram of the example modeling study

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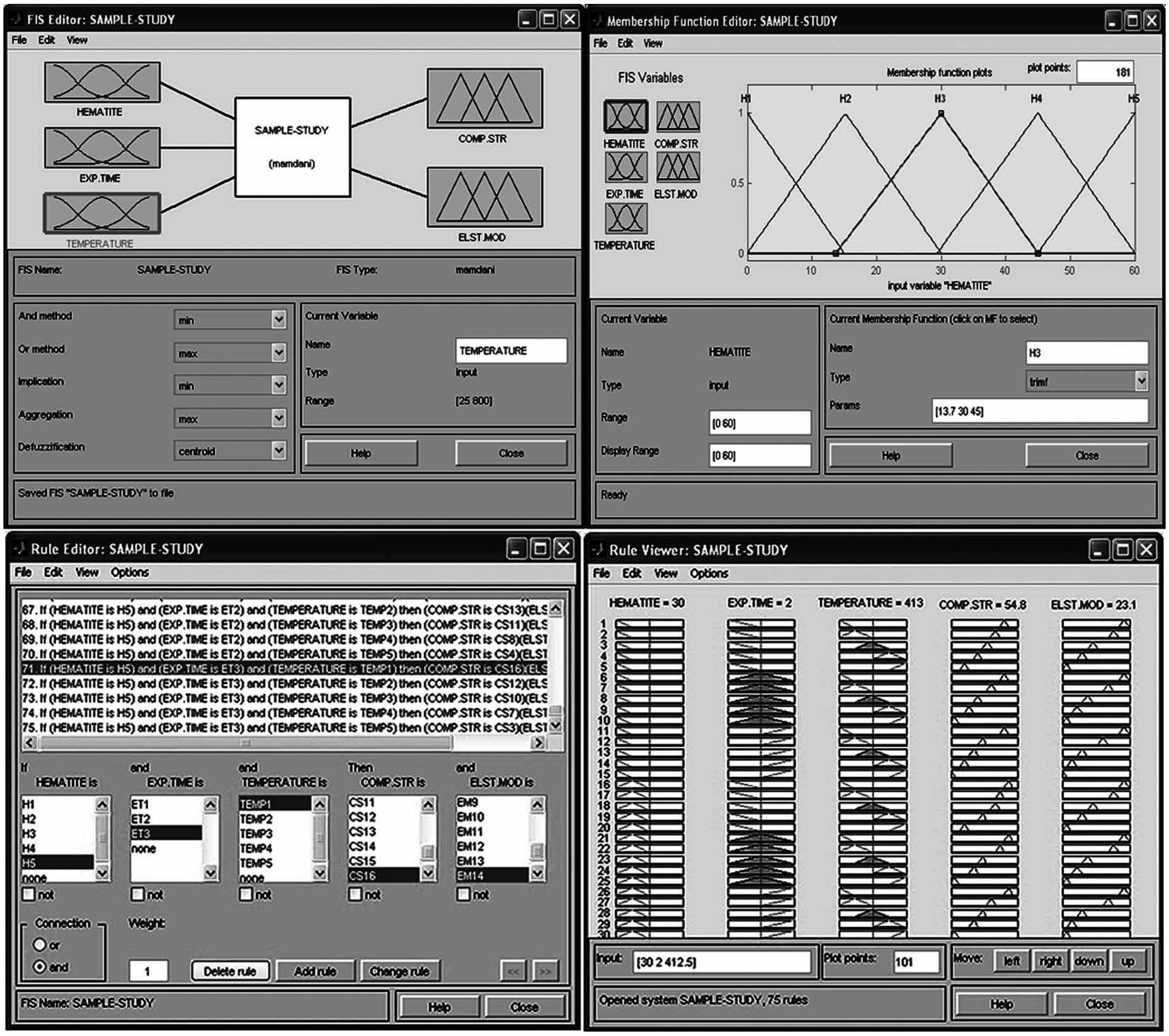
Figure 4. Fuzzy Inference System (FIS) Editor

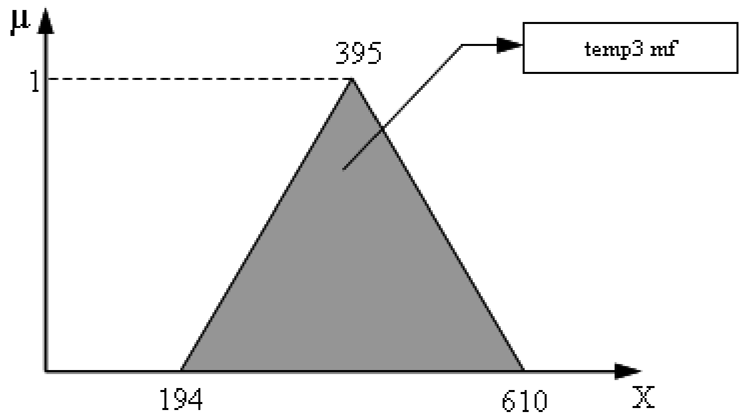


- Combination of two Gaussian membership functions.
- Generalized bell membership function.
- Pi-shaped membership function.
- Product of two sigmoid membership functions.
- S-shaped membership function.
- Sigmoidal membership function.
- Trapezoidal membership function.
- Triangular membership function.
- Z-shaped membership function.

Users can choose the type of MFs most related to their own works. All membership functions of inputs and outputs were selected as Triangular MFs in the example study. After selecting the type of all MFs, the numerical ranges, the names and parameters of each MF of inputs and outputs were defined using MF Editor. A sample triangle membership function of the example study is given in Figure 5 (the name of sample triangle membership function is "temp3").

Each membership function has an analytical form. The triangular fuzzy membership functions

Figure 5. A sample triangle membership function of the example study (temp 3 as input)



in analytical form for an input membership function (temp3 as a MF of temperature input) and an output membership function (CS 7 as a MF of compressive strength output) are shown in Box 1.

For example, if the temp3 set is used, consider the values of temperature which has a value less than 194 and greater than 610. These values have "0" membership degree in the set of temp3. When the temperature has 395 as its value, it is a full member of temp3 and the level of membership degree of other values can be calculated with the given formula.

In the third step, the rules were created by using Rule Editor (Figure 4). The rules are a collection of linguistic statements that describe how the FIS should make a decision to classify an input or control an output. At this stage, all matchings of the membership functions of the inputs must be written as rules to reach a correct approximate reasoning. Some relationships occur between inputs and outputs according to the formed rules in the model (Figure 6). In the example study, 75 rules had been devised (Figure 4c). Since all matchings of the membership functions of the inputs could be represented by 5x3x5=75 rules, a fuzzy rule has the form: If *x* is *A* then *y* is *B*, in which *A* and *B* are fuzzy sets, defined on universes *X* and *Y*, respectively, where the antecedent is '*x* is *A*', and the consequent is '*y* is *B*'. Examples of such rules in everyday conversation can be written as: If it is dark, then drive slowly or If the room is cold, then increase the heat (Topçu & Saridemir, 2008a). In the fourth step, by using Rule Viewer, the crisp values of output are obtained (Figure 4d). The Rule Viewer enables users to view detailed behavior of a FIS responding to changing input variables. Furthermore this window helps us to take crisp results.

STUDIES ABOUT THE USABILITY OF FUZZY LOGIC IN CONCRETE TECHNOLOGY

There are many studies in the literature on the usability of fuzzy logic in concrete technology. The following lists the range of studies available. Ahmadi-Nedushan (2012) proposed an adaptive network-based fuzzy inference system (ANFIS) model and three optimized nonlinear regression models to predict the elastic modulus of normal and high strength concrete. Akkurt, Başyigit, Kilincarslan, and Beycioglu (2010) developed a FL model to determine the radiation shielding properties of concretes containing barite in the ratio of 0%; 50%; 60%; 70%; 100%; and different water-to-cement ratio (w/c). Demir and Korkmaz (2008) examined the theory of fuzzy sets

Table 1. System requirements for MATLAB (Fuzzy Logic Toolbox) release R2014a

Operating Systems	Processors	Disk Space	RAM
Windows 32-Bit and 64-Bit MATLAB and Simulink Product Families			
Windows 8.1 Windows 8 Windows 7 Service Pack 1 Windows Vista Service Pack 2 Windows XP Service Pack 3 Windows XP x64 Edition Service Pack 2 Windows Server 2012 Windows Server 2008 R2 Service Pack 1 Windows Server 2008 Service Pack 2 Windows Server 2003 R2 Service Pack 2	Any Intel or AMD x86 processor supporting SSE2 instruction set*	1 GB for MATLAB only, 3–4 GB for a typical installation	1024 MB (At least 2048 MB recommended)
For Mac 64-Bit MATLAB and Simulink Product Families			
Mac OS X 10.9 (Mavericks) Mac OS X 10.8 (Mountain Lion) Mac OS X 10.7.4+ (Lion)	All Intel-based Macs with an Intel Core 2 or later	1 GB for MATLAB only, 3–4 GB for a typical installation	1024 MB (At least 2048 MB recommended)
For Linux 64-Bit MATLAB and Simulink Product Families			
Qualified distributions*: Ubuntu 12.04 LTS, 13.04, and 13.10 Red Hat Enterprise Linux 6.x SUSE Linux Enterprise Desktop 11 SP3 Debian 6.x	Any Intel or AMD x86 processor supporting SSE2 instruction set**	1 GB for MATLAB only, 3–4 GB for a typical installation	1024 MB (At least 2048 MB recommended)

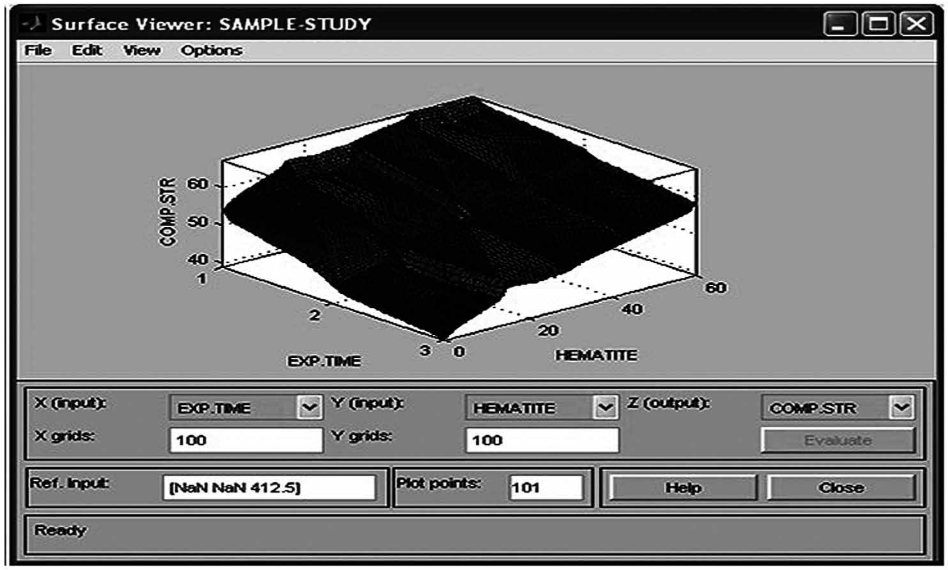
in their paper and they studied a fuzzy modeling as a method to predict elastic modulus of High Strength Concrete. Demir (2005) proposed a FL model to determine elastic modulus of both normal and high-strength concrete. Duan, Kou, and Poon (2013) showed the possible applicability of ANNs to predict the compressive strength of recycled aggregate concrete. Golafshani, Rahai, Sebt, and Akbarpour (2012) developed ANN and FL models to predict the bond strength of steel bars in concrete. Güler, Demir, and Pakdamar (2012) presented a fuzzy approach for modelling of high strength concrete under uni-axial loading.

Ozcan, Atiş, Karahan, Uncuoğlu, and Tanyildizi (2009) developed an ANN and FL study to predict the compressive strength of silica fume concrete. Sarıdemir, Topçu, Özcan, and Severcan (2009) developed ANN and FL models for prediction of long-term effects of ground granulated blast furnace slag on compressive strength of concrete under wet curing conditions. Topçu and Saridemir (2008a) demonstrated that properties of fresh

Box 1.

$$\mu temp3\left(x\right)=\begin{Bmatrix} 0, & x\le 194 \\ \dfrac{x-194}{395-194}, & 194<x<395 \\ 1, & x=395 \\ \dfrac{610-x}{610-395}, & 395<x<610 \\ 0, & x>610 \end{Bmatrix}\mu CS7\left(x\right)=\begin{Bmatrix} 0, & x\le 40 \\ \dfrac{x-40}{45-40}, & 40<x<45 \\ 1, & x=45 \\ \dfrac{50-x}{50-45}, & 45<x<50 \\ 0, & x>50 \end{Bmatrix}$$

Figure 6. Surface Viewer of example study



concrete could be determined without attempting any experiments by using ANN and FL models. Their later works developed ANN and FL models for predicting the 7, 28 and 90 days compressive strength of concretes containing high-lime and low-lime fly ashes (Topçu & Saridemir, 2008b) as well as models in ANN and FL systems for predicting compressive and splitting tensile strengths of recycled aggregate concretes containing silica fume at the time frames of 3, 7, 14, 28, 56 and 90 days (Topçu & Saridemir, 2008c). Finally, Unal, Demir, and Uygunoğlu (2007) developed a new approach for predicting stress–strain curve of steel fiber-reinforced concrete (SFRC) under compression, by use of FL system.

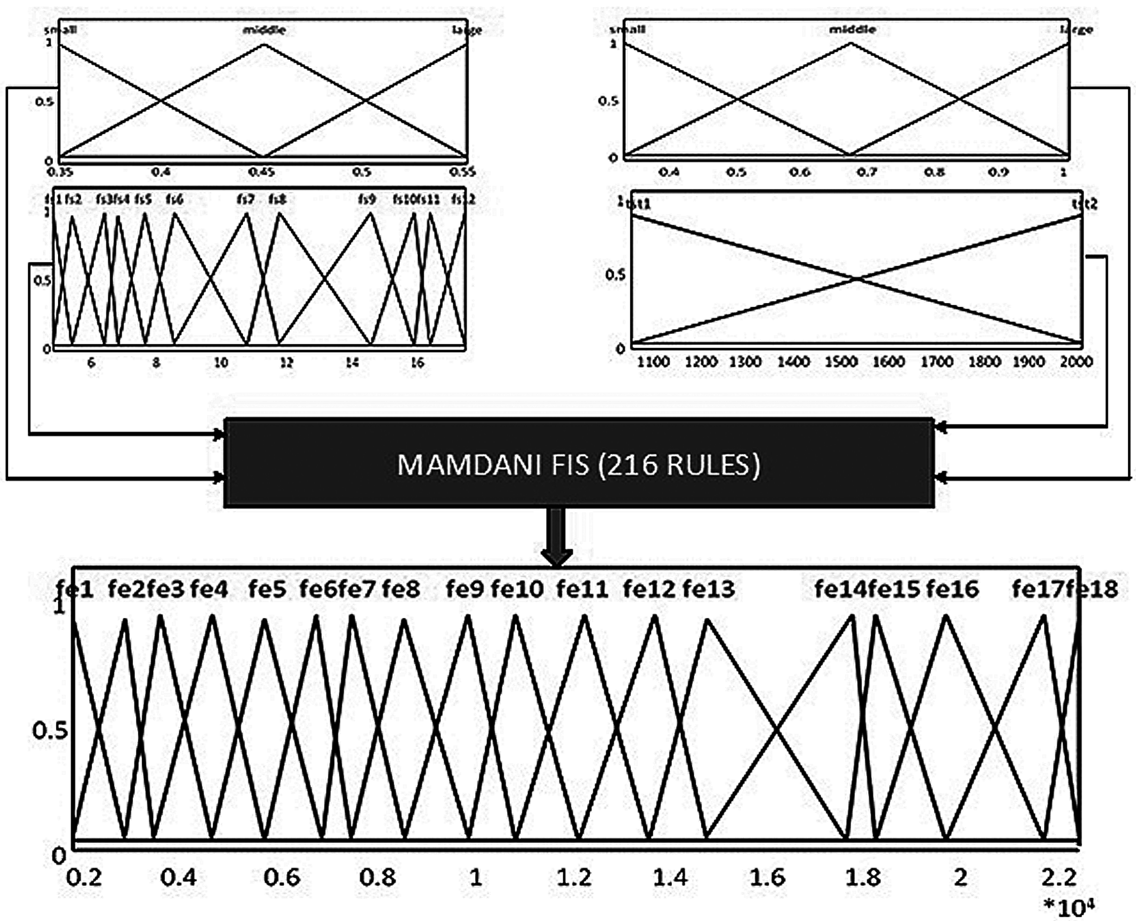
In this part of the chapter, three key studies from the literature are reviewed in more detail below.

Example Study 1

Köksal et al. (2012) developed a rule based FL model for prediction of fracture energies of concretes (N/m) by using w/c, tensile strength of steel fibre (N/mm^2), steel fibre content (%) and flexural strength of concrete samples (N/mm^2) as inputs. In the model, the membership functions and their numerical ranges were selected as 3 trimf and 0.35-0.55 for w/c, 2 trimf and 1050-2000 for tensile strength of steel fibre (tsf), 3 trimf and 0.33-1 for steel fibre content (sfc), 12 trimf and 4.8-17.3 for flexural strength (fs), 18 trimf and 1700-2.22e+004 for fracture energy (fe). The general structure of the FL model developed in the research is given in Figure 7. After determining membership functions details, 216 rules were formed using the experimental results.

In the study, the values obtained from the model and experiment divided 3 sets (each set has 6 experimental results) according to the w/c ratios to evaluate FL model predictability. When the results were compared using the coefficient of determination (R^2) values, the values found were 0.9962 for Set I, 0.9959 for SET II and 0.9679 for SET III. These R^2 values show very acceptable relations between the model results and experimental results. As a result of their study, Mamdani type FIS showed a satisfying relation with experimental results and suggested an alternative approach to evaluate fracture energy estimation using related inputs.

Figure 7. The general structure of the model developed by Köksal et al. (2012)



Example Study 2

Subaşı, Beycioğlu, Sancak, and Şahin (2013) developed a FL model for predicting compressive strength of concretes containing Silica Fume (SF) (0, 5, 10%) using nondestructive testing results (ultrasonic pulse velocity (km/h) and Schmidt hardness (R). In the study, experimental results of non-destructive tests and the amount of the SF were used to construct the model. Various destructive and Non-Destructive Test (NDT) methods have been developed for determining compressive strength. Among the available non-destructive methods, the Schmidt Hardness (SH) test is one of the most commonly used in practice. It has been used world-wide as an index test for a testing equipment to estimate strength of concrete due to its rapidity and ease in execution, simplicity, portability, low cost, and non-destructiveness. The Ultrasonic Pulse Velocity (UPV) is one of many non-destructive methods. As the technique uses compressional waves, it does not result in damaging the concrete element being tested. The method involves measuring the travel time over a known path distance of a pulse of ultrasonic waves. The pulses are introduced into the concrete by a piezo-electric transducer and a similar transducer acts as receiver to monitor the surface vibration caused by the arrival of the pulse (Subaşi et al., 2013).

The authors used the experimental results of non-destructive tests and the amount of the SF built up the model. In their study, the membership functions for SF, UPV, SH, 7 day compressive strength (MPa), 28 day compressive strength (MPa) and 90 day compressive strength (MPa) were chosen 3-4-4-10-10-10 respectively. The general structure of model, membership functions for input, and output parameters used for fuzzy modeling are shown in Figure 8. The numerical ranges are 0-10 for Silica fume, 3,68 – 4,2 for UPV, 24-42 for SH, 22.8 - 32.85 for 7 days CS, 27.8 - 48.3 for 28 days CS and 31.8 - 46.8 for 90 days CS.

After modeling the process, the results obtained from the developed model were compared with the experimental results using some statistical parameters. The coefficient of simulation efficiency (COE) was calculated as 0.884909 and root-mean-squared (RMSE) error was calculated as 2.275194. Also R^2 between FL model and experimental results were 0.74 for 7 days, 0.82 for 28 days and 0.90 for 90 days. The results showed that values obtained from the FL model were very close to the experimental results. The authors concluded that FL systems have strong potential for predicting 7, 28 and 90 days compressive strength using ultrasonic pulse velocity (km/h), Schmidt hardness (R) and silica fume content (%) as inputs.

Example Study 3

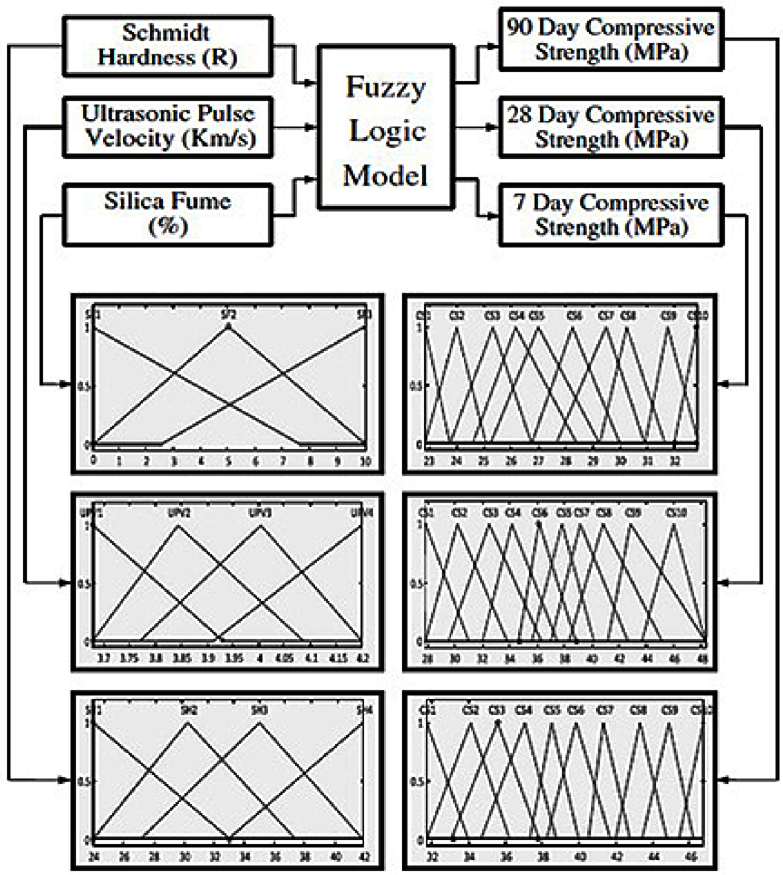
Tanyildizi (2009a; 2009b) developed a FL prediction model for compressive and splitting tensile strength of lightweight concrete made with scoria aggregate and fly ash after exposed to high temperature (200, 400 and 800°C). The FL model in Tanyildizi (2009b) had three input parameters: Fly ash (by weight of 0%, 10%, 20% and 30% of Portland cement), cement dosage (400 and 500 kg/m^3) and temperature (20, 200, 400 and 800°C). The author used these input parameters to estimate two output parameters: Compressive strength (MPa) and Splitting tensile strength (MPa). The author compared the obtained results with FL with the experimental methods and results. The compressive and splitting tensile strength using FL was estimated with a small error (7.88% and 6.48%). His research revealed that FL can be used to predict the compressive and splitting tensile strength of lightweight concrete after being exposed to high temperature.

APPLICATIONS OF AI METHODS IN POSTGRADUATE ENGINEERING CURRICULUM: INSTRUCTIONAL APPROACHES

In this part of the chapter described the instructional applications of AI methods in a postgraduate course titled *Applications of Artificial Intelligence in Engineering*. Details on the course structure, teaching activities and feedback from students are presented.

- **University:** Düzce University.
- **Department and Program:** Graduate School of Science Engineering and Technology - Composite Material Technologies.
- **Course Name**: Applications of Artificial Intelligence in Engineering.
- **Level of Course**: Postgraduate.
- **Semester Taught:** 2nd semester.
- **Number of Students:** 12.
- **Teaching Resources:**
    - Fuzzy Logic Toolbox: Design and simulate fuzzy logic systems. Website link http://www.mathworks.com/products/fuzzy-logic/).
    - Ross, T. J. (2010). *Fuzzy logic with engineering applications* (3rd ed.). West Sussex, UK: John Wiley & Sons.
    - Fuzzy Logic Toolbox™ User's Guide. Website link http://www.mathworks.com/help/pdf_doc/fuzzy/fuzzy.pdf.

Figure 8. The general structure of the model developed by Subaşi S. et al (2013)



Target Students for the Course

Graduate students from engineering sciences with interests in the application, development and research in engineering sciences.

Aim of the Course

The course is designed to provide MSc graduates with the ability to use MATLAB modeling tools in computer-supported simulations.

Expected Learning Outcomes

On successful completion of the course, the students are expected to have the following skills:

- Learn the basic principles of modeling techniques;
- Gain ability to use modeling methods in a real applications;
- Develop logic abilities when faced with sets having sharp boundaries;
- Develop fuzzy logical thinking abilities and capacities for developing alternative solutions.

Teaching Environment

This course utilizes small group teaching that facilitates individual feedback to students. Students are assigned to individual computers and computer stations in the classroom are placed in a manner that facilitates students' view of the projector that shows the applications carried out on the instructor's computer screen. The necessary specifications for computers, according to the MathWorks Inc.'s (2014) recommendations, are presented in Table 1 based on the latest version of MATLAB.

Instructional Methods Used: Description and Justification

The postgraduate course used a variety of instructional methods such as the traditional lectures, demonstrations of the software and steps in the use of MATLAB modeling tools, collaborative group work and individual work by students. Table 2 describes the instructional methods and justifies their use in the course.

RESULTS OF STUDENT COURSE FEEDBACK

Quantitative Results from Student Feedback

At the end of the course, opinions of students were obtained by using the course evaluation form shown in Table 3. The quantitative results from student feedback showed that the majority of the students had positive responses to the course especially its applicability to the field of engineering.

At the end of the course (2nd semester), it was determined that 10 of 12 students gained this skill in a basic level. A few students demonstrated the ability to potentially use the acquired knowledge for an application related to their own engineering area as a student prepared a scientific article on his work and another student developed a predictive model that was used in a process of the factory where he worked.

Qualitative Student Feedback on Course

This section presents the qualitative feedback from students on the course. Their comments are provided verbatim retaining their original expressions and their pseudonyms are used.

- **Student 1:** E.B.
    - **Educational Status:** BSc: Construction Education, Architectural Drafting Program; MSc: Civil Engineering – Ongoing
    - We had a new thought system with artificial intelligence applications in engineering course. This course allowed us to understand the logic of human brain with computer models. During the application in the course, we obtained numerical data sets created which experimentally and we attempted to teach program that how we achieve results by linking sets and rules. Artificial intelligence applications students should have some important characteristics like creative thinking and spirit of ownership. Students came face to face with some problems. These can be listed as follows;
        - While study on Fuzzy Logic, creating sets and commenting about rules are so difficult. So we surely need to consult someone who has a command of issue.
        - Determine the sets by trial and error technique takes a lot of time.
        - It's difficult to edit experimental data sets with Office programs before and transfer the data by using MATLAB.
- **Student 2:** H.C.

Table 2. Instructional methods used: description and justification

Teaching Methodology	Weeks	Description of Instructional Methodology in the Course	Advantages of Instructional Methods and/or the Impact of these Techniques on the Students' Learning Process
Lecture/ Presentation	2	This method is used to explain simple principles of soft computing (especially FL) to students. Visual presentation aids were used to assist teaching of content.	This method is an effective means of teaching the basic principles of new information to a large heterogeneous group in a short period of time.
Demonstration	3	The process of FL modeling was demonstrated through examples.	Demonstration helps students to keep the steps of application in mind. It is very useful for students to grasp underlying principles of application. The steps may be video recorded for future use and this may stimulate student interest for future study.
Collaborative group work	3	An example study is used for modeling, and the students had to further develop the project in small groups. This allowed the students to actively participate in the learning process by talking to each other and listening to others' points of view.	This method encourages the students to become active rather than passive learners by developing collaborative group learning skills. This method offers to students the opportunity to learn from and to teach each other.
Individual Study Phase	4	Each student developed a modeling study related to their fields of engineering. The study was evaluated by lecturer for determining the course grade of students	This stage is crucial to determine the answer to the main question of whether the students have ability to use the acquired knowledge for an application related to their own engineering area. The studies prepared by the students were used to evaluate their performance.

- **Educational Status:** BSc: Naval Architecture and Marine Engineering; MSc: Manufacturing engineering – On going

- I understood the importance of this course for all engineering students when I learn the course. Through the course, we have learned that applications of this course are used for many

Table 3. Course evaluation form and results of student feedback

Course Evaluation Form	Very Poor	Poor	Fair	Good	Very Good	
Course content	-	-	-	3	9	9+3=12
Materials used in the course	-	-	-	2	10	2+10=12
Class location & equipment	-	-	4	6	2	4+6+2=12
	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**	
I understood the objectives of the course	-	-	-	4	8	4+8=12
The length of the course is appropriate to cover content	-	-	3	6	3	3+6+3=12
The course provided me with new information	-	-	-	5	7	5+7=12
Lecturer used the appropriate examples to teach during the course	-	-	-	3	9	3+9=12
This course is useful for engineering students	-	-	-	6	6	6+6=12

Note: The number shown in the table shows the number of students who selected this option.

areas as direct and indirect applications. In this course, I learned how I can improve a predictive model about specific problems and I applied an AI method in my business life. For example, I am working at a facade cladding company. In the factory which I work, I calculated the consumption of the foam block for CNC mold making jobs approximately by using older foam block data consumption. For me, the most important problem in this course is that the examples shown in the course were out of my engineering area. This situation created many challenges me to adapt to the course.

- **Student 3:** E.Y.
    - **Educational Status:** BSc: Construction Education, Architectural Drafting Program; MSc: Construction Education; PhD: Composite Material Technologies – On going
    - Firstly, I want to say that someone who wants to learn these techniques, as a priority, should have a good practice on Office applications like MS Word-MS Excel. In this course, lecturer showed examples of real applications of AI methods. It was very useful in terms of learning. I noticed that students have some difficulties of finding experimental data to use for modeling in this learning phase. The students should have experimental experiences about data used for modeling (to create sets and to write appropriate rules) I recommend that students should study as group when making practice on these techniques outside the course. The students should follow the course regularly for success. I could not go to course for two times. I had to get help from my friends and lecturers for compensating shortfall. It was quite difficult to understand the issues which I did not learn in the lesson time.
- **Student 4:** L.S.B.
    - **Educational Status:** BSc: Mechanical Engineering; MSc: Composite Material Technologies – On going.
    - First of all, I want to say that it was difficult to work to obtain results by creating verbal rules. If you want to make your job easy, you should learn the logic of creating model sets. Besides, you should find an expert who can help you about writing model rules by using his/her experiences. I could not develop a predictive model during the course. I think, the most important problem for me is that I did not attend the course regularly. I figured out that the most important problem in this course is to attend the course regularly. Every topic of lesson is like a part of the puzzle. You must follow courses regularly and repeat learned applications except course time to succeed this course.

Reflections on Experience

Based on the student feedback obtained and instructor reflection on the teaching experience, the following improvements would be incorporated into the course in future semesters:

- Lectures should be conducted while the MATLAB and other supporting software. applications are opened in each student's computer station.
- Instructors should use concrete examples to explain modeling steps.

- Instructors should summarize all application steps periodically and at the conclusion in each lesson.
- Instructors should allocate a question and answer session for students to clarify any doubts at the end of each lesson.
- Practical work should be done by students in each lesson.

FUTURE RESEARCH DIRECTIONS

In the world today, many researchers have given attention to AI with the rapid development of computer technology. One of the most popular artificial intelligence methods is FL, which was firstly developed by Zadeh (1965), and currently much research work is carried out in this field. The FL method has been extensively used in civil engineering particularly in fields of applications that involves materials selection or assessment such as construction management, building materials, hydraulic, geotechnical, and transportation engineering (Emiroğlu, Beycioğlu, &Yıldız, 2012). This chapter described the principles of FL methods that can be easily taught to engineering students through MATLAB graphical user interface that was carried out in a postgraduate course on Applications of Artificial Intelligence in Engineering. In this context, the application of Mamdani type in concrete technology was discussed. The chapter also highlighted key studies related to the usability of FL in concrete technology.

There are many studies in the literature about the applicability of AI methods to assess building materials especially properties of concrete such as compressive strength, splitting tensile strength, abrasive strength, thermal conductivity of light weight concrete, rheology, durability, etc. Many of the studies have reported successful results obtained by modeling concrete properties and several works used the materials selected in concrete production as inputs in the modeling process which indicated positive developments regarding the applicability of AI in concrete technology. Despite of positive developments, an important issue that should be keep in mind is that the properties of concrete can be affected by other materials that are used to prepare concrete. In future studies, researchers should expand the models to accommodate all possible parameters that can affect the characteristics of concrete materials such as aggregate amount, water-cement ratio, pozzolans, and different curing conditions.

CONCLUSION

In conclusion, concrete is well known as a type of composite and heterogeneous material. Generally, destructive and non-destructive methods are used for determining the mechanical properties of concrete in the field of engineering. Nowadays, AI methods such as FL, ANN, and Genetic Algorithm are gaining popularity for application in more engineering disciplines. As a consequence, researchers of concrete technology have started to study the usability of AI methods in the field of concrete technology. Since experimental studies in civil engineering and particularly concrete technology can be difficult to conduct and usually involves the costs of time and materials, the feasibility of applying AI in modelling materials behavior becomes very important. This chapter had demonstrated that there are simple AI methods available that can be taught at postgraduate level in universities and also applied to meet industry needs.

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KEY TERMS AND DEFINITIONS

Anfis: A kind of artificial intelligence which integrates both neural networks and fuzzy logic principles.

Artificial intelligence (AI): A field of computer science that emphasizes the creation of intelligent machines that work and react like humans.

Artificial Neural Networks: A data modeling tool that is able to capture and to represent complex input/output relationships.

Civil Engineering: A professional engineering discipline that deals with the design, construction, and maintenance of the physical and naturally built environment, including works like roads, bridges, canals, dams, and buildings.

Concrete Technology: A field related to concrete materials and its applications.

Fuzzy Logic: A form of many-valued logic that deals with reasoning that is approximate rather than fixed and exact.

Modeling: The application of representing a real-world object or phenomenon as a set of mathematical equations.

Prediction: A method of identifying results that may occur in the future.