Tipping point analysis of electrical resistance data with early warning signals of failure for predictive maintenance

V. N. Livina\textsuperscript{1}, A. P. Lewis\textsuperscript{1} and M. Wickham\textsuperscript{1}
\textsuperscript{1}National Physical Laboratory, Teddington, United Kingdom

Abstract

We apply tipping point analysis to measurements of electronic components commonly used in applications in the automotive or aviation industries and demonstrate early warning signals based on scaling properties of resistance time series. The analysis utilises the statistical physics framework with stochastic modelling by representing the measured time series as a composition of deterministic and stochastic components estimated from measurements. The early warning signals are observed much earlier than those estimated from conventional techniques, such as threshold-based failure detection, or bulk estimates used in Weibull failure analysis. The introduced techniques may be useful for predictive maintenance of power electronics, with industrial applications. We suggest that this approach can be applied to various electromagnetic measurements in power systems and energy applications.

1 Introduction

A significant challenge in the design and development of high-reliability electronic assemblies is in relating the results from testing with real-world performance. The key issue is that, due to the wide range of applications, standardised tests may not predict the range of harsh environments to which an electronic assembly will be exposed. As a consequence for high-reliability use, particularly in safety-critical applications, a common approach is to use a standardised test which utilises over stress conditions to accelerate failures. Weibull reliability analysis \cite{Scholz1999} uses a parametric Weibull model to estimate a probability density and failure rate function based on the parameters of the distribution of parts failure, which provide information about the average behaviour of parts of expected quality. Factors such as time-to-first failure and analysis of Weibull distributions are used to give indications of when components/assemblies should be replaced. However, since there are significant uncertainties in real stress conditions and quality of materials and manufacturing process, these indicators are chosen to be highly conservative. Therefore alternative methods are sought to
give a more reliable indication of the remaining useful life. One method which
has shown promise is the use of prognostic devices for monitoring solder joints
[Chauhan et al. 2014]. These can be components (e.g., zero-ohm resistors) which
are incorporated into an electronic assembly and are designed to fail before any
other component. As they are a part of the assembly, they will experience the
same manufacturing, environmental and detrimental factors. As part of a fea-
sibility study on a range methods for measuring the progression of failure for a
solder joint (between a printed circuit board PCB and a zero-ohm resistor), an
experiment was conducted which looked at the evolution of the DC resistance as
the solder joint underwent thermal cycling. The thermal cycling ageing process
can cause cracks to form in the solder interconnect due to mismatches in the
coefficients of thermal expansion between the substrate, contact pads, solder
and components. These cracks cause discontinuities in the electrical circuit,
although the resistance change during the crack initialisation tends to be minor
until a failure event where the resistance increases significantly by several orders
of magnitude, potentially to open circuit. The question that this article seeks
to answer is whether small changes in electrical resistance and in the pattern of
their fluctuations (such as short- and long-term memory) can be used as early
warning indicators to predict impending failure events. Early warning signals
based on these changes proved to be of general applicability in generic dynamical
systems, and bringing them into the area of predictive maintenance may
serve as a cross-disciplinary advantage for the manufacturing industry.

Tipping points in dynamical systems have recently become a topic of high
interest in the area of climate change; see, for example, [Lenton et al. 2008].
Applications of the tipping point analysis have been found so far in geophysics
[Livina and Lenton 2007, Lenton et al. 2009, Livina et al. 2010, Livina et al. 2011,
Livina et al. 2012, Lenton et al. 2012a, Lenton et al. 2012b, Livina and Lenton 2013,
Cimatoribus et al. 2013, Livina et al. 2013, Prettyman et al. 2018], statistical physics
[Vaz Martins et al. 2010, Livina et al. 2013], structure health monitoring [Livina et al. 2014,
Perry et al. 2016], as well as in ecology (see [Dakos et al. 2012, Scheffer et al. 2009]
and references therein). There is a debate about various types of tipping citeash-
win and false alarms [Ditlevsen and Johnsen 2010], but for practical applications
in industry, non-bifurcational transitions (without structural change of the
dynamical system), may be as important as bifurcations and require ade-
quate analytical tools and techniques of analysis. One of the advantages of the
tipping point methodology is that it does not require extensive training datasets
(unlike many other techniques of machine learning), and therefore can be useful
in situations where there is limited operational data available, or where stress
conditions are unknown.

A dynamical system with observed time series of measurements can be mod-
elled by the following stochastic equation with state variable $z$ and time $t$:

$$
\dot{z} = D(z, t) + S(z, t),
$$

(1)

where $D$ and $S$ are deterministic and stochastic components, respectively. The
probability density of the system can then be approximated by a polynomial of
even order (the so-called potential system, see Livina et al 2010). The stochastic component, in the simplest case, may be Gaussian white noise, although in real systems it is often more complex, for example, with power-law correlations, multifractal and other nonlinear properties.

Tipping points can be described in terms of the underlying system potential \( U(z, t) \), whose derivative, if it exists, defines the deterministic term in Equation (1), i.e. \( D(z, t) = -U'(z, t) \). If the potential structure (number of potential wells) changes, the tipping point is a genuine bifurcation. If the potential structure remains the same, while the trajectory of the system samples various states, such a tipping point is transitional. An example of such transition may be the record of global temperature, which has the same structure of fluctuations with a drift (under forcing or noise-induced).

The methodology has general applicability for studying trajectories of dynamical systems of arbitrary origin and serves to anticipate, detect and forecast tipping points. In this paper we apply the first stage of the tipping point analysis, the early warning signals for anticipation of tipping points, which is based on degenerate fingerprinting [Held and Kleinen 2004] with further modifications of the technique using Detrended Fluctuation Analysis [Livina and Lenton 2007] and power spectrum [Prettyman et al 2018].

2 Data

A PCB test vehicle was designed to enable the evaluation of test methods to measure the remaining useful life of solder joints. To accelerate the ageing process, the test boards were placed in a thermal cycling chamber cycling from \(-55^\circ\text{C}\) to \(125^\circ\text{C}\) at a rate of \(10^\circ\text{C}\ \text{min}^{-1}\) and with 5-minute dwells at the temperature extremes. The test boards were 1.6 mm thick copper clad FR-4 with a NiAu finish. The test components were zero-ohm 2512 chip resistors connected with a Pb-free solder interconnect. An image of the test board is given in Figure 1.

We analysed measured resistance datasets from nine chips, which experience failure (critical rise of resistance) after repeated testing cycles, see Figure 2.

3 Methodology

Anticipating tipping points (pre-tipping or early warning signal) is based on the effect of slowing down of the dynamics of the system. When a system state becomes unstable and starts a transition to some other state, the response to small perturbations becomes slower. This signal of “critical slowing down” is detectable as increasing autocorrelations quantified by the autocorrelation function (ACF) in the time series [Held and Kleinen 2004].

Alternatively, the short-range Detrended Fluctuation Analysis [Livina and Lenton 2007] or power spectrum scaling exponent [Prettyman et al 2018] can be monitored. These three techniques are essentially equivalent as they are monitoring the
Figure 1: Image showing test boards. Each test board could host up to 10 surface mount chip resistors. Each component was connected to four pads to enable a 4-point probe method of resistance monitoring.

Figure 2: Nine time series of measured resistance with critical rise indicating the failure of the units after repeated test cycles.
changes of “memory” (autocorrelations) in the data, with the difference of DFA taking care of trends in case if they affect data, which is often useful for distinguishing trend-based transitions. We explain in full the ACF-indicator technique, which is simplest of the three, and provide further references on DFA and PS-indicators for those who are interested in applying all three techniques for comparison. In particular, differences between ACF and DFA indicators denote presence of trends, as DFA has built-in detrending. The early warning signal value is calculated in sliding windows of fixed length (or variable length for uncertainty estimation) along a time series. These dynamically derived values form a curve of an early warning indicator whose pattern describes the behaviour of a time series. If the curve of the indicator remains flat and stationary, the time series does not experience any critical change (whether bifurcational or transitional). If the indicator rises to the critical value of one (the monotonic rise is assessed using Kendall rank correlation), it provides a warning of critical behaviour.

Lag-1 autocorrelation is estimated by fitting an autoregressive model of order one (linear AR(1)-process) of the form:

\[ z_{t+1} = c \cdot z_t + \sigma \eta_t, \]

where \( \eta_t \) is a Gaussian white noise process of unit variance, and the “ACF-indicator” (AR(1) coefficient) is as follows:

\[ c = e^{-\kappa \Delta t}, \]

where \( \kappa \) is the decay rate of perturbations, \( \Delta t \) is the time interval and \( c \to 0 \) as \( \kappa \to 0 \) while a tipping point is being approached. This analysis can be performed using several early warning indicators, with and without detrending data in sliding windows [Livina et al 2012].

4 Results and discussion

We have calculated two early warning indicators, ACF- and DFA-based, and compared the timing of the obtained early warning signals with the conventional threshold-based warning. As a threshold of failure, one can consider triple-nominal resistance. In the beginning of the experiment, the resistance values of the tested units were about 0.008 Ohm, and therefore the threshold would conventionally be established at about 0.025 Ohm.

We first calculate the ACF-based indicator with uncertainty quantification and estimate the time of the early warning signals for them when the ACF-indicator reaches a high value of 0.9, as shown in Figure 3. In addition, we consider the average curve of the ACF-indicator and along this curve calculate linear extrapolation of the indicator to estimate when in future it would reach critical value 1 (for DFA, the critical value is 1.5). By doing this, we obtain a set of possible times when the failure would happen, which forms a histogram — this histogram is then used to generate the kernel density of the future failure times.
Figure 3: ACF-indicators with uncertainty quantification based on varying window size (10-50% of time series length) for nine time series of measured resistance with clear critical rise prior to failures. Dashed lines denote the high level of auto-correlation that indicates approaching transition. Red curves correspond to probability densities (kernel distributions of the times of projections of subsets of the indicators when critical value 1 would be reached (estimation of proximity of failure).

The peak of such a kernel density is the most likely time of failure, statistically. We illustrate this in Figs.3,4 and also use this information in Fig.5.

We also apply the DFA-indicator to assess early warning signals by the alternative technique, as shown in Figure 4:

We then map the time points that can be seen in the rising indicators to the plot with the data, in which we also highlight where the electrical interconnect fails and goes open circuit, and observe that early warning signal indicators provide much earlier forewarning than the conventional technique, see Figure 5.

5 Discussion

We have applied early warning signal indicators in to the power measurement data and, to our best knowledge, for the first time observed the effective early forewarning of a failure in the electromagnetic measurements. Although the techniques applied here provide advance early warnings that could be suitable
Figure 4: DFA-indicators with uncertainty quantification based on varying window size (10-50% of time series length) for nine time series of measured resistance with clear critical rise prior to failures. Dashed lines denote the critical value of the DFA-indicator [Livina and Lenton 2007]. Red curves correspond to probability densities (kernel distributions of the times of projections of subsets of the indicators when critical value 1 would be reached (estimation of proximity of failure).
Figure 5: Comparison of forewarning performance of two early warning signal indicators (green arrow — lag-1 ACF-indicator, blue arrow — DFA indicator) and triple-nominal resistance threshold denoted by the dashed line (red arrow for the time stamp). The reported cycles when the units went open circuit: r.1c.1 (run 1 channel 1) — 540, r.1c.2 — 1000, r.1c.3 — 750, r.2c.1 — 1000, r.2c.2 — 815, r.2c.3 — 810, r.3c.1 — 910, r.3c.2 — 543, r.3c.3 — 516. Both early warning signal indicators provide much earlier forewarning of the upcoming failure of units with critically rising resistance. The locations of green and blue arrows are based on the peaks of kernel distributions in Figs.3,4.
for early safe replacement of endangered units, we understand that in industrial practice, economic considerations may dictate later predictive maintenance than is indicated by the proposed techniques. Finding the balance of early forewarning and further use of the unit undergoing the critical change will be the object of our further study. Acknowledgements

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