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INCORPORATING PRODUCT ROBUSTNESS LEVEL IN FIELD RETURN RATE PREDICTIONS

PRZEWIDYWANIE RZECZYWISTEGO WSKAŹNIKA ZWROTÓW TOWARU Z UWZGLĘDNIENIEM POZIOMU ODPORNOŚCI PRODUKTU

Reliability and return rate prediction of products are traditionally achieved by using stress based standards and/or applying accelerated life tests. But frequently, predicted reliability and return rate values by using these methods differ from the field values. The primary reason for this is that products do not only fail due to the stress factors mentioned in the standards and/or used in accelerated life tests. There are additional failure factors, such as ESD, thermal shocks, voltage dips, interruptions and variations, quality factors, etc. These factors should also be considered in some way when predictions are made during the R&D phase. Therefore, a method should be used which considers such factors, thus increasing the accuracy of the reliability and return rate prediction. In this paper, we developed a parameter, which we call Robustness Level Factor, to incorporate such factors, and then we combined this parameter with traditional reliability prediction methods. Specifically, the approach takes into account qualitative reliability tests performed during the R&D stage and combines them with life tests by using Artificial Neural Networks (ANN). As a result, the approach gives more accurate predictions compared with traditional prediction methods. With this prediction model, we believe that analysts can determine the reliability and return rate of their products more accurately.

***Keywords**: reliability and return rate estimation, artificial neural networks, defining different failure types, product maturity level, product robustness level, field failures, product level testing, board level testing, design quality.*

Niezawodność i wskaźniki zwrotów towaru przewiduje się tradycyjnie przy użyciu norm obciążeniowych i/lub stosując przyspieszone badania trwałości. Jednakże, często wartości niezawodności i wskaźnika zwrotów przewidywane za pomocą tych metod różnią się od ich wartości rzeczywistych. Główną tego przyczyną jest fakt, że produkty nie ulegają awarii wyłącznie pod wpływem czynników obciążeniowych wymienianych w normach i/lub wykorzystywanych w przyspieszonych badaniach trwałości. Istnieją dodatkowe czynniki wpływające na intensywność uszkodzeń, takie jak wyładowania elektrostatyczne, wstrząsy termiczne, spadki, przerwy w dostawie i zmiany napięcia, czynniki jakościowe, itp. Te czynniki także powinny być w jakiś sposób uwzględnione przy dokonywaniu predykcji na etapie badań i rozwoju (R&D). Dlatego też zwiększenie trafności predykcji niezawodności i wskaźników zwrotów towaru wymaga metody, która uwzględniałaby tego typu czynniki. W niniejszej pracy opracowaliśmy parametr, nazwany przez nas "czynnikiem poziomu odporności", który pozwala na uwzględnienie takich czynników, a następnie wykorzystaliśmy ów parametr w połączeniu z tradycyjnymi metodami przewidywania niezawodności. W szczególności, przedstawione podejście bierze pod uwagę jakościowe badania niezawodnościowe wykonywane na etapie R&D łącząc je z badaniami trwałościowymi przy użyciu sztucznych sieci neuronowych ANN. Dzięki temu, w podejściu tym uzyskuje się bardziej trafne predykcje niż w tradycyjnych metodach prognozowania. Jesteśmy przekonani, że użycie powyższego modelu predykcyjnego umożliwi analitykom bardziej trafne wyznaczanie niezawodności oraz wskaźników zwrotów wytwarzanych przez nich produktów.

***Słowa kluczowe**: ocena niezawodności i wskaźnika zwrotów produktu, sztuczne sieci neuronowe, definiowanie różnych typów uszkodzeń, poziom dojrzałości produktu, poziom odporności produktu, awarie w warunkach rzeczywistych, badania na poziomie produktu, badania na poziomie płyty testowej, jakość konstrukcyjna.*

1. Introduction

Consumer electronics reliability has become a major concern for manufacturers in recent years, as consumer electronics prices have dropped quite dramatically. The cost of warranty failure support has become a greater percentage of the profit margin. In Europe, the average cost per failure, including logistics costs, is greater than $150 [13]. Due to this, manufacturers strive to increase the reliability of their products in order to decrease service costs. On the other hand, this improvement causes an increase on design and manufacturing cost.

Companies attempt to reach to the optimum reliability value point, which can only be reached with an accurate reliability and return rate estimation. This estimation should be performed in the R&D stage, prior to mass production. System designers need reliability information during the design phase, to determine the initial, maintenance and total system costs, as well as system-level reliability and availability [5] to perform design changes if needed.

In addition to this, with accurate return rate estimation companies can determine the number of spares to be produced for their services, determine the size of the stock area for spares and also estimate their risk when a product is introduced into market earlier than planned.

Various methods and standards are available for predicting reliability and return rate [4, 6, 8, 10, 12], such as stress based standards which are widely used. Stress based standards, like MIL-HDBK-217F, mainly define the reliability and failure rate of components according to the stress levels on the components. Defined stress factors are temperature, voltage and power dissipation [3]. Additionally, many companies perform accelerated life tests at higher stress and usage rates [15] and analyze the test data with statistical distributions. To accelerate the failure mechanism; temperature, relative humidity, voltage, temperature cycling and vibration are typically used in electronics as the stress factors [1]. The results of these tests are then used to perform reliability predictions under field stress conditions. But frequently, predicted reliability and return rate values by using stress based standards or utilizing accelerated life tests turn out to be significantly different from the actual reliability and return rate value in the field [7]. One reason for this is that sufficient number of samples/prototypes for testing cannot be afforded therefore, accelerated life tests are performed with small sample sizes [11], thus increasing the uncertainty of the predictions. In addition, and in our experience, another significant reason is that the stress factors considered in the standards and used in accelerated life tests are not the only contributors to failures observed in the field during the life period of the product. For example, some additional failure factors for a consumer electronics product can be:

- Electro Static Discharge,
- Inrush Current,
- Voltage Dips-Interruptions-Variations,
- Lightning/Surge Voltages,
- Loose Plugs etc.

During development phase, there is a variety of qualitative tests performed to consider the above mentioned failure factors. However, the outcome of such tests is not considered in the final reliability predictions. Therefore, a method which would consider the outcome of such tests and combine them with the other prediction methods (e.g. accelerated life tests) is needed.

In this paper, a unique approach for determining reliability and field return rate in R&D phase is presented, by introducing a new parameter called Robustness Level Factor (RLF a.k.a. maturity level [14]). This new parameter is obtained by applying a set of electrical, environmental and mechanical tests in R&D phase and prior to mass production. This set of tests typically simulates different stress factors and failure mechanisms faced in the field, which are not life/durability related. These set of tests may also include approval and validation tests at both board and product level. Once the Robustness Level Factor is obtained, Artificial Neural Networks (ANN) is used to combine this parameter with traditional predictions. To demonstrate the methodology and the accuracy of the model, a real life case study on 4 LCD TFT TV projects is given.

2. Determination of the Robustness Level Factor

To determine the Robustness Level Factor (RLF), a set of tests which will simulate the non-life related failure modes which are possible in the field should be created, i.e. robustness tests. These tests should be determined according to type, specification, usage conditions, etc., of the product. In addition, the tests and the corresponding failures found should be assigned numerical values according to their severities in order to determine the risk of the observed failures during testing, relative to the robustness of the final product. These numerical values can be decided by analyzing field returns of similar products.

The calculation method of the RLF for an LCD TFT TV set is given as a real case study, to demonstrate the concept. For this product, the test set consists of electrical, environmental and mechanical tests and these tests can further be grouped as pass/fail tests, early life period tests and design verification tests [9]. All tests have "scoring points" and these points are given according to the importance of the tests. The importance of the tests can be decided by considering the specifications and usage environment, analyzing production line failures, field returns from similar projects etc. As an example, if a product is designed to operate in high temperature environments then a high temperature test will be assigned more scoring points. If a test is thought to be more effective on finding failures, then this test will have higher scoring points.

In addition to this, the failures found during testing are grouped according to their severities, as "showstopper," "high," "medium," and "low". These failure severities are assigned "losing points" [2]. These points are also decided by analyzing field returns of similar projects, [9]. For example, in our application ESD (electrostatic discharge) is a common failure cause (as observed in our field returns), thus, as we will show later, the ESD test and any failures during that test will be assigned high scoring points and severity.

The scoring points and the losing points affect the result of the prediction method. It is very important to determine the scoring points of the tests and the losing points of the failure severities correctly. If the scoring points and the losing points are determined correctly the results of the prediction method will be closer to the actual value. In our application, the scoring points and the losing points were decided after very long tests and analysis of service data.

In our company, we classified the different robustness tests as follows:

2.1. Pass/Fail Tests

Pass/Fail tests are also referred to as "reliability approval tests". The main objective of such tests is to find major design flaws. These tests are performed on a product level, and usually with a small sample size. Table 1 provides a list of such tests and the associated scoring points used in our application.

Table 1. List of Pass/Fail Tests

Test Category	Test Name	Scoring Points
Electrical	Voltage Current Stress Test	100
	Temperature Stress Test	100
	Open/Short Circuit Test	100
	ESD Test	100
	Surge Test	25
	Lightning Test	50
	Voltage Dips, Interruption and Variation Test	50
	Power On/Off Test	50
	Inrush Test	75
Environmental	Heat-Run Test	100
	High Temperature Test	50
	Low Temperature Test	50
	High Humidity Life Test	50
Mechanical	Vibration Test	25
	Wall Holder Strength Test	25
	Drop Test	50
	Total	**1000**

2.2. Early Life Period Tests

Early life period (ELP) tests are performed with minimum 20 samples, on a board level. These tests are performed to determine component quality problems, assembly problems, solder-joint problems and failures occurred in early life, for example infant mortality failures. An example of such tests used in our organization is given in Table 2.

Table 2. List of Early Life Period Tests

Test Category	Test Name	Scoring Points
Environmental	Thermal Cycling Test	75
	High Temperature High Humidity Test	50
	Thermal Shock Test	50
Mechanical	Random Vibration Test	50
	Total	**225**

2.3. Design Verification Tests

Design verification tests (DVT) are not the same as the pass/fail tests mentioned above. These tests provide feedback to designers about the weakest points of the design. DVTs are performed with large sample sizes and at a product level, where the test period is longer than pass/fail tests. The main purpose of DVTs is to determine minor design problems. In addition, in these tests combined stress factors are used to accelerate failure mechanism. The list of design verification tests and corresponding scoring points used in our company is given in Table 3.

Table 3. List of Design Verification Tests

Test Category	Test Name	Scoring Points
Electrical	Powered / Unpowered Temperature Cycling Test	100
	ESD Step Stress to Failure Test	50
Environmental	Combined High Temperature High Humidity Test	50
	Thermal Shock Test	75
	Temperature Step Stress to Failure Test	50
	Operational High / Low Temperature Humidity Test	50
	High Humidity Storage Test	25
	Temperature Cycle Test	50
Mechanical	Constructional Inspection Test	50
	Unpackaged Shock Test	50
	Random Vibration Step Stress to Failure Test	25
	Total	**575**

2.4. Total Scoring Points and Losing Points

After the scoring points of the tests are decided, total scoring points are obtained

Then, the “losing points” of the failure severities are determined. As mentioned above, these losing points are decided based on field experience and criticality of the failure based on design specifications.

Table 4. Total Scoring Points

Test Type	Scoring Points
Pass / Fail Tests	1000
Early Life Period Tests	225
Design Verification Tests	575
Total Scoring Points (TSP)	**1800**

Table 5. Losing Points and Failure Severities

Failure Severity	Losing Points
Showstopper (S)	120
High (H)	45
Medium (M)	24
Low (L)	9

When the severities of the failures are decided, total losing points of the project can be calculated from equation (1).

$$TLP = (A \cdot S) + (B \cdot H) + (C \cdot M) + (D \cdot L) \qquad (1)$$

TLP: Total Losing Points
A: Number of “Showstopper” Failures
B: Number of “High” Failures
C: Number of “Medium” Failures
D: Number of “Low” Failures

2.5. Calculation of the Robustness Level Factor, RLF

By using equation (2), the parameter, “Robustness Level Factor” (RLF), is calculated.

$$RLF = 1 - \frac{TLP}{TSP} \qquad (2)$$

RLF: Robustness Level Factor
TLP: Total Losing Points
TSP: Total Scoring Points

Robustness Level Factor is a number between 0 and 1. This parameter expresses the robustness of the final product related to the failure causes mentioned above. With this parameter, we will attempt to predict the reliability and the return rate of the final product by combining it with life test results and predictions.

3. Combining RLF with life predictions

At this point, the challenge is to combine the computed Robustness Level Factor with predictions made from life tests. As mentioned previously, the motivation is to consider these qualitative failures in our predictions since they represent possible failures in the field. Failing to consider the design robustness in any predictions could result in less accurate estimations. Since the RLF is a qualitative factor (i.e. it does not represent an actual probability) it cannot be easily related to field failures. In order to so, we chose ANN, where a relationship between RLF and life test predictions vs. actual field return rate (based on past projects) can be established/learned. In other words, from past projects, RLF and reliability predictions based on life tests will be the inputs and the actual field return rate the output, and an ANN will be used to “learn” the function between them. Based on the established function, the RLF and the life test reliability prediction of the product under development, we will infer its field return rate.

In engineering and science, ANN are used whenever a function between inputs and outputs needs to be established, where such function is very complex to be determined with other methods or non-applicable (e.g. linear regression). The problem under investigation of combining robustness tests results and life test results falls under this category where no known relationship exists thus using ANN offers an approach to establish it

4. Reliability and return rate estimation

Traditionally, reliability and field return rate predictions were made based on prediction standards (e.g. MIL-217F) and/or life test results. In this paper we consider accelerated life tests where samples are tested at different stress conditions and the results are extrapolated to use level stress conditions. Predicting reliability based on accelerated life tests is a very useful approach; however, such predictions only consider life related failure mechanisms such as electromigration, thermal fatigue, corrosion, etc. In addition, predictions made under this approach are sensitive to the test's sample size. For smaller sample sizes this can result in high uncertainty in the predictions.

In order to increase the accuracy in the predictions and to take into account the robustness level of the design, ANNs will be utilized. In other words, the proposed methodology aims to improve the field return rate prediction by taking into account the accelerated life test results and the RLF. ANN requires existing inputs and outputs to be provided and based on those a function is built. The existing inputs and outputs are called the "training set." In other words, these are the set of values where the algorithm will learn the pattern. In our application, the training set will be the RLF, reliability predictions based on life tests and actual field returns of past projects. The higher the number of past projects used in the training set the more accurate the relationship between inputs and outputs is expected to be. It should also be noted that the proposed methodology and the past projects used apply when making predictions for similar products and for products where history exists (i.e. evolutionary designs).

There are different techniques and algorithms for creating ANNs which are beyond the scope of this paper. In our application and since we only consider two inputs and one output, we used a simple single layer ANN. A real life case study for a LCD TFT TV set is given in the following section.

5. Real life case study

A real life case study to predict reliability and 1st year field return rate values of 3 LCD TFT TV Set projects, with CCFL and LED panels, is given by using 4 older projects' RLF values, accelerated life test predictions, and actual field return rate data (Table VI). These 3 products are currently in the field for more than a year, and their actual 1st year return rates will be provided as a comparison to the predicted ones, to illustrate the applicability of the model.

Table 6. RLF values, accelerated life test results and actual fiedl return rate values

Project	RR_{ALT} (%)	90% 1S UPPER RR_{ALT} (%)	RLF	AFRR (%)
1	4.00	7.98	0,6494	4.19
2	1.82	9.26	0.8275	2.60
3	0.26	4.60	0.9360	0.87
4	2.83	11.75	0.8950	1.57

In Table VI, each project number refers to a real TFT LCD TV product. RRALT denotes the estimated return rate (50% confidence level) calculated by applying accelerated life tests, 90% 1S UPPER RRALT denotes the 90% upper one-sided bound return rate, and RLF denotes "robustness level factor" calculated by applying the tests described in Section II and using the same scoring points provided in that same section. AFRR denotes actual field return rate.

There are a few observations that can be made by examining the information provided in Table VI.

1. The upper bounds are significantly higher than the estimated values. This is due to the small sample sizes used during the ALT.
2. The upper bounds are significantly higher than the actual field return rates.
3. The estimated values (i.e. 50% confidence level) are closer to the actual field return rates.

One could observe that the actual field return rates are below the upper bound computed from the ALT analysis, which is of course the reason of using confidence bounds, i.e. to contain the uncertainty due to sample size. The statement that can be made is that we are 90% confident that the true field return rate will be below the upper bound. However, it can be seen that this bound is very conservative and additionally we need to keep in mind that it does not consider any robustness related failures in the field. In other words, even though the true values given in Table VI are contained within the bounds, one needs to be careful because it is no indication that the robustness related failures are included in the estimation. There may very well be situations where if sufficient number of samples were tested during the ALT, the upper bound would be close to the estimate and could also be below the actual.

We would now like to better understand the relationship between the ALT predictions and the robustness of the product in order to make more intelligent field return rate predictions. For this, we will use ANN as described in Section III. Table VII provides the ALT results and the RLF values for 3 projects currently in the field over 1 year. The actual field return rates are known but we will use the proposed methodology to estimate them and later compare them to the actual values.

Table 7. RLF values and accelerated life test results

Project	RR_{ALT} (%)	90% 1S UPPER RR_{ALT} (%)	RLF
5	0.48	0.66	0.9100
6	0.46	19.55	0.8856
7	1.21	13.73	0.9100

In Table VII we can see that for Project 5 it is expected that the true field return rate will be below 0.66% based on the ALT analysis. In this project it can also be seen that the 90% upper bound is close to the estimated value. This is due to the fact that sufficient samples were tested and for sufficient duration during the development of this product. On the other hand, in projects 6 and 7, less time and samples were available during development and this is reflected in the width between the estimated values and the upper bounds. Based on the history of these products (these 3 products are evolutions of the previous 4 products given in Table VI), we do not expect the actual field return rate to be as high as predicted by 90% upper bound estimates. In addition, our robustness tests have shown that the robustness of these 3 products is high as reflected in the RLF values.

To summarize, we have high confidence in the prediction for project 5 and the actual field return rate is expected to be close to this prediction. However, we need to keep in mind that this prediction does not take into account any robustness related failures which may occur in the field. On the other hand, we are more uncertain about the ALT predictions for projects 6 and 7 and we believe (based on history) that the actual field return rate should be less than these predictions, which also do not include robustness related failures. Finally, all 3 projects have quite high RLF values thus we expect less robustness related failures in the field.

5.1. Analysis and results

To apply the methodology described in section III, we will use the values provided in Table VI as the "training set" for the ANN algorithm. Based on this training set, the ANN will create a relationship between the inputs which are the ALT estimates and the RLF values, and the output which is the AFRR. We will use the 90% upper confidence bound estimate as the ALT input since it provides an estimate which contains the uncertainty of the result.

An ANN was created using the training set described above. We used a single layer ANN with 0 neurons in hidden layers, a minimum weight delta of 0.0001, a learning rate of 0.3, and a zero-based Log-sigmoid-function for the activation function. Based on this ANN and the training set of Table VI, the field return rate of the 3 projects with inputs given Table VII was predicted, and is given in Table VIII.

Table 8. Predicted field return rate values

Predicted Field Return Rate Values (%)	
$PFRR_5$	0.929
$PFRR_6$	2.277
$PFRR_7$	1.459

The following observations can be made from the results of Table VIII;

1. The predicted field return rate for Project 5 is higher than the 90% upper bound value based on ALT analysis. This outcome is actually reasonable, since, as we mentioned previously, the ALT does not consider any robustness related failures where in the field we do expect to see such failures.
2. For projects 6 and 7 the predicted field return rates are much lower than the 90% upper bound value based on ALT analysis. This is also a reasonable outcome as these projects have historically much less failures than what was predicted by the ALT analysis and in addition, they also have a high RLF value which implies consistency and/or improvement over past projects thus similar expectations regarding robustness related failures.

5.2. Comparison of predictions with actual field return rates

As mentioned before, these 3 products are already in the field for more than a year. To illustrate the accuracy of the proposed model and prediction, the actual field returned rates (as obtained from our service department) are given in Table IX and are compared to the predicted values in Table VIII.

As it can be seen from Table IX, the results of the predicted field return rate values by using proposed method are very close to the actual field return rate values and thus more realistic.

Table 9. Actual and predicted 1st year field return rate values

Project	Predicted Field Return Rate (%)	Actual Field Return Rate
5	0.929	1.19
6	2.277	1.14
7	1.459	1.47

6. Conclusions

Reliability and return rate predictions are currently performed mainly by using stress based standards or applying accelerated life tests. However, these methods may not capture every failure reason seen in the field, and specifically robustness related failures. In addition, there is typically a variety of robustness tests performed during development whose outcome indicates the likelihood of observing such failures in the field. Traditionally, the lessons learned and the outcomes of these tests are not taken into consideration when field predictions are performed. It is reasonable to assume that such information regarding a product's robustness should have an influence on the field return rate. For these reasons, we first proposed a parameter to quantify a product's robustness, RLF, using scoring points for the different robustness tests (as described in section II), and we then used this parameter in conjunction with life test results in order to make more realistic field return rate predictions. To do so, we used information from past projects and Artificial Neural Networks in order to create a relationship between the life test results, the RLF and the actual field return rate. The choice of ANNs as a technique was based on the fact that we are not certain about the form of the relationship between these inputs and the output, which could also vary by the application, the product, the historical information, etc. Thus, ANNs provide a general approach which can be used in a variety of products and industries.

The methodology has been used internally in our company and has been proved to be a very useful approach by providing more realistic predictions, which was also demonstrated in this paper by the provided case study. Further utilization of this approach by other industries or reliability engineers would be helpful in order to determine its applicability and value. It should also be noted that our presented approach is an attempt to consider this very real case of including information regarding the robustness of a product and in general any type of qualitative information and test results in the final field return rate prediction. We hope that this approach can also generate interest in this topic and provide stimulation for further research. In fact, the authors are currently also considering other approaches such as the use Bayesian statistics. The research is in its early stages thus no comparisons and results could be reported at the time of this writing.

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