FUZZY NEURAL NETWORK BASED ESTIMATION OF POWER ELECTRONIC WAVEFORMS

M. Godoy Simões

Escola Politécnica da Universidade de São Paulo
Departamento de Engenharia Mecânica - Mecatrônica
Av. Prof. Mello Moraes, 2231
05508-900 São Paulo / S. Paulo

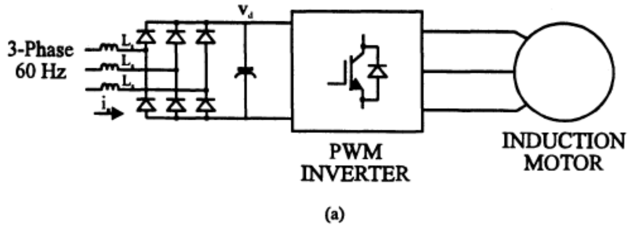
Bimal K. Bose

Department of Electrical Engineering
The University of Tennessee
Knoxville, TN 37996
USA

Abstract — Neural networks and fuzzy logic are showing a good promise for application in power electronics and motion control systems. They have been applied in feedback control of converter and drives, estimation of waveforms and signals, and performance enhancement control. Fuzzy logic and neural networks are appropriate where the plant model is ill-defined, non-linear and has parameter variation problems. Besides, such technologies have distinct advantages when compared to a digital signal processor (DSP) based implementation, like fast response, robustness and immunity to harmonic noise. They are model-free estimators since they "learn from experience" with numerical and linguistic data. The present work uses a fuzzy-neural-network (FNN) where a neural network topology emulates fuzzy reasoning. Such neural network permits automatic identification of fuzzy rules and tunes the membership functions. The distorted line current waves in a three-phase diode rectifier feeding an inverter-machine load have been taken into consideration and a FNN has been applied to estimate rms current and fundamental rms current. The results of the estimation have been compared with the actual values, and indicate good accuracy. Although the paper considers a relatively simple estimation problem, the fuzzy-neural-network technique can be extended to more complex waveforms and in the estimation of signals of scalar or vector-control drives.

I. INTRODUCTION

Power electronic converters characteristically generate complex voltage and current waves. For control and monitoring purposes, it is often necessary to process these waves and generate the variables, such as total rms value, fundamental rms value, active power, reactive power, displacement factor, distortion factor and power factor. Sometimes, it becomes necessary to estimate the above from waveforms recorded by oscilloscope or chart recorder. Electronic instrumentation (hardware and software) techniques are extensively used for such measurements. For example, on-line fast fourier transform (FFT) analysis of a distorted wave can give valuable information for such measurements. It is also possible to make estimation from the basic mathematical model of a system, if such a model can be obtained. This approach is difficult because the model equations tend to be nonlinear and complex, and in addition, there may be parameter variation problems. One difficulty in all the above estimation methods is that the response tends to be slow because of the processing involved, therefore a fuzzy neural network solution would be a faster solution when implemented in a parallel hardware circuit. In addition, the conventional numerical method usually gets the estimated parameters from one or multi-dimensional look-up tables in microcomputer memory. However, for improvement of accuracy, the size of the look-up table should be large or



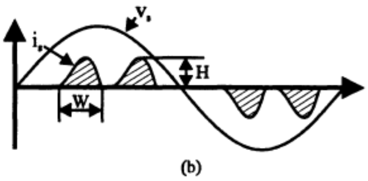


Fig. 1 (a) Three-phase diode rectifier supply for inverter-fed induction motor drive, (b) Input phase voltage and current waves.

interpolation calculation would be required. In this paper, a fuzzy neural network has been systematically explored for the estimation of a distorted line current waveform of a three-phase diode rectifier feeding an inverter-machine load as shown in Fig. 1. The input signals for estimation are wave pulse (W) and peak value (H) as indicated. The estimation algorithm can be extended for other waveforms and various signals estimations of drives as well. The estimation for rectifier input current, shown in Fig. 1, is somewhat involved because there are no simple closed form mathematical expressions available to guide the formulation of the estimation algorithm. The magnitude of the variables W and H of a waveform are determined by the dc link voltage, supply peak voltage and the Thèvenin inductance of the line. The supply voltage imbalance is neglected in our study. Assuming the filter capacitance very large, i.e., neglecting the ripple voltage in the dc link, the dc link voltage is constant and the pulse current increases from time t_0 to t_1 in accordance to Fig. 2.

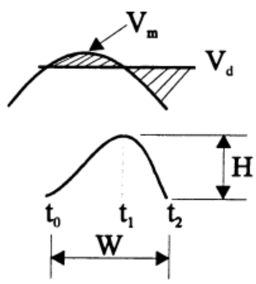


Fig. 2 Voltage-time across line inductance

When the voltage across the line inductance reverses, the pulse current decreases from the peak value (H) to zero from time t_1 to t_2. Since the integral of the voltage across the inductance is zero, the following relationship given by (1) holds. After some manipulations, the equations for height (H) and width (W) result, as given by (2) and (3). The expressions in (4) and (5) are used for displacement power factor (DPF) and for power factor (PF).

$$\int_{t_0}^{t_1} V_L\,dt = \int_{t_0}^{t_1} \left(V_m \sin\omega_e t - V_d\right)dt \tag{1}$$

$$H = \frac{2}{L_s\omega_e}\left[V_m\cos\left(\omega_e \sin^{-1}\left(\frac{V_d}{V_m}\right)\right) - V_d\left(\frac{\pi}{2} - \sin^{-1}\left(\frac{V_d}{V_m}\right)\right)\right] \tag{2}$$

$$W = 2\cos^{-1}\left(\frac{V_d}{V_m}\right) + \Delta\theta \tag{3}$$

$$DPF \approx A - BW \tag{4}$$

$$PF = DPF\,\frac{I_f}{I_s} \tag{5}$$

where V_L = inductance voltage, V_d = dc link voltage, V_m = peak value of supply phase voltage, L_s = per phase source inductance , ω_e = supply frequency, $\Delta\theta$ is the angular interval of current such that the voltage-time integral across the inductance reduces the current to zero, I_s is the total rms current and I_f is the fundamental rms current.

Obviously, I_s and I_f are function of W and H, and their values increase as W or H increases. However, the DPF is insensitive to H but has some inverse relation with W, as shown. The above equations indicate that the estimation is appropriate for I_s, I_f, and DPF, while PF can be directly obtained from (5). In order to create numerical input/output data for training the fuzzy neural network (as explained latter), the system shown in Fig. 1 was simulated, with large dc link filter capacitor, and using the volts/Hz control method. Then, I_s and I_f functional relation with W and H were generated, with help of numerical calculation of RMS value of current (I_s) and FFT analysis for fundamental RMS value of current (I_f). The parameters V_d, V_m and L_s were manipulated to generate such results.

II. FUZZY LOGIC AND NEURAL NETWORK CONTROL AND ESTIMATION

The fuzzy logic modeling and estimation techniques have been developed based on Zadeh's theory [1] and on Sugeno's approach [2], and were considered for applications, such as chemical fermentation process [3], automated car parking [4], and blast furnace smelting process. The fuzzy approach is particularly appropriate where the mathematical model of the plant does not exist or is ill-defined, the system is nonlinear, complex and multi-dimensional and has parameter variation problem, or the system generates complex output where simple and straightforward estimation is not possible.

A fuzzy logic system has four blocks as shown in Fig. 3. The input variables are evaluated with the correspondent membership values for each input fuzzy set. The decision-making-logic together with the knowledge base determine the outputs of each fuzzy IF-

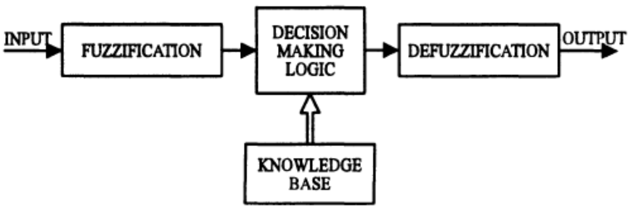


Fig. 3 Fuzzy system architecture

-THEN rules, which are combined and converted to crisp values with the defuzzification block.

Of course, the fuzzy estimation is based on heuristic or trial-and-error approach, and therefore, the algorithm development may be time-consuming, and often the accuracy may be limited. Recently, fuzzy logic tools are indicating promise for power electronics control and estimation [5]. These have been applied in the control of converters and drives [6] [7], modeling power system's load [8]; fuzzy logic has been considered also for estimation in power electronics [9] and for performance enhancement for ac machines drives[10] [11]. Neural networks have been applied for control and signal processing in power electronics [12] [13]. The estimation of feedback signals in vector-controlled drive systems is presented in [14].

A fuzzy neural network (FNN) applies neural network principles to fuzzy reasoning. It emulates a fuzzy logic controller in the neural network topology. The FNN has a structure in a such way that it directly maps weights of different layers into the required membership functions and fuzzy rules, relieving the designer of the task of assigning and generating those membership functions and fuzzy rules.

III. FUZZY NEURAL NETWORK PRINCIPLES

The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning, by attaching linguistic attributes into a rule base framework. While fuzzy theory enables such a powerful inference mechanism, its main limitations are the trial-and-error procedure for design and analysis, the lack of completeness of the rule base and the difficulty in a definite criteria for selection of the shape of membership functions, their degree of overlapping and the levels of quantization. The computation with neural networks offer exciting advantages such as learning, adaptation, fault-tolerance, and generalization. In view of this versatility of neural networks, they are potential building blocks for a variety of machine learning mechanisms. Table 1 presents a brief comparison between fuzzy systems and neural networks.

Table 1 Comparison of Fuzzy Systems and Neural Networks

Features	*Fuzzy Systems*	*Neural Networks*
Knowledge acquisition	Human experts	Numerical data
Training method	Interaction / induction	Algorithms / adjusting weights
Type of uncertainty	Qualitative / quantitative	Quantitative
Reasoning	Heuristic search	Parallel computations
Language interface	Explicit	Not evident
Fault tolerance	Not evident	Very high
Robustness	Very high	Very high

The term "fuzzy neural network" (FNN) refers to the incorporation of fuzziness into a neural network system. One way to introduce fuzziness in a neural network is through the fuzzification of the data input. As an example, suppose that a neural network receives a temperature information ranging from 45 ^{o}F to 85 ^{o}F. This input signal is analog, which after normalization and scaling ranges from 0 to 1, as the temperature varies from 45 ^{o}F to 85 ^{o}F. The same temperature information could be divided into five levels, and the neural network would have five binary inputs, that would indicate in which region is the temperature. Finally, those five crisp inputs could have membership functions that define the fuzzy degree of each level in the temperature, and the network would have five analog inputs. Another way to incorporate fuzziness into the neural network is by arranging the neural network connections or the transfer functions at each neuron to perform some sort of fuzzy operation on the numerical information arriving at each node. There are several fuzzy-neural-networks approaches, but the one proposed by Horikawa [15] seems to be interesting because it emulates fuzzy reasoning in a neural network topology. After training by backpropagation algorithm, the network weights can be interpreted, and a rule base and membership functions of a regular fuzzy algorithm can be constructed. Since in complex systems the creation of rules and membership functions are a laborious process, FNN takes over the work of developing a fuzzy algorithm, by learning the system behavior and generating fuzzy rules and membership functions automatically.

The fuzzy neural network structure can be either on rule based topology, where the IF-THEN rules relate fuzzy inputs to fuzzy outputs, or on fuzzy relational estimation (Sugeno's method) where the IF part of the rules (premises) are fuzzy logic operations and the THEN part (consequents) are linear functions of the input variables. Fig. 4 shows the principle of fuzzy rule based estimation and fuzzy relational estimation techniques.

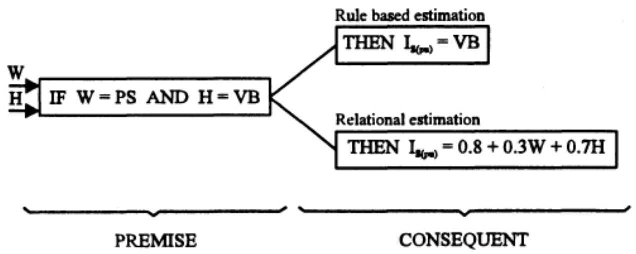


Fig. 4 Principle of rule based and relational fuzzy estimation

Since the fuzzy relational approach is a hybrid method which combines fuzzy reasoning with mathematical relationships, the size of the rule table is more compact than a regular rule based method. However, the fuzzy relational approach can only be used if input/output data is available for identification, and multi-regression of such data is performed.

In the FNN topology the membership functions are Gaussian-type, constructed by sigmoid functions. The neural structure for such a membership function is shown in Fig. 5, where the weight ω_c controls the spacing, whereas the weight ω_g controls the slope of the membership functions.

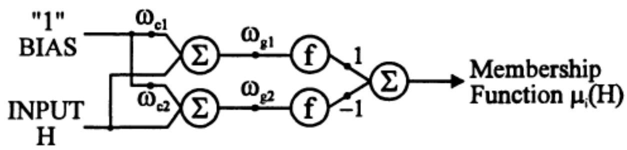


Fig. 5 Neural structure for membership function of a FNN

Fig. 6 shows the neural structure for arrangement of fuzzy premises. In such a figure there are three fuzzy sets for the variable W (Small, Medium, and Big) and three fuzzy sets for the variable H (Small, Medium, and Big). It is good to emphasize that although there are four nodes in the neural network input layer, they represent three membership functions because the fuzzy sets Small and Big are considered to have shoulders to the sides. The node indicated with the letter π is a neuron that makes the multiplication of the incoming signals. Since multiplication is a *t*-norm, it can also perform the fuzzy *and* operation. Therefore, the results for the *and* operation of the nine possible combinations for each input fuzzy set are given in the correspondent outputs of

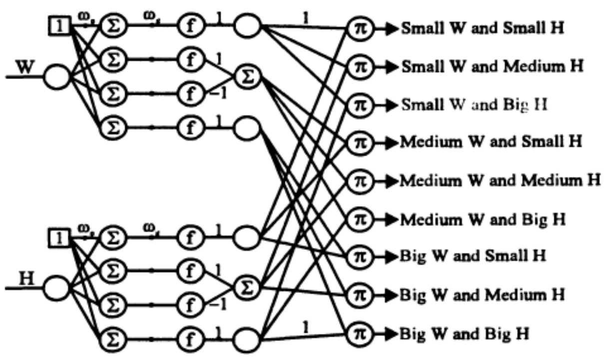


Fig. 6 Neural structure for premises of a FNN

Fig. 6. Each output is the truth value (confidence in the rule being true) for each *and* premise.

The rule based fuzzy neural structure is shown in Fig. 7. It is based on the height defuzzification method, since the weights ω_f are the fuzzy singletons for the consequents and, the output is the summation over each rule truth value multiplied by the correspondent singleton ω_f.

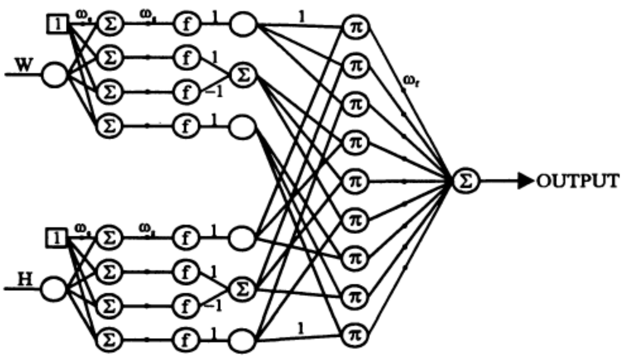


Fig. 7 Rule based fuzzy neural network

To implement the relational based fuzzy neural network it is necessary to use the neural structure for relational consequents given in Fig. 8, where the linear equation parameters are given by the weights ω_{ao}, ω_{a1}, and ω_{a2}.

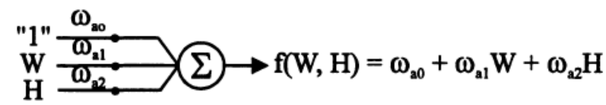


Fig. 8 Neural structure for relational consequents.

IV. FUZZY NEURAL NETWORK ESTIMATION FOR RECTIFIER LINE CURRENT

Fig. 9 shows the full-fledged relational based fuzzy neural network used for estimation of total rms value (I_s) and fundamental rms value (I_f) with width (W) and height (H) as inputs. The top of the figure is the implementation of the premises with three fuzzy sets and the bottom shows the linear relational structures for I_s and I_f estimation. There are nine rules, each one fires a linear relation of the input variables W and H. The neural network of Fig. 9 was trained with the help of NeuralWorks Professional II/Plus [16] by back-propagation training algorithm. After 12,000 training steps the index of performance, i.e., the total network rms error in per-unit was 0.05.

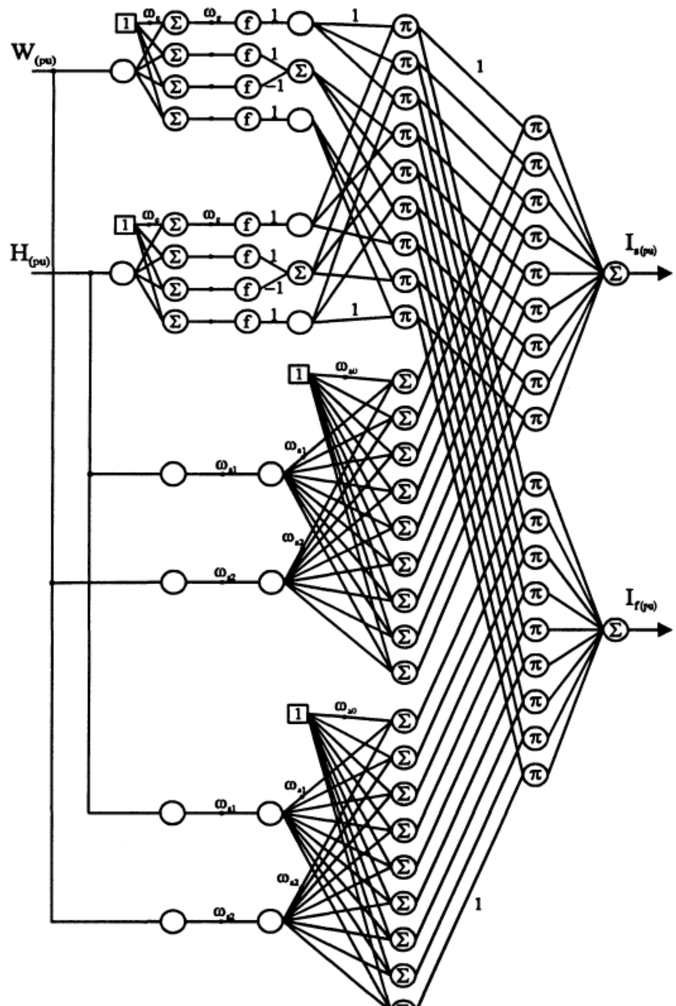


Fig. 9 Topology of fuzzy neural network used for estimation.

The resulted input membership functions for W and H are shown in Fig. 10. The estimated values are compared with the actual values in Fig. 11, where the increasing machine load of Fig. 1 provided currents in successive experiments with increasing W and H values. The horizontal variable in Fig. 11 is an experimental sequence, where for each experiment number the machine load determined how much current was flowing in the front-end rectifier. The fuzzy neural network is very powerful because it combines the numerical processing features of a neural network with linguistic descriptions of fuzzy logic. Such fuzzy model can advance the design of a fuzzy controller as a mathematical model is helpful in the design of a conventional controller.

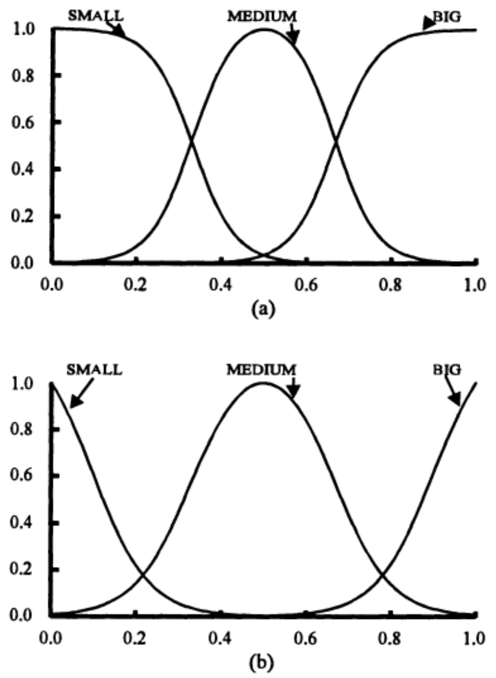


Fig. 10 Membership functions learned by FNN (a) Pulse width (W), (b) Peak value (H).

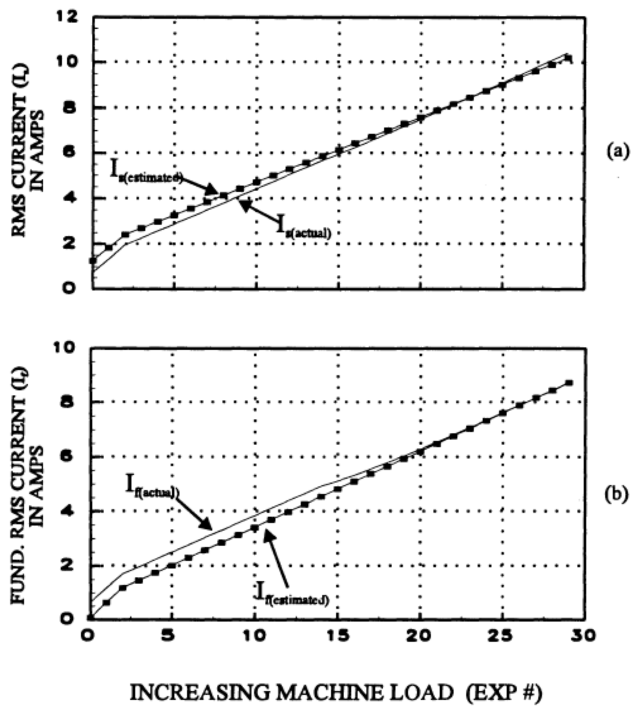


Fig. 11 Fuzzy estimation accuracy for rectifier input current wave (a) RMS current (I_S), (b) Fundamental RMS current (I_f).

V. CONCLUSION

This paper presented a fuzzy-neural-network (FNN) where a neural network topology emulated fuzzy reasoning. Such neural network permitted automatic identification of fuzzy rules and tuning of membership functions. The distorted line current waves in a three-phase diode rectifier feeding an inverter-machine load have been taken into consideration and a FNN has been applied to estimate rms current and fundamental rms current. The results of the estimation have been compared with the actual values, and indicated good accuracy. Such technique can be extended to more complex waveforms and in the estimation of signals of scalar or vector-control drives.

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BIOGRAPHIC DATA

Marcelo Godoy Simões, was born in São Paulo, Brazil, on February 03, 1963. He received his Bachelor of Science degree in Electrical Engineering from "Escola Politécnica da Universidade de São Paulo" on December 1985. Upon graduation he worked for "Fundação para o Desenvolvimento Tecnológico da Engenharia - FDTE," a research institution that belongs to The University of São Paulo, for three years. He also ran a small company for development of switching power supplies. He has been a professor at the University of São Paulo (Brazil) since 1989, and obtained his Master of Science degree in July, 1990, at the University of São Paulo. He was awarded a Brazilian scholarship to pursue his doctoral degree at The University of Tennessee, Knoxville, where he actively worked in the research of fuzzy logic and neural networks applications to power electronics, drives and machines control. During his doctoral studies at The University of Tennessee, he published five papers in IEEE conferences, where two of them were accepted for publication in IEEE Transactions. He has also two patents pending for the new strategies presented in his Ph.D. dissertation for control of drives and performance enhancement of wind generation systems. He received the Doctor of Philosophy degree in December, 1995, and now he is working as a professor at The University of São Paulo (Brazil), doing research and development of systems on the application of artificial intelligence in power electronics and drives.

Bimal K. Bose, (Fellow, IEEE) received the B.E. degree from Bengal Engineering College, India, the M.S. degree from the University of Wisconsin, Madison, and the Ph.D. degree from Calcutta University, India, in 1956, 1960, and 1966, respectively. Early in his career, he served as a faculty member in Calcutta University (Bengal Engineering College) for 11 years. In 1971, he joined Rensselaer Polytechnic Institute, Troy, NY, as Associate Professor of Electrical Engineering, and in 1976, he came to General Electric Corporate Research and Development, Schenectady, NY, as Electrical Engineer and served there for 11 years. He currently holds the Condra Chair of Excellence in Power Electronics at The University of Tennessee, Knoxville, where he has been responsible for organizing power electronics teaching and research programs. He is also the Distinguished Scientist (formerly, Chief Scientist) of EPRI-Power Electronics Applications Center, Knoxville, Honorary Professor of Sanghai University of Technology, China, and Senior Advisor of Beijing Power Electronics Research and Development Center, China. His research interests are power converters, ac drives, microcomputer control, and applications of expert systems, fuzzy logic, and neural network in power electronics. He has published more than 100 papers in international conferences and authored five books in power electronics and ac drives.