ARTIFICIAL NEURAL NETWORK-BASED DISTRIBUTION SUBSTATION AND FEEDER LOAD FORECAST

J. Yasuoka$^{1}$  J. L. P. Brittes$^{2}$  H. P. Schmidt$^{1}$  J. A. Jardini$^{1}$

$^{1}$ Escola Politécnica da Universidade de São Paulo - Brazil  
$^{2}$ Companhia Paulista de Força e Luz - CPFL - Campinas, SP - Brazil

ABSTRACT

Artificial Neural Networks (ANNs) have been successfully applied to the problem of forecasting future load values, especially in the short term framework (a few minutes to a few hours ahead). Traditional analytical models have shown difficulties when dealing with (i) the highly variable demand curve shapes, (ii) some independent variables that exhibit random behaviour, and (iii) the identification of variables that could explain relevant load variations, such as weather variables. Current available ANN applications to this problem are by far aimed at a systemwide level, where the load behaviour is more regular than at substation or even primary feeder levels.

This work presents the application of an ANN-based methodology for forecasting load values in two time frames, namely one or more 15-minute intervals and 24 hours. Input variables are current and past values of demand and ambient temperature. Output variables are forecasted (future) values of demand. Demand data can be originated either from distribution substation transformers or from primary feeders.

This methodology has been implemented as a software tool which is currently running on a local computer in the Campinas Centro substation. This is one of the most important CPFL’s distribution substation, and is equipped with three 138/11.9-kV, 40-MVA transformers. Input values are made available through the substation’s data-acquisition system.

Results obtained with this implementation are very encouraging, even when using as little historical data as 3 months. Forecast error is also very low when a demand curve substantially different from the ones presented to the Artificial Neural Network in its training phase are used in the processing mode. A separate module for dealing with load transfers between primary feeders during contingencies is currently in its final stages of development.
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ABSTRACT

A methodology for estimating future demand values at both distribution substation and primary feeder levels is described in this paper. The software implementation of the proposed methodology is already running in a 138/11.9-kV, 3x40-MVA distribution substation. Results obtained with this implementation are very encouraging, even when using as little historical data as 3 months. Forecast error is also very low when a demand curve substantially different from the ones presented to the Artificial Neural Network in its training phase are used in the processing mode. A separate module for dealing with load transfers between primary feeders during contingencies is currently in its final stages of development.

1. INTRODUCTION

Artificial Neural Networks (ANNs) have been successfully applied to the problem of forecasting future load values, especially in the short term framework (a few minutes to a few hours ahead) (1), (2), (3). Traditional analytical models have shown difficulties when dealing with (i) the highly variable demand curve shapes, (ii) some independent variables that exhibit random behaviour, and (iii) the identification of variables that could explain relevant load variations, such as weather variables. Current available ANN applications to this problem are by far aimed at a systemwide level, where the load behaviour is more regular than at substation or even primary feeder levels.

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The paper is organised as follows. Section 2 describes the most relevant aspects of the proposed methodology. Section 3 presents and discusses the results obtained in a number of study cases obtained from the online operation of the software tool. Section 4 discusses the automatic detection of load transfer between primary feeders, a major improvement which is currently being incorporated in the proposed methodology, and it also presents the conclusions of the paper.

2. METHODOLOGY

2.1 - Introduction

This section presents the most important aspects of the proposed methodology. For the sake of clarity, topics are grouped in the following sub-sections: Multi-Layer Perceptron (MLP) model, input and output variables, short-term forecast and 24-hour forecast, and online operation of the software tool.

2.2 - MLP model

The MLP model is the most popular paradigm of ANNs (4). This success is primarily associated with its ease of implementation and testing. An MLP network can be seen as a very versatile interpolator that produces a set of output values (output vector) for a given set of input values (input vector), thus being able to mimic complex mappings between input and output variables in situations where the physical relationship linking these variables is difficult or even impossible to obtain.

To achieve this, the MLP possesses a number of basic units called neurons (5), (6). These neurons are arranged in layers in the same way that biological neurons are found in the human brain. The working rules of artificial neurons are also inspired on their biological counterparts. Basically, an artificial neuron computes the weighted sum of its inputs and applies a non-linear function to the result. Inputs for a neuron in a particular layer are the outputs of the neurons in the preceding layer. In the particular case of the first layer, inputs to each neuron are the inputs to the MLP itself. Conversely, outputs of the neurons in the last layer are the very outputs of the MLP.

The fact that every single neuron applies a non-linear function to the sum of its weighted inputs makes the MLP capable of representing complex functions. The
weights applied to the inputs of each neuron represent the degrees of freedom of the MLP model. They are modified during the training phase, whereby sets of input vectors and their associated output vectors are sequentially presented to the MLP. The modification of the weights is automatically executed by the training algorithm so as to minimise the difference between a calculated output vector and the corresponding desired output vector. For this reason, MLP training is of supervised type, because reference values for the outputs must be known prior to starting the training phase. Most MLP training algorithms are derived from a basic procedure called Error Back Propagation (5), (6). MLP training is an iterative procedure that possesses a few control parameters for evaluating convergence and deciding when to stop iterations.

After the training phase is completed, all MLP weights have a well-defined value that will not change in time (unless more training iterations are performed). In this moment, the MLP is ready for use in processing mode, where only input vectors are presented to it.

Besides the ability of constructing representations of complex functions just by processing pairs of input and output vectors (and thus without knowing the underlying analytical expressions), the MLP model offers the following advantages: (i) it is capable of producing a good output vector for an input vector that it never saw during the training phase (generalisation ability), and (ii) CPU times required in processing mode are almost always negligible, making the MLP a suitable choice for online applications.

### 2.3 - Input and output variables

The proposed methodology considers the following variables for defining the MLP input vector:

- time of forecast;
- recorded demand at current time;
- recorded demand at previous times;
- ambient temperature at current time;
- ambient temperature at previous times,

which will be explained as follows. The time of forecast is the time at which a demand value will be forecasted. It is represented by an integer number varying between 1 and 96, the value 1 corresponding to the interval between 0h00min and 0h15min and the value 96 corresponding to the interval between 23h45min and 0h00min (15-minute intervals used). The recorded demand at any time \( t \) \((1 \leq t \leq 96)\) represents the average demand in kW registered in the interval associated with time \( t \). The ambient temperature daily curve is treated exactly in the same way as the demand daily curve. The first three input variables listed above (time of forecast, recorded demand at current time and recorded demand at previous times) are mandatory, whereas the last two (ambient temperature at current time and ambient temperature at previous times) are optional. This allows for estimating the influence of ambient temperature on the load forecast quality, as will be seen in the next Section. Demand values for a particular MLP setup can be originated either from any of the substation transformers or from any of the primary feeders. Ambient temperature values are those recorded at the substation.

The output vector is defined using one or more values of future demand; that is, demand values at times \( t \) greater than the current time. Table 1 shows an example of an input vector and its associated output vector for:

- time of forecast \( t = 36 \);
- 1 current demand value \((t = 35)\);
- 3 previous demand values;
- 2 future demand values;
- no ambient temperature considered.

During normal operation, the MLP reads input vectors made available by the data-acquisition system and produces estimates of future load using the knowledge acquired during training (stored in its weights).

#### 2.4 - Short-term forecast and 24-hour forecast

Demand forecasts can be produced within two time frames, namely one or more 15-minute intervals and one 24-hour interval.

In the first case, referred to as short-term forecast, the input vectors contain a few current/previous demand values (typically 3 to 5) and the output vectors contain 1, 2, 4 or 8 future demand values (1 for 15-minute ahead forecast, 2 for 30-minute ahead forecast and so on). In the example shown in Table 1, 4 current/previous demand values and a 30-minute ahead forecast were considered. The short-term forecast is aimed at estimating the transformer future loading looking through a very short time perspective, regardless of other longer-term information such as recorded loading in the preceding days.

**TABLE 1 - Example of input vector and associated output vector**

<table>
<thead>
<tr>
<th>Address</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>36</td>
</tr>
<tr>
<td>2</td>
<td>( D_{35} )</td>
</tr>
<tr>
<td>3</td>
<td>( D_{34} )</td>
</tr>
<tr>
<td>4</td>
<td>( D_{33} )</td>
</tr>
<tr>
<td>5</td>
<td>( D_{32} )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Address</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( D_{36} )</td>
</tr>
<tr>
<td>2</td>
<td>( D_{37} )</td>
</tr>
</tbody>
</table>

Estimated demand values with an anticipation of 15, 30, 60 or 120 minutes allow a fast thermal analysis of the transformer to be performed, so there would be enough time to make decisions as to whether or not accept
temporary overloads in the presence of unexpected high demand values. The final goal in this case is to develop a transformer management strategy based not only on loading, but also on thermal and loss of life parameters.

In the second case, referred to as 24-hour forecast, each day is represented by 24 values (hourly demand values). An input vector always represents an integer number of days, thus containing a number of values that is multiple of 24. The output vectors always represent a unique day, and therefore contain exactly 24 values. 24-hour forecast is aimed at taking into account relevant information that may affect a particular day’s demand curve, within a time frame of one, two or three previous days.

2.5 - Online operation

Figure 1 shows a representation of the software tool, as well as its interface with the distribution substation data acquisition system.

The implementation consists of four main modules (Modules 1, 2, 3 and 4). Module 1 is responsible for producing estimates of future load according to the methodology described in the previous subsections. Module 2 reads the load estimates produced by module 1 and carries out a thermal analysis of the substation transformer, whereby future values of temperature of the transformer’s hot spot are estimated. Module 3 then generates values of short-term firm available power (FAP), which give the amount of power (MVA) that can be extracted from the transformer during emergency conditions without implying dangerous temperature values. FAP values are computed with a time frame of 0.5, 1 and 2 hours ahead, so the operational personnel owns important information regarding the individual situation of each transformer. The computation of FAP values also takes into account the associated risk of transformer failure as a function of the transformer loading and health condition (identified by measurements of gas, humidity, etc.). Risk estimation is performed by Module 4. At present, Modules 1 are 2 are already implemented, while Modules 3 and 4 are in their final stages of development.

Existing power transformers and primary feeders at Campinas Centro substation provide online data through Intelligent Electronic Devices (IEDs). These data feed the SCADA system with voltage and current values averaged at 1-minute intervals. The SCADA system initially stores this information in a built-in online database, and then passes it on to an external, historic database. Communication among all system components is provided by a local Ethernet network using the TCP/IP protocol. Although not part of the scope of this paper, it is worth mentioning that the third transformer installed in the substation has built-in optical sensors that allow a better evaluation of hot spot temperature.

3. RESULTS

3.1 - Introduction

This Section presents results produced by the current implementation of the load forecast software tool. A few combinations of transformer/primary feeder, short-term/24-hour forecast and with/without ambient temperature are presented in the following sub-sections.

3.2 - Substation transformer 24-hour forecast

In this case, ambient temperature information was not considered. Figure 2 shows the transformer daily demand curves used in MLP’s training. These curves correspond to Mondays between 01 January 1998 and 28 December 1998 (total of 41 days).

Figure 3 shows a particular testing set, which consists of Mondays 04 and 11 January 1999 (input vectors) and Monday 18 January 1999 (reference output vector).

Figure 4 shows the reference curve (E1) and the output curve (C1) calculated by the MLP for Monday 18 January 2000.
The number of MLP inputs and outputs in this case are 48 and 24, respectively, with two 15-unit hidden layers. Average error, maximum forecast error and standard deviation of the error are 5.7%, 9.4% and 2.1% respectively.

Figure 3 - Testing set for transformer 24-hour forecast

Figure 4 - MLP performance for transformer 24-hour forecast

### 3.3 - Substation transformer short-term forecast

In this case, ambient temperature was not considered. Training days were all Mondays between 21 June 1998 and 20 September 1998. Two different training sets were assembled: one for 1-interval forecast (15 minutes ahead) and other for 8-interval forecast (2 hours ahead). Testing day was taken as Monday, 21 September 1998.

In the first case, average error, maximum forecast error and standard deviation of the error are 1.4%, 5.2% and 0.9% respectively. Figure 5 shows reference (E1) and calculated (C1) curves.

In the second case (8-interval forecast), the MLP estimates 8 values of future load, the first of them corresponding to the 15-minute ahead forecast. This value is directly comparable to the forecast produced in the first case (1-interval forecast), and the resulting average error, maximum forecast error and standard deviation of the error for this interval are 1.6%, 7.5% and 0.9% respectively. This values are greater than those of the first case, as expected, because in the second case the MLP possesses a greater number of weights and outputs.

Figure 5 - MLP performance for transformer short-term, 1-interval forecast

Average error, maximum forecast error and standard deviation of the error for the 8th interval are 5.0%, 24.8% and 3.5% respectively. Again, larger errors for the 8th interval in comparison to the 1st interval were expected because the more distant in future time the forecast, the less influence of current and past demand values.

Figure 6 shows reference (E1) and calculated (C1) curves for the second case.

Figure 6 - MLP performance for transformer short-term, 8-interval forecast

### 3.4 - Substation transformer short-term forecast with ambient temperature

In this case, ambient temperature was considered. Training days were Mondays between 21 June 1998 and 13 September 1998. Only 1-interval forecast (15 minutes ahead) was considered Testing day was taken as Monday, 14 September 1998.

Average error, maximum forecast error and standard deviation of the error for this case are 1.4%, 3.8% and
0.7% respectively. These values are slightly smaller than the corresponding ones when ambient temperature were not considered (sub-section 3.3), indicating that this parameter has little influence on forecast precision. This conclusion is currently under thorough investigation.

Figure 7 shows reference (E1) and calculated (C1) curves for this case.

![Figure 7 - MLP performance for transformer short-term, 1-interval forecast, including ambient temperature](image)

3.5 - Primary feeder short-term forecast

In this case, ambient temperature was not considered. Training days were all Mondays between 01 July 1999 and 13 September 1999. Only 1-interval forecast (15 minutes ahead) was considered Testing day was taken as Monday, 20 September 1999.

Average error, maximum forecast error and standard deviation of the error for this case are 1.6%, 7.9% and 1.1% respectively. Errors in primary feeder forecast are usually larger than in transformer forecast, since daily load curves of feeders are less regular than transformer daily load curves. Figure 8 shows reference (E1) and calculated (C1) curves in this case.

![Figure 8 - MLP performance for primary feeder short-term forecast](image)

4. CONCLUSION

This paper has presented a methodology for producing estimates of future load values in distribution systems using ANNs. A software tool is currently running in a real-world distribution substation and preliminary results are very encouraging regarding forecast errors.

Besides the continuing development of Modules 3 and 4 (FAP value estimation and risk assessment), an important extension that is in advanced stage of development corresponds to the automatic detection of load transfer between feeders and/or substations during contingency situations. The problem in this case is how to produce accurate estimates of future demand values knowing that a switching operation in the primary network has a substantial impact on the load profiles of the involved feeders. An MLP network trained with normal data only (without contingency situations) does not perform well when such situations arise. On the other hand, assembling comprehensive training sets allowing for all switching combinations leads to enormous amount of data and additional training difficulties.

REFERENCES


