ASSESSMENT OF THE CHANGE IN THE NUMBER OF NEURONS IN HIDDEN LAYERS OF NEURAL NETWORKS FOR FAULT IDENTIFICATION IN ELECTRICAL SYSTEMS

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Abstract: This work describes performance evaluation of ANNs (Artificial Neural Networks) used to identify faults in electrical systems for several number of neurons in the hidden layers. The number of neurons in the hidden layers depends on the complexity of the problem to be represented. Currently, there are no reliable rules for determining, a priori, the number of hidden neurons, so that such number depends largely on the experience of the practitioners who are designing the ANNs. This paper reports experiment results using neural networks varying the number of hidden neurons to aid the neural network user to find an adequate configuration in terms of number of neurons in the hidden layers so that ANNs be more efficient particularly for fault identification applications.

1 INTRODUCTION

The need for assessing the performance of ANNs in terms of the number of neurons in the hidden layers emerged during the development of a system for identifying faults in electrical systems. This work is described briefly below.

The research was divided into the following main parts: (i) study of power systems and the problem of identification of its faults, (ii) study of artificial intelligence and intelligent systems and (iii) system model to support and test ANN configurations and learning algorithms. It is not difficult to notice the increasing use of energy as a promoter of economic and social development. This is essential either for large industries, banks and all kinds of business or to homes, even the humblest of them. There is a growing demand for high quality energy needed to also supply an increasing number of digital equipment.

The prompt identification of failures can help to achieve these requirements. The operators of electrical systems may have trouble in identifying faults properly and make the right decisions on corrective actions to be adopted, which could lead to fault misidentification. The investigation of the problem also involves interviews with experts in the area, aiming not only to grasp the specific knowledge about the problem but also to find the best solution to solve it. The system modelling and system development characterizes the system architecture so that simulations are performed to test the ANN configurations.

2 SYSTEM MODEL

A typical electrical substation was chosen to be investigated as detailed in sequence.

That substation was divided into functional units called bays. For this substation, there are five types of bays for a total number of 19 bays. Table 1 shows the general data for those bays, such as the number of alarms and faults defined for each of those bays.

That is a typical problem of pattern classification, where ANNs can be used to map groups of alarms on failures.

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Table 1: General Data of Bays in a Substation.

Type of BAY	Quantity.	Alarms for a Bay	Failures to a Bay	Total alarms by Bay	Total failures Bay
Feeder	11	16	20	176	220
Capacitor Bank	2	19	20	38	40
General Secondary	2	19	62	38	124
Line	2	13	32	26	64
Backward	2	67	157	134	314
TOTAL:	19	134	291	412	762

3 INTELLIGENT SYSTEM MODELLING

Intelligent System modelling and development involves defining the architecture and simulation strategies that will define the necessary tests and simulations (Silva, D.T., 2008).

The first alternative uses a single neural network that receives all the alarms and returns their failures. Such neural network would have 412 inputs (alarms) and would deal with 762 faults. It resuls in a very large neural network and would require too much time to train it.

As the substation can be divided into functional blocks, called bays which are repeated in other substations, that approach was adopted in order to characterize the system identification failures. The adopted model comprises a set of ANNs, responsible for identifying the faults.

The advantage of using several ANNs, one for each functional block, or bay, will be apparent later on.

The general system diagram is depicted in figure 1.

The identification of faults is carried out by a set of five ANNs, each specializing in a bay of the electrical system (Feeder, Capacitor Bank, General Secondary Line and Backward). Each ANN has the function to map groups of alarms into specific failures. It is, therefore, a typical problem of pattern classification (Biondi, 1997), where each neural network is trained using the backpropagation algorithm. The used patterns for training are provided by experts, consisting of combinations of 412 alarms, for a total number of 762 faults.

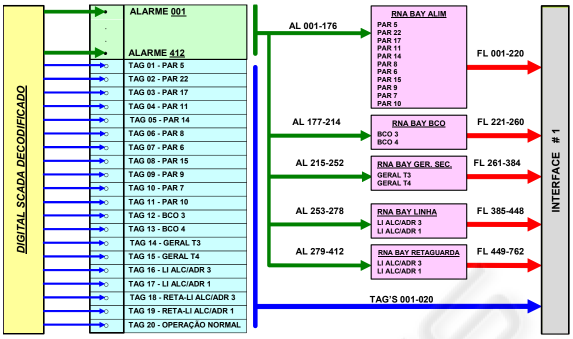

Figure 1: Failure identification System diagram.

For each type of bay, two ANNs models were considered. For the first model, the first layer had a number of output neurons which was the same as the number of possible failures for that bay. The second model had a single neuron in the output.

4 NUMBER OF NEURONS IN THE HIDDEN LAYER

The number of neurons in the input layer is determined by the number of alarms in a bay, i.e., there is one neuron for each alarm and the number of neurons in the output layer equals the number of possible failures for a given bay, such as the case of an ANN with multiple neurons in the output according to the first model.

The number of neurons in the input and output are fixed, so this paper will consider changing the number of neurons in the hidden layers.

It should be noted that for the ANN with multiple neurons in the output layer there are two hidden layers and the ANN with one neuron in the output there are three hidden layers.

In order to better organize the simulations equal numbers of hidden layers neurons were used, although the simulations could be easily adapted for testing with different numbers of neurons in those layers.

Now some simulations results are presented involving some investigated ANNs.

Figure 2 shows a Feeder bay ANN with multiple neurons in the output.

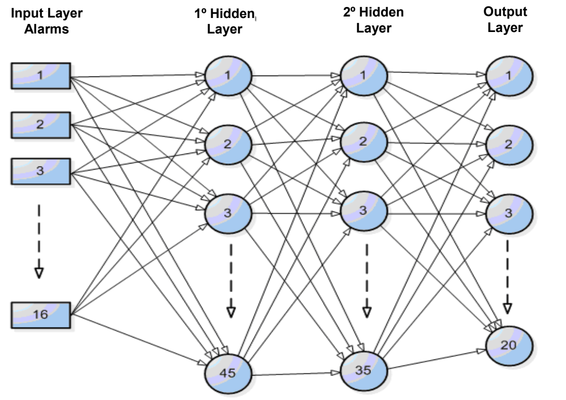

Figure 2: Feeder bay ANN with multiple neurons in the output.

The main characteristics used in the training simulation test for the feeder bay were:

- Learning Algorithm: Resilient;
- Minimum number of neurons in all hidden layers: 10;
- Maximum number of neurons in the inner layers: 125;
- Number of tests for each number of neurons: 10;
- Step increase of the number of neurons in relation to the last setting: 5;

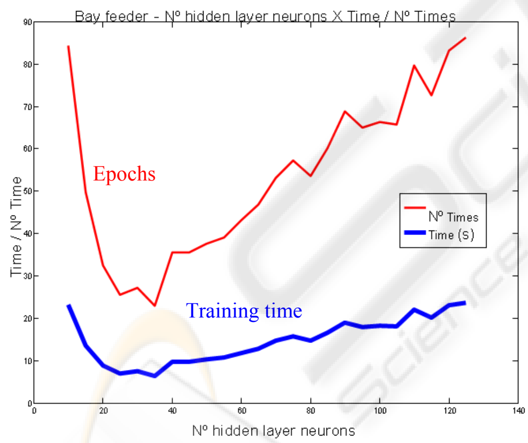

Figure 3: Hidden layers neurons X time & epochs for feeder bay and multiple neurons output ANN.

Figure 3 shows that the best configuration in terms of minimum number of epochs and training time is the one with 35 neurons in the hidden layers. The resulting training time was about 7 seconds.

Figure 4 depicts a Capacitor bank bay ANN with multiple output neurons.

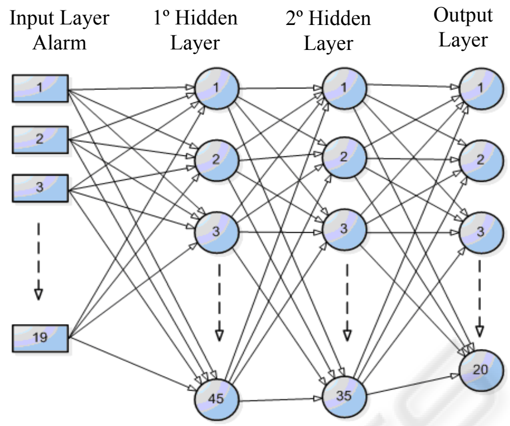

Figure 4: Capacitor bank bay ANN with multiple neurons in the output.

For training such neural network the simulation test parameters were:

- Learning algorithm: Resilient
- Minimum number of neurons in all hidden layers: 10;
- Maximum number of neurons in all hidden layers: 115;
- Number of tests for each number of neurons: 10;
- Step increase of the number of neurons in relation to the last setting: 5;

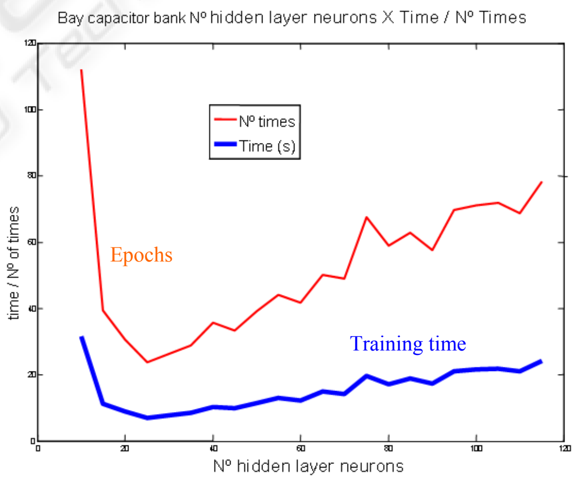

Figure 5: Hidden layers neurons X time & epochs for capacitor bank bay and multiple neurons output ANN.

One can see in figure 5 that the best configuration is the one with 25 neurons in the hidden layers and the corresponding training time is about 7 seconds and an average number of epochs of 23.8.

Next, a line bay ANN is considered with multiple output neurons as shown in figure 6.

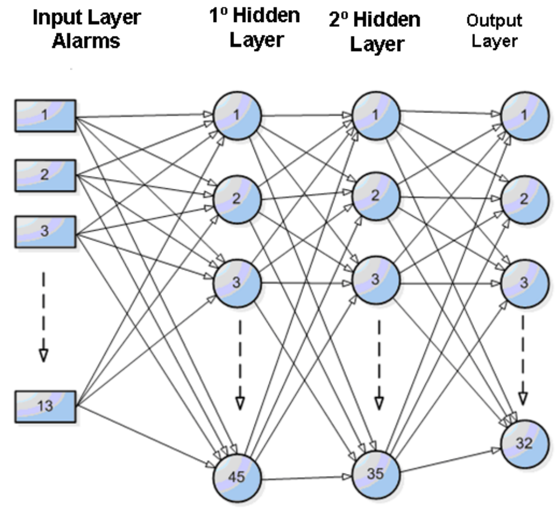

Figure 6: Line bay ANN with multiple neurons in the output.

The main characteristics used in the training simulation test for the line bay were:

- Learning Algorithm: Resilient
- Minimum number of neurons in all the hidden layers: 10;
- Maximum number of neurons in all the hidden layers: 85;
- Number of tests for each number of neurons: 10;
- Step increase of the number of neurons in relation to the last setting: 5;

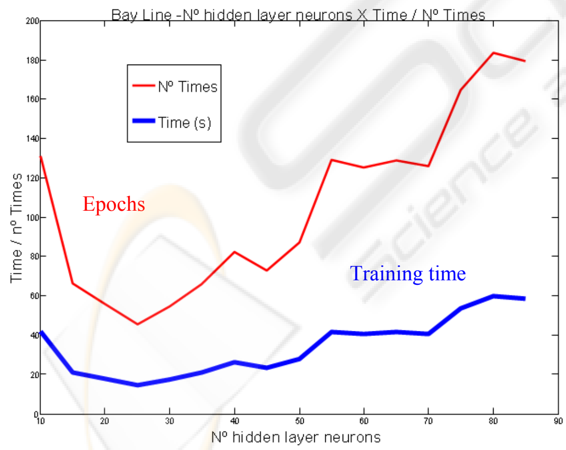

Figure 7: Hidden layers neurons X time & epochs forline bay and multiple neurons output ANN.

Figure 7 shows that the best configuration is the one with 25 neurons in the hidden layers. The training time was 14.5 seconds and the corresponding number of epochs was 45.4.

The last simulation test that was carried out considered a feeder bay ANN with one output neuron.

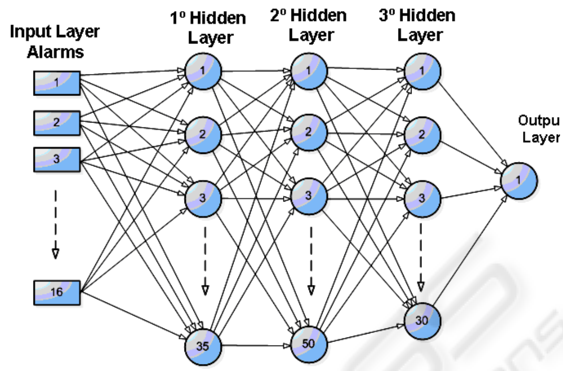

Figure 8: Feeder bay ANN with one output neuron.

For training such neural network the simulation test parameters were:

- Learning Algorithm: Resilient
- Minimum number of neurons in all the hidden layers: 15;
- Maximum number of neurons in all the hidden layers: 75;
- Number of tests for each number of neurons: 10;
- Step increase of the number of neurons in relation to the last setting: 5;

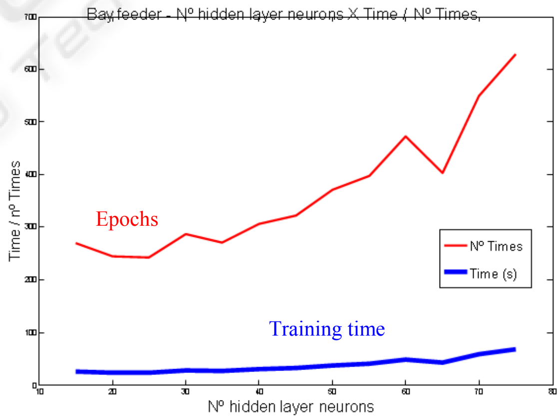

Figure 9: Hidden layers neurons X time & epochs for feeder bay and one output neurons ANN.

It can be seen in figure 9 that the best ANN configuration in the sense of minimum training time is the one with 20 neurons in the hidden layers. The corresponding training time was 23 seconds. Concerning the number of epochs, the best ANN with such a minimum number is the one with 20 neurons in the hidden layers which yielded 242 epochs.

5 CONCLUSIONS

This paper presented preliminary results based on experiments from simulations involving the training of ANNs with different configurations in terms of number of neurons in the hidden layers. The applications concerned fault identification in electrical systems. The aim of such experiments was to search for some evidence and patterns that might be useful for finding procedures and methods for determining the number of neurons in the hidden layers of feed forward ANNs. The simulation tests indicated some regularity concerning the best selected ANN in terms of training time.

There is some ongoing research done worth mentioning e.g. Ostafe (Ostafe, 2005) uses a clustering technique to help in the determination of the optimal number of neurons in the hidden layer. More recently Xu and Chen (Xu, 2008) proposes an elegant way to find such an optimal number using a complexity regularization approach for data mining applications. They find an expression of the number of neurons in the hidden layer which is based on the target function which is unknown on most practical problems. Therefore they propose to optimize a similar such an expression to derive the number of neurons from the observed data e.g., the training pairs, using a complexity regularization approach.

Future research directions include to properly select the training data and using some variations on the optimization criteria performed by Xu and Chen (Xu, 2008) and also combine part of the simulations tests described in the previous section to aid in assessing the efficiency of the optimization process.

REFERENCES

Biondi, L. N., 1997. *Hybrid System for Decision Support for Detection and Fault Diagnostics in Electrical Networks.* M.Sc. Dissertation, PUC-Rio, Rio de Janeiro, R.J., Brazil. In Portuguese.

Silva, D. T., 2008. *Decision Support System for Fault Identification in Electrical Energy Distribution Systems Networks Using Artificial Neural Networks*. M. Sc. Dissertation, State University of Rio de Janeiro, R.J., Brazil. In Portuguese.

Ostafe, D., 2005. Neural Network Hidden Layer Number Determination Using Pattern Recognition Techniques. In *Proceedings of the 2nd Romanian-Hungarian Joint Symposium on Applied Computational Intelligence (SACI 2005).*

Xu, S., and Chen, L., 2008. A Novel Approach for Determining the Optimal Number of Hidden Layer Neurons for FNN's and Its Application in Data Mining. In *Proceedings of the 5th International Conference on Information Technology and Applications (ICITA 2008).*