THE DEVELOPMENT OF A FUZZY NEURAL SYSTEM FOR LOAD FORECASTING

Liam Paull, Howard Li, Liuchen Chang

Department of Electrical and Computer Engineering
University of New Brunswick, Fredericton, New Brunswick
Liam.Paull@unb.ca Howard@unb.ca Lchang@unb.ca

ABSTRACT

In order to design an aggregate domestic load control system, a controller requires accurate predictions of load curves to make decisions about which loads should be connected to the grid. This paper presents a 24-hour load forecaster to be used by the controller. The forecaster will employ an Artificial Neural Network (ANN) structure with one input provided by a fuzzy weather controller. The use of fuzzy logic will enhance the performance of the system as well as make it more transparent and adaptable. A unique method is introduced to efficiently incorporate a larger number of inputs into the fuzzy controller without the problem of having an unmanageable rule base. The results show that the fuzzy neural system performs better than the artificial neural network load forecaster with further gains possible by fine-tuning the fuzzy logic block.

Index Terms— Load Forecasting, Fuzzy Neural Networks, Fuzzy Logic, Backpropagation

1. INTRODUCTION

Accurate Short Term Load Forecasting (STLF) has become increasingly important as energy markets become more competitive [1]. STLF can have a significant influence on the operational efficiency of a power system. Specifically, unit commitment and demand-side management are affected by accuracy of load forecasts and have a large effect on the economic operation of the utility [2, 3, 4].

Classical load forecasting techniques include: time series, multiple linear regression, and auto regressive moving average [4]. All of these methods have difficulty coping with non-linearities of weather patterns and weekend and holiday variances [3, 5, 6].

Artificial Neural Networks (ANN) have been proposed to compensate for these shortcomings [2, 3, 4, 5, 7, 8]. The strength of the ANN approach is that the system is able to learn highly non-linear input-output mappings directly from the training data. Furthermore, given a sufficiently diverse set of training data and the appropriate inputs, the system can interpolate input patters that are new to the network and produce good results [3,5,9]. However, the ANN approach has the disadvantages that there is high dependence on the choice of inputs and there is often very slow time for convergence [4,9]. Many researchers have suggested the incorporation of some type of Fuzzy Logic (FL) to improve results [2, 3, 4, 5, 6, 9]. Fuzzy theory and ANN theory can be seen as complimentary. ANNs are low-level computational structures that are very good at learning but not good at reasoning. Fuzzy systems are less computationally intense, but are much more transparent and exploit human knowledge to solve problems [3].

Different approaches have been taken to combine these two theories to design load forecasters. Tamimi and Egbert use a FL module as a pre-processor to an ANN [3]. This approach is able to achieve small gains, however, the FL block only considers temperature and not other weather data which can also have an effect on load profiles. Yu-Jun and You-Chan use FL to classify the temperature highs and lows of the two previous days and then use these as inputs to an ANN [5]. They assume that the load curve can be accurately reconstructed from the daily peak and valley load values, which is not always the case.

The proposed system will use the output of a FL block as an input to an ANN. The FL block will account for all weather parameters deemed to have a significant effect on the load profile. A novel approach to implementing the rule base will be used to account for the high number of input variables and rules.

This paper contains the following sections: Section 2 describes the proposed Fuzzy Neural System (FNS) in detail, Section 3 describes an ANN system developed for the purposes of comparison, Section 4 presents some simulation results and discussion, and Section 5 is the conclusion.

2. FUZZY NEURAL SYSTEM IMPLEMENTATION

The system diagram is presented in Fig 1. The Fuzzy Weather Controller (FWC) is used to account for the effect of weather factors on the load predictions using only a single input neuron. The advantage of this design is that the processing of weather data happens in a very tunable and controllable way. The resulting ANN structure requires fewer input neurons to be able to process all of the data.

CCECE/CCGEI May 5-7 2008 Niagara Falls. Canada
978-1-4244-1643-1/08/$25.00

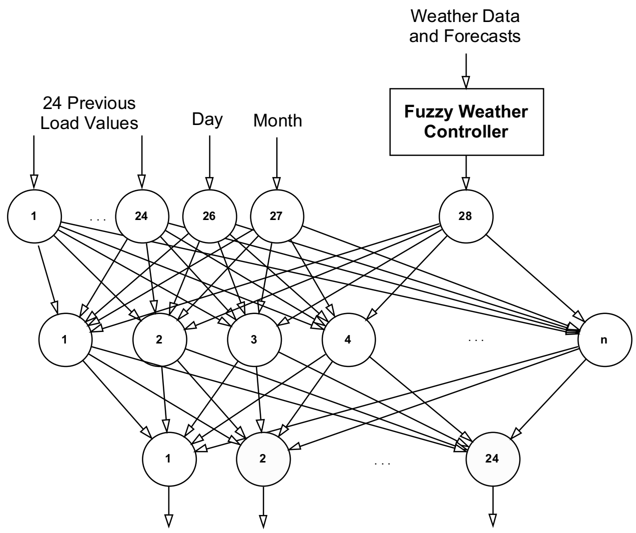

FIG 1 Proposed FNS Description

2.1 Fuzzy Weather Controller

The goal of the FWC is to take all relevant weather data from the previous day, and weather forecasts for the current day, and produce a weather factor in the range [-1,1] to represent how much the forecasted load profile will differ from the profile of the previous day. The specific inputs used are the previous day's maximum temperature, and the forecasted change in temperature, humidity, wind speed, and precipitation. The fuzzy output is generated using the max-min decomposition and the defuzzification method is the centroid [10].

2.1.1 Membership Functions

All inputs have three membership classes presented in Fig 2 and Fig 3. The output has seven possible fuzzy classes as shown in Fig 4.

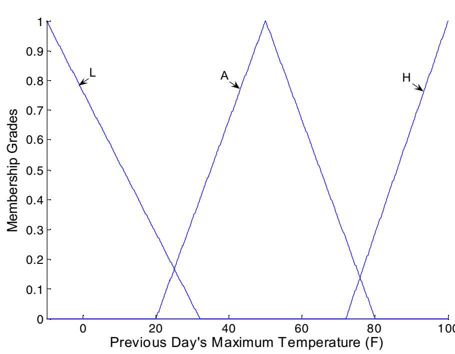

FIG 2 Membership Functions for the Previous Day's Maximum Temperature

In Fig 2, L, A, and H correspond to Low, Average and High temperatures.

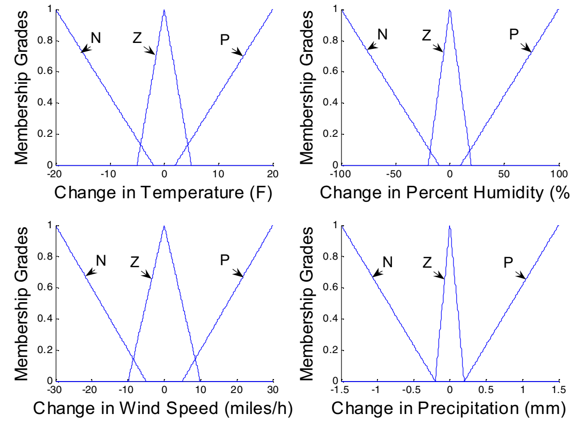

FIG 3 Membership Functions for Relative Inputs

In Fig 3, N, Z and P represent Negative, Zero and Positive. The crisp values are calculated by subtracting the forecast for the current day from the actual value of the previous day. Fuzzifying these values decreases the importance of small errors in weather forecasts.

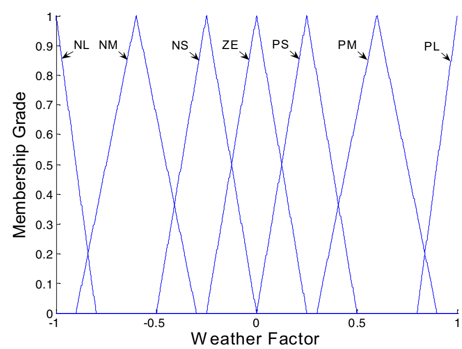

FIG 4 Output Membership Functions

In Fig 4, The terms NL, NM, NS, ZE, PS, PM and PL represent Negative Large, Negative Medium, Negative Small, Zero, Positive Small, Positive Medium, and Positive Large.

2.1.2 Rule Base Definition

The fuzzy rule base is not defined as a matrix as this would require a five dimensional matrix with $3^5 = 243$ rules. Instead, the linguistic rules are implemented using a series of conditional statements that combine to define the appropriate output membership function for each combination of inputs. An example of a rule could be:

```
IF Temperature is High AND
Change in Temperature is Positive AND
Change in Humidity is Positive AND
Change in Precipitation is Zero
THEN Weather Factor is Positive Medium
```

If we map the output classes (NL, NM, NS, ZE, PS, PM, PL) to the indices (-3,-2,-1,0,1,2,3) and make sure to initialize the output to 0 at the start, then we can implement this rule with the following conditionals:

```
If Temperature is High
   If Change in Temperature is Positive
      Increment Weather Factor
   If Change in Humidity is Positive
      Increment Weather Factor
…
```

The result is that the "Weather Factor" will have moved from Z to PS to PM, as is specified by the rule definition. For this example, the rest of the conditionals will not be satisfied.

In the case of high temperature, the "Change in Wind" input is not used as it is expected that it would have little affect on the load profile. Consequently, it is not mentioned in the rule and when computing the fuzzy output using the max-min decomposition, the fuzzy value of the "Change in Wind" input is not considered.

By implementing the rules using conditional statements, it is simple to include some of the inputs in some rules and not in others.

2.2 Artificial Neural Network

Refer to Fig 1 for a description of the full system structure. The network is a fully connected back-propagation network using the sigmoid activation function [10]. There are 27 inputs:

- the normalized previous 24 load values
- the normalized day of the week (holidays implemented with a value of eight)
- the normalized month of the year
- output of the fuzzy controller

The 24 outputs correspond to the load forecasts for an entire day.

3. ARTIFICIAL NEURAL NETWORK USED FOR COMPARISON

The FNS is compared to an ANN system whose construction is shown in Fig 5. This system has 62 input neurons:

- the normalized previous 24 load values
- the normalized day of the week
- the normalized month of the year
- the normalized previous 24 temperature values
- the normalized previous and forecasted day's maximum temperature, minimum temperature, humidity, wind speed, and precipitation.

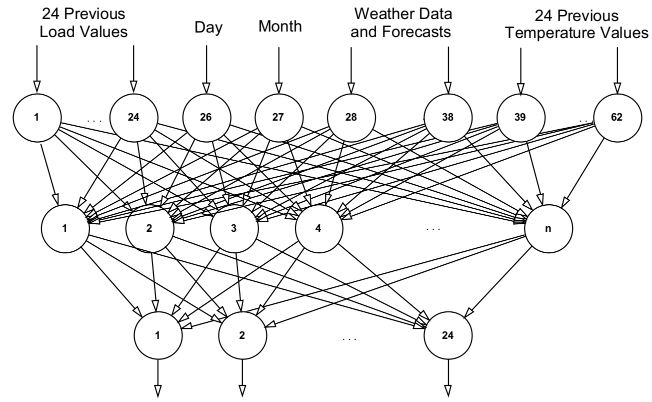

FIG 5 ANN Structure

4. SIMULATION RESULTS AND DISCUSSION

Load Profile data was provided by Saint-John Energy. Weather data was obtained from Environment Canada weather archives[11]. Ten days at random were chosen randomly for testing and were not used in the training of system. Different learning rates, numbers of hidden neurons, and numbers of training epochs were used. The learning rate was found to have less affect on the outcome as the other parameters, so it was held constant at 0.3.

The results for the ANN and FNS system are shown in Table 1 and Table 2 respectively. The accuracy was evaluated using the Mean Absolute Percentage Error (MAPE) [8]:

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{P_A^i - P_F^i}{P_A^i} \times 100\%$$

P^i_A and P^i_F represent actual and forecasted loads respectively. N is the number of samples available.

Epochs	Hidden Neurons	MAPE
100	20	8.6%
1000	50	5.0%
1000	50	4.2%
10000	20	3.9%

TABLE 1 Results of Testing the ANN

Epochs	Hidden Neurons	MAPE
100	20	6.8%
100	50	5.2%
1000	20	4.4%
10000	20	3.5%

TABLE 2 Results of Testing the FNS

Sample plots of daily load curves using the ANN and the FNS systems are provided in Fig 6 and Fig 7.

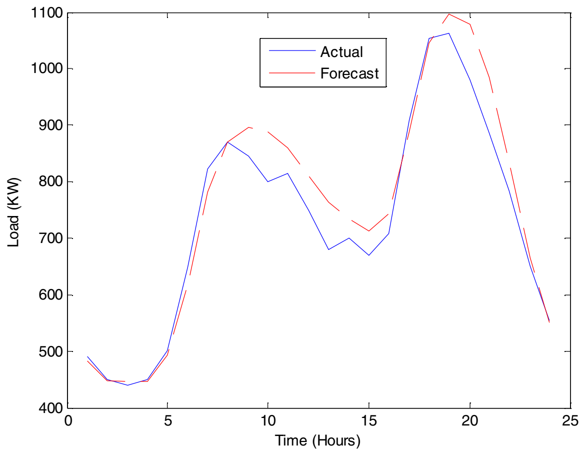

FIG 6 Forecast and Actual Load Values for November 16, 1997, Predicted Using the ANN, 1000 Epochs

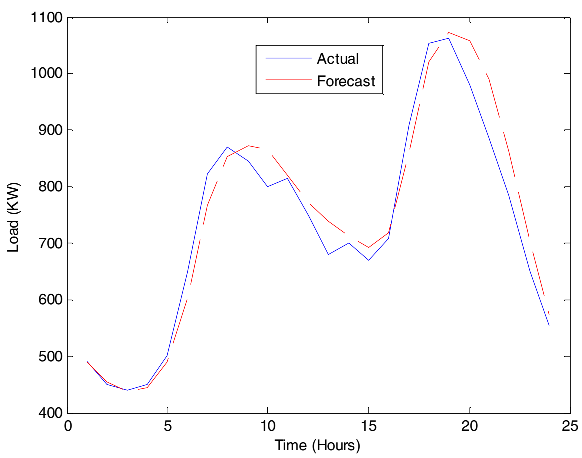

FIG 7 Forecast and Actual Load Values for November 16, 1997, Predicted Using the FNS, 1000 Epochs.

From the results it is clear that the FNS outperforms the ANN. The ANN requires less computation to train, so if the load forecasting is used for a real-time application, then the ANN could be preferable, but in all other cases the FNS represents an improvement. The choice of rules and membership functions for the FNS has a significant effect on the performance of the system. Although the results are quite good, rules that more accurately describe the complex relationship between the weather and the load profiles would yield even better results. This will be attempted in the future.

5. CONCLUSIONS

This paper presents a fully functional FNS for load forecasting that outperforms the alternative ANN structure.

The minimum MAPE for the ANN alone was found to be 3.9%, and the minimum MAPE for the FNS was found to be 3.5%. It is suspected that there are further gains to be made by fine-tuning the membership functions and rules of the FL block.

The framework introduced here is very extendable as there is no limitation to how many inputs or rules can be included in the FL block if different climactic factors were present.

6. REFERENCES

[1] Hippert, H.S.; Pedreira, C.E.; Souza, R.C. Neural networks for short-term load forecasting: a review and evaluation. Source: *IEEE Transactions on Power Systems*, v 16, n 1, Feb. 2001, p 44-55.

[2] Ling, S.H.; Leung, F.H.F.; Lam, H.K.; Tam, P.K.S. Short-term electric load forecasting based on a neural fuzzy network. Source: *IEEE Transactions on Industrial Electronics*, v 50, n 6, Dec. 2003, p 1305-16.

[3] Tamimi, M.; Egbert, R. Short term electric load forecasting via fuzzy neural collaboration. Source: *Electric Power Systems Research*, v 56, n 3, 1 Dec. 2000, p 243-8.

[4] Gwo-Ching Liao; Ta-Peng Tsao. Application of fuzzy neural networks and artificial intelligence for load forecasting. Source: *Electric Power Systems Research*, v 70, n 3, Aug. 2004, p 237-44.

[5] He, Yu-Jun; Zhu, You-Chan; Duan, Dong-Xing; Sun, Wei. Application of neural network model based on combination of fuzzy classification and input selection in short term load forecasting. Source: *Proceedings of the 2006 International Conference on Machine Learning and Cybernetics, ICMLC 2006*, 2006, p 3152-3156.

[6] Rashidi, M.; Rashidi, F.; Monavar, H. Peak load forecasting in power systems using emotional learning based fuzzy logic. Source: *SMC'03 Conference Proceedings. 2003 IEEE International Conference on Systems, Man and Cybernetics. Conference Theme - System Security and Assurance (Cat. No.03CH37483)*, 2003, pt. 2, p 1985-8 vol.2.

[7] Wamkeue, R.; Kandil, N.; Saad, M.; Georges, S. An efficient approach for short term load forecasting using artificial neural networks. Source: *International Journal of Electrical Power & Energy Systems*, v 28, n 8, Oct. 2006, p 525-30.

[8] Senjyu, T.; Takara, H.; Uezato, K.; Funabashi, T. One-hour-ahead load forecasting using neural network. Source: *IEEE Transactions on Power Systems*, v 17, n 1, Feb. 2002, p 113-18.

[9] Ruey-Hsun Liang; Ching-Chi Cheng. Short-term load forecasting by a neuro-fuzzy based approach. Source: *International Journal of Electrical Power & Energy Systems*, v 24, n 2, Feb. 2001, p 103-11.

[10] F. Karray and C. W. de Silva, "Soft Computing and Intelligent Systems Design", Addison-Wesley, New York, 2004

[11] Environment Canada Weather Archives. Visited March 6, http://www.climate.weatheroffice.ec.gc.ca/climateData/canada_e.html.