

Missouri University of Science and Technology Scholars' Mine

Electrical and Computer Engineering Faculty Research & Creative Works

Electrical and Computer Engineering

01 Jan 2005

An Adaptive Mamdani Fuzzy Logic Based Controller for a Static Compensator in a Multimachine Power System

Salman Mohagheghi

Ganesh K. Venayagamoorthy Missouri University of Science and Technology

Ronald G. Harley

Follow this and additional works at: https://scholarsmine.mst.edu/ele_comeng_facwork

🔮 Part of the Electrical and Computer Engineering Commons

Recommended Citation

S. Mohagheghi et al., "An Adaptive Mamdani Fuzzy Logic Based Controller for a Static Compensator in a Multimachine Power System," *Proceedings of the 13th International Conference on, Intelligent Systems Application to Power Systems, 2005,* Institute of Electrical and Electronics Engineers (IEEE), Jan 2005. The definitive version is available at https://doi.org/10.1109/ISAP.2005.1599268

This Article - Conference proceedings is brought to you for free and open access by Scholars' Mine. It has been accepted for inclusion in Electrical and Computer Engineering Faculty Research & Creative Works by an authorized administrator of Scholars' Mine. This work is protected by U. S. Copyright Law. Unauthorized use including reproduction for redistribution requires the permission of the copyright holder. For more information, please contact scholarsmine@mst.edu.

An Adaptive Mamdani Fuzzy Logic Based Controller for a Static Compensator in a Multimachine Power System

S. Mohagheghi, Student Member, IEEE, G.K. Venayagamoorthy, Senior Member, IEEE, R.G. Harley, Fellow, IEEE

Abstract-- An adaptive Mamdani based fuzzy logic controller has been designed for controlling a Static Compensator (STATCOM) in a multimachine power system. Such a controller does not need any prior knowledge of the plant to be controlled and can efficiently control a STATCOM during different disturbances in the network. A model free approach using the controller output error is applied for training purposes that adaptively changes the controller output parameters based on a gradient descent method. Moreover, shrinking span membership functions are used for a more stable and accurate control performance. Simulation results show that the proposed controller outperforms the conventional PI controller during dynamic and transient disturbances.

Index Terms—Adaptive Fuzzy Logic Controller, Mamdani Controller, STATCOM, Multimachine Power System,

I. INTRODUCTION

S TATIC Compensators (STATCOM) are power electronics based shunt Flexible AC Transmission Systems (FACTS) devices which can control the line voltage at the point of connection to the electric power network. Regulating reactive power injected by this device into the network, and the active power absorbed from the network, provide control over the line and over the DC bus voltage inside the device respectively [1].

A power system containing generators and FACTS devices is a highly nonlinear system. It is also a non-stationary system since the power network configuration changes continuously as lines and loads are switched on and off. In recent years most of the papers have suggested methods for designing STATCOM PI controllers using linear control techniques, in which the system equations are linearized at a specific operating point and the PI controllers are tuned at that point based on the linearized model, in order to have the best possible performance [2]-[4].

The drawback of such PI controllers is that their parameters are mostly tuned based on a trial and error approach. Moreover, their performance degrades as the system operating conditions change. Nonlinear adaptive controllers on the other hand can give good control capability over a wide range of operating conditions, but they have a more sophisticated structure and are more difficult to implement compared to linear controllers. In addition, they need a mathematical model of the system to be controlled [5]-[7].

Fuzzy logic controllers offer solutions to this problem. They are nonlinear controllers that are usually independent of a mathematical model for the plant to be controlled. Moreover, they can provide efficient control over a wide range of system operating conditions. Conventional fuzzy logic controllers have been widely applied in power systems [8]-[11]. However, the main drawback of the conventional fuzzy controllers is that their control parameters are fixed and are not adaptively updated to adjust to the system operating conditions changes, sensors/equipment aging and suchlike.

This paper designs an adaptive Mamdani based fuzzy logic controller for a STATCOM connected to a multimachine power system, using Shrinking Span Membership Functions (SSMF) [12] and backpropagation (steepest descent) training method [13]. Simulation results are provided to compare the performance of the proposed fuzzy controller with that of the conventional PI controller.

II. STATCOM IN A MULTIMACHINE POWER SYSTEM

Figure 1 shows a STATCOM connected to a multimachine power system. The system is a 10 bus, 500 kV, 5000 MVA power network and is simulated in the PSCAD/EMTDC environment. The generators are modeled together with their automatic voltage regulator (AVR), exciter, governor and turbine dynamics taken into account. Detailed parameters of the network can be found in [14].

Manuscript received April 1, 2005. Financial support by the National Science Foundation (NSF), USA under grants ECS #0400657 and ECS #0348221, and from the Duke Power Company, Charlotte, North Carolina, USA, for this research is greatly acknowledged.

S. Mohagheghi is with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332-0250 USA (e-mail: salman@ece.gatech.edu).

G.K. Venayagamoorthy is with the Real-Time Power and Intelligent Systems Laboratory, Department of Electrical and Computer Engineering, University of Missouri-Rolla, MO 65409-0249 USA (email: gkumar@ieee.org).

R.G. Harley is with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332-0250 USA (e-mail: rharley@ece.gatech.edu), and a Professor Emeritus at the University of KwaZulu-Natal, South Africa.

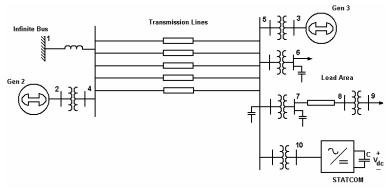


Fig. 1. STATCOM in a multimachine power system.

The STATCOM is first controlled using a conventional PI controller as described in [2]. The d-axis and q-axis voltage deviations are derived from the difference between the actual and reference values of the power network line voltage ΔV and the DC bus voltage (inside the STATCOM) ΔV_{dc} respectively, and are then passed through two PI controllers to generate the control outputs Δe_d and Δe_q (Fig. 2). Those values in turn determine the modulation index and inverter output phase shift applied to the pulse width modulation (PWM) module.

$$m_{a} = \frac{\sqrt{\Delta e_{d}^{2} + \Delta e_{q}^{2}}}{V_{dc}},$$

$$\alpha = \cos^{-1}(\frac{\Delta e_{d}}{\sqrt{\Delta e_{d}^{2} + \Delta e_{q}^{2}}}).$$
(1)

Controlling the voltage V at the point of connection to the network is the main objective of the STATCOM considered in this paper.

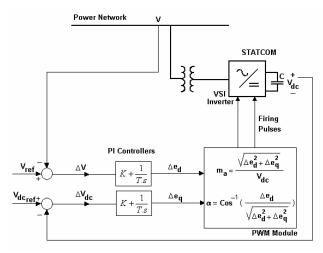


Fig. 2. STATCOM internal control structure.

Parameters of the STATCOM PI controllers are fine tuned at one specific operating point. Step changes are applied to the reference values of the STATCOM and the parameters of the PI controllers are selected in a way that they provide satisfactory and stable performance based on their time domain responses.

III. FUZZY LOGIC INFERENCE SYSTEMS

A. Fuzzy Logic

Mathematical models/equations are the basis of the analytical approaches traditionally used for modeling and control of power networks. However in a non-stationary and highly nonlinear system such as a power network, a number of simplifying assumptions need to be made before deriving a mathematical model, such as linearizing a nonlinear system, or approximating a higher order system by a low order model.

Fuzzy logic is a tool that can compensate for the above problems, since it is a technique that can deal with imprecise, vague or fuzzy information [15]. Fuzzy logic controllers consist of a set of linguistic control rules based on fuzzy implications and the rule of inference. By providing an algorithm, they convert the linguistic control strategy based on expert knowledge into an automatic control strategy [16].

In contrast to the mathematical models or other expert systems, fuzzy logic controllers allow the representation of imprecise human knowledge in a logical way, with approximate terms and values, rather than forcing the use of precise statements and exact values; thus making them more robust, more compact and simpler [17]. Also, as opposed to indirect adaptive neuro-controllers, in most of the cases fuzzy logic controllers do not need a model of the plant to be controlled.

Fuzzy logic systems provide a nonlinear mapping from a set of crisp inputs to a set of crisp outputs, using both intuition and mathematics. In order to do that, each fuzzy logic system is associated with a set of *if-then* rules, which heuristically define the dynamics of the plant to be controlled. Different fuzzification and defuzzification techniques are used in the literature in order to map the sets of crisp inputs onto fuzzy sets and vice versa. Gaussian fuzzifiers and the centroid defuzzifier are used in this paper as the mapping techniques [16].

B. Shrinking Span Membership Functions

Due to simplicity, most researchers tend to design the input/output fuzzy membership sets using the equal-span

mathematical functions, such as triangular or Gaussian functions. However, these functions do not necessarily provide the optimum solution for all problems. Instead a prior knowledge of the plant to be controlled, and its dynamics, might lead to different standard or non-standard fuzzy membership functions with various physical shapes in order to design a more efficient fuzzy logic controller [18]. Moreover, when the control response is closer to the system set point, it can be intuitively seen that the fuzzy membership functions for that specific linguistic term should have narrower spans, in order to be able to provide smoother results with less oscillations.

Shrinking span membership functions (SSMFs) are used in this study in order to compensate for the above problems [13]. This method creates membership functions with shrinking spans (Fig. 3), in a way that the controller generates large and fast control actions when the system output is far from the set point and makes moderate and slow changes when it is near the set point. SSMFs were used in the authors' earlier work in [19] for designing a Takagi-Sugeno fuzzy logic controller and the results proved to be more efficient than the conventional membership functions.

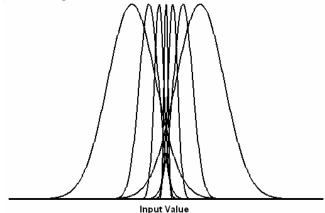


Fig. 3. Shrinking span membership functions.

The details of designing a SSMF fuzzy controller in a general case (multiple input multiple output systems) is rigorously described in [13]. Nevertheless, it is briefly revisited here for this specific problem (single-input-single-output system).

Different Gaussian functions for the input variables can be expressed as in (2):

$$F_{i}^{j} = e^{-(\frac{u_{i}-\mu_{i}}{\sigma_{i}})^{2}},$$

for $j = -m,...,m$ (2)

where *m* is the index for the input set, resulting in 2m+1 linguistic terms for each input variable u_i and output *y*. In this work, the parameter *m* is selected to be 3, therefore 7 shrinking span membership functions are assigned to the input and output variables. These membership functions are associated with the terms *Negative Big*, *Negative Medium*, *Negative Small*, *Zero*, *Positive Small*, *Positive Medium* and

Positive Big for each variable.

The centers and the dispersions of the membership functions are selected as:

$$\mu^{j}{}_{i} = \frac{\iota}{m} \times s^{m-|\iota|},$$

$$\sigma^{j}{}_{i} = k \times \mu^{j}_{i}.$$
(3)

where $s \in [0,1]$ is the shrinking factor for the input variable u_i . A typical shrinking span of 0.7 is selected for this study.

Using the Mamdani inference mechanism, the output of the controller can be written as follows:

$$u(t) = \frac{\sum_{j=-m}^{m} w_j \cdot \beta_j}{\sum_{j=-m}^{m} w_j},$$
(4)

where w_j and β_j are the rule firing strength and the consequent parameters respectively.

IV. STATCOM ADAPTIVE FUZZY CONTROLLER

Designing an efficient fuzzy controller requires heurisitc information of the plant *a priori*. This information need not be in the form of a mathematical model, but it should reflect the nature of the system response to various control signals. More accurate information results in a better and more robust performance of the fuzzy controller. However, even information available on the behavior of the plant does not necessarily lead to optimal fuzzy controller parameters; therefore, the parameters of the fuzzy controller should be adapted in order to ensure an optimal performance [20].

In an adaptive fuzzy logic controller, the membership functions and linear mappings can be a function of time. In order to do that an error function is defined which serves as a performance measure, and the time varying parameters of the fuzzy controllers are modified based on this metric. Several training techniques have been proposed in the literature in order to update the fuzzy controller parameters [13],[18]. This paper applies an adaptive fuzzy scheme based on the controller output error [21]. This method is selected since it is efficient, easy to implement and does not need the plant output error to be backpropagated through a plant model.

A. Fuzzy Controller Structure

The fuzzy controller designed in this study, replaces the line voltage PI controller of the STATCOM. The second PI controller in Fig. 2 (DC link voltage) is not replaced by a fuzzy logic controller. The PI controller is able to maintain the capacitor voltage within defined limits and unlike the power network, the STATCOM topology does not change.

The fuzzy controller has two inputs, the line voltage error $\Delta V(t)$ and the change in the error $\Delta E(t) = \Delta V(t) - \Delta V(t-1)$. Providing the latter helps the controller to respond faster to the disturbances in the system. A time step of 100 µs is selected for calculating the change in error, which is large enough to ensure that all the computations can be carried out in one simulation cycle. Figure 4 shows the schematic diagram of the proposed fuzzy controller.

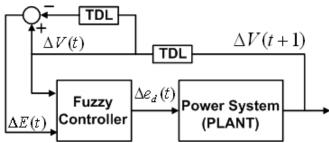


Fig. 4. Fuzzy logic controller structure for line voltage deviation control.

B. Rule Base

Table I shows the rule base which is implemented for the fuzzy controller. The appropriate fuzzy output variables for different combinations of the fuzzy input variables are heuristically selected based on the overall performance of the plant and the corresponding results proved efficient. This heuristic approach can be applied in this problem due to the rather straightforward control dynamics of the STATCOM. However, for more complicated case, e.g., multi-input multi-output control problems, systematic approaches based on artificial neural networks exist in the literature that enable the designer to use competitive learning schemes for deriving appropriate rule base [22],[23].

Table 1. Fuzzy controller rule base.							
ΔV ΔE	NB	NM	NS	Z	PS	РМ	РВ
NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NB	NM	NS	NS	Z
NS	NB	NB	NM	NS	NS	Z	Z
Z	NB	NM	NS	Z	PS	PM	PB
PS	Z	Z	PS	PS	PM	PB	PB
PM	Z	PS	PS	PM	PB	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

Table I. Euzzy controller rule base

C. Controller Output Error Method

This method for training a fuzzy controller was introduced by Andersen *et al* in [21]. The suggested method uses the controller output error in order to modify the parameters of the membership functions as well as the consequent parameters β_j . In this work, the former is considered to be fixed and only the β_j parameters are adaptively modified. For the details of the method along with mathematical proof, the reader is referred to [21]. Nevertheless, the equations for this special case will be briefly explained here.

At any time step *t* the controller generates a control signal Δe_d that drives the plant output from $\Delta V(t)$ to $\Delta V(t+1)$. The fuzzy controller is now tested to see if it generates the exact

same control output if asked to drive the system through the same transition, i.e. with $\Delta V(t+1)$ as the new reference for the line voltage error. Clearly the controller will produce a control signal $\Delta \hat{e}_d(t)$ which is not exactly equal to $\Delta e_d(t)$. A cost function can now be formed as a result of the difference in the values of the control signals:

$$J(t) = \frac{1}{2} [\Delta e_d - \Delta \hat{e}_d]^2.$$
⁽⁵⁾

Gradient descent method is now used for updating the consequent parameters β_j in order to minimize the controller output error J(t):

$$\beta_j(t+1) = \beta_j(t) - \eta \cdot \frac{\partial J(t)}{\partial \beta_j(t)}.$$
(6)

where η is the learning rate parameter, which typically is a small positive number in the range of [0,1]. A learning rate of 0.01 is used in this study. The partial derivative of the cost function with respect to the β_j parameters can be further simplified as:

$$\frac{\partial J(t)}{\partial \beta_j(t)} = -\frac{w_j \cdot [\Delta e_d - \Delta \hat{e}_d]}{\sum_{j=-m}^m w_j}.$$
(7)

This training algorithm is performed online during the operation of the fuzzy controller.

V. SIMULATION RESULTS

Several tests have been conducted in order to evaluate the performance of the proposed controller.

A. Case Study 1

A 100 ms three phase short circuit is applied to the system in Fig. 1 at the middle of one of the transmission lines. The line is disconnected as a result of the fault and it is switched back on 50 ms after the fault is cleared. Simulation results with the different controllers appear in Fig. 5.

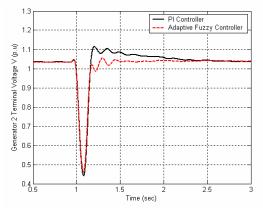


Fig. 5. Terminal voltage of Generator 2 during a 100 ms three phase short circuit at the middle of one of the transmission line.

The controllers are also compared in terms of the injected reactive power into the network (Fig. 6). It can be seen that the fuzzy controller is faster in responding to the fault as well as settling down to the post-fault value.

Figures 5 and 6 indicate that the fuzzy controller is more successful than the PI controller in damping the line voltage swings during the fault. This is because the PI controller has been fine tuned at only one operating point for small disturbances, while a severe fault like a three phase short circuit changes the operating condition of the network drastically.

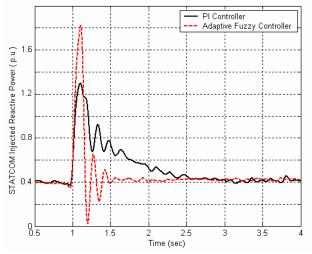


Fig. 6. Reactive power injected by the STATCOM during a *100* ms three phase short circuit at the middle of one of the transmission line.

B. Case Study 2

In another test, a 100 ms three phase short circuit occurs at the terminals of the generator 3. The generator is isolated and switched back into the network 50 ms after the fault is removed. Figure 7 shows the voltage at the point where the STATCOM is connected to the network.

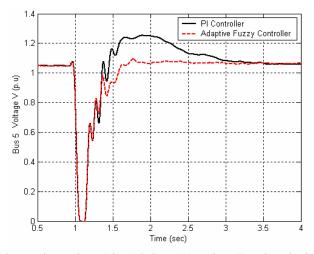


Fig. 7. Voltage at bus 5 (Fig. 1) during a *100* ms three phase short circuit at the terminals of generator 3.

The controllers can also be compared in terms of the control action generated by each one. The modulation index applied to the STATCOM inverter is a measure of control action and it is clear from Fig. 8 that with the PI controller in the system, the inverter modulation index goes towards over modulation for a considerable amount of time, which in turn causes unwanted harmonics. Moreover using the adaptive fuzzy controller would require a lower current rating for the inverter switches.

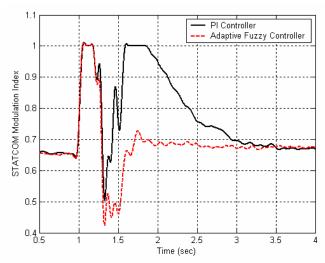


Fig. 8. STATCOM modulation index during a 100 ms three phase short circuit at the terminals of generator 3.

C. Case Study 3

The system is now exposed to two successive short circuit tests: a 150 ms three phase short circuit at the terminals of generator 3 at 1 sec, followed by a 100 ms three short circuit at the middle of one of the transmission lines at 2 sec. Figures 9 and 10 show some typical results, which again illustrate that the fuzzy controller requires less effort from the inverter while providing more damping and a better dynamic response than the PI controller.

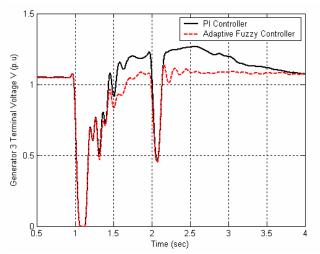
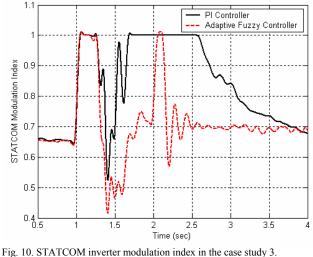


Fig. 9. Generator 3 terminal voltage in the case study 3.



VI. CONCLUSION

An adaptive Mamdani based fuzzy logic controller is developed in this paper for the control of a STATCOM in a multimachine power system. The proposed fuzzy controller utilizes shrinking span membership functions (SSMF), and the controller output error method is applied for training its consequent parameters.

SSMF fuzzy controllers can adapt to many processes and be more effective than the conventional fuzzy membership functions, especially when there is not enough information available on the dynamics and behavior of the plant to be controlled. These functions provide larger control effort when the system is far from the set-point and reduced control effort as it gets closer to the set-point, resulting in faster rise time and lower overshoot.

Controller output error method can serve as an efficient technique for adaptively modifying the controller parameters. While the proposed fuzzy controller proves to be more effective than the non-adaptive design with the same choice of membership functions, it is as easy to implement and does not require any mathematical models of the plant to be controlled, unlike most of the direct and indirect adaptive based fuzzy logic controllers.

Simulations are carried out and the performance of the proposed fuzzy controller is compared with that of the conventional PI controller for the line voltage deviations. These results show better and faster damping compared to that of the conventional PI controller. Moreover, this increased damping is provided with the less control effort, i.e. less reactive power injected by the STATCOM, which results in smaller inverter currents as well as less harmonics injected to the power system.

REFERENCES

 N.G. Hingorani and L. Gyugyi, Understanding FACTS, Concepts and Technology of Flexible AC Transmission Systems, IEEE, New York 1999, ISBN 0-7803-3455-8.

- [2] L. Dong, M.L. Crow, Z. Yang, C. Shen, L. Zhang and S. Atcitty, "A Reconfigurable FACTS System for University Laboratories", *IEEE Transactions on Power Systems*, Vol. 19, Issue 1, February 2004, pp 120 – 128.
- [3] D. Shen and P.W. Lehn, "Modeling, Analysis and Control of a Current Source Inverter-Based STSTCOM", *IEEE Transactions on Power Delivery*, Vol.17, No.1, January 2002, pp 248-253.
- [4] P. Rao, M.L. Crow and Z. Yang, "STATCOM Control for Power System Voltage Control Applications", *IEEE Transactions on Power Delivery*, Vol. 15, No. 4, October 2000, pp 1311-1317.
- [5] F. Liu et al, "The Nonlinear Internal Control of STATCOM: Theory and Application", *International Journal of Electrical Power & Energy Systems*, Vol. 25, Issue 6, 2003, pp. 421 – 430.
- [6] Q. Lu et al, "Nonlinear Disturbance Attenuation Control for STATCOM", IEEE Power Engineering Society Winter Meeting, Columbus, OH, USA, January 28-February 1, 2001, Vol. 3, pp 1323-1328.
- [7] Z. Yao et al, "Nonlinear Control for STATCOM Based on Differential Algebra", Proceedings of the 29th Annual IEEE Power Electronics Conference, May 17-22, 1998, Vol. 1, pp 329-334.
- [8] P.K. Dash, et al, "Damping Multimodal Power System Oscillation Using a Hybrid Fuzzy Controller for Series Connected FACTS Devices", *IEEE Transactions on Power Systems*, Vol. 15, No. 4, November 2000, pp 1360-1366.
- [9] S. Mishra, et al, "TS-Fuzzy Controller for a UPFC in a Multimachine Power System", *IEE Proceedings on Generation, Transmission and Distribution*, Vol. 147, No. 1, January 2000, pp 15-22.
- [10] Y.Y. Hsu and C.H. Cheng, "A Fuzzy Controller for Generator Excitation Control", *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 23, No. 2, March/April 1993, pp 532-539.
- [11] K.L. El-Metwally and O.P. Malik, "Fuzzy Logic Power System Stabilizer", *IEE Proceedings- Generation, Transmission, Distribution*, Vol. 142, No. 3, May 1995, pp 277-281.
- [12] C.L. Chen and C.T. Hsieh, "User Friendly Design Method for Fuzzy Logic Controller", *IEE Proceedings- Control Theory Applications*, Vol. 143, No. 4, July 1996, pp 358-366.
- [13] J.M. Mendel and G.C. Mouzouris, "Designing Fuzzy Logic Systems", *IEEE Transactions on Circuits and Systems II- Analog and Digital Signal Processing*, Vol. 44, No. 11, November 1997, pp 885-895.
- [14] C.W. Taylor, N.J. Balu and D. Maratukulam, *Power System Control and Stability*, McGraw-Hill Companies, EPRI Power System Engineering Series, 1993, ISBN 0070631840.
- [15] Y.H. Song and A.T. Johns, "Applications of Fuzzy Logic in Power Systems, Part 1: General Introduction to Fuzzy Logic", *IEE Power Engineering Journal*, October, 1997, pp 219-222.
- [16] C.C. Lee, "Fuzzy Logic in Control Systems: Fuzzy Logic Controller, Parts I & II", *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 20, No. 2, March/April, 1990, pp 404-435.
- [17] Y.H. Song and A.T. Johns, "Application of Fuzzy Logic in Power Systems, Part 2: Comparison and Integration with Expert Systems, Neural Networks and Genetic Algorithms", *IEE Power Engineering Journal*, August 1998, pp 185-190.
- [18] J.M. Mendel, Uncertain Rule-Based Fuzzy Logic Systems, Prentice Hall, New Jersey, 2001, ISBN 0-13-040969-3.
- [19] S. Mohagheghi, R.G. Harley and G.K. Venayagamoorthy, "Modified Takagi-Sugeno Fuzzy Logic Controllers for a Static Compensator in a Multimachine Power System", Proceedings of the 39th IEEE Industry Applications Society Annual Conference, Seattle, WA, USA, October 3-7, 2004, pp 2637-2642.
- [20] E. Cox, "Adaptive Fuzzy Systems", *IEEE Spectrum*, February 1993, pp 27-31.
- [21] H.C. Anderson, A. Lotfi and A.C. Tsoi, "A New Approach to Adaptive Fuzzy Control: The Controller Output Error Method", *IEEE Transactions on Systems, Man and Cybernetics- Part B: Cybernetics*, Vol. 27, No. 4, August 1997, pp 686-691.
- [22] C.T. Lin and C.S.G. Lee, "Neural-Network-Based Fuzzy Logic Control and Decision System", *IEEE Transactions on Computers*, Vol. 40, No. 12, December 1991, pp 1320-1336.
- [23] C.T. Lin and C.S.G. Lee, "Reinforcement Structure/Parameter Learning for Neural-Network-Based Fuzzy Logic Control Systems", *IEEE Transactions on Fuzzy Systems*, Vol. 2, No. 1, February 1994, pp 46-63.