An Application of Ordered Fuzzy ARTMAP Neural Network in Online Short Term Load Forecasting

SHAHRAM JAVADI
Azad University – Tehran Central Branch
Electrical Engineering Department

Moshanir Power Electric Company
IRAN

HOSSEIN SHOURESTANI
University of Science & Technology
Computer Engineering Department

Moshanir Power Electric Company
IRAN

SHAHRIAR JAVADI
Azad University
Computer Engineering Department

IRAN

Abstract:
This paper presents the application of a new version of Fuzzy ARTMAP neural network named **ordered fuzzy artmap** for evaluating on-line short term load forecasting.
Fuzzy ARTMAP can operate in *off-line* or *on-line* modes. In the on-line mode, the network must process the data as it becomes available, without storing or reusing it. In the off-line mode, the data can be stored and repeatedly presented to the network. In this paper, we consider the off-line operation of fuzzy ARTMAP in classification inputs and then used this classified input to forecast daily load of power network. In particular, we consider one of the major limitations of fuzzy ARTMAP, its dependence on tuning parameters. The performance of fuzzy ARTMAP depends on the values of two parameters called the choice and vigilance parameters, and also on the order of pattern presentation for the off-line mode of training.
To demonstrate the effectiveness of the proposed neural network, short term load forecasting is performed on the IRAN power system. Test results indicate that the special neural network is very effective in improving the accuracy of the forecast hourly loads. For on-line training, the Fuzzy ARTMAP network was found to be a better choice than the other neural networks. Also to enhance performance of specified neural network in off-line classification, we develop it to Ordered Fuzzy ARTMAP network, which has a better performance in input classification.
Keywords: Power Systems, Short Term, Load Forecasting, Ordered Fuzzy ARTMAP, Neural network

1. Introduction

To forecast loads of a day, the hourly load pattern and the maximum and minimum and average of temperature must be determined. A number of algorithms have been suggested for the load-forecasting problem. In our previous paper, we proposed an effective method for on-line short term load forecasting [1]. In that paper a special neural network, named fuzzy ARTmap is used in this regard. You can see such that network, is a good candidate for online applications. In this paper we improve off-line mode of mentioned network, which will effect on total performance of that. To demonstrate the effectiveness of the proposed neural network, short term load forecasting is performed on the IRAN power system. Test results indicate that the special neural network is very effective in improving the accuracy of the forecast hourly loads.

Pattern classification is a key element in many engineering applications. According to Simpson's Fuzzy Min-Max paper [2], a pattern classifier should possess some properties as follows:

1) On-line Adaptation
2) Nonlinear Separability
3) Short Training Time
4) Soft and Hard Decisions
5) Verification and Validation
6) Independent from Tuning Parameters
7) Nonparametric Classification
8) Overlapping Classes

A neural-network classifier that satisfies most of the aforementioned properties is fuzzy adaptive resonance theory mapping (fuzzy ARTMAP) [3]. Fuzzy ARTMAP is capable of establishing arbitrary mappings between an analog input space of arbitrary dimensionality and an analog output space of arbitrary dimensionality. Fuzzy ARTMAP is a member of the class of neural-network architectures referred to as *ART architectures* developed by Carpenter, Grossberg, and colleagues. The ART-architectures are based on the *ART theory* introduced by Grossberg [4].

Fuzzy ARTMAP can operate in *off-line* or *on-line* modes. In the on-line mode, the network must process the data as it becomes available, without storing or reusing it. In the off-line mode, the data can be stored and repeatedly presented to the network. In this paper, we consider the off-line operation of fuzzy ARTMAP in *classification problems*. In particular, we consider one of the major limitations of fuzzy ARTMAP, its dependence on tuning parameters [which is a violation of property (6) above. It has been documented in the literature that the performance of fuzzy ARTMAP depends on the values of two parameters called the choice and vigilance parameters, and also on the order of pattern presentation for the off-line mode of training. To circumvent the first problem, most fuzzy ARTMAP simulations that have appeared in the literature assume zero values for the choice and vigilance parameters. One of the main reasons for the popularity of this choice is that it tends to minimize the size of the resulting network architecture. This is quite desirable, especially when performance comparisons are made between fuzzy ARTMAP and other neural-network architectures that offer more compact representations of the data, such as multilayer perceptrons [5]. The problem of pattern ordering is not as easy to solve. One way around it is to consider different orders of presentations of the training data, in order to find the one that maximizes the performance of the network. The drawbacks of this approach include the considerable experimentation that is required to find a random order of pattern presentation that achieves a good network performance, and the fact that this is essentially a guessing exercise.

In this paper, we preprocess the training data by applying a systematic procedure (based on the Max–Min clustering algorithm [6]), which identifies a fixed order of pattern presentation. We refer to this procedure as the *ordering algorithm*. When the training input patterns are presented to fuzzy ARTMAP according to this fixed order we end up with a trained fuzzy ARTMAP whose generalization performance is better than the average generalization performance of fuzzy ARTMAP, and in certain cases as good as, or better than the best network generalization performance. In the former case we consider the average of a fixed number of experiments corresponding to random orders of training pattern presentations, and in the latter case we consider the best of a fixed number of experiments corresponding to random orders of training pattern presentations. For simplicity, we refer to fuzzy ARTMAP trained with the fixed order of input pattern presentations as ***ordered fuzzy ARTMAP***. Ordered fuzzy ARTMAP has the following desirable properties:

1) It achieves good generalization performance without requiring parameter tuning.

2) The sizes of the networks that ordered fuzzy ARTMAP creates are comparable to the sizes of the networks that fuzzy ARTMAP creates when trained using a random order of pattern presentation.

3) Under mild conditions, the computational overhead imposed by the ordering algorithm is small compared to the computations required to perform the training phase of fuzzy ARTMAP for a single random order of pattern presentation.

Section 2 introduces a brief description of Fuzzy ARTMAP network at a level that is necessary to understand the main results of this paper. In Section 3, we introduce the ordering algorithm. The effect of the ordering algorithm on the categories created by fuzzy ARTMAP, and we explain the motivation for choosing this ordering algorithm. The experiments are discussed and the results are presented in section 4. Finally, the conclusions are drawn in section 5.

2. The Fuzzy ARTMAP network

Fuzzy ARTMAP is a network with an incremental supervised learning algorithm, which combines fuzzy logic and adaptive resonance theory (ART) for recognition of pattern categories and multidimensional maps in response to input vectors presented in an arbitrary order. It realizes a new minimax learning rule, which jointly minimizes the predictive error and maximizes code compression, and therefore generalization [3].

A match tracking process that increases the ART vigilance parameter achieves this by the minimum

amount needed to correct a predictive error. The Fuzzy ARTMAP neural network is composed of two Fuzzy ART modules, namely Fuzzy ART_a and Fuzzy ART_b, which are shown in figure (1).
The Fuzzy ARTMAP in prediction mode is shown in figure (2).
A detailed description of the fuzzy ARTMAP neural network can be found in [3], [7-8].

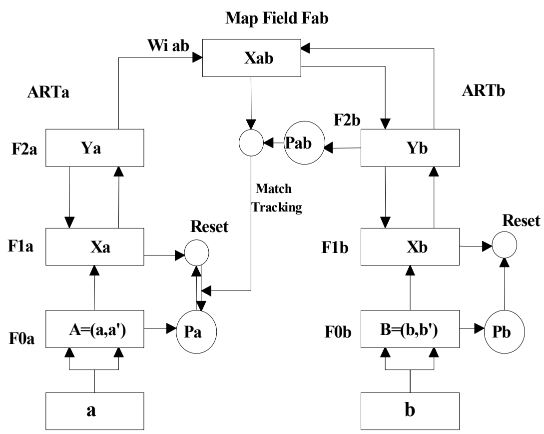

Fig.1. A typical Fuzzy ARTMAP architecture

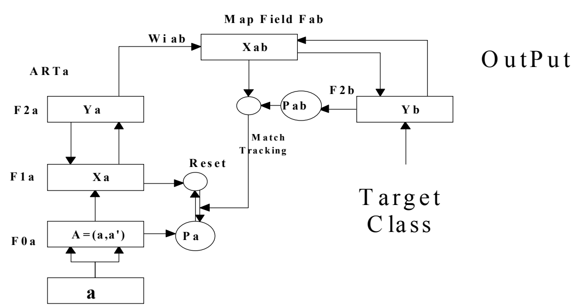

Fig.2. Fuzzy ARTMAP network for classification

3. The Ordering Algorithm

The purpose of the ordering algorithm of ordered fuzzy ARTMAP is to identify the order in which patterns should be presented during the training phase of fuzzy ARTMAP. This task is accomplished by following a systematic procedure that consists of three stages. Before we discuss these stages let us first define the parameters $n_{cluster}$, *PT*, and the set S_T that appear in the algorithm's description. In this paper, the parameter $n_{cluster}$ is taken to be either equal to the number of distinct classes or equal to one more than the number of distinct classes associated with the pattern classification task.
The parameter *PT* stands for the number of input–output pairs in the training list. Finally, S_T is, prior to the application of the ordering algorithm, the set of all training input patterns.
In Stage 1, we choose the first pattern to be presented. This pattern corresponds to the first cluster center of the training input patterns. In Stage 2, we choose the next ($n_{cluster}$-1) patterns to be presented. These patterns correspond to the next ($n_{cluster}$-1) cluster centers of the training input patterns, and are identified using the *Max–Min* clustering algorithm [6].
In Stage 3, we choose the remaining (*PT*- $n_{cluster}$) patterns to be presented. These patterns are chosen according to the minimum Euclidean distance criterion from the cluster centers defined in Stages 1 and 2. Below, we describe in more detail each of these stages.

Stage 1—The First Pattern:

For each pattern $I=(a_1,\dots,a_{Ma},a_{M+1},\dots,\ a_{2Ma})$ in the training set we compute (3). The pattern from the training set that maximizes the above sum is the first pattern presented to ordered fuzzy ARTMAP, and the first cluster center used in Stage 2. The training pattern that maximizes the above sum is removed from the training set. The following two stages of the ordering procedure involve calculation of Euclidean distances among patterns in the training set. In the calculation of these distances only the first M_a components of the input patterns are used (i.e., the a portion of the **I** vector). To avoid switching back and forth between **a** and **I** notation, we refer to these distances as the distances among the **I**'s.

Stage 2—The Next ($n_{cluster}$-1) Patterns:

This stage uses the Max–Min clustering algorithm to define ($n_{cluster}$-1) appropriate cluster centers (patterns), which constitute the next ($n_{cluster}$-1) input patterns to be presented during the training phase of ordered fuzzy ARTMAP. The steps followed to define these cluster centers are as follows. The index *r*, initialized and updated in the step-by-step description of Stage 2, corresponds to the number of clusters that have been identified, at various points, during the implementation of Stage 2.

1) Denote the first cluster center (input pattern) identified in Stage 1 by I_0^1, and initialize the index *r* to one.

2) Compute the Euclidean distance of every input pattern in the training set S_T to the *k*th cluster center, and find the minimum one, d_{min}^I. That is,

$$d_{min}^{\ I} = \min_{1\le k\le r}\left\{ dist\left(I, I_0^k\right)\right\} \qquad (1)$$

3) Find the input pattern from the training set S_T that maximizes d^{I}_{min}, $I \in S_T$. Designate this input pattern by the generic name **I**. The next cluster center, designated by I_0^{r+1}, is equal to **I**, that is $I_0^{r+1} = I$. This cluster center constitutes the next input pattern to be presented during the training phase of ordered fuzzy ARTMAP. Increment by one, and eliminate input pattern **I** from the training set S_T.

4) If $r = n_{clust}$ this stage is completed; otherwise, go to Step (2).

At the end of Stages 1 and 2, we have identified n_{clust} cluster centers that correspond to the input patterns I_0^r, $1 \le r \le n_{clust}$ of the training set. The next stage identifies the order according to which the remaining input patterns should be presented to the ordered fuzzy ARTMAP.

Stage 3—The Remaining (PT-n_{clust}) Input Patterns:

The steps followed in this stage are as follows.

1) Set index r to the value n_{clust}. The patterns in the training set S_T are all of the training input patterns except the ones identified as cluster centers in Stages 1 and 2.

2) Calculate the Euclidean distance of every pattern **I** in the set S_T from the n_{clust} cluster centers.

3) Find the minimum of these distances. Assume that it corresponds to input pattern **I**. This pattern is the next in sequence input pattern to be presented in the training phase of fuzzy ARTMAP. Eliminate **I** from the set S_T, set $I_0^{r+1} = I$, and increment r.

4) If $r = PT$ this stage is complete; otherwise, go to Step (2).

After the end of Stage 3, we have identified the ordered set of patterns $I_0^1, I_0^2, \cdots, I_0^{PT}$. This is the order according to which the patterns in the training set will be presented to the ordered fuzzy ARTMAP. The corresponding outputs of this ordered sequences of input patterns are the outputs from the training list that these input patterns need to be mapped to.

For example, if $I_0^1 = I^2$, then I_0^1's corresponding output is O^2. It is worth mentioning that the ordering algorithm produces is independent of any permutations of the input training patterns.

4. Load Forecasting problem

A number of algorithms have been suggested for the load-forecasting problem. Previous approaches can be generally classified into two categories in accordance with techniques they employ. One approach treats the load pattern as a time series signal and predicts the future load by using various time series analysis techniques [9-15].

The idea of the time series approach is based on the understanding that a load pattern is nothing more than a time series signal with known seasonal, weekly, and daily periodicities. These periodicities give a rough prediction of the load at the given season, day of the week, and time of the day. The difference between the prediction and the actual load can be considered as a stochastic process. By the analysis of this random signal, we may get more accurate prediction. The techniques used for the analysis of this random signal include the Kalman filtering [16], the Box-Jenkins method, the autoregressive moving average (ARMA) model [17], and spectral expansion technique.

The Kalman filter approach requires estimation of a covariance matrix. The possible high nonstationarity of the load pattern, however, typically may not allow an accurate estimate to be made.

These methods are very time consuming and difficult. More recently the application of neural network has developed in many of engineering problems. One of these problems is forecasting of load hourly by back propagation method [18] or KOHONEN neural network classifier.

In this paper, a different approach is proposed for load forecasting. This approach is based on Fuzzy ARTMAP network. Because of self-organized characteristic of these networks, they can be used online in power systems for load forecasting. It is shown in figure (3).

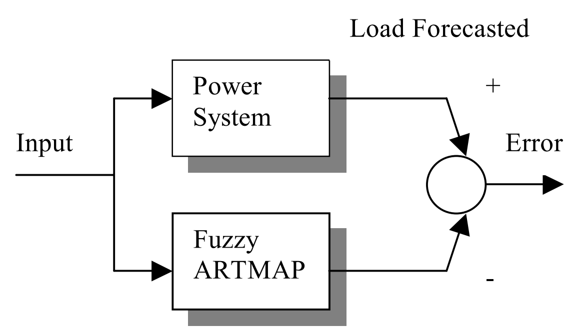

Fig.3. On-Line Training

5. Simulations

In order to test the algorithm for its effectiveness in Load Forecasting of a power system, we chose data, which is obtained from dispatching center of TAVANIR Co and in order to better understand the differences between a random order of training pattern presentation and the proposed fixed order of training pattern presentation, we present some illustrative examples.

We study 2 cases. In cases 1, we use Fuzzy ARTMAP Network and in case 2, an ordered Fuzzy ARTMAP Network is used. Finally the obtained results are compared.
In each case, performance error of neural network is calculated according to the following formula [19]:

$$E = \frac{1}{N}\left(\sqrt{\sum_{i=1}^{N}\left(y_{di} - y_{ai}\right)^2}\right) \qquad (2)$$

Where,
y_{di} : Desired output of Neural Network.
y_{ai} : Actual output of Neural Network.
N : Number of Data Set for Training.

Case 1 (Fuzzy ARTMAP network):
In this case we use a Fuzzy ARTMAP neural network to predict load of next day according current day. In this test, parameter ρ was chosen to be ρ_a=0.95, ρ_b=0.94, ρ_{ab}=0.93. A set of 1000 training patterns was selected from the entire set. After training the network with 1000 patterns, the set of 1000 remained patterns was used to test network. It can be shown in figure (4).

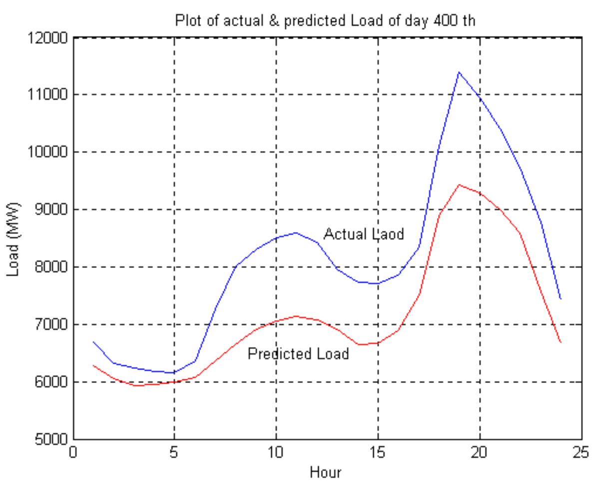

Fig.4. Actual Load respected to Predicted Load by FAM neural network

Case 2 (Ordered Fuzzy ARTMAP):
In this case we used a fuzzy ARTMAP Neural-Network with fixed ordered data in training mode. Also we used the same input bit patterns. Error in this case is higher than the above cases and computing time for training is too high. It is shown in figure (5).

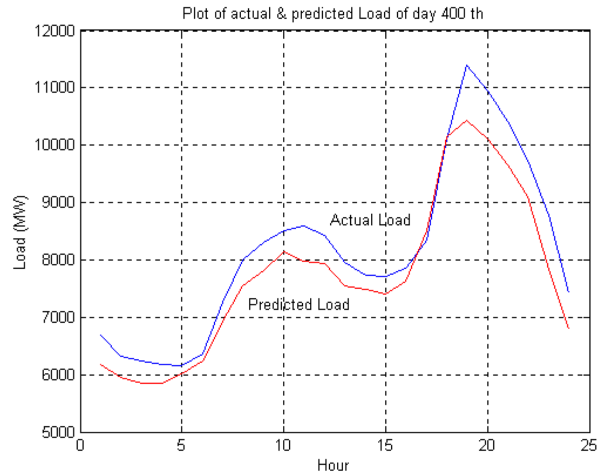

Fig.5. Actual Load respected to Predicted Load by Ordered FAM neural network

The major motivation for our work was the design of a fuzzy ARTMAP algorithm that is independent of the tuning of parameters, and achieves good generalization by avoiding excessive experimentation. The dependence of fuzzy ARTMAP on the choice parameter and the vigilance parameter is an inherent characteristic of the algorithm. Choosing these parameters equal to zero frees the experimenter from the tedious task of optimizing the network performance with respect to these two parameters. With the choice parameter and the vigilance parameter chosen equal to zero, one ends up with a fuzzy ARTMAP algorithm that exhibits a significant variation in generalization performance for different orders of training pattern presentations. Furthermore, it is not an easy task to guess which one of the exceedingly large number of orders of pattern presentations exhibits the best generalization.

6. Conclusions

In this paper we introduced a procedure, referred to as the ordering algorithm that identifies a fixed order of training pattern presentation for fuzzy ARTMAP. The ordering algorithm is based on the Max–Min clustering algorithm. The combination of the ordering algorithm and fuzzy ARTMAP is called ordered fuzzy ARTMAP. Experiments with nine different classification problems have shown that ordered fuzzy ARTMAP attains a superior generalization performance as compared to the average performance of fuzzy ARTMAP, and in certain cases as good as, or better than the best fuzzy ARTMAP generalization performance. The average and best generalization performances are obtained over a fixed number of experiments with fuzzy ARTMAP corresponding to different orders of training pattern

presentations. We also demonstrated that under mild conditions on the pattern classification tasks, the operations required by the ordering algorithm is a fraction of the operations required by the training phase of fuzzy ARTMAP for a single order of training pattern presentation.
Furthermore, the sizes of the network architectures that ordered fuzzy ARTMAP creates are comparable to the average size of the network architectures that fuzzy ARTMAP creates.

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