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–Review Paper–

A CRITICAL REVIEW OF THE MOST POPULAR TYPES OF NEURO CONTROL

Morteza Mohammadzaheri, Lei Chen, and Steven Grainger

ABSTRACT

In this review article, the most popular types of neural network control systems are briefly introduced and their main features are reviewed. Neuro control systems are defined as control systems in which at least one artificial neural network (ANN) is directly involved in generating the control command. Initially, neural networks were mostly used to model system dynamics inversely to produce a control command which pushes the system towards a desired or reference value of the output (1989). At the next stage, neural networks were trained to track a reference model, and ANN model reference control appeared (1990). In that method, ANNs were used to extend the application of adaptive reference model control, which was a well-known control technique. This attitude towards the extension of the application of well-known control methods using ANNs was followed by the development of ANN model-predictive (1991), ANN sliding mode (1994) and ANN feedback linearization (1995) techniques. As the first category of neuro controllers, inverse dynamics ANN controllers were frequently used to form a control system together with other controllers, but this attitude faded as other types of ANN control systems were developed. However, recently, this approach has been revived. In the last decade, control system designers started to use ANNs to compensate/cancel undesired or uncertain parts of systems' dynamics to facilitate the use of well-known conventional control systems. The resultant control system usually includes two or three controllers. In this paper, applications of different ANN control systems are also addressed.

Key Words: Control, neural network, adaptive, feedback linearization, predictive, model reference, perceptron, radial basis.

I. ARTIFICIAL NEURAL NETWORKS USABLE IN CONTROL

Artificial neural networks (ANNs) are special mathematical models inspired by human neural networks. An ANN usually includes neurons, connections and biases. Neurons are arranged in 'layers'. There are a variety of neural networks suitable for different purposes [1, 2]. In neuro control, it is a difficult and unsolved problem to find the best ANN structure for each specific application; thus, a fairly large ANN is usually employed to deal with relatively complex approximation problems [3]. In this paper, the most common types of artificial neural networks in the area of control are introduced: multi layer perceptrons (MLPs) and radial basis function networks (RBFNs). Both of these are known as universal approximators of systems [4, 5]. The advantage of RBFNs is their quick training process compared with MLPs; however, for complicated systems with many inputs, the number of neurons in RBFNs are usually considerably higher than MLPs [1, 2]. Regardless of the main structure, if the output of an ANN depends not only on the current

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The authors are with University of Adelaide, Australia.

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input to the network but also on the current or previous inputs, outputs, or states of the network, it is a recurrent ANN. In other words, in recurrent networks, the (delayed) output of each neuron may be returned to the neurons of the same or previous layer. This does not happen in feedforward or static ANNs.

1.1 Multi layer perceptrons

Multi layer perceptons (MLPs) are the most popular neural networks used in control [6]. A MLP may have some layers and each layer comprises neurons and a bias. A neuron includes a sum operator and an activation function (see Fig. 1). The inputs to a neuron are summed and the result passes through a function, namely an 'activation function'. The neurons are connected by 'connections'. Connections have different 'weights'. The output of each neuron passes a connection and is multiplied by the connection's weight, and then the product enters the neurons of the next layer. Biases are constant numbers (usually one) installed in the structure of the ANN. The product of the bias and the weight of its connection enter the neurons of the next layer. For the *i*th neuron of a layer of an ANN, if $p_1, \ldots, p_R$ are the outputs of the neurons of the previous layer, W_{ij} is the weight of the connection between the neuron and the *j*th neuron of the previous layer, b is the bias of the previous layer, and f is the activation function of the layer; the output of the layer (a) is presented in (1):

$$a = f\left(\sum_{j=1}^{R} W_{ij} p_j + b\right). \tag{1}$$

Figures 1 and 2 show a neuron and a (feedforward) MLP neural network respectively.

In MLPs, activation functions are fixed and weights are subject to change during the training process. Multi layer perceptrons have been investigated comprehensively for control purposes [7–9] and a wide variety of control applications such as the control of printing devices [10], heat exchangers [11] and spacecraft manoeuvring [12] have been found for perceptrons.

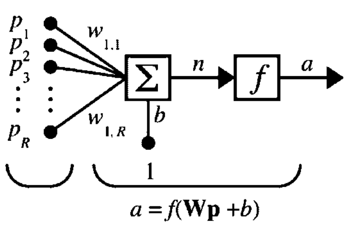

Fig. 1. A typical neuron of an ANN [2].

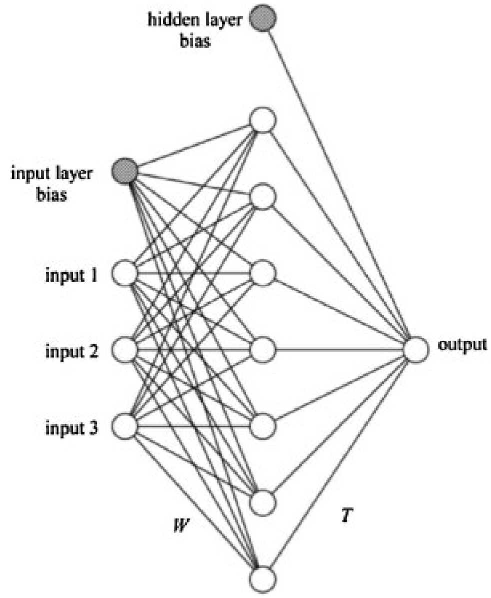

Fig. 2. A perceptron with three layers of neurons and two layers of connections.

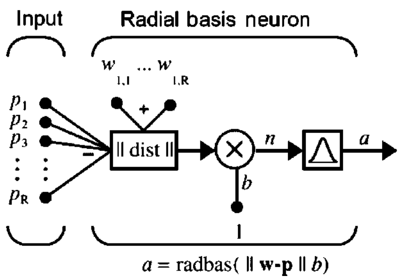

Fig. 3. A scheme of the first layer of a RBFNN [2].

1.2 Radial basis function networks

Radial basis function networks (RBFNs) are the second most popular type of neural network for control purposes with a variety of applications [13–16]. These ANNs usually have two layers of neurons; the first layer is completely different from perceptron layers but the second layer is similar to perceptron layers. Figure 3 shows a radial basis neuron in the first layer of a typical RBFN.

The ||dist|| box in Fig. 3 receives the input vector **p** and the weight vector **IW**, and produces the dot product of these two vectors; the outcome is multiplied by the bias b, which is the input to the radial basis transfer function:

$$\text{radbas}(x) = e^{x^2}. \tag{2}$$

If the input layer weight vector of **IW** has S_1 elements (weights), the second (linear) layer weight vector of **LW**

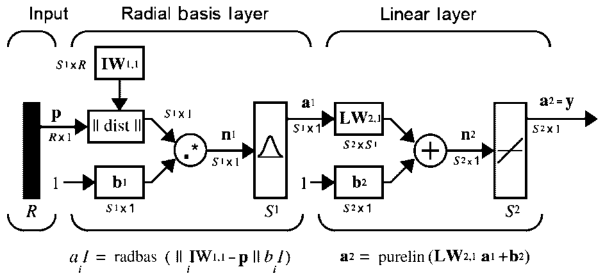

Fig. 4. A typical RBFNN [2].

has $S_1 \times S_2$ elements (weights) as shown in Fig. 4, the input vector of **p** has R elements, the output vector of **y** has S_2 elements, and biases of the input and second layer are $\mathbf{b}_1$ and $\mathbf{b}_2$ then

$$y_k = \sum_{i=1}^{S_1} \text{radbas}\left(\sum_{j=1}^{R} IW_{ij} P_j + b_{1j}\right) \times LW_{ik} + b_{2k}. \quad (3)$$

II. AN INTRODUCTION TO NEURO CONTROL

Control system design is the process of making a path from the *system dynamics* to a *control system* that consists of architecture (*i.e.* feedforward or cascade), a controller(s) structure (mathematical form) and controller(s) parameters. In other words, the control system design process starts from the system dynamics. System dynamics includes all the knowledge about the system available to the designer and applicable for control system design. Input–output data of systems have been used in control design from the 1940s [17]; for instance, a system's response to step or sinusoidal inputs has been used for linear control systems design [17, 18]. However, artificial neural networks significantly increased the value of system input–output data as a type of knowledge about the system. Input–output data were used to design a variety of nonlinear controllers using ANNs, which was unprecedented in control. Different classifications are found in the literature for neuro controllers [6, 19, 20]. In this paper, the five most popular neuro control methods are briefly introduced in chronological order, so as to cover both well-established and emergent methods. In this article, it is assumed that, in neuro control systems, neural networks are directly involved in generating the control command. Thus, control systems with ANN observers without neuro controllers [21–24] are not addressed.

In the late 1980s, artificial neural networks were employed to map the measured output to the control command. ANNs, trained using such data, could produce a control command which would lead to a desired output. This approach is called inverse dynamics or the inverse modeling method and used to be the dominant approach in the era of the pioneers of neuro control [25, 26] without directly mentioning the word "inverse" as the name of the method. The term "inverse" gradually appeared to introduce this approach in the early 1990s [27, 28]. Narendra and Parthasarathy used two ANNs for modeling and control at the same time and devised model reference neuro control [29]. In the 1990s, ANNs were employed to generalize well-known nonlinear control methods [30]. In 1991, ANN model predictive (neuro-predictive) control emerged as the generalized form of nonlinear model predictive control. A neuro-predictive controller includes a predictive model (an ANN) and an optimiser/controller, which may also be an ANN [31]. The neuro-predictive method was followed by ANN sliding mode control [32] and ANN feedback linearization control [33]. Later, ANNs were employed to compensate uncertain or complicated parts of systems dynamics rather than for the purpose of routine feedback linearization [34]. From the early 2000s, in some research works, after ANN compensation, the resultant dynamics was still nonlinear and was controlled using well-known nonlinear control methods [35]. In this review, these control systems are named 'control systems with ANN compensation'. The following classes of ANN control systems are addressed in more detail in this paper:

1. ANN inverse dynamics control systems
2. ANN model reference control systems
3. Neuro-predictive control systems
4. ANN feedback linearization control systems
5. Control systems with ANN compensation

For less common types of neuro controllers, such as reinforcement-learning-based controllers and neuro control systems based on NLq theory, discrete-event automata, receding-horizon neural regulators, backstepping, and stochastic recurrent neural networks, there exist some useful survey and introductory articles [36–46].

2.1 ANN inverse dynamics control systems

Consider the mathematical model of a first order single-input-single-output (SISO) system, with one-step delay:

$$y(k+1) = F_D(y(k), u(k)) \quad (4)$$

where y, u, and k are output, input, and index respectively, and F_D is the direct model of the system. F_I, as described in (5), will be the inverse model of the same system:

$$u(k) = F_I(y(k+1), y(k)). \quad (5)$$

If F_I is known, the input which leads to a desired value of the output (y_d) at the next stage can be found:

$$u(k) = F_I(y_d, y(k)). \quad (6)$$

Thus the inverse model can be used as a control law. If an ANN is employed as the inverse model, the system will be an ANN inverse dynamics control system. These control systems are used either as sole feedforward controllers [28, 47–49] or along with a feedback controller such as proportional [25], proportional-derivative [50], and proportional-integrator-derivative [26] controllers or another ANN [51]. Since 1993, the stability of ANN inverse dynamics control systems has been addressed [50–53].

The reference (setpoint) is often employed as the input to ANN inverse dynamics controllers [25, 26, 28, 47, 51, 52]; disturbances have also been used as the input to these controllers [54] since the late 1990s. Both reference and measurable disturbances have either been used as the input to these neuro controllers [55].

If only off-line (recorded) data are used in training ANN inverse models, the control system is not adaptive [26, 28, 48, 52]; however, since 1991, many ANN inverse controllers benefit from the on-line training capability of neural networks and are adaptive [47, 49–51].

Inasmuch as internal model control (IMC) is based on inverse modelling [56] in many cases, ANN inverse dynamics control systems are referred to as ANN IMC systems [27, 52, 57–59].

2.2 ANN model reference control systems

In model reference control, an ANN is often used as a feedforward controller. Usually, this ANN receives the reference and generates the control command. It is expected that the generated control command makes the plant track a stable mathematical model called the "reference model" [29]. The weights of the ANN controller are adjusted to minimise a cost function involving the discrepancy of output of the plant and the reference model. The reference model can be a gain of one; in this case, the ANN controller is simply trained to force the system to follow the reference and the approach becomes closely similar to the ANN inverse dynamics control method and may be called ANN direct adaptive control [60, 61]. The ANN model reference control method is an adaptive approach by its nature [60–63]. Stability of these control systems has also been well addressed [61, 63]. Sometimes, an ANN model is used, instead of the plant, in training ANN model reference controllers prior to implementation. In these control systems, there will be two different neural networks: a model and a controller [6, 29]. Figure 5 shows a schematic of an ANN model reference control system, where e_c is the control error, and r is the reference. Occasionally, ANN model reference controllers are used together with feedback controllers [63] or as feedback controllers (with control error input) [64].

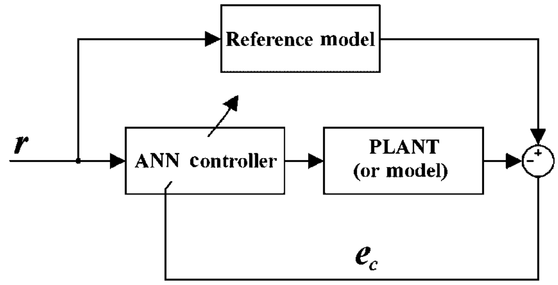

Fig. 5. A schematic of an ANN model reference control system.

2.3 Neuro-predictive control systems

Neuro-predictive controllers often use a neural network model of a nonlinear system repeatedly to predict the response of the system for a period of time in the future. This period of time or the number of instants (prediction time divided by sampling time) is called the "horizon" (see Fig. 6).

In Fig. 6, y_s is the estimated output of the system, u' is the tentative control input, and z^{-1} is unit delay. After the estimation stage, a performance function is defined which usually includes the predicted errors and the change in control input value. Then, a controller or optimiser calculates the control input that will minimise the defined performance function.

In terms of predictive modeling, the most popular structures are MLPs [65–74], RBFNs [75–77] and neuro-fuzzy networks [78], all in recurrent form. In some cases, on-line (real-time) training of ANNs has been effectively used and adaptive neuro-predictive controllers have been designed [71, 75, 77, 79].

A wide variety of optimisation/control algorithms have been employed in neuro-predictive control such as sequential quadratic programming [69–71, 73–77], linear quadratic Gaussian [80] or self-tuning PI [71] control, Levenberg-Marquardt [65], fuzzy gradient-descent [67] and genetic [81] optimisation algorithms. An additional ANN can also play the role of the controller/optimiser [66, 79, 82]. In some research

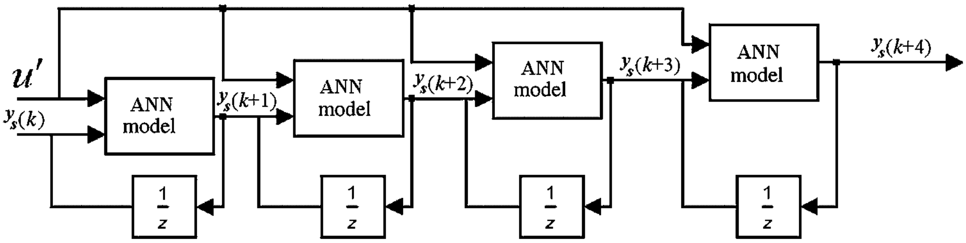

Fig. 6. Prediction of the output value with a horizon of 4 [65].

works, the model and the control law have been designed so that the whole control system is stable [71, 79]. Nonlinear chemical and thermal processes are the main areas of the application of neuro-predictive controllers [67, 69, 71, 74–77, 79, 83]; however, the neuro-predictive approach has also been utilized in the control of model helicopters [65, 84], robots [66], insulin injection (for diabetic patients) [68] and manufacturing processes [70].

2.4 ANN feedback linearization control systems

Feedback linearization is aimed at cancelling nonlinearities. This technique can be easily applied to a class of nonlinear systems which can be described by "companion form" models [85]. For a SISO system, a companion form model is given by:

$$y^{(n)} = f(\mathbf{y}) + b(\mathbf{y})u \tag{7}$$

where u is the scalar control input, y is the scalar output of interest, and $\mathbf{y}$ is the state vector

$$\mathbf{y} = [y, \dot{y}, \ldots, y^{(n-1)}]^T \tag{8}$$

and $f(\mathbf{y})$ and $b(\mathbf{y})$ are nonlinear functions of the states. In classical feedback linearization, this type of control problem can be transformed to a linear control problem (*e.g.* solvable by pole-placement) using an auxiliary control input [85]. The combination of the aforementioned auxiliary control input and the system is a linear system or the reference.

Considering realizability issues, for SISO systems, a companion form model in a discrete domain is defined as [2]:

$$y(k+d) = f(\mathbf{y}, \mathbf{u}) + b(\mathbf{y}, \mathbf{u}).u(k+1) \tag{9}$$

where $\mathbf{y} = [y(k), y(k-1), \ldots, y(k-n+1)]^T$, $\mathbf{u} = [u(k), u(k-1), \ldots, u(k-m+1)]^T$, and n and m are the orders of y and u in the system, respectively. If such a model can be fitted to a system, at the instant k, the control input at the next instant $u(k+1)$ can be defined so that $y(k+d)$ converges towards the reference ($y_d(k+d)$) with the following control law:

$$u(k+1) = \frac{y_d(k+d) - f(\mathbf{y}, \mathbf{u})}{b(\mathbf{y}, \mathbf{u})}. \tag{10}$$

Neural networks are employed to approximate the functions f and b. It is obvious that not all systems can be fitted to such a model, and it is a restriction of this method [2, 6]. In practice, NARMA-L2 is another name for this method [2, 6, 86–88]. Sometimes, in companion form as presented in (9), control increment (Δu) substitutes for control input (u), so the control algorithm calculates Δu [3]. In some cases, classical feedback linearization is enhanced by neural networks, *e.g.* for uncertainty compensation [23, 89]; these cases are not considered as ANN feedback linearization systems in this paper. MLPs [86–88, 90, 91] and RBFNs [3, 92], both in the recurrent form, are the most popular neural networks in ANN feedback linearization. In many cases, using the capability of ANNs in on-line learning, the designed ANN feedback linearization control system is adaptive [3, 90, 92–94]. In these control systems, the ANN's structure and learning laws can be defined so that the control system is stable [3, 90–92]. In contrast to the neuro-predictive method, ANN feedback linearization has been widely used to control second-order mechanical systems [87, 88, 90, 92], and first-order processes/mechanical systems [86, 91, 94] have also been controlled by this method.

2.5 Control systems with ANN compensation

Conventional control methods offer significant advantages in terms of, for example, stability and robustness. However, usually, these methods can be applied only to systems with particular dynamics that do not match real systems completely. Recently, neural networks have been employed to tackle this problem, mainly by cancelling/compensating undesirable or uncertain parts of the system dynamics. In this category of control systems, the neural network is not the sole control law and there usually exist two [89, 95–99] or three [100–103] controllers working jointly. ANN control laws have already been used together with proportional [104], proportional-integral-derivative [99, 103], sliding mode (conventional [101] and intelligent [97, 98]), back stepping [95, 100, 102], H_∞-based robust [89], feedback linearization [89] and model reference adaptive [105] controllers. These hybrid control systems, in almost all cases referred to in this paper, are adaptive and stable. Different types of ANNs have been used in these control systems, such as MLPs [100, 103, 106], RBFNs [89, 97], neuro-fuzzy networks [101, 102], wavelet-based ANNs [98], and sigma–pi neural networks [99].

As ANN design in this control approach is highly dependent on the complementary conventional controller(s) and the dynamics of the system, there is no routine for control system design, unlike previously introduced neuro control systems. Roughly speaking, two different general models are introduced in this paper which match most of control problems solved through control systems with ANN compensators. The first model [89, 103] is

$$\text{Model I}: \quad x^{(n)} = f(\mathbf{x}) + b(\mathbf{x})u + f_B(\mathbf{x}, u), \tag{11}$$

where $\mathbf{x}$, u, and n are the state vector of the system, system order and control input respectively, and index B stands for "bad". That is, $f_B(\mathbf{x}, u)$ contains undesirable or uncertain parts of the system dynamics which will be compensated by the compensator control command of

$$u_c = -\frac{\hat{f}_B(\mathbf{x}, (u_c + u_o))}{b(\mathbf{x})}, \tag{12}$$

where u_o is the resultant of all other control commands except for the compensator command, and $\hat{f}_B(.)$ is a neural network which approximates $f_B(.)$. If $f_B(\mathbf{x}, u)$ is compensated/cancelled, (11) will be transformed to a companion form equation. However, there is no guarantee that (12) always results in a solution. If $f_B(.)$ is a function of $\mathbf{x}$ solely, this problem will be easier to solve [89]. With quite probable difficulties in solving (12), it is not surprising that the aforementioned ANN compensation approach is not popular or applicable for systems with models like (11).

The second model is

$$\text{(Model II)}: u = f_G(\mathbf{x}) + f_B(\mathbf{x}), \tag{13}$$

where index G stands for "good". That is, providing that only $f_G(\mathbf{x})$ exists on the right-hand side of (13), the equation would suit one of the well-known conventional control methods. If a neural network is employed to approximate $f_B(.)$, then the compensator control command will be $u_c = \hat{f}_B(\mathbf{x})$, and, if $u = u_c + u_o$, we will have

$$\begin{cases} u_o = f_G(\mathbf{x}) \\ u_c = \hat{f}_B(\mathbf{x}). \end{cases} \tag{14}$$

As shown in (14), the neural network is used as a straightforward compensator control law. The systems with dynamics that match Model II are very good cases for ANN compensation control [95–102, 105, 106]. These systems are often mechanical systems whose behavior is explained through Newton's or Euler's laws. The control input is force or torque which appears alone (not multiplied by system parameters or states or as a function of them) in the corresponding model equations. In these problems, if linear or angular displacement is addressed, the control problem will be second order [89, 98, 100, 10, 102–104], and, if linear or angular velocity is controlled, the problem will be first order [95, 97, 105].

III. SUMMARY

In this paper, the progress of neuro controllers since their appearance in more than 20 years ago was reviewed. The main types of neuro controllers were briefly introduced, and it has been shown that the outstanding capability of neural networks in function/system approximation was the motivation behind their application in control. Two main points can be mentioned to summarize the chronological review of neuro controllers.

First, as a general trend, the initial neuro controllers (ANN inverse dynamics controllers) were used in conjunction with other controllers (mainly conventional ones). The next generation of neuro controllers gradually lost this feature and started to play the role of a sole control law. These controllers were extended versions of well-known nonlinear controllers. However, neuro controllers of the most recent generation always accompany other controllers. In these neuro controllers, ANNs are used to compensate the effect of uncertain or undesirable parts of the system dynamics. It seems that neural network controllers have had a journey from auxiliary controllers to sole controllers and back again to auxiliary controllers. However, in their return as auxillary controllers, newly designed hybrid ANN controllers frequently offer stability and adaptiveness to the control system which was rare in initial ANN control systems.

Second, in terms of application, some neuro controllers are more suitable for specific applications. Neural networks are typically trained using input–output data only, so it may seem that ANN control approaches can be applied to all systems, provided that enough training data are available. However, this is not correct. For instance, neuro-predictive controllers suit process plants exceptionally well, and ANN compensation control systems are particularly appropriate for mechanical systems; however, these methods have not been specially designed for the aforementioned purposes. This point has not been mentioned explicitly in the literature. The research community may need to define some characteristics of systems to guide designers in choosing appropriate neuro controllers; these characteristics may be an area of novelty in future investigations.

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Morteza Mohammadzaheri was born in Tuyserkan, Iran, in 1979. He received his B.Eng., M.Eng., and PhD degrees in mechanical engineering from K. N. Toosi University of Technology, Iran (2002), University of Tehran, Iran, (2005), and University of Adelaide, Australia (2011), respectively. He has published/presented more than 40 technical articles in the area of intelligent control and system identification. He is currently with Mechanical Engineering School of the University of Adelaide as a postdoctoral fellow.

Lei Chen received his B.Eng. and M.Sc. degrees in electrical and electronic engineering from Huazhong University of Science and Technology, China, and the Ph.D. degree in Mechatronics from Flinders University, Australia. He is currently Senior Lecturer in the School of Mechanical Engineering at University of Adelaide, Australia. His research interests include nonlinear control systems, intelligent control systems, and robotics.

Steven Grainger is a lecturer in Control and Embedded Systems at University of Adelaide's School of Mechanical Engineering, Australia. He obtained his Ph.D. on the control of electric drives from Glasgow Caledonian University, Scotland and holds undergraduate degrees in computing and electronic engineering. Current research interests include nanopositioning systems and autonomous vehicles. He is a Member of the IEE, a Chartered Engineer, and Member of the IET.