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DEVELOPMENT OF AN INTELLIGENT AUTOMATIC GENERATION CONTROL SYSTEM FOR ELECTRICAL POWER PLANTS

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ABSTRACT

The United States electric grid is a complex structure that requires high precision control of frequency and tieline power flows among different generation areas. Highly varying loads introduce a major challenge for the present automatic generation control systems. Arc furnaces, rolling mills and other large motors can create large demands on the system which result in an unsatisfactory area control error (ACE). Recent studies have shown that very-short term load prediction can be incorporated into control schemes which are then able to compensate for the highly varying demand. Using a neural network prediction of the area load a new fuzzy logic controller has been developed that adjusts the set point of the area generation to attempt to match the upcoming changes on the system. Performance of the neural-fuzzy controller in a two-area tie-line model with actual load data from a collaborating utility is demonstrated and compared with the present AGC system through simulations.

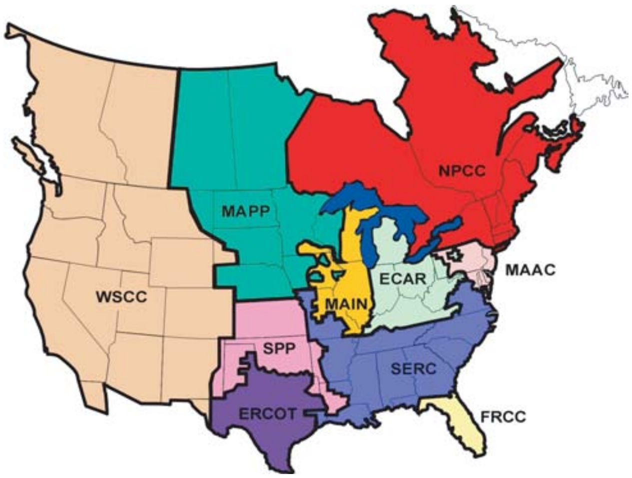

Figure 1. NORTH AMERICAN ELECTRIC RELIABILITY COUNCIL

1 INTRODUCTION

Interconnection of the electric grid in the United States and Canada began in 1962 when seven interconnections were closed to form the largest synchronized system in the world. When a blackout occured in the northeast in 1965 the U.S. Federal Power Commission recommended that an organization be formed to coordinate the policies of all regional coordinating councils. In 1968, after the passing of the Electric Power Reliability Act (1967), the North American Electric Reliability Council (NERC) was formed to coordinate regional operating strategies so that the reliability of the interconnected system could be improved.

The nonprofit organization is comprised of nine regional coordinating councils, as shown in Figure 1, that promote the reliability of the electricity supply in North America by instituting guidelines and criteria for utilities to follow that ensure proper control of their systems and their interaction with surrounding systems. The areas that comprise the nine regional councils are called control areas and the entities that operate them are control area operators. Not every utility, power producer or system operates a control area, but every energy supplier must be included in a control area.

A mechanism for modeling the surpluses or deficiencies of generation in a control area is called the area control error

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(ACE). ACE is a numeric value, in megawatts (MW), that relates the deviation from scheduled tie-line flow and the deviation from scheduled frequency to the generation supplied to the system. Many AGC algorithms in service today use the integral of ACE to regulate the supplementary control for units on AGC. Classical Proportional-Integral (PI) controllers and the filters associated with them, developed in the 1960's, use the ACE value to regulate the supply of generation in a control area. While this mechanism of control has shown ease of use, there is an inherent time delay in its operation which causes generation to lag the changing demand.

Researchers have investigated the use of very short-term load forecasting in an attempt to enhance dispatch of local area generation. Using short-term predictions, a control area operator can respond to changing loads before they occur, and maintain the error between generation and load on their system more accurately. Methods that attempt to perform this operation are called intelligent automatic generation control systems (IAGC)

Very short-term load forecasting has been performed by Charytoniuk and Chen (2). The authors use several ANN's to perform very short-term load prediction from 20 to 60 minutes ahead. Liu et al (3) use a four layer feedforward neural network that incorporates net interchange, frequency deviation and ACE along with 30 previous load values are used to predict the load change out to thirty minutes in one minute intervals. Longer prediction horizons were used by (4; 5; 6; 7; 8).

Fuzzy logic has also recently been used to enhance the control of power systems, Chang and Fu (9) use fuzzy gain scheduling of the PI controller in a common AGC system to try and adapt the controller as time and conditions change. Other research has gone into reducing the movement of generation units to short-term deviations in ACE. Chown and Hartman (10) detail the purpose and development of a fuzzy logic controller that was integrated into the AGC system of Eskom in South Africa. The fuzzy controller uses ACE and its derivative as the inputs into the system and outputs a new ACE value which is fed to the conventional AGC algorithm. Shoureshi and Hoffner et al (11) reduce the generator movement with a fuzzy controller that completely replaces the conventional AGC controller.

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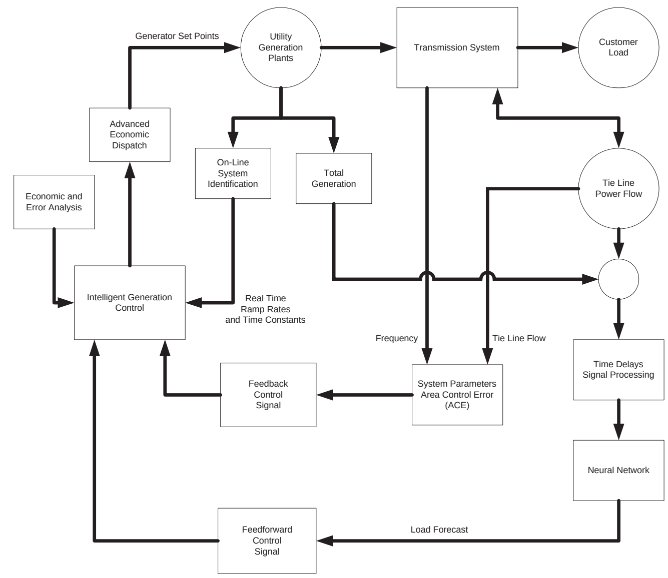

Figure 2. BLOCK DIAGRAM OF PROPOSED IAGC SYSTEM

2 INTELLIGENT AUTOMATED GENERATION CONTROL

The development of IAGC systems has recently become feasible with the advances in technologies such as high speed telecommunications and the availability of high computational power to solve high speed numerical algorithms. IAGC systems have the ability to regulate system performance even during load changes that cause large deviations in frequency and tie line flow. Figure 2 illustrates the different components of an IAGC system and their interactions.

By applying IAGC techniques to the control system utilities will be able to better meet the changing nature of the electric industry. The IAGC system developed in this paper can be broken down in to three main parts, Very short-term load prediction, fuzzy logic, and neural networks. Together they are applied to lower the effects of non-conforming loads such as arc furnaces and rolling mills on the electric grid. To complete this IAGC system a load-scheduling algorithm is being developed. This algorithm will form a feedback loop with the customer load and in so doing minimize the disturbance produced by simultaneous highly varying loads.

3 TWO-AREA TIE-LINE MODEL

The most widely used mathematical model for AGC is a two-area interconnected linear tie-line model. This model is still commonly used to analyze and simulate the interconnected power generation system in the electrical utility community. Figure 1 shows an illustration of the model with a proportional-integral supplementary controller in areas one and two.

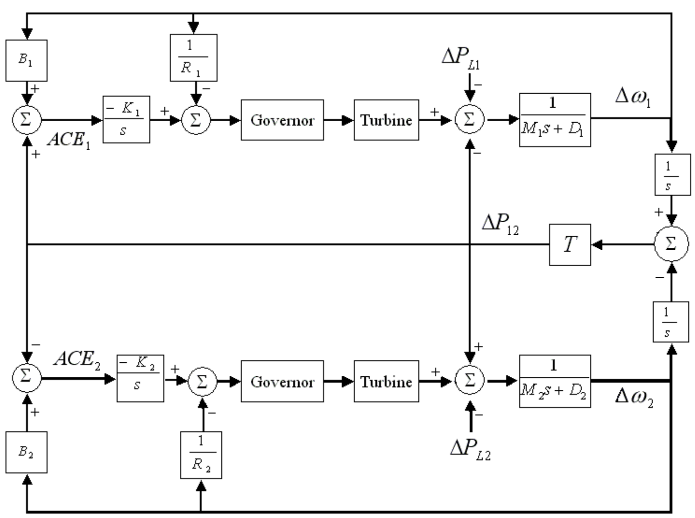

Figure 3. TWO-AREA TIE-LINE MODEL

The new neuro-fuzzy controller was simulated in this system by replacing the supplementary controller in area 1. The actual load data from the sponsoring utility was used for the load disturbance in area 1, and a separate load profile was used as the load disturbance in area 2. The model used a standard governor and reheat turbine model with parameters found in (14), 5% speed droop, and inertia, damping, frequency bias and tie-line stiffness developed by (12) for the sponsoring utility. Each area in the model was simulated with the same parameters for simplicity, and simulations were performed on three systems, the neuro-fuzzy controller, a two-input fuzzy controller and a PI controller, which was used as the benchmark.

4 NEURAL-BASED SHORT-TERM LOAD FORECASTING

The growing acceptance of Artifical Neural Networks (ANN) for non-linear system identification in industry has prompted researchers to investigate applications of ANN for load forecasting. Because of the random nature of loads in most control areas, the task of predicting the future response of the system has proven to be a difficult and

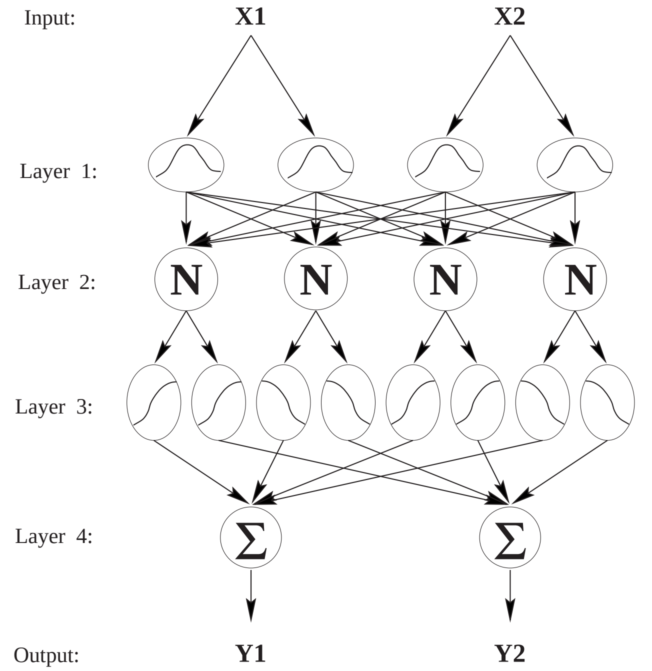

Figure 4. TSUKAMOTO-TYPE NEURAL FUZZY INFERENCE NETWORK

complicated. Moreover, utilities that serve customers that have highly varying loads (HVL), such as arc furnaces and rolling mills, are confronted with an even more challenging problem of modeling loads that can change by hundreds of megawatts in a matter of minutes. The development of a new ANN to face and resolve these challenges was initiated by the Power Research Center at the Colorado School of Mines. The challenge of this problem was to develop a network that was reliable and accurate but which was able to adapt quickly, meaning it had to be able to retrain itself very quickly. The Tsukamoto-type neural fuzzy inference network (TNFIN) was developed to serve this purpose. The TNFIN is a multi-layer feedforward network that uses the generality of fuzzy logic in its architecture.

Work initially performed by Hu (15) produced a four layer ANN that exhibited desirable features such as fast training times, reduced number of parameters to learn, the ability to avoid falling into local minima, and the adaptability to change the number of inputs and outputs associated with the network. Figure 4 shows a two input-two output model of the TNFIN. However, the architecture can be extended to any number of inputs and outputs. The parameters adapted during training are the function parameters in layers one and three.

The details of the layer architecture and training can be found in the June 2000 proceedings of the American Control Conference (13).

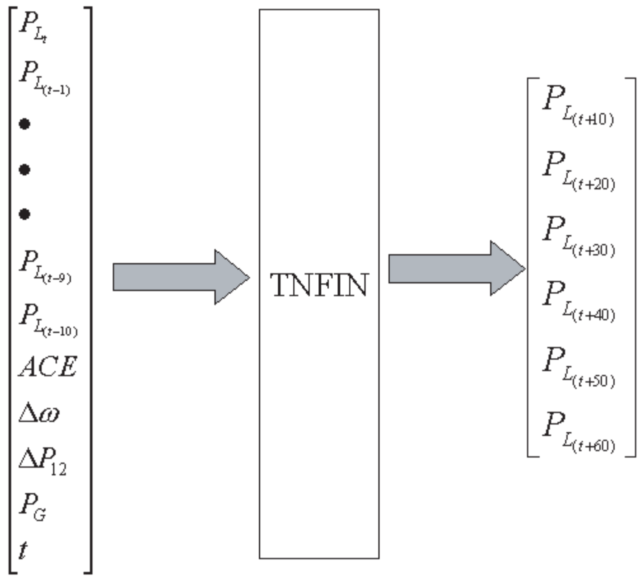

Figure 5. ORGANIZATION OF TNFIN INPUTS AND OUTPUTS

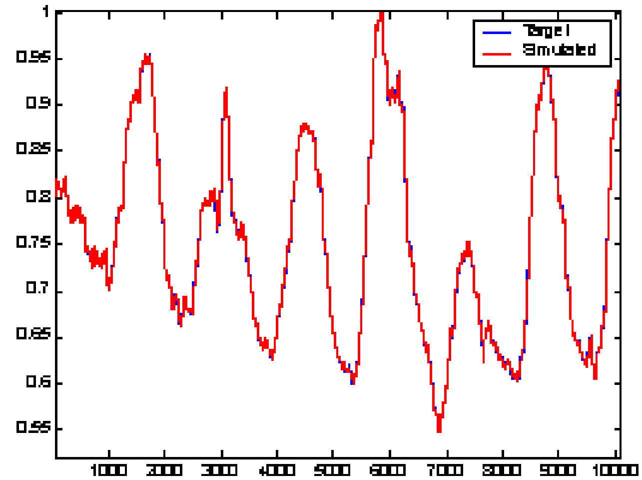

Figure 6. TEN MINUTE TNFIN PREDICTION

The TNFIN structure and training developed by Hu was applied to load forecasting in this research. The development of a set of inputs to the network is imperative for predicting the dynamics of the actual load. In order to attempt to predict the load of the host utility, the initial simulations of the network used 15 inputs:

- Ten minutes of total load values
- Area Control Error
- Frequency
- Tie Line Flow
- Total Generation
- Current Time

and 6 outputs:

- Future 10, 20, 30, 40, 50 and 60 minutes of load predictions

Figure 5 illustrates how these system variables were incorporated to predict the future demand on the system.

Because of the nature of the electric grid, high frequency deviations of the load from its general trend are very common. A deviation of 100 MW is a large amount of power that needs to be tracked, but smaller deviations representing 10-30MW, were deemed to be too random in nature to predict. It was also assumed that trying to track these smaller loads would cause more maintenance problems for the utility than the realizable economical gains from tracking this load. Therefore, the actual load values were filtered to eliminate the very high frequency load deviations. Initially a large amount of filtering was used to validate that the TNFIN was able to track this load. Figure 6, shows the load prediction result by using TNFIN.

5 FUZZY CONTROL DEVELOPMENT

The ACE is the main input into the normal regulation component of AGC. With the selection of, ACE and $\int ACE$, as control inputs, a set of control rules were extracted from operator experience based on these two variables. The neural network prediction, $NNOut$, was then used as an additional input to incorporate a feedforward control loop into the system.

In the design of this controller, both ACE and $\int ACE$ are partitioned into 5 linguistic values which are Negative Large (NL), Negative Small (NS), Zero (Z), Positive Small (PS), and Positive Large (PL), respectively. The neural network prediction is partitioned into 3 linguistic values, Negative Large (NL), Zero (Z), Positive Large (PL). The control signal u is partitioned into 9 linguistic values which are Negative Very Large (NVL), Negative Large (NL), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM), Positive Large (LP), and Positive Very Large (PVL), respectively. Triangular membership functions are assigned to each linguistic value of the three fuzzy input variables, ACE, $\int ACE$ and $NNOut$, and the fuzzy output variable, (u), and each one overlaps the adjacent functions by 50%. Figure 7 shows the outlined membership functions for the four fuzzy variables: ACE, $\int ACE$, $NNOut$ and u, respectively.

Figure 8 shows the fuzzy control rule matrix. Given the

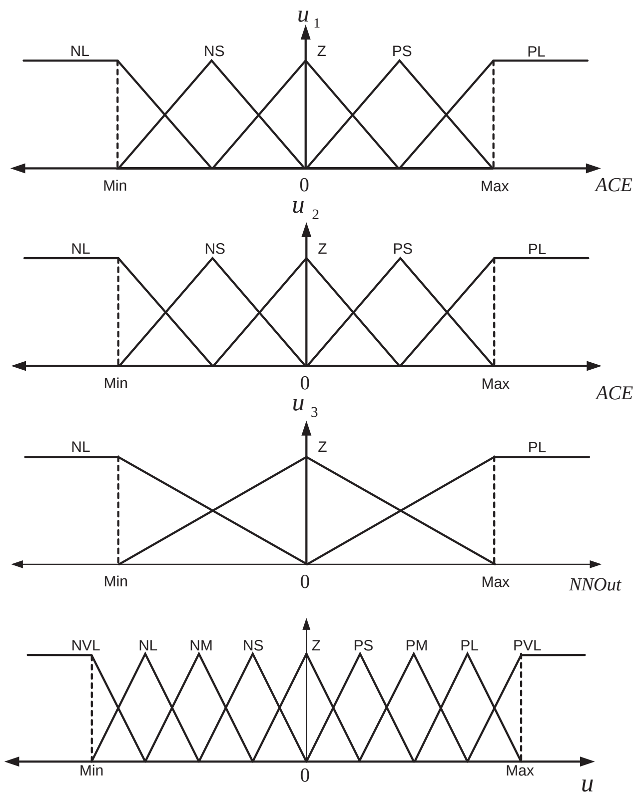

Figure 7. MEMGERSHIP FUNCTIONS FOR ACE, $\int ACE$, $NNOut$ and u

number of linguistic values for our fuzzy variables, the total number of fuzzy rules should be 25 (5 times 5) for each value of $NNOut$. Based on interviewing the system dispatchers of the collaborating utility and using an understanding of power system dynamics, only 17 fuzzy rules out of the 25 are selected for the zero (Z) membership function of $NNOut$. The reason for not using the remaining eight rules is acceptable if we consider $\int ACE$ as *error*, then ACE should be $\frac{d(error)}{dt}$ and the antecedent part of the remaining eight rules may be represented by either '*error* is positive and $\frac{d(error)}{dt}$ is negative' or '*error* is negative and $\frac{d(error)}{dt}$ is positive'. Even without any control efforts, the remaining eight rules automatically drive *error* to zero because the sign of *error* is always opposite to that of $\frac{d(error)}{dt}$. If any of above eight rules are fired, no control effort is produced.

The addition of the two remaining $NNOut$ membership functions creates a tensor of fuzzy control rules. The firing of a PL or NL $NNOut$ membership function causes a shifting of the fuzzy rule base diagonally up or down. If a PL membership function is fired the controller has a greater tendency to create a positive output signal even though the

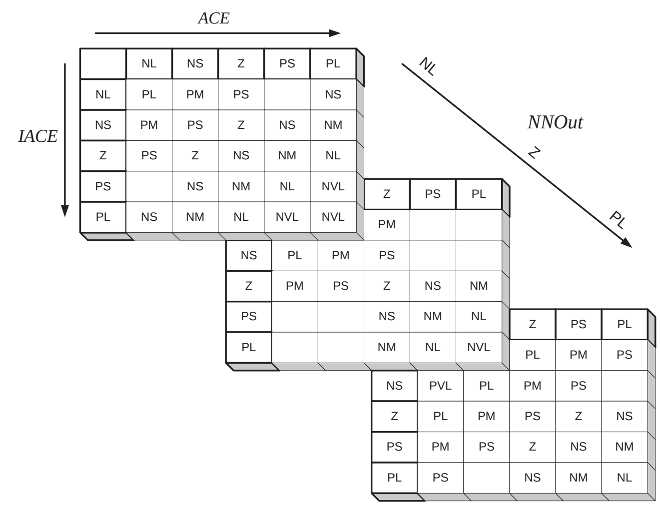

Figure 8. FUZZY CONTROL RULE TENSOR

ACE and $\int ACE$ membership function may not have warranted the larger output. A similar tendency occurs for the firing of a NL membership function.

The fuzzy inference used for this controller is Mamdani's minimum implication and a center of area (COA) strategy is used to defuzzify the linguistic values of the controller to the crisp values of the control signal.

6 SIMULATION AND RESULTS

Simulation was carried out on the two-area model with the matrix software, Simulink. Because of the nature of the electric grid, high frequency deviations of the load from its general trend are very common. A deviation of 100 MW is a large amount of power that needs to be tracked, but smaller deviations representing 10-30MW, were deemed to be to random in nature to predict. It was also assumed that trying to track these smaller loads would cause more maintenance problems for the utility than the realizable gains from tracking this load, therefore, the actual load values were filtered to eliminate the very high frequency deviations.

Figures 9 and 10 show a section of the actual load data compared to the two filtered load data sets, Load Data 1 and Load Data 2, respectfully. These two sets of filtered load data were used to simulate the neural-fuzzy controller. The initial simulations used the highly filtered load data, Load Data 1, as the load disturbance in area 1 and as the input into the neural network prediction.

The system was simulated using 45 days of load data sampled at one minute intervals. ACE, the change in tie-line flow and the change in frequency were monitored for three systems, the feedforward fuzzy controller, a fuzzy controller

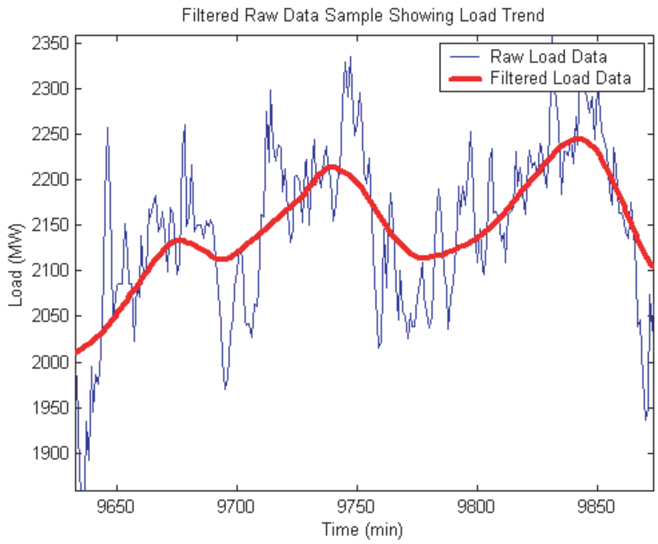

Figure 9. ACTUAL LOAD AND LOAD DATA

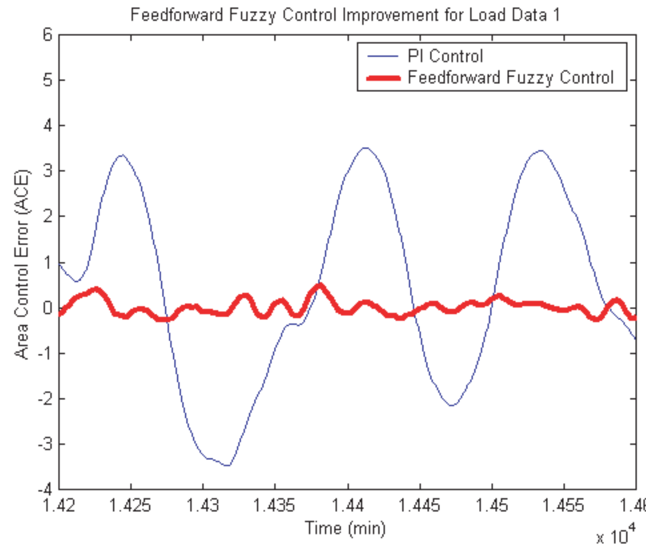

Figure 11. AREA CONTROL ERROR COMPARISON WITH LOAD DATA

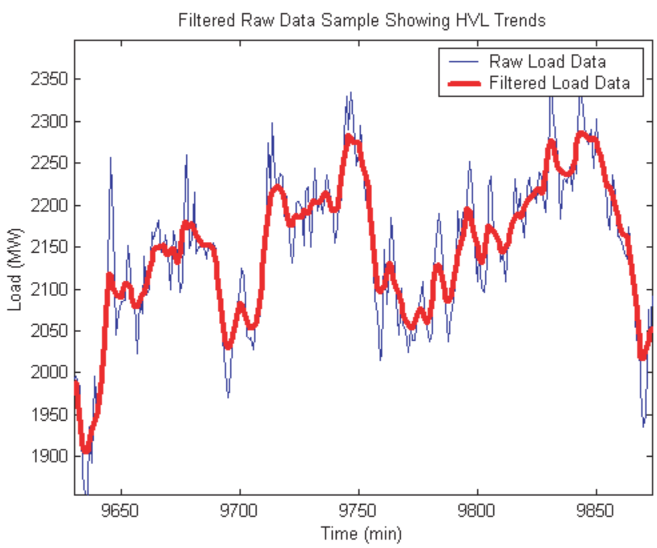

Figure 10. ACTUAL LOAD AND LOAD DATA

without a neural network prediction and a PI controlled system. The ACE values simulated on the three systems were used for comparison by comparing the numerical integration of their absolute values:

$$Improvement(\%) = \left(1 - \frac{\int_0^{t_f} |ACE_{Fuzzy}|}{\int_0^{t_f} |ACE_{PI}|}\right) \times 100 \quad (1)$$

and also by comparing the standard deviations of their histograms:

$$Improvement(\%) = \left(1 - \frac{\sigma_{Fuzzy}}{\sigma_{PI}}\right) \times 100 \quad (2)$$

Figure 11 shows a section of the ACE values from the feedforward fuzzy controlled system versus that of the PI controlled system. The overall improvement of the area 1 ACE value over that of the PI controlled area 1 ACE is 83.96% and 84.42% using the numerical integration (NI) and sigma (σ) criterion, respectfully. The change in tie-line flow also shows a significant improvement of 86%.

The feedforward fuzzy controller also shows an improvement over that of the fuzzy controlled system by 8.05% (NI) and 9.28% (σ). Figure 12 shows a histogram of the ACE values for the two controllers.

Usually improvements such as these are at the cost of the change in frequency, therefore, another goal of the simulation was to maintain or improve the change in frequency between all simulations. Figure 13 is a histogram of $\Delta\omega_{PI}$ and $\Delta\omega_{FF}$ which shows that the frequency of the feedforward fuzzy controller maintained better frequency control than did the PI controller.

In order to incorporate a load profile that showed more variations, Load Data 2 was used as the load disturbance in area 1. Figure 14 shows the same section of ACE values as shown for the previous simulations. A 28.48% (NI) and 28.18% (σ) ACE improvement and a 36% change in tie-line

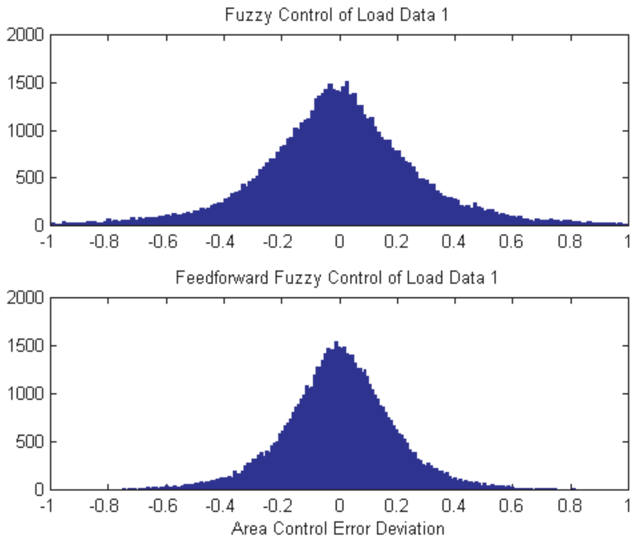

Figure 12. HISTOGRAMS OF ACE USING LOAD DATA

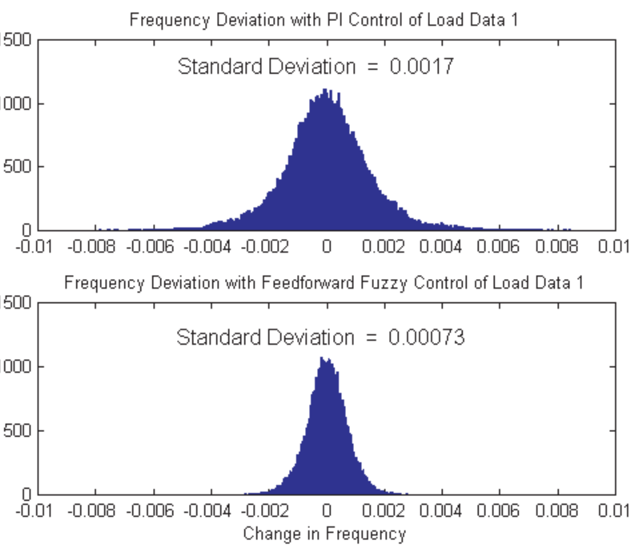

Figure 13. CHANGE IN FREQUENCY DIFFERENCE WITH LOAD DATA

improvement was shown by the feedforward fuzzy controlled system. Figure 15 shows that there is still an improvement made by the feedforward fuzzy controller over that of the fuzzy controlled system, and Figure 16 shows that the change in frequency was still similar between the two systems. While this improvement was substantially less than that of the highly filtered simulations, the control gained

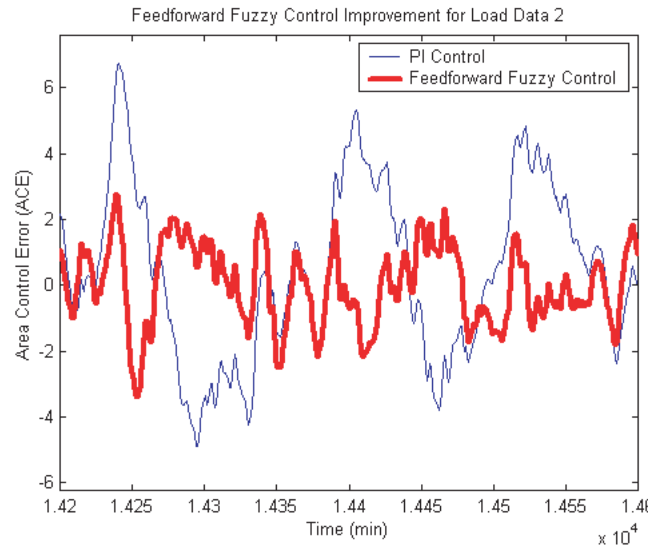

Figure 14. AREA CONTROL ERROR COMPARISON WITH LOAD DATA

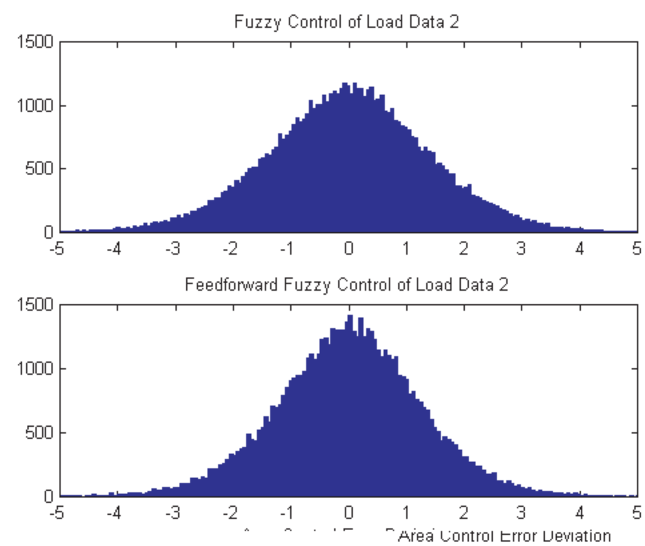

Figure 15. HISTOGRAMS OF ACE USING LOAD DATA

over the system is evident.

A summary of the improvements shown with the two-input fuzzy controller and the feedforward fuzzy controller over that of the PI controlled system are shown in Table 1

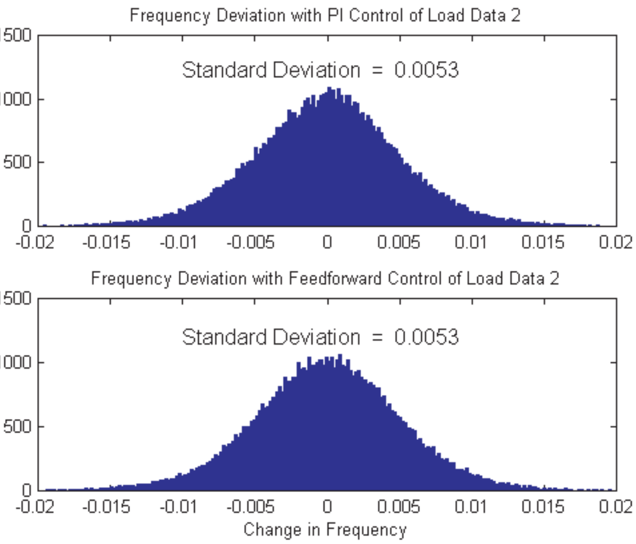

Figure 16. CHANGE IN FREQUENCY DIFFERENCE WITH LOAD DATA

Table 1. SUMMARY OF FUZZY LOGIC CONTROLLER IMPROVEMENTS(%)

Data Set	Load Data 1	Load Data 2
Fuzzy(σ)	75.14	23.96
Feedforward Fuzzy(σ)	84.42	28.18
Fuzzy(NI)	75.91	21.00
Feedforward Fuzzy(NI)	83.96	28.48

7 CONCLUSIONS

In this paper, portions of a new IAGC system were developed that feature a neural fuzzy controller. This controller uses ACE, $\int ACE$ and a neural network prediction of future load $NNOut$ to control a two-area tie line model using actual utility load disturbances. Simulations were run on three systems, the feedforward fuzzy controller, a fuzzy controller and a PI controlled system. Both of the fuzzy systems show significant improvement over the current method of load-frequency control. A controller that incorporates the knowledge of a feedforward loop is able to improve system response significantly over that of pure feedback systems. This is a major portion of a true IAGC system. In the future load scheduling will be preformed via a optimal dispatch algorithm that will further increase the ability of the controller to match changing demand accurately. Combined the feedforward controller and the optimal dispatch will form a fully functional IAGC system.

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REFERENCES

Jaleeli,N., VanSlyck,L.S., “NERC’s New Control Performance Standards,” IEEE Trans. on Power Systems, Vol. 14, No. 3, pp. 1092-1099, 1999.

Charytoniuk,W., Chen,M., “Very Short-Term Load Forecasting Using Artificial Neural Networks,” IEEE Trans. on Power Systems, Vol. 15, No. 1, pp.263-268, 2000.

Liu,K., Subbarayan, S., Shoults, R.R., Manry,M.T., “Comparison of Very Short-Term Load Forecasting Techniques,” IEEE Trans. on Power Systems, Vol. 11, No. 1, pp.877-882, 1996.

Kim,K., Park,J., Hwang,K., Kim,S., “Implementation of a Hybrid Short-Term Load Forecasting System Using Artificial Neural Networks and Fuzzy Expert Systems”, IEEE Trans. on Power Systems, Vol. 10, No. 3, pp.1534-1539, 1995.

Srinivasan,D., Tan,S., Chang,C.S., Chan E.,“Parallel Neural Network-Fuzzy Expert System Strategy for Short-term Load Forecasting: System Implementation and Performance Evaluation”, IEEE Transactions on Power Systems, Vol. 14, No. 3, pp. 1100-1106, 1999.

Ho,K., Hsu,Y., Yang,C., “Short Term Load Forecasting Using a Multilayer Neural Network with an Adaptive Learning Algorithm,” IEEE Transactions on Power Systems, Vol. 7, No. 1, pp. 141-149, 1992.

Yoo,H., Pimmel,R., “Short term load forecasting using a self-supervised adaptive neural network,” IEEE Transactions on Power Systems, Vol. 14, No. 2, pp. 779-784, 1999.

Khotanzad,A., Hwang,R., Abaye,A., Maratukulam,D., “An Adaptive Modular Artificial Neural Network Hourly Load Forecaster and its Implementation at Electric Utilities,” IEEE Transactions on Power Systems, Vol. 10, No. 3, pp. 1716-1721, 1995.

Chang,C., Fu,W., “Area load frequency control using fuzzy gain scheduling of PI Controllers,” Electric Power Systems Research, Vol. 42, pp. 145-152, 1997.

Chown,G., Hartman,R., “Design and Experience with a Fuzzy Logic Controller for Automatic Generation Control (AGC),” IEEE Transactions on Power systems, Vol. 13, No. 3, pp. 965-970, 1998.

Shoureshi,R., Hoffner,B., Hu,Z., Kramer,R., “Neural-Based Generation Control for Highly Varying and Uncertain Loads,” Power Tech Conference, Institute of Electrical and Electronics Engineers, Porto, Portugal, Sent 2001.
Li,Hanchu., “Neural-Based Feedforward/Feedback Control for Disturbance Rejection with Applications to Electric Power Generation,” Ph.D dissertation of Colorado School of Mines, 1997.
Hu,Zhi, Shoureshi,R., Torgersen,D.,Work,J., “Tsukamoto-Type Neural Fuzzy Inference Network,” American Automatic Control Conference, June 2000.
Kundur,Prabha, “Power System Stability and Control,” EPRI Power System Engineering Series, McGraw-Hill Inc., pp.418-430, 1994.
Hu,Zhi, “Neuro-Fuzzy Short-term Load Forecast and Generation control of Electrical Power Systems,” Ph.D dissertation of Colorado School of Mines, 2000.