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Application of Grey Prediction Model for Failure Prognostics of Electronics

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Abstract: Reliability prediction is becoming more and more important for electronics components and devices, such as avionics. In this paper, a grey prediction model based prognostics approach was developed to perform the failure prediction of electronics. The grey prediction model first makes the original data set into a new data set with less randomness in order to find the tendency. Then, history data is needed for training the algorithm and predicting the future condition. Last, the predicted result in the new data set is transferred back to the original data set. Compared with traditional data-driven method, this approach was especially useful for reliability prediction with small sample size. The whole prognostics approach was also verified by two case studies. One was performed on electronic boards with ball grid array (BGA) and quad flat package (QFP) components under thermal cycle loading. The other was performed on electronic boards with capacitors under temperature, humidity and bias tests.

Keywords: *electronics, failure prediction, grey prediction models, prognostics*

1. Introduction

A failure prognostics is a process of predicting the useful life of a product based on an assessment of its current state-of-health and its past operational and/or performance conditions [1]. Failure prognostics for electronics provides information that can be used to meet several critical goals, including (1) providing advance warning of failures; (2) minimizing unscheduled maintenance, extending maintenance cycles, and maintaining effectiveness through timely repair actions; and (3) reducing the life-cycle cost of equipment by decreasing inspection costs, downtime, and inventory [2].

The failure prognostics process involves monitoring data on the operational and performance parameters of the product in field. This data is often collected in real-time or near real-time and used in conjunction with prediction models to provide an estimate of its state-of-health or degradation and the projection of remaining life. The prediction models can be physics-based or data-driven. Physics-based models compare the strength of the product versus the damage caused by cumulative exposures to environmental and operational conditions. Data-driven methods characterize the normal operating and performance conditions of the product and track the changes in these conditions to assess the state-of-health and predict the future state or remaining life of the product.

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The models used in data-driven approaches can be based on wide variety of mathematical and statistical methods. The grey prediction model is part of the grey system theory, and can be classified as a data-driven approach to perform failure prognostics. The grey system theory was developed by Deng [3] in 1982. The main function of it is the effective processing of the analysis, modeling, prediction, decision making and control with incomplete data. The grey prediction model has been applied in many areas, such as information technology [4], energy and power [5], industry and economics [6], accident and risk [7], engineering [8], the environment [9] and so on. This paper presents the first application of the grey prediction approach for failure prognostics.

2. Grey prediction model

The steps used in the grey prediction model are shown in Figure 1 [5]. AGO means the accumulated generating operation, and IAGO means the inverse accumulated generating operation.

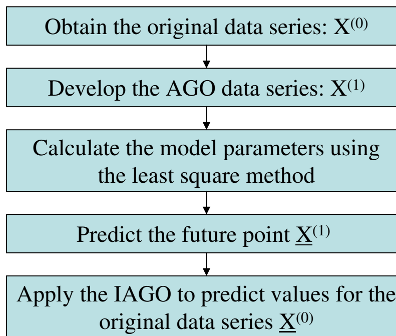

Figure 1: Grey prediction procedure

The accumulated generating operation (AGO) is used to transform an original set of data into a new set that highlights trends, but has less noise and randomness. The equation used in generating the AGO series is:

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i) \tag{1}$$

where, $X^{(0)}$ represents the original data series, and $X^{(1)}$ represents the AGO series.

After $X^{(1)}$ is obtained, the grey differential equation is built. The general grey differential equation with one variable is:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{2}$$

where, $X^{(1)}$ represents the AGO series. The coefficients a and b express the relationship between dX/dt (rate of change of state) and X is the current state.

Parameters a and b are determined using the least-square method, which are shown in the following equations:

$$A = \begin{bmatrix} a \\ b \end{bmatrix} = [\beta^T \beta]^{-1} \beta^T Y \tag{3}$$

where,

$$\beta = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \tag{4}$$

$$Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \vdots \\ X^{(0)}(n) \end{bmatrix} \tag{5}$$

$$Z^{(1)}(i) = \frac{X^{(1)}(i-1) + X^{(1)}(i)}{2} \tag{6}$$

Then the predicted data points for the AGO series are calculated. $\underline{X}^{(1)}$ represents the predicted AGO series. The equation used in this process is the integral result from equation (2), and can be written as follows:

$$\underline{X}^{(1)}(i+1) = \left(X^{(0)}(1) - \frac{b}{a} \right) e^{-ai} + \frac{b}{a} \tag{7}$$

where $X^{(0)}(1)$ represents the first data in the original series. Then the inverse accumulated generating operation (IAGO) is used to get the inverse data series from AGO. It is then used to transform the forecasted AGO data series back into the original data series. This is achieved using the following equation:

$$\underline{X}^{(0)}(i+1) = \underline{X}^{(1)}(i+1) - \underline{X}^{(1)}(i) \tag{8}$$

where $\underline{X}^{(0)}$ is the predicted original data series. Combining equations (7) and (8), we can get equation (9) as follows:

$$\underline{X}^{(0)}(i+1) = \left(X^{(0)}(1) - \frac{b}{a} \right)(e^{-ai} - e^{-a(i-1)}) \tag{9}$$

To improve the prediction accuracy, several researchers have presented enhanced grey prediction models. One is residual grey prediction model, which can be used to minimize prediction error [10]. It has been also found that the basic grey prediction model can be used well with slow growth time sequences, but these often perform poorly and make delay errors for quick growth time sequences [7]. Mao *et al*. [7] suggested an improved method based on a modified Z series calculation, and a modified Equation (6) was proposed in his work.

3. Failure prognostics of electronic boards

A printed circuit board (PCB) with ball grid array (BGA) and quad flat package (QFP) components shown in Figure 2 was exposed to thermal cycling loads. From experiments, the main failure mechanism is solder joint fatigue failure. The solder joint failure was checked by trending its resistance drift as shown in Figure 3. In order to consider the effect of temperature to resistance, it is important to calculate the residual value (resistance drift) rather than resistance only. The failure is defined as the resistance drift obtains 0.5Ohm from previous experience.

In the first step, the grey prediction model accuracy was verified for component QFP256, and compared with other prediction models. The first eight data points (resistance drift) were used to verify the prediction accuracy of the ninth point, and the results were shown in Table 1. Compared with other models, grey prediction models show more accurate results. From previous experience, the signals collected from electronic systems vibrate a lot. Therefore traditional prediction methods show larger prediction discrepancy, while the grey prediction model focused more on the accumulated effect, and showed the more stabilized prediction results.

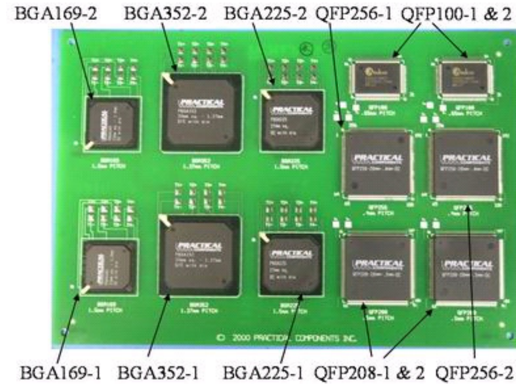

Figure 2: Test board under thermal cycle loading

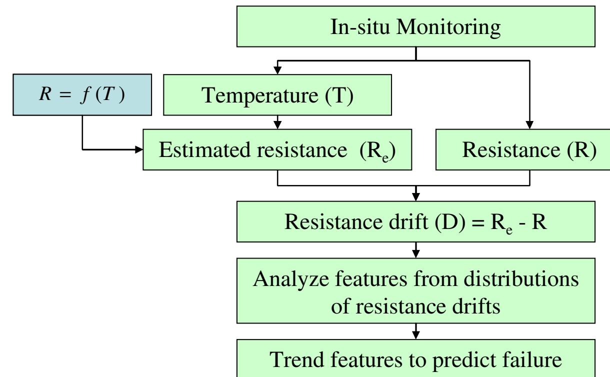

Figure 3: Failure prognostics for solder interconnect failure under temperature cycling

Comparison was also made of the grey prediction model and other prediction models in the literature [11], such as linear, exponential, and polynomial prediction models, which revealed that the grey prediction model gives the most precise and accurate prediction. In addition, assumptions regarding statistical distributions of data are not necessary when applying the grey prediction model [12]. Compared with the auto-regressive (AR) model, the grey prediction model has the advantage of needing less data for training, while the AR model needs much more data to get a corresponding accuracy [3]. Compared with the auto-regressive integrated moving average (ARIMA) model, the grey prediction model also shows more accuracy when using the same size of training data [13]. The essential feature of the grey prediction model is dealing with a small sample size of data. Therefore, it is suitable to carry out the dynamic prediction in-situ. In addition, for the grey prediction model, the newest data is considered more important than the old historic data. The old data will be updated using new data, so the prediction can give more accurate results when approaching the actual point.

The prediction results based on grey prediction models for different components (QFP208, QFP256, and BGA352) are shown in Figure 4, Figure **5**, and Figure **6** as demonstration. The initial 300 hours data was used for algorithm training purposes. The decision making points are chosen based on either of the following two criteria.

Table 1: Comparison of different prediction models

Prediction model	Initial Discrepancy (%) – Based on few data points
Grey prediction model	1.05%
Linear	-45.26%
Quadratic	-50.00%
Exponential	-64.21%
Moving average	-40.53%
ARIMA	15.67%

One is that the data meets half of the defined failure level (in this case: 0.5/2=0.25Ohm). The other is that the data is out of the $\bar{x}+3\sigma_x$ or $\bar{x}-3\sigma_x$ bounds, where $\bar{x}$ is the mean and σ_x is the standard deviation for a certain data window. These bounds were also chosen by Ku [14] and Lin [8]. This criterion is set to capture sudden changes of the data. When the decision making point is obtained, it will continue the prediction process until the result meets the failure criteria (when the resistance drift obtains 0.5Ohm). Figure 4, Figure **5**, and Figure **6** show that the prediction results match well with actual failure point. In addition, the results are conservative, and provide advance warming, which means the predicted failure point is always earlier than the actual failure point.

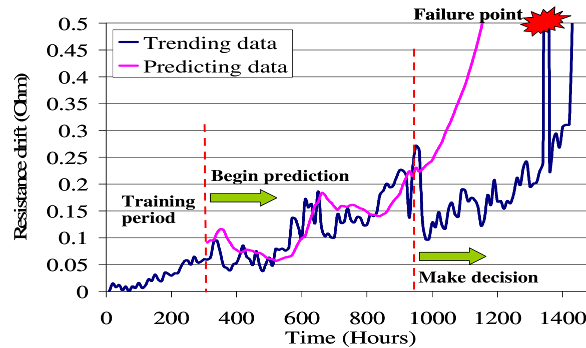

Figure 4: Failure prediction for QFP208

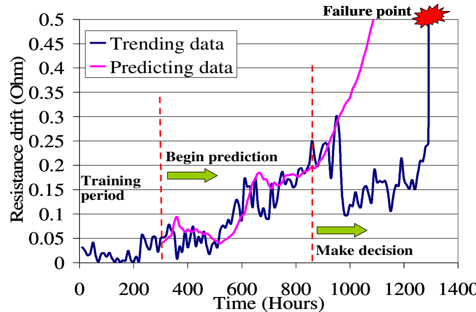

Figure 5: Failure prediction for QFP256

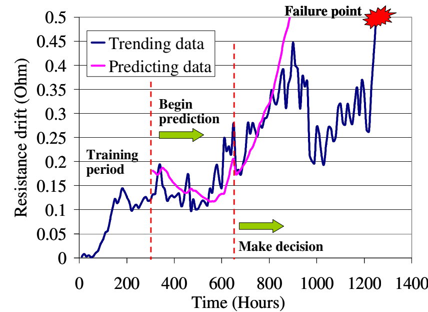

Figure 6: Failure prediction for BGA352

4. Failure prognostics of capacitors

In this experiment, 96 multi-layer ceramic capacitors (MLCC) were selected for in-situ monitoring and life testing in elevated temperature (85°C) and humidity (85% RH) conditions with one of 3 DC voltage bias levels: rated voltage (50V), low voltage (1.5V), and no voltage (0V). Four MLCC types were included, two of which were flexible-termination MLCCs and two were standard-termination MLCCs. The insulation resistance (IR), capacitance (C), and dissipation factor (DF) were monitored in-situ during testing. An LCR meter was used to measure capacitance and dissipation factor. A high resistance meter was used to measure insulation resistance. In this setup, 96 capacitors were tested together and a multiplexer and data logger allowed the measurement of electrical parameters for each capacitor once every 200 minutes. The total test lasted for around 1240 hours. More details can be found in the previous study [15].

The prognostics approach used in this study is regression, residual, detection and prediction analysis (RRDP), which shown in Figure 7. The first step was to select the survived capacitors as the training data set. From the training data set, we could calculate the mean and standard deviation for each parameter (IR, C and DF), which can be used to perform data normalizations. After normalization, regression analysis was performed to build a relationship between the normalized IR, normalized C and normalized DF and calculate the residual. When the new incoming IR, C and DF data were obtained, data normalization was performed using the mean and the standard deviation calculated from the training data set, and then calculate the residual again. By comparing this new residual value with the residual value in the training data set, anomaly detection could be performed, and then followed up by the grey prediction for failures.

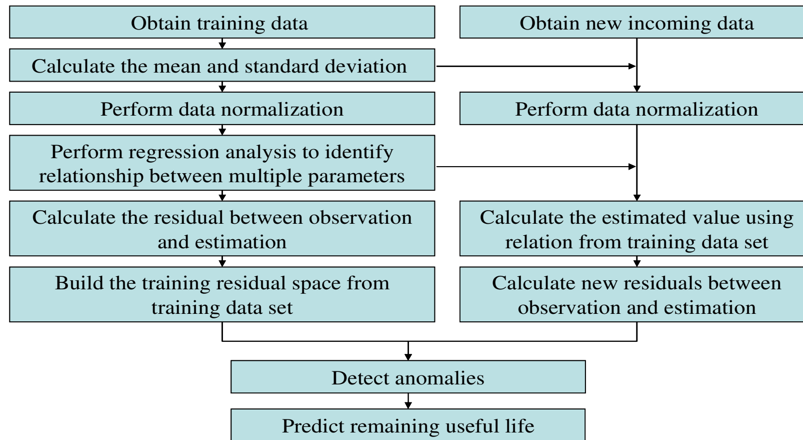

Figure 7: Regression, residual, detection and prediction analysis

The prediction result obtained using the grey prediction model for one capacitor is shown in Figure 8. The prediction algorithm was triggered when the residual value crossed the 95% confidence interval (around 2 sigma range) line. The predicted failure time was hour 753 when the prediction result is below 99.9% confidence interval (around 3 sigma range). When new incoming data were obtained, the updated prediction result was more accurate (hour 800). This approach was repeated for all 96 capacitors, and the results were summarized in Table 2. It was found that out of 96 capacitors, the 8 failed capacitors could be detected by residual analysis with no missed alarms. Five out of the

eight capacitors that failed gave an advance warning of failure. Among the other 88 survived capacitors, there were eight false alarms.

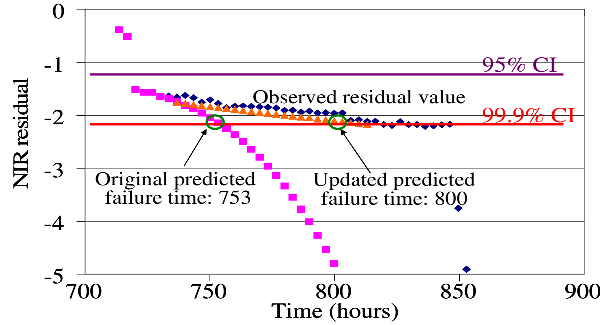

Figure 8: Failure prediction for one capacitor

Table 2: Summary of prediction results for all 96 capacitors

Manufacturer	Termination	DC bias (V)	No. of samples	No. of failures from experiment	No. of missed alarms	No. of false alarms
A	Flexible	50	10	5	0	0
		1.5	10	0	0	0
		0	4	1	0	0
B	Flexible	50	10	0	0	0
		1.5	10	0	0	0
		0	4	0	0	0
B	Standard	50	10	0	0	1
		1.5	10	0	0	0
		0	4	0	0	0
C	Standard	50	10	0	0	2
		1.5	10	0	0	3
		0	4	2	0	2

5. Conclusions

In this paper, the application of the grey prediction model was investigated for failure prognostics of electronics. The grey prediction demonstrated a higher level of accuracy when dealing with small sample size data. Two case studies were used for the results verification. In the first experiment, electronic boards with components were under thermal cycle loading, and the grey prediction model was used to develop the trend of the resistance drift in order to perform prognostics to identify the time it takes to fail. The results revealed that the grey prediction method successfully provided advance warning of failure. In the second experiment, the grey prediction model showed good promise for predicting failures for multilayer ceramic capacitors in the temperature, humidity and bias tests. Both experiments demonstrated that the grey prediction model can be implemented to perform failure prediction for electronics. Future work can be focused on the combination of the physics-of-failure (PoF) model with the grey prediction model. The failure probability can be used to trigger the grey prediction model rather than the traditional statistical approach in order to make predictions more accurate.

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