

Artificial neural network approach for functional fault diagnosis of complex Printed Circuit Boards

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Abstract

With the continuous increase in the complexity of electronic systems the issue of testing such systems is becoming an increasingly difficult task. The large number of constituent components on a printed circuit board and their internal complexity rules out traditional simulation-based techniques and emphasis upon using techniques which are based on artificial intelligence. This work is a continuation of research carried out by Arslan et al. [2] in which diagnosis is performed using example failure reports produced by Automatic Test Equipments (ATEs). The work of Arslan has also illustrated that expert system-based techniques could be used for the diagnosis procedure, however, the construction of expert systems is a lengthy procedure and their subsequent customisation for different circuits and ATEs require significant modifications to both knowledge-base and rule-base. This task could only be performed by experienced knowledge engineers. In this paper the use of artificial neural networks is investigated in the diagnosis process. A number of neural architectures are investigated mainly based upon Multi-Layer Perceptron and Learning Vector Quantization. Artificial neural networks are designed such that they process test data output from ATEs and indicate possible faults which may cause the failure of a given printed circuit board. The paper describes the neural network architectures investigated and the diagnosis performance achieved. In addition the paper reports on the ability of the neural networks in dealing with noise and duplicate reports that are a characteristic of failures represented in the test data.

1 Introduction

Electronic products and components are an integral part of our everyday life. Their applications extend from leisure to major safety critical ones such as medicine and defence. For this reason testing electronic systems is an important task and is increasingly becoming an integral part of the design procedure as in Wilkins [1]. Testing involves applying a set of input stimuli which will result in a different response for the faulty and fault-free circuits. In the past, these input stimuli were generated manually; however, as circuit complexities increase manual methods are replaced (fully or partially) by test pattern generation programs and the testing procedures are performed by computer-based equipment, termed automatic test equipment (ATE). One of the complex issues in the testing procedure is the process of isolating faulty components coming from a manufacturing line or those failed in use, see Arslan et al. [2].

The complexity of the fault isolation procedure has increased dramatically by the recent development in VLSI technology which has led to a significant reduction in component size at all levels (chip and PCB) with an accompanying increase in complexity. This increase in complexity makes the traditional intuitive approach to testing, based on testing signal flow through the circuit with the aid of instruments such as oscilloscopes and voltmeters, ineffective as explained in Wilkins [1].

Typical examples of products manufactured currently are multi-chip systems in which the following are major components:

- 1) ICs containing mixed analogue digital circuitry.
- 2) Pure digital or analogue ICs.
- 3) Individual analogue components (inductors, capacitors, etc.).

Interaction among the above components is highly complex specifically among those in (1) and (2). This makes the process of testing such circuits very complex even when advanced ATEs are used. The large combination of possible failures associated with systems such as the above makes a functional approach to testing more common. During functional testing the ATE is programmed to apply input stimuli which exercise the circuit input under typical operation conditions and examine external and test outputs as described in Arslan et al. [3]. This process usually produces a failure report for each failed system or PCB indicating the failed tests. Due to the complex nature of such systems, failed tests do not directly correspond to exact failed components and hence require further analysis by test engineers in order to isolate the individual component. This analysis procedure is lengthy and time consuming due to the complexity of the units involved and their high degree of interaction. Test engineers require a great deal of experience both with the PCB circuit and the test procedure to identify the failures. For this reason and in order to increase speed of fault isolation and maintain yield even if test engineers of less experience are employed, the possibility of an AI-based technique was considered.

The work of Arslan et al. [2] illustrated that the use of an expert system is well suited for an application such as above and can produce good diagnosis yield. However, the construction of such an expert system is a lengthy procedure and its customisation for different systems and ATEs require additional modifications to the knowledge-base and rule-base. This could only be performed by a knowledge-engineer. The use of an artificial neural network (ANN) for fault isolation requires minimum customisation once the network architecture is selected.

This paper describes the results of further investigation to the use of ANNs in the diagnosis of multi-module PCBs. Results are produced which indicate the efficiency of ANNs when used for fault isolation in such an environment. ANNs have been successfully used as a tool in fault diagnosis in a number of application fields. One application area is fault diagnosis for chemical processes as would be seen in the work of Venkatasubramanian & Chan [4], Sorsa et al. [5], Fan et al. [6] and Hoskins et al. [7]. Other applications are in the field of power systems, e.g. Ranaweera [8], Fernando & Watson [9], Chen & Voumard [10], Sagar et al. [11] and Guglielmi et al. [12]. In addition, ANNs have been applied to fault diagnosis of electronic components and digital or analogue electronic circuits by Meador et al. [13], Collins et al. [14], Reeder & Koos [15], Kagle et al. [16] and Ruthkowski [17].

This paper describes the neural network architectures investigated and the diagnosis performance achieved. In addition the paper reports on the ability of the neural networks in dealing with noise and duplicate reports that are a characteristic of failures represented in the test data.

2 Test data and representation

The ANNs directly process test data output from the ATEs. The data consist of large amounts of reports, each report describes a number of failed tests (test 1 to test n), where n is the number of failed tests in the data (a total of 131 tests). The reports usually point to one or more of the faults, fault 1 to fault m, where m is the number of possible faults on the PCB (a total of 18 faults). The data also contain some ambiguities and noise that are believed to be due to misdiagnosis by test engineers and continuous updates in the circuit.

In this study a printed circuit board was used consisting of different components, such as ICs (including analogue and digital circuits), capacitors, fuses, etc. Faults in these components are associated with outputs of the ANN whereas the failed tests are associated with the input of the ANN. The percentage distribution of tests in each fault is shown in figure 1.

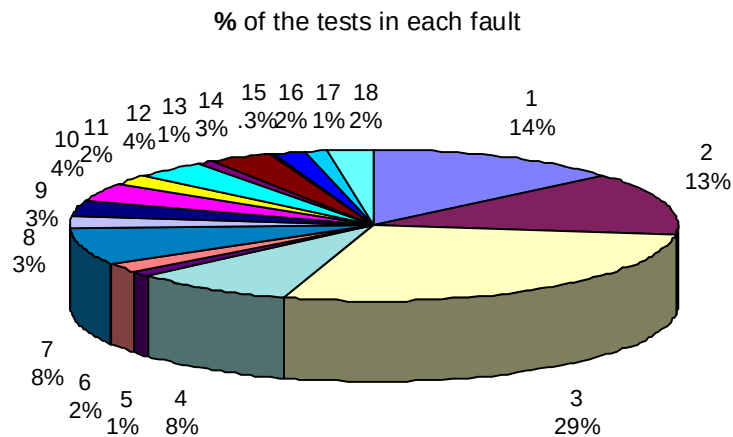


Figure 1: Percentage distribution of tests in each fault.

Different methods of representing the data were considered, our investigation showed that the best is to represent input data by a 1 when a test fails and 0 when a test passes. Outputs representing faults are coded in a matrix with 1 in the diagonal elements and 0s in the remainder. Figure 2 illustrates the use of ANNs in the fault diagnosis environment.

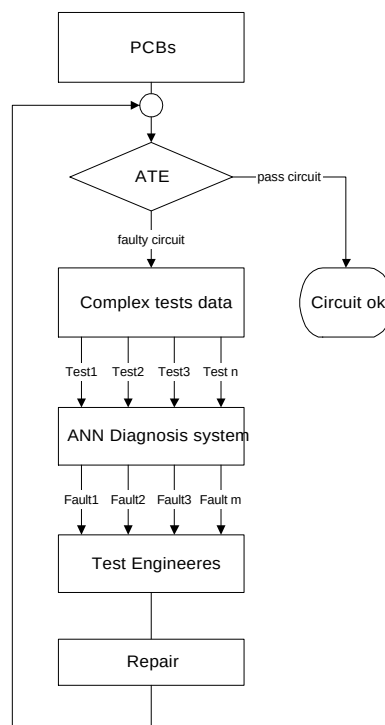


Figure 2: Block diagram of the diagnosis environment.

3 Network architectures

Two types of neural networks have been investigated, Multi-Layer Perceptron (MLP) with backpropagation algorithm and Learning Vector Quantization (LVQ), see Pham & Liu [18] and Wasserman [19].

The MLP network was structured such that it consists of 131 neurons in the input layer each corresponding to one of the 131 tests. Eighteen neurons were used in the output layer each corresponding to the different components in the circuit. The network was found to perform best with the following attributes: a single hidden layer with 25 neurons, momentum rate = 0.4 and learning rate = 0.9. The network was trained from an initial weight of -2s and +2s. Figure 3 shows the configuration of the network used in this study.

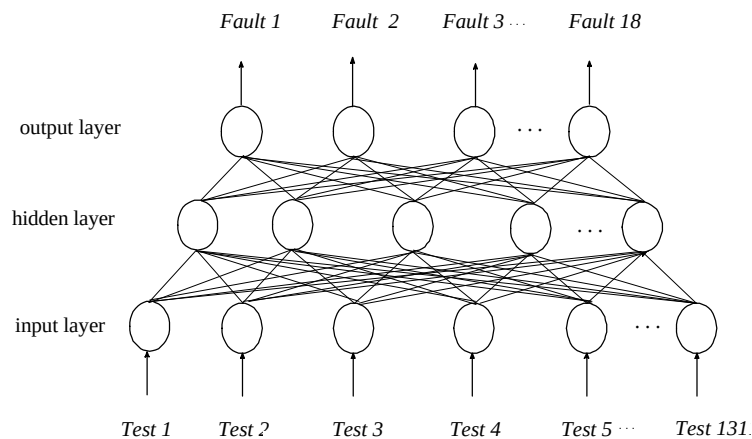


Figure 3: Three layers MLP network.

The LVQ network used the same number of inputs and outputs as for the MLP. One hundred and eight Kohonen neurons were used with each output having 6 vectors.

4 Results

The MLP with backpropagation algorithm was investigated with different number of parameters, the results of the simulation are shown in table 1. The best diagnosis performance is 89.1 % with the following parameter values: number of hidden layers = 1, number of neurons in the hidden layer = 25, momentum rate = 0.4 and learning rate = 0.9. While the worst diagnosis

performance is 63.3 % with the same learning and momentum rates and three hidden layers with 15, 10 and 5 neurons respectively.

No. of hidden layers	No. of neurons	RMS error	Performance %
1	10	0.1005	87.5
1	25	0.0909	89.1
2	40 / 10	0.1156	83.9
3	15/10/5	0.1697	63.3

Table 1: Results of MLP network.

Table 2 shows the confusion matrix [20] which represents the diagnosis performance for each fault (f1 to f18) and its confusion with other faults. Some of the faults were classified correctly 100 % such as faults f5, f6, f9, f11, f12, f13, f15 and f17. Others such as f8, f10, f14, were classified with smaller performance rates. For example, in the case of f8 the diagnosis performance was 71.4 % because it has six failure reports two of which are duplicated with f6 and f7. The lowest classification performance was 25 % as in f16 because this fault has relatively few example failures (4) some of which have been duplicated in other faults (f4 and f9).

	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11	f12	f13	f14	f15	f16	f17	f18	Perf.%
f 1	29	1	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	85.39
f 2	2	30	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91
f 3	0	0	64	3	0	0	2	0	0	0	0	0	0	0	0	0	0	0	92.8
f 4	0	0	1	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.24
f 5	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	100
f 6	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	100
f 7	0	0	0	0	0	1	17	0	0	0	0	0	0	0	0	0	0	1	89.47
f 8	0	0	0	0	0	1	1	5	0	0	0	0	0	0	0	0	0	0	71.4
f 9	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	100
f10	0	0	1	1	0	0	0	0	1	7	0	0	0	0	0	0	0	0	70
f11	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	100
f12	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	100
f13	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	100
f14	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	1	87.5
f15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	100
f16	0	0	0	2	0	0	0	0	1	0	0	0	0	0	0	1	0	0	25
f17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	100
f18	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	4	66.7

Table 2: Confusion matrix of MLP network.

Two groups of data were selected randomly one for training the ANN (learning data) and the other for testing the diagnosis performance of the ANN (testing data), see figure 4. The aim is to compare the performance of the ANN with that of the test engineer at different stages of experience with the circuit. For example with 80 % of data used for learning and 20 % of data subsequently used for testing the ANN, 92 % of the learning data and 56 % of the testing data were diagnosed correctly.

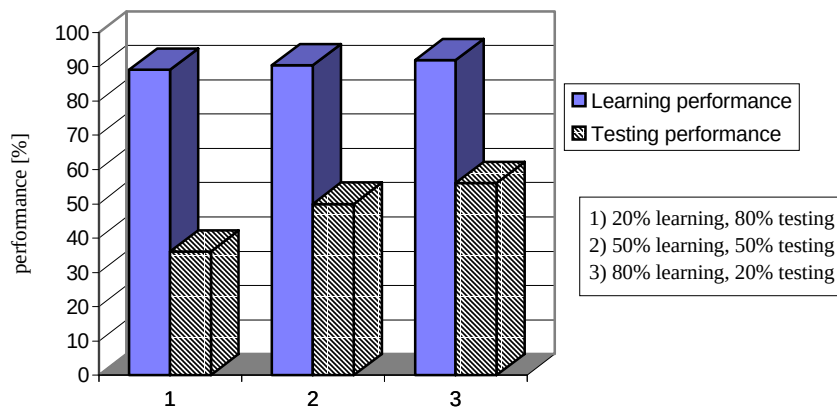


Figure 4: Performance of ANN with different learning and testing data.

Similar investigations were carried out with the LVQ network however a maximum diagnosis performance of 87 % was achieved. This does not compare favourably with that of the MLP network (89.1 %).

5 Conclusion

This paper reports on work done in investigating the use of ANNs for the diagnosis of complex PCBs by training the network with previous examples of failure reports produced by ATEs.

Both MLP and LVQ networks have been used in this investigation. The MLP network using the backpropagation algorithm produced the best diagnosis performance.

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