Neural networks and fuzzy logic in electrical engineering control courses

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Abstract Control system education must include experimental exercises that complement the theory presented in lectures. These exercises include modelling, analysis and design of a control system. Key concepts and techniques in the area of intelligent systems and control have been discovered and developed over the past few decades. While some of these methods have significant benefits to offer, engineers are often reluctant to utilise new intelligent control techniques, for several reasons. In this paper fuzzy logic controllers have been developed using speed and mechanical power deviations, and a neural network has been designed to tune the gains of the fuzzy logic controllers. Student feedback indicates that theoretical developments in lectures on control systems were only appreciated after the laboratory exercises.

Keywords fuzzy logic; intelligent control; modelling; neural networks

Undergraduate students in computer science learn best when they are given the opportunity to apply software concepts to real world systems, and intelligent control applications present attractive possibilities for giving them such opportunity. An example of how to take advantage of these possibilities is given in this paper, which describes a specific neural network technique that has been developed and applied to the problem of tuning fuzzy controllers.

To master the technique, the students start by learning about neurons and fuzzy logic, but they soon find themselves 'training' a multilayered neural network that they themselves have built.

The electronic computer has been used extensively in the electric power industry from the moment the computer became commercially available. This was a natural development since the size and complexity of most power system problems make the computer an essential tool for the electric power system analyst and designer.

Electric power system analysis tools, with computational power similar to or better than programs first developed during the 1960s and 1970s, and easy-to-use, attractive, and providing a graphical user interface, are just becoming available.[1,2]

The main difficulty in a control course is the large amount of mathematical models and equations. The repetitive algebra and the necessity for a complete understanding of the physical concepts embedded in the equations require the use of a suitable computational tool. The introduction of MATLAB in this course is due to its facility to build up mathematical functions and also due to its powerful graphical user interface in order to display the results.

We describe a laboratory exercise required in a control class and the relationship between the exercise and the theory presented in lectures. We conclude with a summary of our experiences with the laboratory exercises and the feedback received from our students and graduates.

Intelligent control

Major concepts and techniques in the area of intelligent systems and control have been discovered and developed over the past few decades.[3] While some of these methods have significant benefits to offer, engineers are often reluctant to utilise new intelligent control techniques for several reasons:

1 there has been a lack of rigorous engineering analysis to verify, for example, stability properties and performance characteristics;
2 there is not an established track record for the reliability and robustness of such techniques;
3 there has not been comparative analysis to determine their advantages/ disadvantages relative to conventional methods; and
4 the approaches are not widely understood by practising engineers. The relative lack of attention given to the potential of intelligent control is cause for some concern, indicating a definite need for applications-directed research and education in these areas.

Curricula for control engineering programs have undergone substantial change in the past years as modern techniques for analysis and design find their way into these courses. It is quite natural then, that newer technologies such as intelligent control should be introduced into university curricula. Along with the continuously evolving curricula, there remains a constant in control engineering education: the recognised need for laboratory experience in the curricula. More and more examples of high-quality control laboratories are appearing in universities worldwide.[4] Moreover, more and more educators recognise the importance of a complete educational experience involving theory and practice.

With these thoughts in mind, it has been our goal to bring the newest technologies into the curricula, through both lecture and laboratory courses. With regard to the treatment of intelligent control in the courses our intent has not been to give an in-depth treatise on the theory of fuzzy sets and neural nets. We found that electrical engineering undergraduates have little difficulty in coming up to speed in the area in a relatively short amount of time.

The graduate students are exposed to the more advanced topics, and at a higher level of sophistication. Several projects in simulation and design analysis are given. The graduate students are required to complete the entire lecture-laboratory course.

Laboratory exercises

We believe that effective control system education must include experimental exercises that complement the theory presented in lectures. Preferably, the exercises should include the design and implementation of a control system. Limited resources make it impossible to offer a laboratory course with every control class in most electrical engineering curricula. The students are divided into groups and each group must independently complete the design project and submit a formal report summarising their results and experiences. Each student must submit an individual commentary on the exercise and the experimental results obtained. Student feedback indicates an increased appreciation of the lecture material and an awareness of the limitations of the theory and simulation that was lacking prior to the introduction of laboratory exercises.

The classes include highly mathematical theoretical derivations which must be justified to our students. The number of credit hours allocated to control is already high relative to other areas and there is no justification for increasing it.

Nevertheless, the courses include highly mathematical developments which many seniors find challenging. The courses include elements of computer-aided control system design. However, some of the limitations of the theory and design recipes are not easily appreciated from the simple problems that can be addressed in lectures and exams.

The exercises include modelling, analysis and design of a control system. Practising engineers often obtain mathematical models of physical systems by evaluating the system parameters in the laboratory, design a controller based on the mathematical model, then use a more complex model in extensive simulations. The simulations provide an economical means of testing the system before implementation. Finally, some modification of the design may be necessary to obtain acceptable performance. Trial and error may be necessary at each stage before the desired results are obtained. Our goal was to develop a take-home exam including laboratory exercises that mimic this general sequence of events. Design problems suitable for in-class exam must involve little or no trial and error due to time limitations.

Using a tool such as MATLAB, the students then design a controller for the gas motor based on its model. They learn that the model used for design can be much simpler than that used for simulation provided that the performance of the closed-loop system is checked using the more complex simulation model. The students are given guidelines for the selection of the design specifications but the design specifications themselves are not provided. An important part of the exercise is that the students have to experiment with the system to be able to choose realistic design specifications. In practice, the design engineer may have some freedom in choosing the specifications so that the design criteria lie in acceptable ranges. In addition, the acceptable ranges for the design criteria are based on an understanding of the physical system and its normal operating conditions.

Gas motor control

Natural gas as a fuel for diesel engines offers the advantage of reduced emissions while retaining the high efficiency of the conventional diesel engine. The engine can operate at high compression ratio with a wide range of gas composition. A disadvantage of natural gas use in diesels is the high auto-ignition temperature. Thus, ignition assistance is needed. Fuel rates are always expressed in terms of higher heating value. Heat balance accounts for all the thermal energy involved in the process of converting fuel to energy. This energy is then converted into mechanical work, by expanding the gas through the motor. The majority of medium- and slow-speed engines are turbocharged, using axial-flow or mixed-flow designs. The data

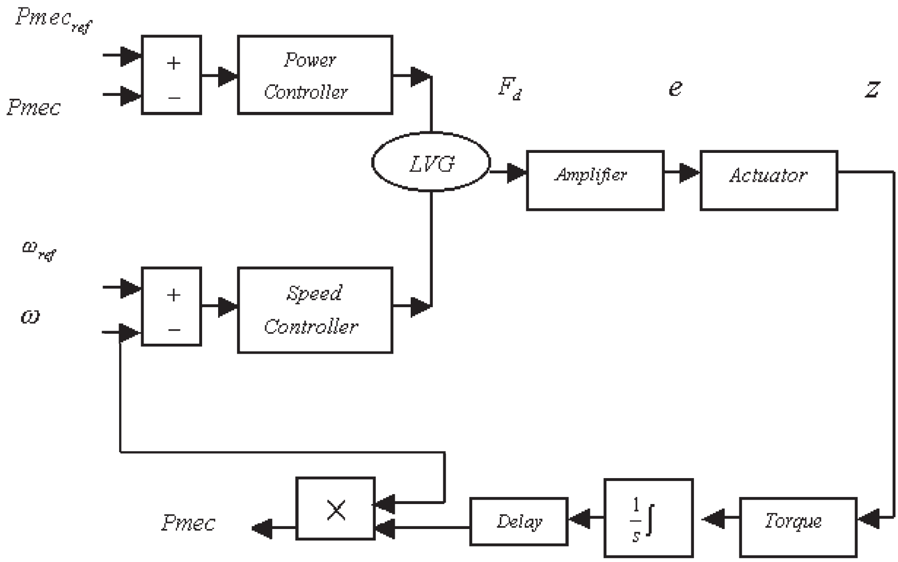

Fig. 1 *Gas motor block diagram.*

required for the model consist of a set of algebraic functions which relate the significant engine variables. These functions are obtained from engine test data.[5–7]

The gas motor controller is modelled by a set of simultaneous linear differential equations relating the engine speed, mechanical power, reference speed and load sharing signal with the fuel demand signal.[8–10]

The gas motor controller regulates both the gas motor and the gas motor generator. For the purpose of this exercise only modulating control of the mechanical side of the gas motor is of interest. The simplified model of the gas motor controller in this exercise consists of two inputs and one output. Inputs to the controller, which are outputs from the gas motor model, are the mechanical power delivered by the motor P_{mec} and the rotation speed of the gas motor ω, related to the electrical frequency of the generator. The output from the controller is the fuel demand signal F_d.

The block diagram of the gas motor control system is presented in Fig. 1. The diagram consists of two feedback controllers. *LVG* stands for Least Value Gate, which transmits the minimum of two incoming signals.

PID controller

Despite huge advances in the field of control systems engineering, PID still remains the most common control algorithm in industrial use today. It is widely used because of its versatility, high reliability and ease of operation.[11] A standard method of setting the parameters is through the use of Ziegler-Nichols' tuning rules.[12] These techniques were developed empirically through the simulation of a large number of process systems to provide a simple rule. The methods operate particularly well for simple systems and those which exhibit a clearly dominant pole-pair, but for more complex systems the PID gains may be strongly coupled in a less predictable way. For these systems, adequate performance is often only achieved through manual and heuristic parameter variation.

Neuro-fuzzy logic controller

Unlike the classical control design, which requires a plant model for designing the controller, fuzzy logic incorporates an alternative way which allows one to design a controller using a higher level of abstraction without knowing the plant model. This makes the fuzzy logic controller (FC) very attractive for ill-defined systems or systems with uncertain parameters.[13]

The recent growth in attention to neural networks (NNs) has led to many suggestions for combined use of fuzzy logic and neural networks in intelligent control.[14,15] In a multi-layer neural network of the feed-forward type, input nodes record the features and pass activation values to the output layer through a hidden layer. The addition of the hidden layers to the two layer perceptron networks allows these networks to represent any continuous mapping from input to output.[16,17] An appropriate training technique adjusts the connection weights of the network to improve the match between the output of the network and the correct results.

To design the FC some variables, which can represent the dynamic performance of the system, should be chosen to be fed as the inputs. In addition to the proper input signals, signal gains and fuzzy subsets should be defined. It is common to use the output error and the rate of derivative of the output as controller inputs.[18,19] In this paper, the motor speed deviation ($\Delta\omega$) and its derivative ($\Delta\omega'$), the acceleration, are considered as the inputs of the first FC and the mechanical power deviation delivered by the motor (ΔP_m) and its derivative ($\Delta P_m'$) as the inputs of the second FC.

Subsequently, $\Delta\omega$, $\Delta\omega'$, ΔP_m and $\Delta P_m'$ signals pass through four appropriate gains or scaling factors, and then are fed to the FCs. The outputs of the controllers are also scaled by passing through the output gains. To convert the measured input variables of the FCs into suitable linguistic variables, seven fuzzy subsets are chosen. Membership functions of these subsets are bell-shaped. Figure 2 shows the membership functions. In this paper, both inputs of the FCs have seven subsets. Thus, two fuzzy rule tables with forty-nine rules are constructed. Figure 3 illustrates the control surface. The centre of gravity method is employed.

Sequential de-centralised control means design of each modulation controller one after the other, so that dynamics of previously designed controllers are taken into account in designing the next controller.[20]

Tuning the fuzzy controllers

In order to tune the FCs, the $\Delta\omega$ is scaled according to the following relation: $\Delta\omega_* = G_{e\omega}\Delta\omega$ and $\Delta\omega'$, $\Delta\omega'_* = G_{r\omega}\Delta\omega'$. The ΔP_m is scaled according to the relation: $\Delta P_{m*} = G_{ePm}\Delta P_m$ and $\Delta P'_m$, $\Delta P'_{m*} = G_{rPm}\Delta P_m$. Also, the output of the first FC is scaled by $G_{u\omega}$ and the output of the second FC is scaled by G_{uPm}. In the aforementioned relations, $G_{e\omega}$, $G_{r\omega}$, $G_{u\omega}$, G_{ePm}, G_{rPm} and G_{uPm} are the scaling factors or gains.

The gains of the FCs are tuned with a neural network, making the FCs adaptable

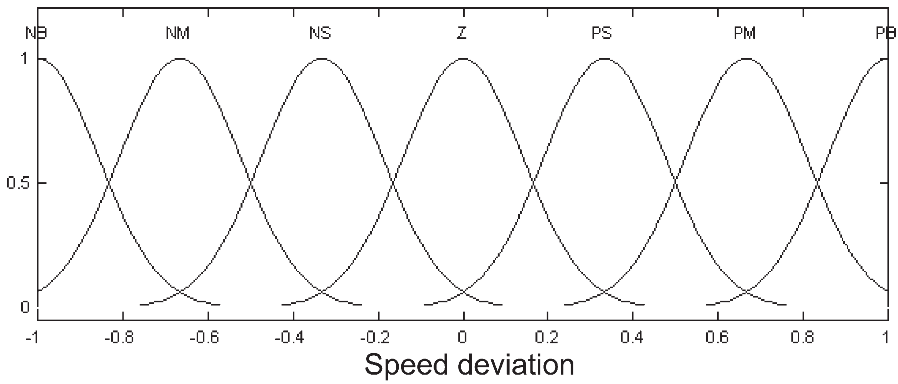

Fig. 2 *Membership functions.*

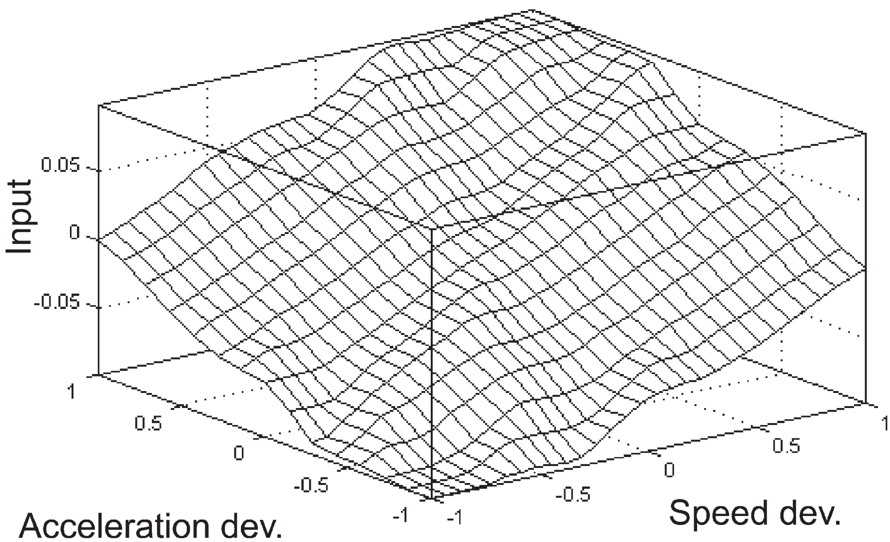

Fig. 3 *Control surface.*

to changes in operating conditions. The FCs are tuned by computing optimum gains, exploiting a neural network. The neural network is composed of three layers (Fig. 4). The active power P, reactive power Q and mechanical torque in the asynchronous motor T_m are selected for input signals to represent the operating condition of the system. For various sets of input data to the NN, the optimum values of gains are searched sequentially using simulations.

A data set has been generated by computer simulation by varying the active power load P, reactive power load Q and torque in the asynchronous motor T_m.[21] The evaluation of the optimality is checked by time domain performance specifications such

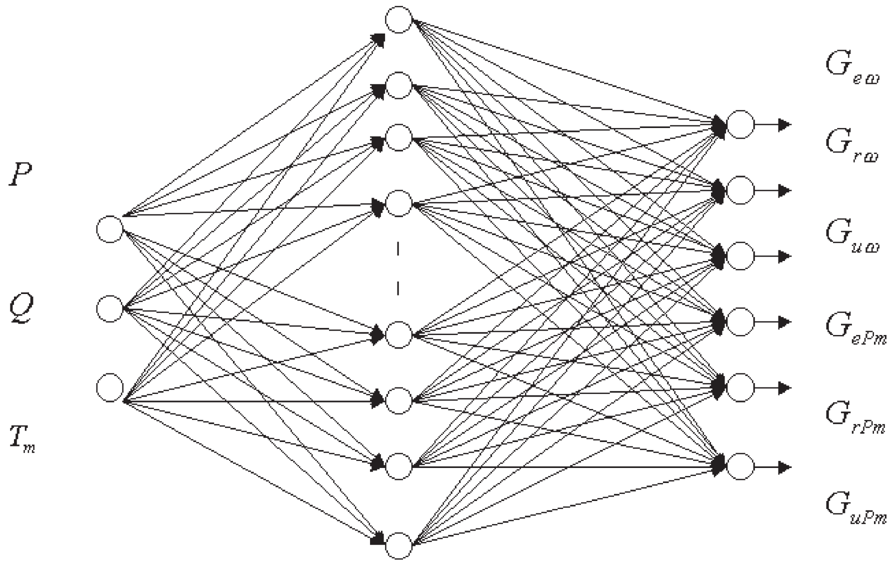

Fig. 4 *Neural network.*

as peak time, percentage overshoot, rise time and settling time. The optimisation was conducted by minimisation of integrated time and squared error,

$$J = \int_0^{T_S} \tau(\Delta\omega(\tau) + \Delta P_m)^2 \, d\tau \tag{1}$$

over a suitable simulation time ($T_S = 1.5$ s) following an applied step in load at $t = 0$. By time-weighting the error signal less emphasis is placed on the initial error, which is largely unavoidable, and greater emphasis on reducing long-duration oscillations. A technique called the Levenberg-Marquardt method is used to train the NN.

Simulation results

A plant consisting of a load and an induction motor is fed from a synchronous generator/gas motor unit (Fig. 5). The gas motor, fuzzy controllers, neural network, synchronous generator and governor system are modelled by MATLAB.[22]

Initially, the induction motor develops mechanical power and the synchronous generator provides active power. The generator controls the voltage at 1 pu and generates active power. Mechanical power from the synchronous generator increases from its initial value to the final value required by the load and induction motor. For a power plant with all three controllers, i.e., PIDs, FCs and NFCs (Neuro-Fuzzy Controllers), the system responses for different conditions were obtained using simulations:

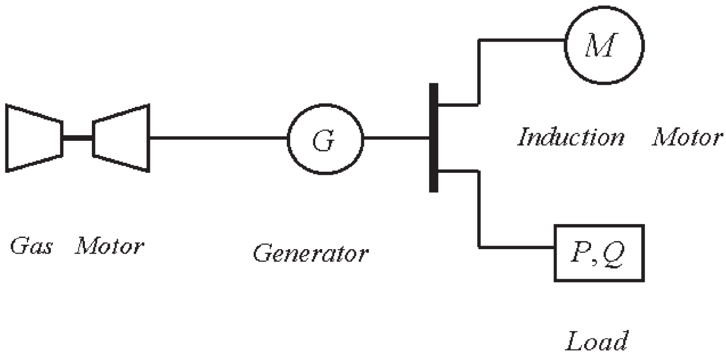

Fig. 5 *System model.*

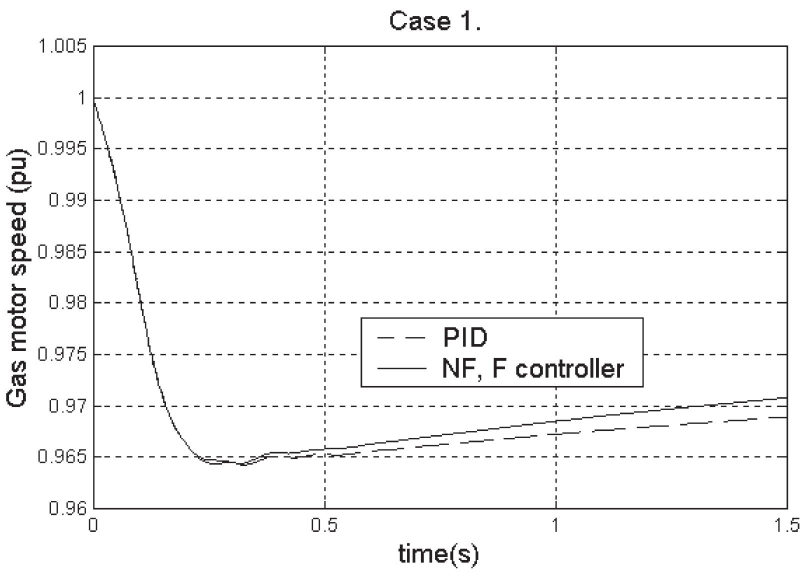

Fig. 6 *Gas motor speed for Case 1.*

- Case 1: Operating point P = 1 MW, Q = 0.5 Mvar and T_m = 8000 N·m. Since FCs and NFCs are designed for this operating condition their responses are optimum and coincident with each other in this case, as is observed from Figs 6 and 7.
- Case 2: Operating point P = 0.9 MW, Q = 0.4 Mvar and T_m = 8000 N·m. The system responses are shown in Fig. 8 and Fig. 9. As shown in the figures, the

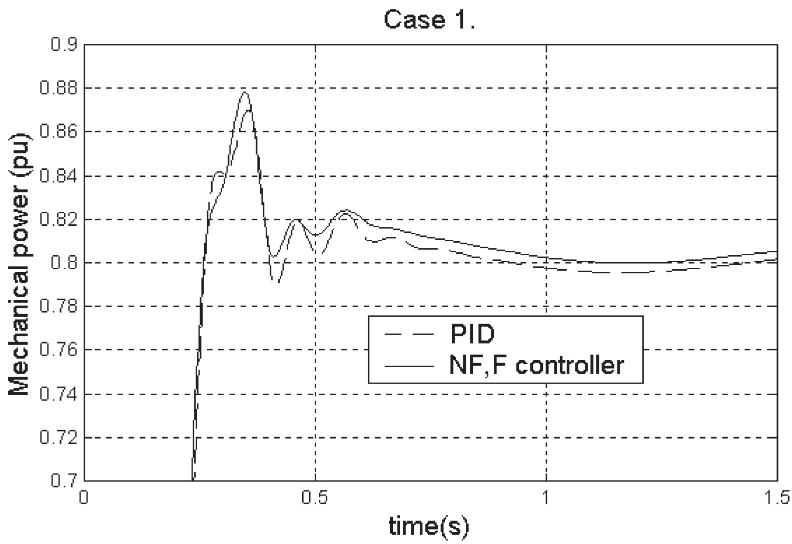

Fig. 7 *Mechanical power delivered by gas motor for Case 1.*

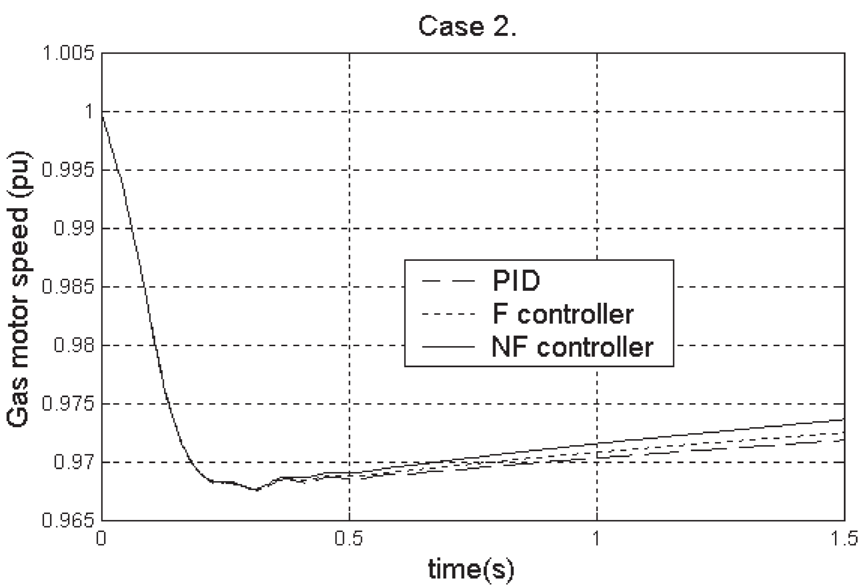

Fig. 8 *Gas motor speed for Case 2.*

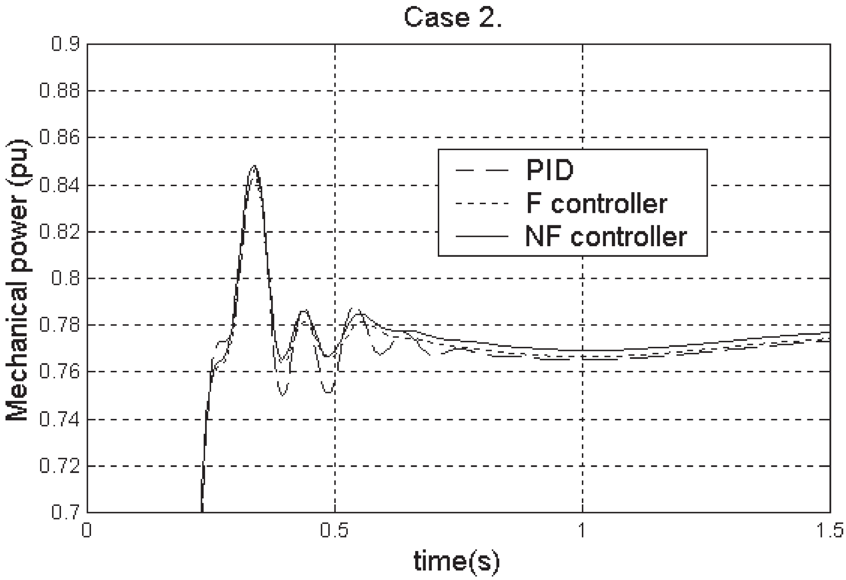

Fig. 9 *Mechanical power delivered by gas motor for Case 2.*

NFCs have optimum responses and the responses are smooth and fast. They have less settling time, compared with the other controllers.

It is shown that by tuning the FCs with the aid of a neural network, the optimum system response can be achieved in a wide range of operating conditions compared to a fixed-parameter FC and a PID controller.

Results

To determine how these concepts and techniques were being used, students were asked to answer several questionnaires throughout the term. The surveys concentrated on determining the students' previous knowledge of intelligent control. The questionnaire included a question on the students' expectation of the use of these techniques. Table 1 shows the students' answers to the main questions in the survey.

Conclusions

In this section we provide a brief discussion of the impact of the course on intelligent control and the intelligent control laboratory. Laboratory exercises are an important part of an electrical engineer's education. One of the main difficulties with laboratory exercises is that they require resources that may be beyond reach for most electrical engineering departments.[23]

For a more complete discussion of the advantages and disadvantages of labora-

TABLE 1 *Results of student survey*

Item	Number
Participation	26
Familiar with PC	26
Familiar with Internet	25
Familiar with fuzzy logic	15
Familiar with neural network	10
Simulation packages were helpful	26
Techniques would be helpful	20

tory exercises, the reader is referred to Ref. [24] Our experience shows that an effective laboratory exercise can be designed as part of classes with limited resources.

Computer simulations allow the student to experiment with mathematical models and develop a feel for their limitations. However, the author believes that simulations can never take the place of hands-on experiments. Our graduates who are currently practising engineers also indicated their deep appreciation for the practical hands-on experience that they gained from our laboratory experiments.

Student feedback indicates that theoretical developments in lectures on control systems were only appreciated after the laboratory exercises. Student evaluations of the state-space course included ‘applying theory to a real system’ as one of the best things about the course. While students could follow most of the steps of the derivations presented in the lectures, they had little appreciation for their significance before observing their effects in the laboratory. Several students indicated in their project reports that the theory made a lot more sense after the experimental exercise.

The students generally responded very positively to lecture and lecture-laboratory courses. There were over 30 students who completed the lecture course in 1999 and 16 students who completed the laboratory. There were about 20 students on the lecture course in 2000 and 10 in the laboratory. The students provided many positive comments on the student evaluations of instruction.

For instance, they felt that the course and laboratory were well synchronised. They liked the laboratory lectures and felt that these helped them to see how they could apply the methods to even more complex industrial applications. Several students made direct use of the intelligent control course and laboratory in their MS research. There were a few complaints about problems with laboratory equipment, but such complaints were minimal as most of the equipment is new. Overall, the students felt that they had been provided with a unique and valuable learning experience that would be of benefit to them in their future careers.

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