

AN ARTIFICIAL NEURAL NETWORK ARCHITECTURE FOR APPLICATION IN GENERAL DIAGNOSTICS

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Abstract - The application of computing rapidly advanced the test field, particularly the development of Automatic Test Equipment (ATE). Typically the application of computers has been focussed on the control of instrumentation, allowing a large number of complex tests to be performed, with relatively little human interaction. The main development in computing that has propagated to the test environment has been the increase in processing power, allowing a greater number of faster, more complex tests and diagnosis to be performed. One area of development, that has not been adopted so rapidly, is the application of Artificial Intelligence (AI). The foundations of modern artificial neural network (ANN) theory were developed half a century ago [1], and although the application of neural networks can be difficult, their use is becoming increasingly widespread. This paper discusses a methodology that will allow AI to be applied, in an ad hoc fashion, in to the contemporary test arena, eliminating the need to for a link between LRU design and ANN development.

INTRODUCTION

The use of artificial intelligence (AI) has become increasingly common in a wide variety of applications ranging from medical diagnosis to market trading. The ability of an artificial neural network (ANN) to learn complex non-linear behaviour and, following suitable training, be able to make subsequent predictions has been

successfully applied in a variety of areas [2]. This behaviour has numerous applications in the field of test, but has yet to be adopted on a wide scale. Cases where AI has been successfully applied typically involve real-time monitoring of a specific component. Here prior knowledge of the physical properties of the component is utilised to identify signatures that can be used by a neural network to determine if the component is operating correctly [3]. Application of neural networks to the prediction of long-term degradation trends in system components has also been shown to be viable [4], but again prior knowledge of the underlying processes is required. There are few examples of the use of a neural network as general diagnostic tool, where an ANN is trained to identify faults, as and when they are discovered.

Although the concept of an adaptive learning machine that readily and accurately supports an ATE system is appealing, the practical application of this technology is rather more difficult. Artificial neural networks can be difficult to train, and this problem is compounded by the wide variety of network types, each offering their own advantages and disadvantages. For AI technology to be widely incorporated in the existing test arena, application of the neural networks must be simplified so as not to require a significant amount of prior development. To this end the ideas presented in this paper are all based on an ad-hoc approach to the application of the neural network. By this, we mean that the network utilises test results as input. The outputs of the network will correspond to specific failure modes, learnt over a

period of time from the conventional test cycle; post-test analysis of the UUT performance will be used to train the network. For example consider a faulty LRU that has failed front line testing, resulting in the LRU being repaired off-line. The test results corresponding to the failure mode and the nature of the failure itself will be fed back into the network. Application of this type of network will require minimal development, as in effect it is working a simple classifier. The trade-off for this simplicity is that it will take time for the performance of the ANN to reach a useful level.

This paper presents a generalised discussion on the application of AI technology to the current test environment, and gives an example of how AI may be integrated into a future test environment utilising parallel testing.

OVERVIEW OF NEURAL NETWORKS

There are many types of ANN available, but all of these can be categorised into two distinct classes: supervised and unsupervised. In a supervised neural network the learning algorithm incorporates the expected output; the network is modified during each training step to tend towards the expected output for the supplied inputs. A supervised ANN is typically used as a classifier, whereby the output is trained to respond to particular input cases in a known way. The major drawback with the application of this type of network in a test application, is that once it is defined and trained it cannot readily be changed to accommodate different inputs patterns, or, have new classifications added to the output.

An unsupervised ANN is only provided with input data during training. Thus the network output is not forced to behave in a pre-determined fashion. This type of network can be used to identify unexpected patterns in input data and can therefore be applied much more generally. An unsupervised ANN cannot autonomously categorise the generated output; it may identify the existence of trends, but interpretation of the data must still be performed.

The ideas presented in this paper are, for the most part, based on the use of a supervised network. This in general would be trained off line, under controlled conditions, and transferred to the ATE system following an update. In this way a change in the information supplied to, or required from the network, e.g. a new test result in the TPS, can be accommodated by the introduction of

a new network. The use of unsupervised networks would most likely be found in the area of prognostics. Here an unsupervised network could be used to isolate abnormal trends in UUT performance.

APPLICATION OF AI TO TEST

There are many areas in the test and measurement field that may benefit from the application of AI technology. In the future we may find an ANN residing on every ATE system. The neural network may monitor the state of the ATE and also optimise the implemented test scheme, provide diagnostics for each UUT, and while exchanging information with other ATE in the fleet monitor time dependent UUT performance to provide prognostic information. Such a grand scheme may be far off, but there are many opportunities for ANN to play a beneficial role in the existing test world.

The focus here is on the application of AI to diagnostics. There are many areas where AI may be applied, prognostics is perhaps the most obvious where the pattern-recognition abilities inherent in AI technology make it an ideal candidate for the role. To clarify the distinction we define diagnostics to be the evaluation of a LRU fault following a failure and prognostics the ability to predict future LRU behaviour, from historical performance.

With ever more stringent control of UUT handling, via regulations such as TEMPEST, the ability to make first-line low-level diagnosis is being degraded, with a subsequent reliance on closed-lid diagnostics. We propose that an ANN could be designed to simply utilise the test results themselves. Training of the network would be performed in an ad-hoc manner; the classification of the fault condition, and the test results pertaining to the fault would be fed back into the neural network. Following a suitable amount of training, the neural network would be able to provide a 'most likely' candidate for reported failures. This would not provide a foolproof diagnosis, as there would be many degenerate cases where different faults resulted in the same failure conditions, but for relatively little effort the maximum amount of information could be extracted from the test results.

We can extend this situation to two special cases, these are the 'no fault found' i.e. a UUT fails an ATP but is found to have no identifiable fault, and

the 'false-pass' i.e. a UUT passes an ATP but when returned to the field is found to be unserviceable. Both of these cases present unique problems because resolving them conventionally relies on the exchange of information from the front-line to the ATE, and vice versa. The use of the data collected during testing is already under particular scrutiny. The proposed Health Utilisation and Monitoring System (HUMS) is a scheme whereby all TPS are recorded and collated at a central station. Part of the proposal already defines the use of knowledge bases, with subsequent analysis of long-term UUT behaviour. In addition identification of erroneous LRU or ATE behaviour, responsible for 'no fault found' and 'false pass' conditions, would be made much more efficient. HUMS in conjunction with integrated diagnostics (advocated by ARGCS) provide the type of vehicle on which the proposed AI processing could be based. The AI-ESTATE (IEEE 1232) Standard [5] is intended to explicitly define the interaction of AI systems with ATE data. The introduction of these information pathways would help to reduce the impact of the problems of 'no fault found' and 'false passes', but in conjunction with an ANN pro-active identification of these situations could be made at the point of test.

Another standard that has been developed recently is the Signal and Test Definition Standard (IEEE P1641). This provides, amongst other things, an XML interface for transportability of complex signal definitions. It is possible to define the implementation of a number of network types purely in terms of XML [6]. Thus a specific implementation of a neural network can be uniquely defined as a STD XML signal. The additional benefit this provides is that STD

compliant signal generation tools, e.g. the Racal Instruments Group Ltd *newWave* tool, are already capable of implementing a STD XML based network. Figure 1 shows a single node from a Multi-Layer Perceptron (MLP) network, implemented using *newWave*. Figure 2 shows the STD XML description of the node.

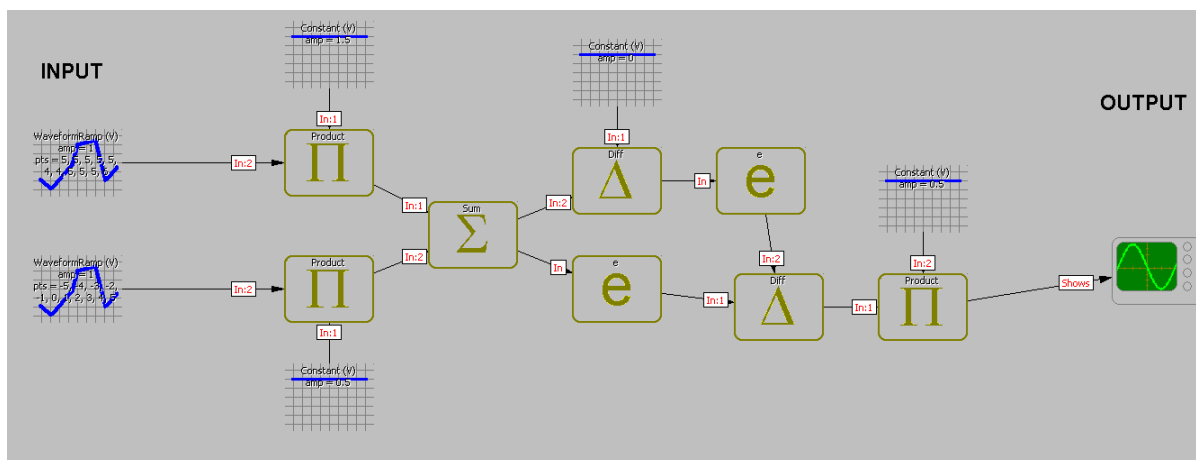
Of course, all these principles mentioned above apply equally well to health monitoring of the ATE, where the test results are supplied from the standard self-checking mechanism.

AI AND PARALLEL TESTING

There are already many developments underway that will affect the way future automated test is implemented. Of these, the most radical divergence from contemporary testing is in the proposed use of parallel testing, which is now feasible due to advances such as synthetic instruments. In this scheme a UUT is stimulated in such a way as to emulate its operational environment completely. The true operational functionality of the UUT can thus be established by, in effect, operating the UUT in the field, on the bench. This differs significantly from conventional testing whereby individual areas of LRU functionality are considered in a piecemeal fashion.

It is envisaged that parallel testing will be implemented utilising a range of arbitrary instruments, which generate all of the signals required simultaneously. One difficulty with this method of testing is how to define the tests, and the pass/fail criteria. A neural network would be ideally suited to this type of testing. One can visualise an advanced networked monitoring all

Figure 1. A graphical representation of a single Multi-Layer Perceptron node, implemented using IEEE P1641 by *newWave*.



the UUT inputs and outputs. While the full range of UUT performance is exercised, the ANN will analyse the inputs and outputs and classify the performance of the UUT. The ANN would be trained using prior knowledge about the LRU design, while also continuously learning. It may also be used to modify the scheme of tests applied, whereby it made decisions based on the UUT performance as to how best characterise the UUT. While this view of testing may seem far-fetched, it may not be long until the TPS as we know it is obsolete.

Figure 2. IEEE P1641 STD XML description of a single Multi-Layer Perceptron node, generated using *newWave*.

```
<?xml version="1.0" ?> <!--encoding="UTF-8"-->
<!-- created with newWave
(http://www.racalstruments.com) by Chris Gorrige
(Racal Instruments) -->
<!--W3C Schema generated by newWave
(http://www.racalstruments.com) -->
<Signal name="" Out="Product12"
xmlns:xsi="http://www.w3.org/2001/XMLSchema-
instance"
xsi:noNamespaceSchemaLocation="D:\Program
Files\Racal Instruments\newWave\signals.xsd">
<Constant name="ConstantVoltage32"
amplitude="1.5" />
<WaveformRamp
name="WaveformRampVoltage15" period="1"
samplingInterval="0.1" points="5, 5, 5, 5, 4, 4, 5, 5,
5, 6" />
<Constant name="ConstantVoltage33"
amplitude="0.5" />
<WaveformRamp
name="WaveformRampVoltage14" period="1"
samplingInterval="0.1" points="-5, -4, -3, -2, -1, 0, 1, 2,
3, 4, 5" />
<Product name="Product10"
In="ConstantVoltage32 WaveformRampVoltage15"/>
<Product name="Product11"
In="ConstantVoltage33 WaveformRampVoltage14"/>
<Constant name="ConstantVoltage34" />
<Sum name="Sum36" In="Product10 Product11"/>
<Diff name="Diff6" In="ConstantVoltage34
Sum36"/>
<E name="E4" In="Sum36"/>
<E name="E5" In="Diff6"/>
<Diff name="Diff7" In="E4 E5"/>
<Constant name="ConstantVoltage35"
amplitude="0.5" />
<Product name="Product12" In="Diff7
ConstantVoltage35"/>
</Signal>
```

CONCLUSION

This paper has presented an overview of some of the opportunities where AI may be implemented in test. Strategies for incorporating AI into current test methods have been described, as well as some speculation regarding the integration of AI into future test platforms. The discussion of current test technologies described how AI might be used to improve the performance of diagnostics. Where we define diagnostics to be the evaluation of a UUT fault following a failure and prognostics the ability of predicting future LRU behaviour, from historical performance.

In all cases the application of AI is envisaged as an ad hoc process, i.e. it relies solely on the capture of UUT data and is not based on, or linked to, the design of the LRU. Such systems would rely heavily on the ability to obtain as much data as possible regarding each LRU. Systems such as HUMS and integrated diagnostics already provide the information pathways that would be essential for the successful application of AI in this way. Thus one of the most significant hurdles that would inhibit application of these systems has already been overcome. Standardisation of the interchange of test results used by AI systems has already been addressed through AI-ESTATE; this would ensure a compliant AI system could integrate into any compliant ATE. The development of the IEEE P1641 Signal and Test Definition standard (STD) is also especially useful, as complete neural networks can be passed in STD XML format.

A significant proportion of the work required to implement AI in test has already been undertaken. It now only requires development of the tools to utilise the information already available, for the full benefit of this technology to be realised.

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