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Intelligent approach to determining optimal burn-in time and cost for electronic products

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Abstract *Burn-in is an engineering method extensively used to screen out infant mortality failure defects. Previous studies have attempted to determine the optimum burn-in time and cost for a device or a system. However, for the mathematical model, many assumptions are inappropriate due to practical concerns, and for the cost model, the required costs are difficult to find. How to effectively determine the optimal burn-in time and cost has perplexed manufacturers for quite some time. In the actual manufacturing process, a new electronic product is always extended from an old product, called the base product. By adopting the relationship between new product and base product, this study presents a neural network-based approach to determine the optimal burn-in time and cost without any assumptions. A case study of the production of a switch mode rectifier demonstrates the effectiveness of the proposed approach.*

1. Introduction

Defects associated with electronic devices can be categorized mainly as patent defects and latent defects. Patent defects do not meet specifications and are readily detectable by inspection or functional testing that includes environmental stress screening. Latent defects cannot be detected by inspection or functional testing until they are gradually transformed into patent defects by environmental stress screening. Burn-in is designed to detect patent infant failure in the electronics industry. The failure rate of an electronic device starts high, decreases rapidly during the infant mortality period, and then stabilizes in the steady-state period. Since infant mortality failure critically affects the overall reliability of devices or systems, determining the burn-in time and cost to effectively screen latent defects in infant mortality is important. This issue has received considerable interest (Kuo *et al.*, 1998).

Stewart and Johnson (1972) developed a cost model using Bayesian decision theory to decide optimal burn-in time and replacement policy. Plesser and Field (1977) used a cost model to obtain an optimal burn-in time for repairable electronic systems. Meanwhile, Nguyen and Nurthy (1982) derived the optimal burn-in time for products sold under warranty. Furthermore, Chou and Tang (1992), and Mi (1996) determined the optimum burn-in time by using a cost

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model, with the costs including set-up costs, direct burn-in cost, repair cost, and warranty cost. Koh *et al.* (1995) utilized temperature stress as the accelerated condition to obtain effective burn-in time. Meanwhile, Chien and Kuo (1996) presented a nonparametric approach that can estimate the optimal system burn-in time without complex parameter estimation and curve fittings. Chien and Kuo (1997) proposed a Bayesian nonparametric approach to determine system burn-in time. Finally, Yan and English (1997) applied environmental stress screening to construct an integrated cost model and determine the optimal burn-in time.

Previous approaches, including curve fitting for a failure model, cost for optimal burn-in time model and environmental stress model, are ineffective in determining optimal burn-in time and cost for practical operations. In the curve fitting for a failure model or an environmental stress model, many assumptions are too broad and, thus, are inappropriate for many cases. Also, although many researchers have adopted Weibull distribution to model the failure rate of electronic components, this is only an approximation. If other distributions, such as lognormal or Gamma distributions, are used for parametric analysis, the overall level of the system failure becomes untractable. In the cost model, these costs are difficult to estimate and in practice more attention may be paid to data collection, with the results usually being sensitive to the assumed costs. Additionally, in the electronics industry, the product line of a firm always extends from the base products, called the product family. In a product family, each product shares very similar characteristics. Obtaining the optimal burn-in time and cost for each product via traditional methods is tedious and monotonous.

When an electronic product enters mass production, its optimal burn-in time and cost must be known. This study presents a neural network-based approach to enhance the analysis of burn-in time and cost. Neural networks are highly parallel computation systems which can learn from examples. Neural networks can be used to construct the desired mapping function without requiring any assumptions concerning the functional form of the relationship between predictors and response (Stern,1996). This capability enables them to be applied in manufacturing. Neural networks are more easily comprehended and implemented than other statistical approaches. This study also performs a case study of the production of a switch mode rectifier and compares it with the statistical approach, to examine the effectiveness of the proposed approach.

2. Burn-in

Burn-in is used to screen infant mortality failure of electronic devices. Jensen and Petersen (1990) described burn-in as a rapidly changing technology and production method used to cope with an increasing awareness of reliability. Most manufacturers have to investigate reliability screening to minimize early failures in the field, and thus minimize guarantee and service expenditure. Yan and English (1997) defined burn-in as a subset of environment-stress-screening that screens out infant failure by combining appropriate electrical and thermal

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environments in a shortened time span. Kuo *et al.* (1998) described burn-in as being completed when reasonable certainty established that all the weak devices have failed, thus leaving the remaining devices in a reliable state. Some problems associated with burn-in in practice include:

- Should burn-in be performed at the product, module, or component levels?
- Should type of burn-in performed differ in a steady and a changeable environment?
- Under what environment conditions should burn-in be performed?
- How long should the burn-in process continue, how reliable should it be (expressed by failure rate), and what are the total costs?

Figure 1 depicts a systematic burn-in procedure based on the above description. This procedure consists of four phases. The first phase is to determine the burn-in policy decision. This decision is always based on customer or engineer experience. According to Kuo *et al.* (1998), an electronic device can be categorized into three levels: systems, subsystems and components. Meanwhile, there are eight possible choices of burn-in policy: no burn-in, component only, subsystem only, system only, component and subsystem, component and system, subsystem and system, and all levels burn-in. In practice, system burn-in is always too expensive, but can remove more incompatibility than lower-level burn-ins. Once the burn-in policy is determined, the next phase is to select a feasible burn-in type. There are three distinct types of burn-in: test during burn-in, static burn-in and dynamic burn-in. Test during burn-in applies an electronic test after a long burn-in process. It is frequently used for DRAM and SRAM processes. Static burn-in applies stresses to the samples at a fixed level or in an elevated pattern. Meanwhile, dynamic burn-in exercises samples by stressing them to simulate real operating environments. Static burn-in is always more effective than dynamic burn-in for defects resulting from corrosion or contamination. This method is very appropriate for IC and control process unit devices. After burn-in type is

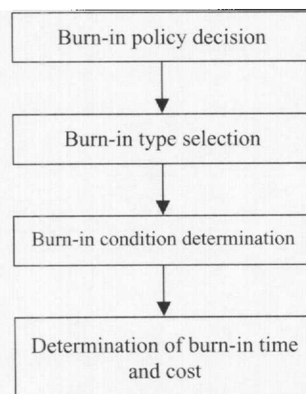

Figure 1.
Burn-in procedure

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determined, an effective burn-in condition should be determined since it will affect burn-in performance. Finally, the last phase is to determine the optimal burn-in time and burn-in cost, which is the purpose of this study.

3. Neural networks

A neural network is a computing system, comprising many processing elements connected between layers. Each processing element (node) has an output signal that fans out along connections to the other processing elements. Meanwhile, each connection is assigned a relative weight. The output of a node depends on the specified threshold and the transfer function. Learning and recall are two major processes of the neural network, where the learning process can modify the connecting weights and the recall process involves understanding how the network creates a response at the output layer by processing a signal through the whole network. Two types of learning are commonly considered: supervised and unsupervised learning. For supervised learning, a set of training input vectors with a corresponding set of target vectors is trained to adjust the weights in a neural network. For unsupervised learning, a set of input vectors is proposed, but no target vectors are specified. Generally, the clustering problem frequently employs the unsupervised learning and the prediction or mapping problem usually employs the supervised learning.

Back-propagation neural network (Figure 2) is the most popular of the several well-known supervised learning networks such as learning vector quantization and counter-propagation neural networks. This study adopts the back-propagation neural network due to its ability to map a complex, non-linear relationship between inputs and corresponding outputs (Funahashi, 1989). A typical back-propagation network consists of three or more layers, including an input layer, one or more hidden layers and an output layer. Figure 1 depicts the topology of a back-propagation network with three layers. Back-propagation learning employs a gradient-descent algorithm to minimize the mean-square error between the target data and the predictions of the neural network (Rumelhart and McClelland, 1989). The training data set is initially collected to develop a back-propagation neural network model. Using a

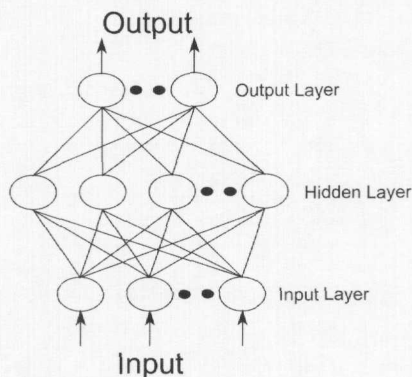

Figure 2.
Topology of the back-propagation neural network

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supervised learning rule the data set comprises input and actual output (target). The gradient-descent learning algorithm enables a network to enhance its performance by self-learning. The training of a back-propagation network involves three stages: the feed-forward of the input training data, the calculation and back-propagation of the associated error, and the adjustment of the connected weights.

4. Proposed approach

The following describes a detailed procedure for determining optimal burn-in time for an electronic product.

Computation of the correlation ratio

Step 1: Identify the base product and new product to be studied.

Step 2: Let the correlation ratio (*CR*) of the base product be 1. Compute the *CR* of the new product as follows:

$$CR = \frac{CC_{new}}{CC_{base}}$$

where

CC_{new} = the total number of critical components in the new product.

CC_{base} = the total number of critical components in the base product.

Optimization based on the base product data

Step 3: Develop a BP network model (Model 1) to obtain the relationship between (burn-in time, correlation ratio) and (burn-in cost, failure rate).

Step 4: Present all possible burn-in times (1~24 hours) and correlation ratios to the Model 1 and compute the estimated burn-in cost and failure rate.

Step 5: Obtain the optimal burn-in time by comparing the estimated data obtained in step 4, that is, find the time with the smallest estimated burn-in cost and failure rate.

Modifications based on practical considerations

Step 6: Develop a BP network model (Model 2) to obtain the relationship between (burn-in cost, failure rate, correlation ratio) and burn-in time.

Step 7: Obtain the estimated burn-in time by inputting the desired burn-in cost, failure rate and correlation ratio into Model 2.

This study initially identified the base product and the new product to be studied. The base product is the technological core for a product family, and the

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new product is a modification of the base product. Some kind of relationship exists between the base product and the new product. Since the number of critical components will influence the reliability of a product or module, this study uses the ratio of critical components between the new product and the base product (called correlation ratio) to represent this relationship. Letting the correlation ratio of the base product equal 1, the correlation ratio for the new product can then be computed.

Previously, burn-in was completed when failure reached predetermined value or time, and this value or time was always set according to customer or engineer experience. By collecting the required data, however, this study can use Model 1 to obtain the estimated burn-in cost and failure rate. Subsequently, comparing these estimated data will reveal the optimal burn-in time. Additionally, to control the burn-in cost and failure rate below a criterion, Model 2 can be used.

5. A case study

Rectifiers are critical products for the telecommunication power systems industry. They convert AC power input into DC power output and supply for wireless and wireline networks. A rectifier in a telecommunication network operation must be highly reliable. Providing a stable power impacts the rectifier manufacturer. Thus, burn-in must be completed before the rectifier is shipped to the customer. Previously, the burn-in time and cost were usually determined by an experienced engineer or gathered based on mass production. However, this approach was ineffective in overcoming infant mortality failure of rectifiers and always increased burn-in process costs. The proposed approach can resolve this problem and obtain the optimal burn-in time and cost.

In the production of a rectifier, defects are divided into two types: patent defects and latent defects. Patent defect can be easily detected visually or by auto-test equipment. Meanwhile, latent defects are only detectable by environmental stress screening over time. Usually, burn-in is utilized to detect latent defects in the rectifier industry.

The product family of Delta's 3000 series rectifier includes four models: ESR-48/50AA, ESR-24/100AA, ESR-24/100AB, and ESR-24/100ABA. ESR-48/50AA, ESR-24/100AA and ESR-24/100AB have long been mass produced. To apply the proposed approach, the burn-in time, burn-in cost, correlation ratio, and the corresponding failure rate were collected (from January to December of 1998), and Table I summarizes those results.

Now, ESR-24/100ABA is a new product, and a pilot-run is proceeded. Owing to ESR-48/50AA, ESR-24/100AB and ESR-24/100ABA being extended from ESR-24/100AA, the correlation ratio of the base product, ESR-24/100AA, is allowed to be 1. From step 2 of the proposed procedure, the correlation ratio can be calculated as follows: ESR-48/50AA vs. ESR-24/100AA is 0.833, ESR-24/100A vs. ESR-24/100AA is 1.25 and ESR-24/100ABA vs. ESR-24/100AA is 1.33.

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Burn-in time (hr)	ESR-24/100AA Failure rate (%)	ESR-24/100AA CR	ESR-24/100AA Burn-in cost (NT$)	ESR-48/50AA Failure rate (%)	ESR-48/50AA CR	ESR-48/50AA Burn-in cost (NT$)	ESR-24/100AB Failure rate (%)	ESR-24/100AB CR	ESR-24/100AB Burn-in cost (NT$)
1	0.00722	1	284.2	0.00371	0.833	169.6	0.00667	1.25	422.3
2	0.00125	1	280.3	0.000741	0.833	174.6	0.00133	1.25	429.5
3	0.00139	1	274.0	0.00111	0.833	173.2	0.00133	1.25	436.6
4	0.00069	1	279.9	0.00037	0.833	184.7	0.00667	1.25	388.3
5	0.00056	1	288.1	0.00111	0.833	183.3	0.00667	1.25	339.9
6	0.00083	1	291.6	0.00037	0.833	194.8	0.00667	1.25	291.5
7	0.00097	1	292.6	0.00037	0.833	206.3	0.00667	1.25	243.1
8	0.00167	1	281.4	0.000741	0.833	211.3	0.00133	1.25	250.3
9	0.00208	1	262.9	0.00037	0.833	222.9	0.002	1.25	250.5
10	0.00167	1	251.7	0.000741	0.833	227.9	0.00133	1.25	257.7
11	0.00056	1	259.9	0	0.833	245.9	0.000667	1.25	271.7
12	0.00042	1	270.6	0.00037	0.833	257.4	0.00133	1.25	278.9
13	0.00056	1	278.8	0.00037	0.833	269	0.000667	1.25	293
14	0.00028	1	291.9	0	0.833	287	0	1.25	314
15	0.00014	1	307.4	0	0.833	305	0	1.25	335
16	0	1	325.4	0	0.833	323	0	1.25	356
17	0	1	343.4	0	0.833	341	0	1.25	377
18	0.00014	1	359	0	0.833	359	0	1.25	398
19	0	1	377	0	0.833	377	0	1.25	419
20	0	1	395	0	0.833	395	0	1.25	440
21	0	1	413	0	0.833	413	0	1.25	461
22	0	1	431	0	0.833	431	0	1.25	482
23	0	1	449	0	0.833	449	0	1.25	503
24	0	0.83	467	0	0.833	467	0	1.25	524

Note: The burn-in cost is cumulative and includes fixed cost, variable cost, and repair and warranty cost

Table I.
The data of base products

At this stage, the aim is to discover the effective burn-in time and cost before the new product enters mass production. Through the proposed approach, the data (shown in Table I) are directly used to develop two back-propagation networks. The trained networks can be used to obtain the relationship between (burn-in time, correlation ratio) and (burn-in cost, failure rate), and also the relationship between (burn-in cost, failure rate, correlation ratio) and burn-in time. This study randomly selects 60 training patterns and 12 testing patterns from Table I. For Model 1, burn-in time and correlation ratio serve as the network inputs, while burn-in cost and the corresponding failure rate are the outputs. Meanwhile, for Model 2, burn-in cost, correlation ratio and failure rate are the network inputs, and burn-in time is the output. The required network model is developed using a neural network package software, Qnet97 (1997). The convergence criterion employed in the network training is the root of mean square error (RMSE). Tables II and III provide several options for the network architecture; the structure 2-4-2 improves performance for Model 1, and the

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structure 3-6-1 improves performance for Model 2. Figures 3 and 4 display the performance vs. training epochs for the networks 2-4-2 and 3-6-1, respectively.

Meanwhile, the above two models also can be fitted by the stepwise method of the statistical regression. For Model 1, two regression functions were formed as follows:

Burn-in cost =19.456593+8.99308*burn-in-time+187.730355* correlation-ratio.
Failure rate = –0.000443–0.000156*burn-in-time+0.003335* correlation-ratio.

The mean square errors of the above two functions are 3027.47 and 0.00000202, respectively. The average of the RMSE of these two regression functions is higher than shown in Table II; therefore, the neural network method is better

Table II.
The performance of five different networks

Architecture	RMSE (training)	RMSE (testing)
2-3-2	0.069525	0.121068
2-4-2	0.049213	0.034822
2-5-2	0.068697	0.071861
2-6-2	0.064026	0.093281
2-7-2	0.063517	0.099602

Table III.
The performance of six different networks

Architecture	RMSE (training)	RMSE (testing)
3-4-1	0.057889	0.075474
3-5-1	0.056801	0.070549
3-6-1	0.056594	0.053956
3-7-1	0.056254	0.079615
3-8-1	0.052744	0.082769
3-9-1	0.054347	0.129000

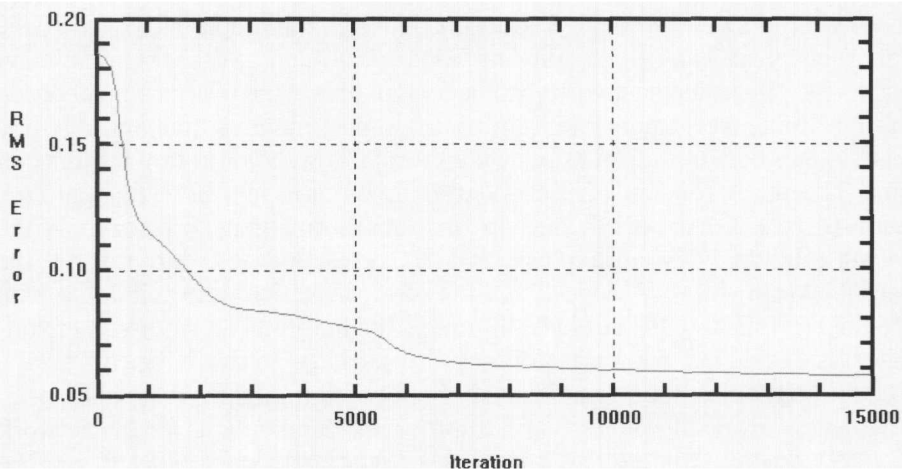

Figure 3.
RMSE vs. number of training epochs for model 1

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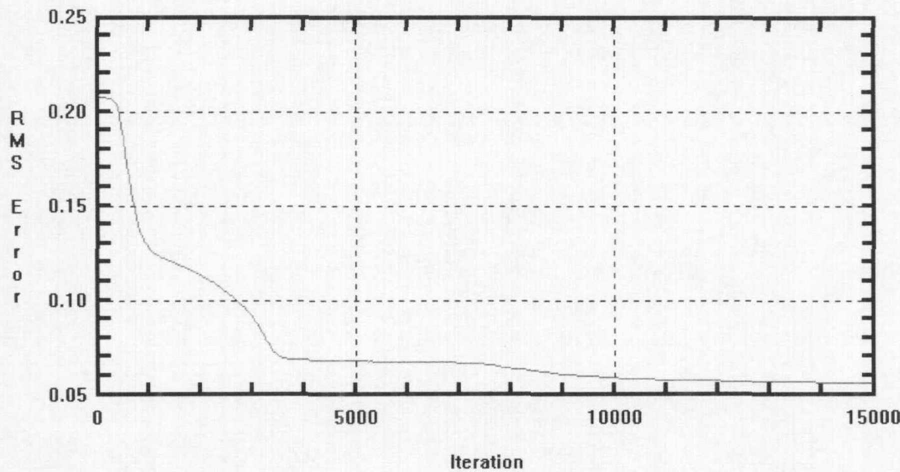

Figure 4. RMSE vs. number of training epochs for model 2

than the regression method in terms of RMSE. Similarly, for Model 2, the regression function can be formed as follows:

Burn-in time = 1.7416–1610*failure-rate–4.4525* correlation-ratio +0.05233*burn-in-cost,

with RMSE value 3.742. This value is higher than those in Table III. The neural network method also performs better than the regression method. Consequently, the trained networks are employed to perform the required estimation.

The burn-in cost and failure rate can be estimated using Model 1. Table IV lists these data, while Figures 5 and 6 plot them. From Figure 6, to obtain the lowest cost, the effective burn-in time can be given at nine hours, reducing the corresponding failure rate to 0.00245. However, to control the burn-in cost under NT$300 and the failure rate under 500ppm, Model 2 can be used to estimate the effective burn-in time, yielding 13.35 hours. Previously, the initial burn-in time was always fixed at 24 hours, and when the corresponding failure

Burn-in time (hr)	1	2	3	4	5	6
Failure rate	0.00562	0.00010	0.00037	0.00554	0.00818	0.00829
Burn-in cost	398.2	463.3	475.1	445.7	395.9	347.1
Burn-in time (hr)	7	8	9	10	11	12
Failure rate	0.00743	0.00493	0.00245	0.00122	0.00070	0.00047
Burn-in cost	307.7	282.7	273.1	274.4	282.5	294.6
Burn-in time (hr)	13	14	15	16	17	18
Failure rate	0.00035	0.00027	0.00022	0.00017	0.00012	0.00007
Burn-in cost	309.4	326.1	344.4	363.9	384.2	404.9
Burn-in time (hr)	19	20	21	22	23	24
Failure rate	0.00002	0	0	0	0	0
Burn-in cost	425.5	445.5	464.6	482.3	498.3	512.6

Table IV. Estimation of burn-in cost and failure rate for ESR-24/100ABA

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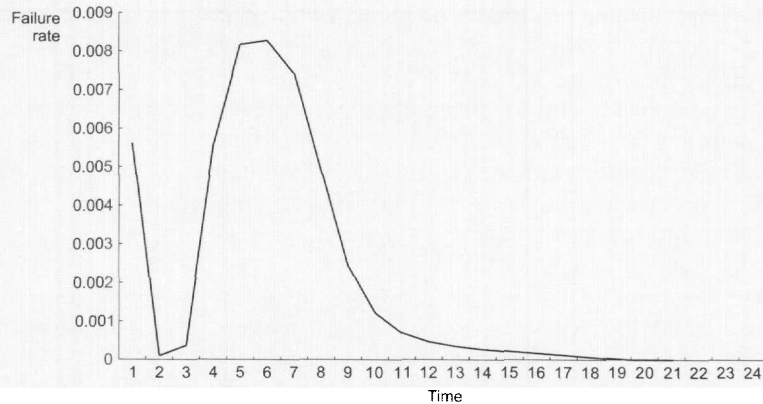

Figure 5. Failure rate vs. burn-in time for ESR-24/ 100ABA

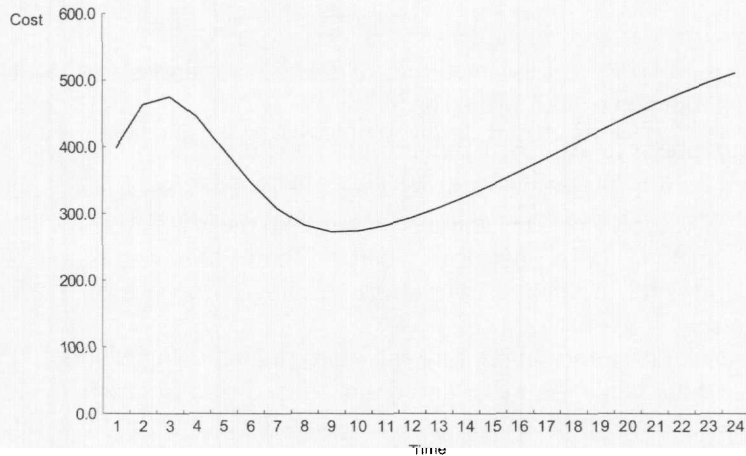

Figure 6. Burn-in cost vs. burn-in time for ESR-24/ 100ABA

rate improved the burn-in time gradually reduced. Over five months (from July to November of 1999), the new burn-in time was set at 14 hours, and Table V summarizes the results. This shows that the proposed approach is very effective in practice.

5. Conclusion

Burn-in is an effective means of screening latent defects in the electronics industry. How to determine an effective burn-in time and burn-in cost has concerned manufacturers for quite some time. Although many burn-in models have been developed, none have been practical. Previously, the optimal burn-in

Table V. Implementation results of ESR-48/100ABA

Monthly	July 1999	August 1999	September 1999	October 1999	November 1999
Failure rate	0.00067	0.00033	0.00033	0	0

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time and cost for an electronic product were determined by customer or engineer experience, which was time consuming and expensive. This study presents an effective neural network-based approach to determine optimal burn-in time and cost. The proposed approach can effectively screen out latent defects before a product is shipped to the customer. A case study of the production of rectifier was performed and compared with the statistical approach. According to those results, the proposed procedure yields a very low failure rate after burn-in.

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