Fuzzy Logic-Based Direct Load Control of Residential Electric Water Heaters and Air Conditioners Recognizing Customer Preferences In a Deregulated Environment

H. Salehfar, and P. J. Noll
Department of Electrical Engineering
University of North Dakota, Grand Forks, ND 58202

B.J. LaMeres, M.H. Nehrir, and V.Gerez
Electrical and Computer Engineering Department
Montana State University, Bozeman, MT 59717

Abstract: With the impending deregulation of electric utility industry, customer satisfaction with utility services will be crucial. Utilities will need to place a greater emphasis on their customers' preferences and desires. This would include the recognition and inclusion of customer comfort and satisfaction into utility demand side management programs. This paper presents a fuzzy logic-based water heater and air conditioner direct load controller recognizing several important customer preferences and desires. Study results show that the proposed controller successfully shifts the average power demand of customer loads and thus improves utility's load factor.

I. Introduction

Population growth along with technological growth force the utility companies to continue struggling to meet the ever increasing need for electricity. With the majority of residents conforming to the 8 AM-5 PM work schedule, the utility companies experience overwhelming demand peaks associated with a large amount of power being consumed at the same time. Complementing this effect are periods of low demand. Although over a period of time, the average amount of power consumed by a community may be easily generated by a utility, that utility still has to provide enough generation to meet its highest power demand peak. As this trend continues, utility companies may inevitably adopt a *real-time-pricing* strategy, where customers will pay more for the electric power they use during high demand periods and less during low demand periods. It is in the best interest of the utility companies as well as the consumer to try to reduce these high peak demand periods and level out their power demand profiles as much as possible.

While reducing their peak demands, however, utilities will also need to compete for new customers and keep current customers satisfied with their performance and services. With the upcoming utility deregulation, customer satisfaction is crucial. Thus, in such a business environment, any attempt to reduce the peak load of the system requires the full support of customers. Any control scheme should consider an adequate representation of the customers' specifications and preferences. If a particular customer's comfort is not kept in mind during the implementation of a control strategy, his or her tolerance level will decrease. Effectively, the customer's willingness to participate in any peak reduction plan also decreases [1]. Not only will unsatisfied customers fail to participate in a DLC program, they may likely choose to purchase their power from another utility which is more supporting of the customers' desires and preferences in the deregulated energy market [2].

Traditionally, one way that the objective of a peak reduction plan has been accomplished is by controlling residential electric water heaters and/or air conditioners. The electric water heaters and air conditioners account for the largest contributors to the total power consumption of a residence. Furthermore, due to their energy storage capabilities, water heaters and air conditioners are the ideal candidates for customer or utility demand-side management (DSM) programs to shift part of the utility power demand from peak periods to off-peak periods [3-5]. Such DSM strategies could be effective in utility peak load shaving and valley filling, and therefore increasing the utility load factor. For this and other similar reasons, electric water heaters and air conditioners have been the focus of many load analysis and demand-side management studies, i.e. [6-9].

Conventional electric water heater and air conditioner DSM strategies focus on brute force *on/off* controls, where a group of heaters and air conditioners are disabled during certain periods of time using a direct load control strategy [10-13]. When these loads are energized (reconnected), they are either *on* consuming a fixed amount of power or they are *off* [1].

This paper presents two new fuzzy logic-based demand control strategies where the power consumed by water heaters and air conditioners can be controlled using the information available from various sources including customer desires and preferences. The proposed strategies or variations of them are ideal for deregulated energy markets.

The second section of the paper presents the air conditioners control model along with its results. The third section discusses the water heater control strategy with its results. Finally, the last section of the paper gives some concluding remarks about the control models described in the paper.

II. Fuzzy Logic-based Air Conditioner Controller

Two parameters are used to quantify the preferences of each individual customer in controlling their air conditioner. The first value is the ambient criterion, or a measure of the internal building temperature that a customer prefers. In this work, the ambient criterion is divided into two parameters: the actual temperature and the preferred temperature of the customer. With the available technology, it is feasible for a utility to monitor and report the internal temperature of a building. The monitoring could either be conducted using a separate sensor or possibly read from the thermostat of the building. The second parameter is the comfort criteria. This is a measure of the range of temperatures that a customer can tolerate. This gives the utility the possible advantage of longer off-times and the customer the satisfaction of being comfortable during the cycling period. By modeling these two parameters the customer will have a direct voice in the DLC program.

The domain of the above parameters was determined to be the temperature measure in degrees Fahrenheit. In [14] the authors have chosen the domain to be in the kilowatt range. While it is easy to determine the kW content of a building from the temperature inside the building, it is not a reasonable thing to do. In order to convert to kW from temperature, the size of the building must be taken into consideration. This could lead to customers with different preferred temperatures having the same preferred ambient criterion.

Along with the above two parameters chosen to model the customer preferences, two more are determined to accurately model the thermal losses of a building. The two parameters that have the most impact are the size of the building, and the overall insulation rating of the building. In [14], the insulation rating is related to the age of the house. This assumption might have been valid 15-20 years ago, but it is not valid today. This is because due to the increasing cost of new housing, many of the older homes that are in use have been remodeled and/or reinsulated so they would no longer fit into this assumption. In this paper the units for the domains of the thermal loss parameters are chosen to be square feet and average BTU loss per square foot.

The global template for the actual temperature of a home is shown in Fig. 1. The number of templates in each of the input variables domain was chosen to be three. This decision was made because it kept the rule-base relatively simple, and provided enough templates to diversify the domains so that accurate results were produced.

Therefore the fuzzy system will have 5 inputs: preferred temperature, ambient temperature, building size, insulation rating, and comfort level, and one output: time off. In order to simplify the fuzzy logic process, the fuzzy logic model was determined as follows: The model was divided into two, two-input fuzzy controllers, and one three-input fuzzy controller.

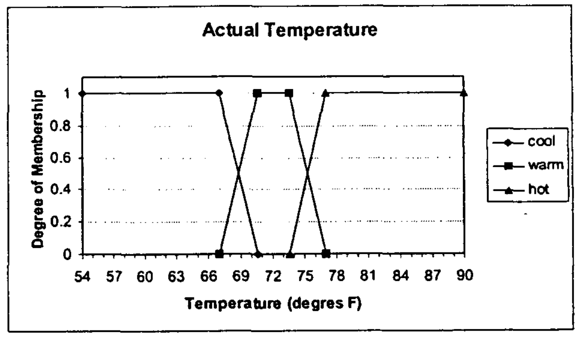


Fig. 1. Membership function: Actual temperature in a building.

The preferred temperature and the actual temperature are the inputs to the first controller with the deviation as the output. The size and insulation of the building are the inputs to the second controller with the thermal losses of the building as the output. The deviation, thermal, and the comfort rating of the customer make up the inputs to the final controller with the time that the air conditioner is disconnected as the output. A block diagram of this is shown in Fig. 2.

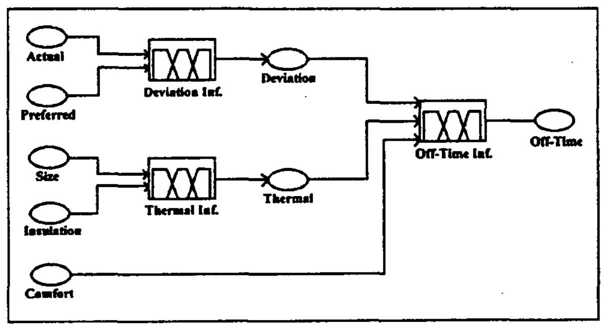


Fig. 2. Air Conditioners Fuzzy Control Block Diagram.

The output fuzzy templates were determined in a similar manner as the input templates. The domains of these fuzzy templates were determined by intuition and consulting. The units on the domain were chosen to be minutes for the off-time, degrees Fahrenheit for the deviation, and BTU/hour for thermal losses. The range of deviation is chosen from the maximum difference between the preferred and actual temperatures as if they were crisp numbers. The thermal domain was divided into three membership functions just as the initial inputs were. The deviation domain (see Fig. 3) was divided into five functions.

This was done because the deviation could be small, medium or large with the medium and large templates being negative or positive. The positive templates take into account the situation when the actual temperature is lower than preferred while the negative templates model the opposite situation. The small deviation template is for situations when both the actual and the preferred temperatures are in the same temperature membership function. Once the fuzzy inputs, outputs, and membership functions were formulated, the rules that governed their interactions had to be determined. A disjunctive set of

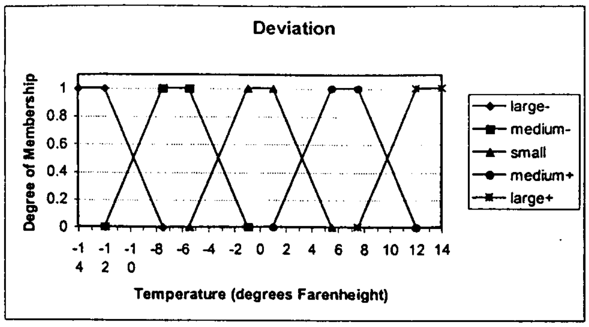


Fig. 3. Membership function: Deviation between temperatures.

rules was chosen to govern all of the fuzzy interactions. All rules formulated were conditional rules. As an example, the rules that were used to govern the thermal losses are shown in Fig. 4.

Size of Building	small	medium	large	
	medium	high	high	poor
Ther. Temp. =	low	medium	high	good
	low	low	medium	excellent
				Insulation Rating

Fig. 4. Rules Governing Thermal Losses.

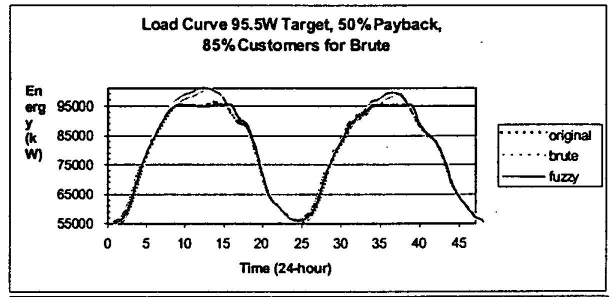
III. Air Conditioners Control Results

The input data for the simulation could either be crisp or fuzzy numbers. In actual implementation, the inputs would be fuzzy as specified by the customers. The customers would specify their preferred temperature, and comfort level. For the size and the insulation of the building, either the customer could specify these or the utility could estimate them, but they too would be fuzzy numbers. The data that were used in the simulations are crisp numbers that are fuzzified by the authors' developed C++ code. The data was provided by a utility in the Midwest region of the country. The insulation distributions were chosen to be uniform.

The simulations were run for various payback amounts. Three sets of simulations were run for target load reductions of 5,000, 7,500, and 10,000 kW. These values give target load levels of approximately 95.5, and 93.5 and 90.5 MW. All simulations were run for two days of DLC, using 1997 load data provided by a utility in the Midwest region of the country.

In Fig. 5 the effects of both a brute force and the proposed fuzzy logic based methods of load control are shown. In this and all other simulations 15,000 air conditioning units are being controlled using the fuzzy logic method, while 12,750 customers are being controlled using a brute force method. In this figure both the brute force method and the fuzzy-logic method are reducing the peaks of the load curve. But, the overall peak load is slightly higher than the desired goal of 95.5 MW in the brute force case while, the fuzzy-logic method obtains the target of 95.5 MW. The average load is reduced considerably with both the brute force method and the fuzzy logic method.

In Fig. 5 the improvement in the load factor is ½ of a percent higher for the fuzzy-logic based method than the brute force method. This is due to the fact that the fuzzy-logic method has a higher load that it can shed each hour. When the number of customers for both the fuzzy-based method and the brute force method are equal, the brute force method has a slightly higher load per hour that could be disconnected. A 3% improvement in the load factor could have a significant effect on the revenue earned by a utility.



Method	Peak Load (kW)	Average Load (kW)	Load Factor	Load Factor Improvement (%)	Load/Hour for disconnection @ 87.5 F	Total Load (MW)	Load Saved (MW)
None	100522	80097	0.797	N/A	N/A	3844.66	N/A
Brute Force	96248	79602	0.827	3.0	7969	3820.90	23.76
Fuzzy Logic	95346	79619	0.832	3.5	9110	3821.71	22.95

Fig. 5. Resulting Air Conditioner Load Curves.

IV. Fuzzy Logic-based Electric Water Heater Controller

Fig. 6 shows the block diagram of the proposed fuzzy controller which has 22 rules, four inputs., and one output signal. A sample of its fuzzy rules is given later in the paper. The inputs of this model are as follows:

1. *Demand*: Average residential electric water heater power demand.
2. *Water_Temp*: Temperature of the hot water at any given time.
3. *Comfort_Level:* A minimum temperature for hot water, set by the customer. Water temperature is not to fall below this value. This temperature is set at 95° F in this study.
4. *Max_Temp:* Maximum water temperature allowed. This temperature is set at 130° F in this study.

The controller takes the four crisp input values, fuzzifies them, assigns a fuzzified control signal to control the voltage applied to the water heater based on the assigned rules and membership functions. The control signal is then converted to a crisp signal through defuzzification process [15].

The decision making process is based on a set of linguistic rules that will map each input signal to a set of membership functions that correspond to that input. These signals are, in turn, mapped to an output signal.

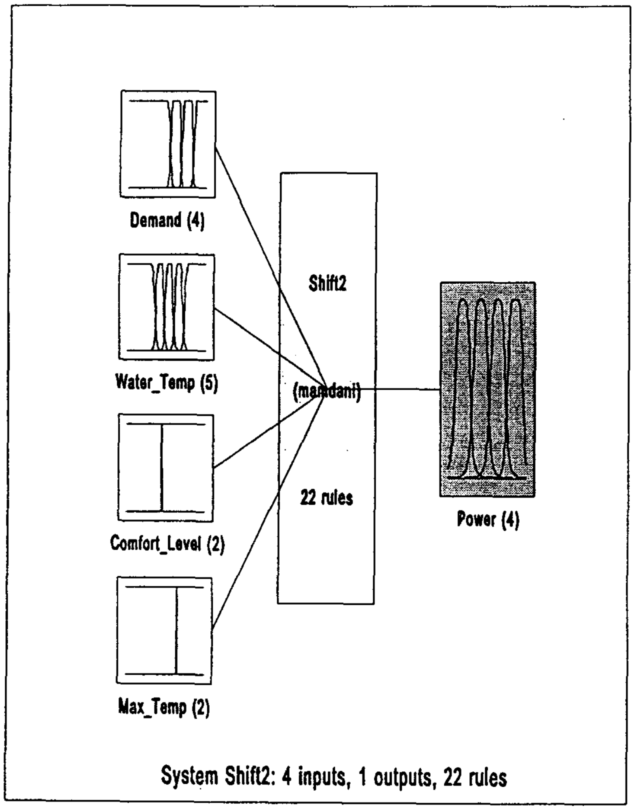


Fig. 6. Water Heaters Fuzzy Control Block Diagram

The voltage applied to the water heater at any given time is the product of the fuzzy controller's output command, which is a number between zero and one, and the water heater's rated voltage. Assuming water heater's heating element is purely resistive, its power consumption is proportional to the square of its voltage which is now a variable. Therefore, the water heater's power consumption becomes a variable. The fuzzy rules and membership functions will be explained in the next two sections.

V. Membership Functions

Gaussian (bell-shape) membership functions were used for the inputs, demand and temperature, and the output signal (power). This type of membership function resulted in the smoothest shifted water heater demand profile. On the other hand, sharp membership functions were chosen for the input variables, comfort level and maximum temperature because of the sharp constraints on those variables. Water temperature shall not drop below the comfort level and shall not exceed the maximum temperature assigned by the customer. The range for the membership functions were chosen based on experience. Fig. 7 shows the shape, range, and the linguistic terms used for the input and output variables.

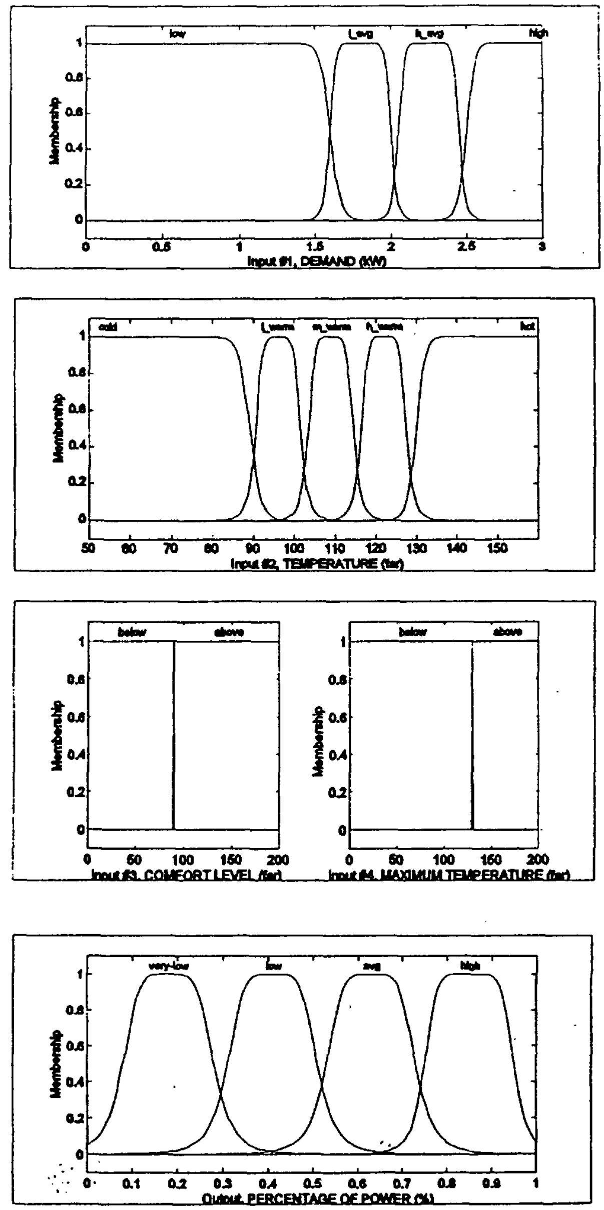


Fig. 7. Membership Functions for the Fuzzy Logic Controller.

The fuzzy rules and membership functions are explained in the next the section.

VI. Water Heater Fuzzy Rules

In the present model, the fuzzy controller is to shift the peaks of the water heater demand profile to periods where total demand, as seen by the utility, is low. At the same time, constraints set by the customer, i.e. the maximum and minimum temperatures for the hot water, should be met. Considering these needs and constraints, a shifted water heater demand profile was obtained using twenty-two rules, some of which are as given below.

If (Demand is low) and (Water_Temp is cold) then (Power is high)
If (Demand is low) and (Water_Temp is l_warm) then (Power is high)
If (Demand is low) and (Water_Temp is m_warm)then (Power is avg)
If (Demand is low) and (Water_Temp is h_warm) then (Power is avg)
If (Demand is low) and (Water_Temp is hot) then (Power is low)
If (Demand is l_avg) and (Water_Temp is cold) then (Power is avg)
If (Demand is l_avg) and (Water_Temp is l_warm) then (Power is avg)
If (Demand is high) and (Water_Temp is hot) then (Power is very-low)
If (Max_Temp is above) then (Power is very-low)
If (Comfort_Level is below) then (Power is high)

The last two rules in the above, set the boundaries for the maximum and minimum temperatures. Note that in this study we have assumed that the temperature cannot exceed a certain limit. Therefore, there is a limit on the amount of power which can be applied to the water heater in order to heat the water during the periods where demand for electricity is low. Otherwise, water temperature will exceed its maximum limit. Similarly, water temperature should not fall below a minimum value set by the customer. Therefore, it may not be possible to reduce the power supplied to the heater all the way to zero during periods of high demand for electricity.

VII. Water Heater Simulation Results

Fig. 8 shows a comparison of the fuzzy-controlled and uncontrolled water heater power demand. It is clear from this figure that under fuzzy control a large percentage of the water heater power demand has been shifted from periods of high demand for electricity to off-peak periods.

Fig. 9 shows the temperature profile of the hot water for a 24-hour period when the water heater is under fuzzy control. Water temperature falls during periods of high demand for electricity because power supplied to the water heater is kept low during those periods. On the other hand, power supplied to the water heater is high during periods where demand for electricity is low, and water temperature rises during these periods. It is understood that cooperation and some planning for the use of hot water is expected from the customers participating in the proposed fuzzy logic-based DSM strategy.

Fig. 10 shows the average power demand profile of one fuzzy-controlled and one uncontrolled water heater and the average power demand of two uncontrolled water heaters. It is clear from this figure that the load factor, defined by equation below, is improved significantly for the average demand profile of one fuzzy-controlled and one uncontrolled water heater as compared to that for two uncontrolled water heaters. The load factor is defined as:

$$\text{Load Factor} = \frac{\text{Average Demand}}{\text{Peak Demand}}$$

VIII. Conclusions

Simulation results show that it is possible to reduce the peaks of average residential water heater and air conditioner power demand profiles and shift them from periods of high demand for electricity to low demand periods using the proposed customer-interactive DSM strategy. As a result, the load factor of the daily average residential power demand can be improved resulting in an improved utility load factor. The proposed strategy can also be beneficial to the customers participating in such DSM programs, specially in a real-time pricing and/or

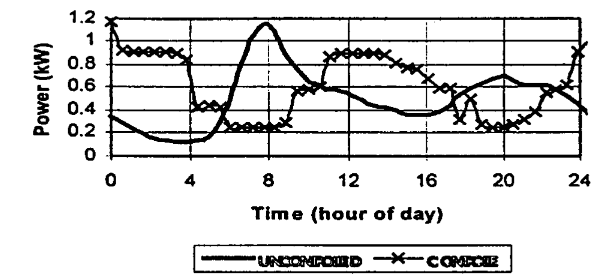


Fig. 8. Controlled and Uncontrolled Water Heater Demand.

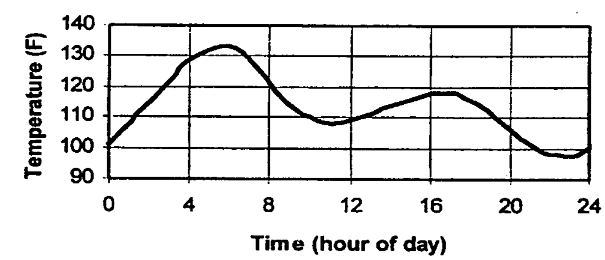


Fig. 9. Controlled Water Heater Temperature Profile.

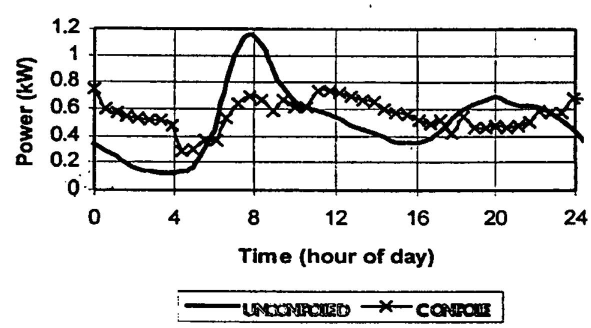


Fig. 10. Average Demand of One Controlled and One Uncontrolled Water Heater and Two Uncontrolled Ones.

deregulated environment. Some cooperation and planning for use of hot water and air conditioner is necessary by the customers participating in such DSM programs.

Acknowledgment

Part of this work was supported by the DOE/EPSCoR and

Montanans on a New Track for Science (MONTS) programs at Montana State University.

References

[1]. H. Salehfar and A.D. Patton, "Modeling and Evaluation of the System Reliability Effects of Direct Load Control," *IEEE Trans. on Power Systems*, Vol 4, No. 3, August 1989.

[2]. Aileen Crowley, "Avoiding a Power Gridlock," *PC Week*, 18 June 1997, 16-7.

[3]. Laurent, J.C.; Desaulniers, G.; Malhame, R.; Soumis, F., "A Column Generation Method for Optimal Load Management via Control of Electric Water Heaters," *IEEE Trans. On Power Systems, Vol.10, August 1995.*

[4]. Biscke, R.F, "Design and Controlled Use of Water Heater Management," *IEEE Trans. on Power and App. and Sys.*, Vol. PAS-104, No.6, 1985.

[5]. Gustafson, M.W.; Baylor, J.S.; Epstein, G.S., "Direct Water Heater Load Control - Estimating Water Heating Load Control Effectiveness Using an Engineering Model," *IEEE Transactions on Power Systems*, Vol. 8, No. 1, 1993.

[6]. Tonder, J.C. and Lane, I.E., "A Load Model to Support Demand Side Management Decisions on Domestic Storage Water Heater Control Strategy," *IEEE Trans. On Power Systems, Vol.11, Nov. 1996.*

[7]. Lane, I.E. and Beute, N., "A model of the Water Heater Load," *IEEE Trans. On Power Systems, Vol.11, Nov. 1996.*

[8]. Dolan, P.S. and Nehrir, M.H., "Development of a Residential Electric Water Heater Model Using Energy Flow Analysis Techniques," *Proceedings*, North American Power Symposium, October 5,6, 1992, Reno, NV.

[9]. Dolan, P.S.; Nehrir, M.H.; Gerez, V., " Development of a Monte Carlo Based Aggregate Model for Residential Electric Water Heater Loads," *Electric Power Systems Research*, Vol. 36, No. 1, 1996.

[10]. Lee, S.H.; Wilkins, C.L., "A practical Approach to Appliance Load Control Analysis: A Water Heater Case Study," *IEEE Trans. on Power and App. and Sys.*, Vol. PAS-102, No. 4, 1982.

[11]. M.W. Gustafson, J.S. Baylor, & Gary Epstein, "Estimating Air Conditioning Load Control Effectiveness Using an Engineering Model," *IEEE Trans. On Power Systems*, Vol. 8, No. 3, August 1993.

[12]. George W. Brazil, "Arkansas Power and Light Company Air Conditioning Load Management Program," *IEEE Power Engineering Society Summer Meeting*, 1979, preprint A 79 513-3.

[13]. Donald V. Stocker, "Load Management Study of Simulated Control of Residential Central Air Conditioners on the Detroit Edison Company System," *IEEE Trans. on Power Apparatus and Systems*, Vol. PAS-99, No. 4, July/August 1980.

[14]. K. Bhattacharyya, and M.L. Crow, "A Fuzzy Logic Based Approach to Direct Load Control," *IEEE Trans. On Power Systems.* Vol. 11, No. 2, May 1995.

[15]. Ross, T.J., *Fuzzy Logic with Engineering Applications*, McGraw Hill 1995.

Biography

H. Salehfar (Member, IEEE) received his B.S. from University of Texas at Austin, and his M.S. and Ph.D. from Texas A&M University, all in Electrical Engineering. He was an Assistant Professor of Electrical Engineering at Clarkson University during 1990-1995. Since 1995 he has been with the Department of Electrical Engineering at University of North Dakota in Grand Forks. His research interests currently include power systems reliability, load management, power electronics, neural networks and fuzzy logic applications to power systems. He has taught power systems, power electronics, engineering reliability, engineering statistics, neural networks, fuzzy logic, electromagnetics, and circuits at graduate and undergraduate level.

Patrick J. Noll received his B.A. degree in Physics from Benedictine College, Atchison, KS in May 1995 and his M.S. degree in Electrical Engineering from the University of North Dakota in August 1998. He joined the Air Transport Flight Controls Department of Rockwell Collins, Cedar Rapids Iowa, in June 1998.

Brock J. LaMeres (Member, IEEE) received the B.S. degree in electrical engineering from Montana State University in December 1998 and joined the Hewlett Packard Co. in Colorado Springs, CO in January 1999.

M. Hashem Nehrir (Senior Member, IEEE) received the B.S., M.S. and Ph.D. degrees from Oregon State University in 1969, 1971, and 1978 respectively, all in Electrical Engineering. From 1971 to 1986 he was with the Department of Electrical Engineering at Shiraz University in Iran, where he became department Chair in 1984. He is now with the Electrical Engineering Department at Montana State University as a full professor. His primary areas of interest are control and modeling of power systems and electrical machinery, renewable power generation, and fuzzy logic control applications to power systems.

Victor Gerez (Senior Member, IEEE) received his engineering degree from the National University of Mexico and his M.S.and Ph.D. degrees from University of California, at Berkeley in 1958, 69, and 72 respectively, all in electrical engineering. In 1973 he became the chairman of Mechanical -Electrical Engineering Department at National University of Mexico. In 1977 he became the director of the power system division in Mexico's Electric Power Research Institute. He joined the Electrical Engineering Dept at Montana State University in 1983, where he is currently a fullrofessor; he was the department's head from 1984 to 1996.