International Journal of Engineering Education Vol. 27, No. 6, pp. 1374–1382, 2011
Printed in Great Britain
0949-149X/91 $3.00+0.00

Laboratory Approach for Teaching and Learning Intelligent Control*

R. AGUILAR, V. MUÑOZ and E. J. GONZÁLEZ
Dpto. de Ingeniería de Sistemas y Automática y Arquitectura y Tecnología de Computadores, Universidad de La Laguna. Av. Astroísico Francisco Sánchez, s/n. Facultad de Física, CP 38071, La Laguna. Spain. E-mail: vmunoz@ull.es

This paper introduces a laboratory approach for teaching and learning an Intelligent Control course delivered to Automation and Industrial Electronics Engineering students. It integrates methods from Control Theory and Artificial Intelligence. Students initially develop a simulated plant controller using the Matlab fuzzy toolbox and the Simulink program. They then apply their design to interconnected tanks in an actual plant. Other experiments include the expert control of an elevator panel using the CLIPS shell and Linux in real time. This is complemented by the design and implementation of a Neural Network for the identification of a proposed plant. A survey of students' opinion about the approach and the impact of the approach to learning were assessed.

Keywords: laboratory education; fuzzy control; expert control systems; neurocontrol

1. Introduction

The Intelligent Control (IC) course that has been designed to teach final year Automation and Industrial Electronics Engineering students the theoretical and practical aspects related to the design of Intelligent Control Systems. This integrates methods from Control Theory and Artificial Intelligence, which are also used to influence the resulting systems [1].

Currently, advanced control and optimization are becoming more commonplace as a way of improving financial objectives and to maximize both product output and quality. But the need to control increasingly complex processes whose behavior models are unknown, with very small tolerances and minimum response times, has led to the use of Artificial Intelligence techniques as control strategies that will allow these characteristics to be achieved.

A survey on the literature on teaching Intelligent Control can be found in Yurkovich and Passino [2], El mahdi Ali and Darwich [3], Huang *et al.* [4] and El mahdi *et al.* [5]. Most of these, however, are based on the use of simulators or on conducting experiments using Matlab, Simulink or Labview, in some cases. In this paper we propose a more practical approach involving experimental set-ups that will allow the student to engage in hands-on training in actual working scenarios, thus providing the experience to handle the various situations that may present themselves in their future professional careers.

2. Course planning

The course on Intelligent Control is taught to final year Automation and Industrial Electronics Engineering students. It is a 6 ECTS credit course (1 ECTS credit is equivalent to 25 hours of work). This load is divided into 3 ECTS theory credits and 3 ECTS laboratory credits. The course involves 24 lecture hours, as well as an additional 6-hour session that all students have to attend in order to give an oral presentation on a project they have done. During laboratory hours the students attend hands-on sessions in the laboratory where the operation of plants or systems they have to control are explained to them. It is their subsequent simulated and actual implementation of these control systems that is explained in this paper.

This course is intended to teach students the following specific technical skills and abilities:

[T1] Identify control elements and their applications in a control system.
[T2] Apply intelligent control principles to control a given plant.
[T3] Apply Artificial Intelligence techniques to classical and modern control systems.
[T4] Analyze control systems problems using suitable simulation software.
[T5] Apply Intelligent Control techniques to improve solutions reached using classical control techniques.

In addition, students will learn the following interdisciplinary skills:

[I1] Acquire transferable skills that could help reaching solutions in a wide range of applications.

* Accepted 28 July 2011.

[I2] Develop creativity and critical reasoning.
[I3] Develop teamwork skills.
[I4] Develop an understanding of various solutions on the environment.

In the lectures they are first given an introduction to the research fields and applications in intelligent control before proceeding to a study of the theoretical bases of Hierarchical Control. The course then focuses on Expert Control, Fuzzy Control and Neurocontrol techniques. In general, all of the hands-on activities promote active participation in the learning and provide support to mitigate any shortcomings (in particular regarding the mathematical aspects).

These activities conclude with a seminar in which the students have to conduct a study on a practical case in Intelligent Control and present it in class to their fellow students. To do this they must perform an online search and find different examples of intelligent control applications. These applications should rely primarily on the knowledge acquired by the students in the class and not be research intensive. Once the case to be studied is decided (for example a fuzzy control system for precision farming [6] or a neurocontrol system for a fermentation process [7]), the student must:

1. Describe the problem that is to be solved
2. Determine the specifications involved
3. Explain why classical and modern control techniques cannot be used
4. Specify which artificial intelligence techniques were used.

This activity will promote the development of teamwork skills and favors the voluntary formation of work groups outside the classroom. This task will allow the students to develop skills [T2–T4 and I3] individually in a non-structured learning environment.

As for the practicals, they will perform three, the first two with actual plants in the laboratory and the third in the Computer Room. These experiments involve:

1. An Expert Control System for an elevator. The control will be carried out in real time with the Linux Operating System [8] and with CLIPS [9] as the tool for developing Expert Systems.
2. Design and Implementation of a Fuzzy Control System for a system of interconnected tanks. This will be done using Matlab and Simulink.
3. Design and Implementation of a Neural Network for the identification of a proposed plant. The Matlab neural network toolbox [10] or any neural network program may be used.

Table 1 lists the skills and abilities to be acquired by the students through the different activities that comprise the Intelligent Control course. As mentioned above, each of the activities presented in the course further develops each skill set. For example, after the lectures the students will know and understand control elements and hierarchy [related to T1], know the characteristics and concepts of intelligent control systems in real problems [T2], know how to integrate Artificial Intelligence techniques in classical and modern control systems [T3], study actual control problems through the use of simulations [T4], and be able to propose solutions based on Intelligent Control for real control problems in which said techniques can yield improvements over classical and modern control techniques and acquire a knowledge of basic and technical matters that will enable them to learn new methods and theories [T5]. The lectures will also provide them with the versatility to adapt to new situations [I1]. The projects and presentation will also allow the students to develop skills [T2–T4], as well as their teamwork skills. Lastly, the practicals will partly satisfy the objectives of skills [T4–T5] and [I3], and give them the ability to solve problems with initiative, decision making, creativity and critical reasoning [I2] and a have concern for quality and the environment [I4].

Table 1. List of activities skills for IC course

IC activities	Related skills
Lectures	[T1] [T2] [T3] [T4] [T5] [I1]
Project and presentation	[T2] [T3] [T4] [I3]
Experiment 1	[T4] [T5] [T6] [I2] [I3] [I4]
Experiment 2	[T4] [T5] [T6] [I2] [I3] [I4]
Experiment 3	[T4] [T5] [T6] [I2] [I3] [I4]

The sections that follow will briefly comment on and describe the techniques used in the practicals, as well as the work to be performed by the students in each.

3. Areas of research and applications in intelligent control

Intelligent Control techniques are being researched and applied in various fields. In designing the course experiments, we focused on three: Expert Control, Fuzzy Control and Neurocontrol.

3.1 Expert control systems

In this section we introduce the concept of Expert Control. We then show how the practical for this part of the course was designed and describe the plant to be used, the programming language and the features of the Expert Control system that the students have to design.

3.1.1 Introduction

An Expert Control System is a type of Expert System [11] whose task it to govern the complete behavior of an object or process. The Expert Control System can interpret the current status of the control systems, predict the future behavior of the process, diagnose problems that may arise and constantly revise and execute the control plans. The Expert Control System, therefore, handles the interpretation, forecast, diagnosis, planning and execution.

Expert Control Systems [12] need to engage in a decision-making process in order to exercise control automatically and independently. The results of their inferences are changes in the knowledge elements as well as the activation of a certain control algorithm.

Unlike traditional Expert Systems that normally work off-line, an Expert Control System has to acquire the information dynamically, on-line, and implement control actions in real time. This real-time requirement implies a series of obstacles that are shown to the students both theoretically and hands-on in the laboratory over the course of the practical. These requirements are [13]:

- Nonmonotonic reasoning
- Asynchronous events
- Temporal reasoning
- Reasoning under time restrictions
- Parallel reasoning
- Working with uncertainty
- Sufficiently high execution speed.

3.1.2 System description

The purpose of this practical is to execute the expert control of a board that simulates the operation of two independent elevators in a four-floor building. The elevator board is connected to the computer via a PIO12, which features three digital 8-bit I/O ports (Fig. 1). This board is used in other courses, and allows the student to compare the Expert Control strategy used with those from previous courses, such as LEYFA (Fundamental of Computer Structure and Architecture Laboratory), which includes the simulated control of elevators using a procedural language such as C.

The information obtained from the system is:

- Elevator position. Each floor provides information on whether either of the two elevators is stopped there or is moving.
- Status of doors. Indicates whether a door is open/closed or in the process of opening/closing.
- External pushbuttons. For each floor of the building there are two buttons to simulate external calls. One of the buttons simulates external requests to go up, and the other to go down.
- Internal pushbuttons. There are four buttons in each elevator to specify the cab request to go to any of the four floors.

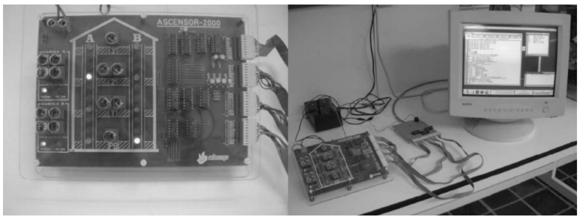

Fig. 1. Elevator board.

3.1.3 Programming language

In this exercise the students have to write a script using the CLIPS language so as to simulate the control of the elevator system in the most efficient and economic way possible.

The CLIPS (C Language Integrated Production System) [9] language is explained to students in the course's lecture classes. It is a tool for the development of Expert Systems created by the NASA/Lyndon B. Johnson Space Center Software Technology Branch. It was designed to facilitate the development of software to model human knowledge for specific purposes. It features high portability, low cost, and ease of integration.

This program was chosen for the students to use in the practical because it is portable, easy to integrate, public domain software that allows handling a wide variety of knowledge (including object-oriented programming). It includes debugging tools, online help and an editor, and it allows for verification of the rules included in the expert system being developed. In addition, extensive documentation on CLIPS can be found on the official webpage [9].

A program written in CLIPS can consist of rules, facts and objects. The CLIPS shell provides the basic elements of an Expert System [11–15]:

- Global data memory (working memory, WM): contains the list of facts.
- Knowledge base: contains the rules for the rule base.
- Inference engine: controls the global execution of the rules.

In our practical, the Expert Control uses a daemon in real time under the Linux operating system [8] to constantly monitor the status of the elevator board. This daemon allows for information on the status of the board to be added to CLIPS in real time, such as the current floor where each elevator is located, the condition of the doors (open/closed) and the existence of internal and/or external calls on a given floor. This allows for facts to be input to the CLIPS working memory automatically whenever an event takes place on the elevator board.

The built-in daemon also provides the programmer with a set of commands to enable control actions to be sent to the elevator board. These commands are move elevator to indicated floor and open or close elevator doors.

For example, the CLIPS script for opening the elevator doors would then be:

```
(defrule open_door
   ?dr <- (door ?elevator closed)
   (stopped ?elevator ?floor)
   =>
   (retract ?dr)
   (send-message (str-cat ‘door ‘ ?elevator ‘ open’))
)
```

As we can see, this is a very simple script for the students to write. It will be complemented by the other rules that they will have to input in order to complete the expert control of the elevators. The characteristics and restrictions of the rule set are explained in the next section.

3.1.4 Characteristics of the Expert Control System to be designed by the students

In order to design the set of rules for controlling the elevator board, the students have to bear in mind how an elevator system behaves in a real setting. They also need to include the necessary intelligence in the system so as to maximize energy savings and so that the service provided by the elevators is as efficient as possible.

Some of the requirements are:

- Internal calls have priority over external calls.
- An elevator does not change direction (up or down) until a new call is made in the opposite direction.
- If both internal and external calls are present at a given floor, and an elevator arrives at said floor, it must accommodate both calls simultaneously (and not open and close the doors twice, once for each call).
- If both elevators are stopped without any pending requests, and an external call is made, the closer elevator will respond.

If an external call is made and an elevator is already in motion in the direction of the call to attend to another request (internal or external), and the floor where the request was made has not been passed, the elevator will make an intermediate stop to attend to the external call.

This exercise is intended to introduce students to IC techniques. Even though the Expert Control system in this case involves an elevator control board, the techniques can be applied to multiple domains within the Control field.

4. Fuzzy control

In this section we introduce the concept of Fuzzy Control, which is explained to the students during the lecture portion of the IC course, with a description of the plant to be used and the characteristics of the practicals the students have to do.

The experiment is structured in two parts: first the students will design the fuzzy controller and conduct a simulation (using the Matlab fuzzy toolbox and Simulink) in order to check it for proper operation.

Once the simulation is checked by the professor, the students will begin the experiment with the tank setup in the laboratory. This allows the students to validate, using a real plant in the laboratory, their preliminary design.

4.1 Introduction

Fuzzy Control [16–17] is a control methodology that uses Fuzzy Logic [18–19] in real systems, given its immediate application to those systems whose behavior is known based on vaguely defined rules. This imprecision arises from the complexity of the system itself. The way to try to solve this type of problem is to reduce the complexity by increasing the uncertainty surrounding the variables. These techniques, then, are very useful and easy to implement in problems that present non-linearities and for which classical control techniques are difficult to apply.

The behavior present in many systems, regardless of their complexity, can be given by a set of rules that are often imprecise, or that employ linguistic terms fraught with uncertainty. Therefore, as a general rule, a knowledge base is defined for the system. This is a set of rules provided by an expert who is in the best position to know the system's behavior, thanks to the experience acquired through the operation of said system.

If the control scheme shown in Fig. 2 is to be applied to a real system, the fuzzy controller has to be adjusted to the sensor and actuator technology in use, which employs concise magnitudes [20]. Therefore, the concise values provided by a sensor have to be converted into the fuzzy values that comprise the variables of the antecedent of the rule base. Likewise, the fuzzy values inferred by the rules have to be converted into the concise values required by the actuators.

4.2 Description of practical

The working system used for the Fuzzy Control practical is an ALECOP model with two interconnected tanks (Fig. 3).

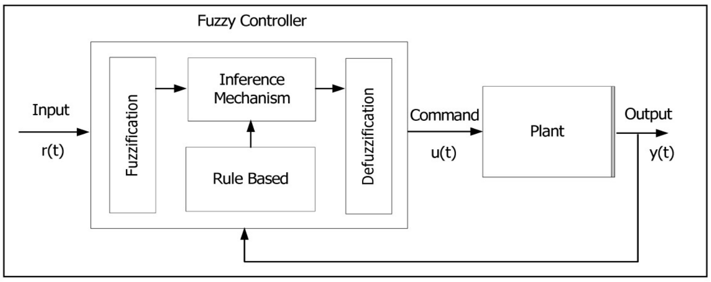

Fig. 2. Feedback loop for a fuzzy controller including fuzzification, inference and deffuzification.

Although this particular system was used, the experimental design is independent and can be used to control any other plant featuring real time or uncertainty requirements, or for which a behavior model of the system to be controlled is not available, since fuzzy control facilitates the modeling and implementation of the regulation systems for complex systems affected by a large number of variables (some with undefined behavior).

The plant used is a second-order system characterized by the following elements: working tanks, connection area, connecting hoses and drainage tanks. There are two identical tanks. The height difference between the tanks can be modified by means of a movable platform. The amount of liquid they contain is measured independently by two level gauges.

A diagram of the system is shown in Fig. 4. We can see that the flow rate supplied by pump q is delivered to the first tank, which dumps its contents, via flow rate q_1, to the second tank, driven by the difference in height between the two tanks. The height of the second tank, h_2, is the variable to be controlled. This tank, in turn, dumps its contents to the drainage tank via flow rate q_2.

Fig. 3. Real plant with interconnected tanks.

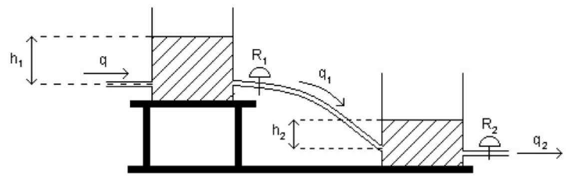

Fig. 4. Diagram of the tank system.

4.3 *Goal of experiment*

The goal of the experiment is to control the level in the second tank by adjusting the flow rate into the first tank. The fuzzy control system, with its inputs and outputs, will be as shown in Fig. 5.

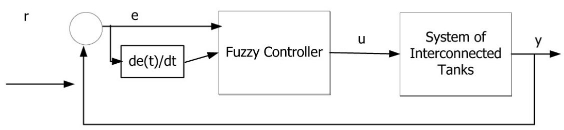

Fig. 5. Fuzzy controller for a system of interconnected tanks.

The students will have to design the fuzzy controller in keeping with the following steps [12]:

- Establish controller's input and output variables (linguistic variables).
- Define the fuzzy sets for each variable.
- Define the membership functions for the sets.
- Establish the rule base.
- Define the fuzzification, inference and defuzzification mechanisms.

4.4 *Fuzzy Control simulation experiment*

Before the controller is implemented, the students have to conduct a simulation to evaluate its performance. This will allow them to become familiar with the system and to conduct several tests in a short period of time. In addition, the simulation results will allow the students to improve and optimize the design of the fuzzy controller and to verify that it will work properly when implemented.

The Simulink tool is used to simulate the system of interconnected tanks. This tool allows the control loop to be implemented through the use of blocks and to insert the fuzzy system made with the fuzzy toolbox as the controller. The control system dia-

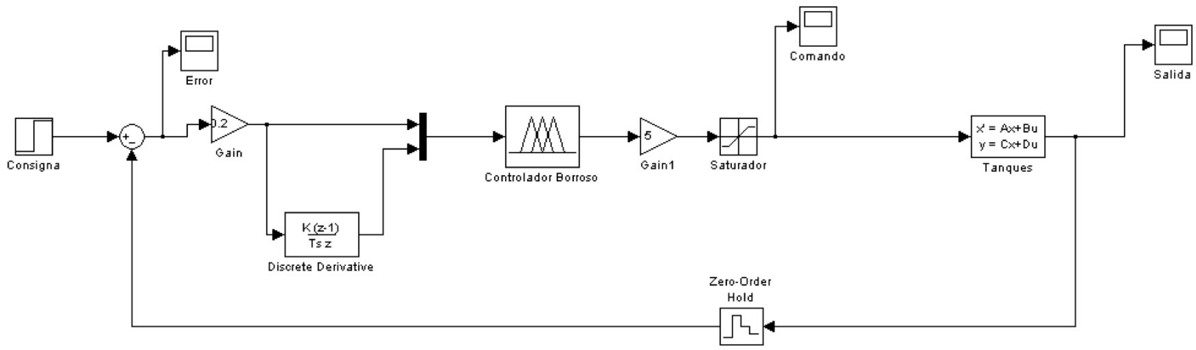

Fig. 6 Simulink diagram for the fuzzy control of the level of the interconnected tanks.

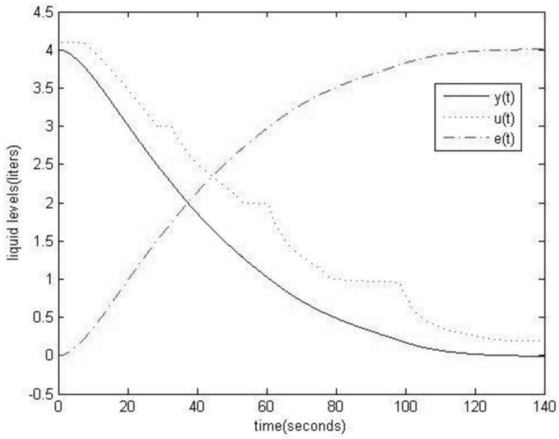

Fig. 7. Output ($y(t)$), Command ($u(t)$) and Error ($e(t)$) of the simulated fuzzy controller for the level of the interconnected tanks.

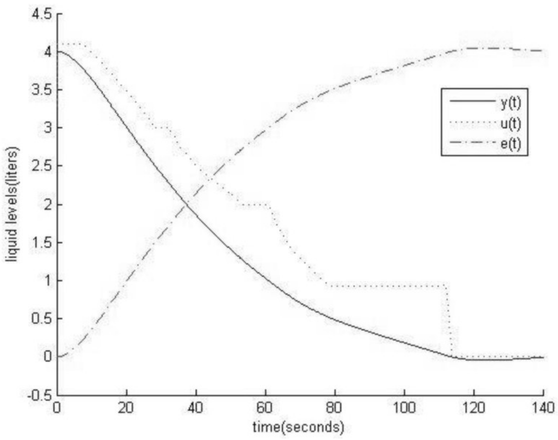

Fig. 8. Output ($y(t)$), Command ($u(t)$) and Error ($e(t)$) of the actual fuzzy controller for the level of the interconnected tanks.

gram would be as shown in Fig. 6. As we can see in the diagram, two amplifiers and a saturator are included in addition to the fuzzy controller and the tanks.

The use of the amplifiers is intended to decrease the error in the steady-state signal by modifying the fuzzy part of the input and output variables. By adding amplifiers at both the input and output of the controller and adjusting their gain, the desired specifications can be achieved.

The presence of a saturator after the output amplifier avoids voltage increases above the maximum allowed. The student will check these aspects both in the simulation and in the experiment to be conducted on the actual plant.

Examples of the results that can be obtained from the simulation are shown in the graph in Fig. 7.

4.5 Fuzzy Control experiment on actual system of interconnected tanks

Once the students complete the simulation of the fuzzy control plant, they have to test and verify its behavior in the laboratory on a real plant. As mentioned previously, the working plant used in the experiment is the ALECOP model of interconnected tanks. This model features a separate control module, used to measure the liquid levels (system output) and from which inputs can be provided to the pump so as to regulate the flow going into tank 1 (system input).

The students will conduct tests to check the fuzzy control of the system for proper operation by entering different set points to be maintained. In addition, perturbations can be induced in the system to see if the controller can adapt to and correct them in real time by opening the valves on the second tank so as evacuate part of its contents. The fuzzy controller has to respond properly to this situation, increasing the command sent to the system so as to attain the desired set point once more.

Figure 8 shows the results obtained on a real system of interconnected tanks (the set point is overshot slightly due to the flow rate, to the residual water left in the hoses and to bubbles).

5. Neurocontrol

In this section we introduce the definition for Neurocontrol, as well as the design of the experiment that students have to carry out for this part of the course.

5.1 Introduction

The term Neurocontrol [21–22] refers to those control methods that involve neural networks. Neural networks are computational models partially based on the operation of the human brain. They consist of a certain number of basic processing units (neurons), connected according to specific rules, where each connection has a weight associated with it. The most important features of a neural network are its architecture (number of neurons, activation function, type of connection between neurons, inputs, outputs, etc.) and the training algorithm used by the network to learn from information received from the environment (Fig. 9).

In a Control context, while linear and time invariant systems can be controlled through conventional means, the identification of non-linear and time variant systems is more complex. This problem can be addressed through the use of training criteria. This method can be completed through training [23], which is the dynamic study of the system to be controlled so as to learn its behavior when faced with different situations.

The use of neural networks in control offers a series of advantages that allow for [24]:

- Learning by experience, the formulation of behavioral or analytical models not being necessary in many applications. This fact is very important when designs have to be done in very short time spans or when the behavioral model for a system in an industrial application is very difficult or impossible to obtain.
- A capacity for approximating non-linear mappings that is better than other approaches (polynomials, etc.).
- The availability of hardware optimized for use with neural networks.
- A capacity to generalize with input series not considered during training.
- A capacity to handle numerical and symbolic data simultaneously.
- Applicability to MIMO systems.

5.2 Experiment description

This practical involves an experiment that will study one of the control uses of Neural Networks (NN). The specific objective is to use an NN to identify a system, allowing us to obtain a model for the system even if a mathematical model is not available.

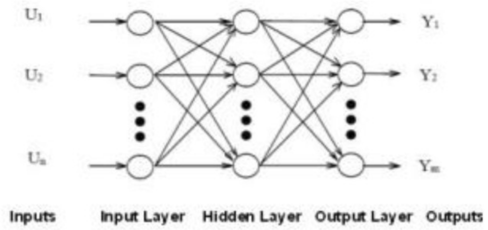

Fig. 9. Diagram of a neural network.

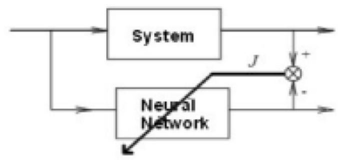

Fig. 10. Diagram of the neural control experiment.

The diagram to be used in the experiment will be as shown in Fig. 10.

The neural network learns the system dynamic, meaning it is not necessary to present a system model. The following elements are shown in the diagram: the system and the Neural Network.

The student is free to choose the system to be used, but it must satisfy the following requirements:

- The student must choose a second order or greater system ($G(s)$).
- Since we are going to interact with the system through the computer, the system must be discretized ($G(z)$). This is done by selecting a suitable sampling period (T). One criterion is that $T = 10^*$ time constants, which is the time taken by the system to reach 63.3% of the final value for a step input. If Matlab is used, since the student has the advantage of having used it in previous courses and laboratories, the c2dm command can be used for the discretization.
- Once the discretized function ($G(z)$) is obtained, the student has to check if its behavior in simulating the system is correct.
- The training patterns consist of the system input $x(k)$ and corresponding output $y(k)$ ($\{x(k), y(k)\}$) pairs. In order to obtain these training patterns, the system has to be converted from the z domain, $G(z)$, to the time domain (Equation 1).

$$\begin{aligned} \mathrm{y(k)} &= \mathrm{ax(k-1) + bx(k-2) + \ldots} \\ &\quad \mathrm{+ cy(k-1) + dy(k-2) +} \end{aligned} \tag{1}$$

With this equation the student is able to create the necessary training vector so that a given set of inputs will result in the corresponding outputs.

Table 2. Weight of each course activity

Activity	Percentage
Lectures	20%
Project and presentation	15%
Experiment 1	20%
Experiment 2	30%
Experiment 3	15%

6. Results

The results of the process will be evaluated in two areas:

- The grades obtained
- The students' degree of satisfaction with the method proposed.

6.1 The grades obtained

The course activities will be graded using a weighted scale, as shown in Table 2.

The lectures are evaluated with questions and practical exercises included objectively in a questionnaire. The project and presentation will be used to evaluate the research work done, the teamwork skills and the quality of the project presentation, both from a formal standpoint as well as from the oral defense of the project. During the practical sessions the reviewing instructor will use a form to subjectively assess the degree of compliance with each skill. This assessment will then be used to assign the numerical grade given to the student. In general, the practicals will be graded according to four criteria:

- A pre-simulation to be performed by the student prior to the laboratory session.
- The hands-on sessions in the laboratory with the real system.
- A personal interview with the student on the conduct of the practicals that will provide more insight into how to grade the student's performance.
- The student must also write a report that explains the project clearly and in detail, as well as the objectives accomplished, both in the simulation and in the practical sessions conducted in the laboratory.

These four sources will yield a broad and diverse evaluation of the learning process and allow for an assessment of the extent to which each of the areas covered in the course were learned, the goal being to find a process that is consistent with the work style implemented (course objectives, importance given to context, method used, etc.).

It is still too early to publish reliable statistics on how the experiments enhanced learning, but the good grades achieved by the 69 students enrolled in the last two years versus those obtained in previous years (without the experiments) seem to indicate a clear improvement in this area (Table 3).

Table 3. Grades obtained by the students

	A	B	C	D	F
Grades with laboratory practicals (2 years, 69 students)	24 (35%)	29 (42%)	11 (16%)	3 (4%)	2 (3%)
Grades without laboratory practicals (3 years, 94 students)	9 (10%)	23 (24%)	43 (46%)	3 (3%)	16 (17%)

6.2 Students' degree of satisfaction with the method proposed

It is important to know the students' opinions in order to carry out the process of evaluating the laboratory practicals [25– 26].

To gather the students' opinions a survey was created for the students to fill out and send electronically to the professor. The survey contained several questions on the practicals, grouped according to different characteristics:

- C1: Reflects the opinion of the students regarding whether the laboratory practicals allowed them to learn the relevant course contents and acquire the skills and abilities related to the course.
- C2: Reflects the extent to which the students considered the laboratory practicals useful in comparison with other materials in gaining the necessary skills and abilities.
- C3: Shows the students' opinions regarding the proper operation of the laboratory and the technical knowledge required for its use and that of the associated tools.

The survey was taken by 69 students. Table 4 shows the percentages for each of the category surveys.

Table 4. Survey percentages for each question

	% Agree	% Neutral	% Disagree	% N/A
C1	94	6	0	0
C2	91	9	0	0
C3	100	0	0	0

7. Conclusions

The objective of this paper was to present the laboratory practicals used to provide hands-on experience with the techniques taught in the Intelligent Control course. Said course teaches students the theoretical and practical aspects involved in the design of Intelligent Control Systems by integrating methods in Control Theory and Artificial Intelligence, stressing as well the optimization of the resulting systems.

To pass the course, the students, in addition to attending lectures and making an oral presentation on a practical case on Intelligent Control, have to design an Expert Control System for an elevator board, design and implement a Fuzzy Control System for a system of interconnected tanks, and design and implement a Neural Network to identify a system. The processes involved in these practicals were described in the corresponding sections.

Although these systems were used, the experimental designs are independent and can be used to control any other plant featuring real time or uncertainty requirements, or for which a behavior model of the system to be controlled is not available.

The good results obtained from a survey taken by the students concerning the skills and abilities gained from the experiments conducted, as well as the grades obtained by the students, show the advantages of being able to rely on said experiments so that the students can experience in the laboratory the theoretical aspects learned in the course.

References

1. Panos J. Antsaklis and Kevin M. Passino, *An Introduction to Intelligent and Autonomous Control*, Kluwer Academic Publishers, 1993
2. S. Yurkovich, and K. Passino, A laboratory course for teaching intelligent control, *Proceedings of the 35th IEEE Decision and Control*, Kobe, Japan, 11–13 Dec. 1996, pp. 3898–3903.
3. Huang, Xu. Intelligent Control and Computer Engineering. *Lecture Notes in Electrical Engineering*, 2011, pp. 317.
4. Ali Zilouchian and Mohammad Jamshidi, *Intelligent Control Systems Using Soft Computing Methodologies,* CRC Press, 2001.
5. El mahdi Ali MOHAMED, Darwich AHMED, *Utilizing MATLAB and SIMULINK in Graduate Course of Intelligent Control,* http://en.cnki.com.cn/Article_en/CJFDTotal-CADD200702015.htm, 2007, Accessed 11 February 2011.
6. X. P. Burgos-Artizzu, A. Ribeiro, M. de Santos, Controlador Borroso Multivariable para el Ajuste de Tratamientos en Agricultura de Precisión, *Revista iberoamericana de automática e informática industrial* (*RIAI*), **4**(2), 2007, pp. 64–71.
7. Baruch, Control Neuronal con término integral para un proceso de fermentación, *Revista Iberoamericana de Automática e Informática Industrial*, **2**(1), 2005, pp. 64–69.
8. SUSE Linux Enterprise Real Time Extension, http://www.novell.com/products/realtime/, Accessed 7 July 2010.
9. CLIPS, A Tool for Building Expert Systems. http://clipsrules.sourceforge.net/, Accessed 7 July 2010.
10. Mathworks, http://www.mathworks.com/, Accessed 7 July 2010.
11. Joseph C. Giarratano and Gary D. Riley, *Expert Systems*, Thomson Learning, 2005.
12. Juan Manuel Martín Sánchez and José Rodellar Benedé, *Control Adaptativo Predictivo Experto: Metodología, Diseño y Aplicación*, Publicaciones UNED, 2005.
13. J. M. Juarez Herrero, J. J. Cañadas Martínez and R. Marin, Control, *Inteligencia Artificial: Técnicas, Métodos y Aplicaciones*, 2008, pp. 589– 646.
14. R. G. Cowell, A. P. Dawid, S. L. Lauritzen and D. J. Spiegelhalter, *Probabilistic Networks and Expert Systems*, Information Science and Statistics, 2003.
15. E. Castillo, J. M. Gutiérrez, and A. S. Hadi, *Expert Systems and Probabilistic Network Model*, Springer-Verlag, 1997.
16. K. Passino and S. Yurkovich, *Fuzzy Control,* Addison-Wesley, 1998.
17. Jang, Sun, Mizutani, *Neuro-Fuzzy and Soft Computing*, Prentice Hall, 1997.
18. J. Kacprzyk, M. Fredizzi and H. Nurmi. Fuzzy logic with linguistic quantifiers in group decision making, *An Introduction to Fuzzy Logic Applications in Intelligent Systems*, Kluwer Academic Publishers, Norwell, MA, 1992, pp. 263–280.
19. L. A. Zadeh, Fuzzy logic, neural networks and soft computing, *Communications of the ACM*, **3**(3), 1994, pp. 77–84.
20. Chuen Chien Lee, Fuzzy logic in control systems: fuzzy logic controller—Parts I & II, *IEEE Trans, on Systems, Man and Cybernetics,* **20**(2), 1990, pp. 404–418 and 419–435.
21. R. M. Aguilar, E. J. Gonzalez, R. L. Marichal, A. Hamilton, L. Moreno, Neural networks teaching using Evenet-2000, *Computer Applications in Engineering Education*, **11**(1), 2003, pp. 1–5.
22. K. J. Hunt and D. S. Barbaro, Neural networks for nonlinear internal model control, *Control Theory & Applications*, **140**(6), 1993, pp. 431–438.
23. G. D. Magoulas, K. A. Papanikolaou, and M. Grigoriadou, Neuro-fuzzy synergism for planning the content in a web-based course, *Informática,* **25**, 2001, pp. 39–48.
24. Jerry Moscinski and Zbigniew Ogonowski, *Advanced Control with Matlab and Simulink*, Prentice Hall, 1995.
25. E. J. González, A. Hamilton, L. Moreno, R. Marichal and S. Torres, A set of microprocessor-based procedures for an industrial engineering course, *Computer Applications in Engineering Education*, **12**(3), 2004, pp. 145–151.
26. L. Moreno, C. S. González, I. Castilla, E. J. González and J. F. Sigut, Applying a constructivism and collaborative methodological approach in engineering education, *Computers and Education*, **47**(3), 2007, pp. 891–915.

Rosa Mª Aguilar received her MS in computer science in 1993 from the University of Las Palmas de Gran Canaria and her Ph.D. in Computer Science in 1998 from the University of La Laguna. She is associate professor in the Department of Systems Engineering and Control and Computer Architecture at the University of La Laguna, Canary Islands, Spain. Her current research interests are decision-making based on simulation of event-discrete systems and knowledge based systems, intelligent agents, and intelligent tutorial systems.

Vanesa Muñoz received her MS in Computer science in 2001 and her Ph.D. in Computer Science in 2007 from the University of La Laguna. She is professor in the Department of Systems Engineering and Control and Computer Architecture at the University of La Laguna, Canary Islands, Spain. Her current research interests are decision-making, discrete event simulation, human–computer interaction, artificial intelligence, intelligent agents, and intelligent tutorial systems.

Evelio González received his MS in Applied Physics in 1998 and his PhD in Computer Science in 2004 from the University of La Laguna, Tenerife, Spain. From 1998 to 2001, he was a Research Student in the Department of Applied Physics, Electronics and Systems at the same university. Currently, he works as Assistant Professor in the University de La Laguna. His areas of interest include simulation, digital control, computer architecture, artificial intelligence and intelligent agents.