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Development of an AI model for electronic board maintenance decision prediction for railway equipment

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ABSTRACT

Railway equipment is required to work fault-free under rugged conditions such as continuous operating heat loads. One of the most important considerations in railway maintenance is the ability to predict failure, due to aging, early enough such that spare parts can be acquired just-in-time which normally takes a lead time of several weeks to up to around a year from the supplier. This study has conceived and tested the RUS Boost Ensemble machine learning algorithm to predict maintenance decisions of railway electronic boards based on measurable component values. Some traditional approaches like MIL-217 are commonly used for electronic reliability prediction but these types of approaches do not consider load profiles, failure root causes, and practical limitations in the number of available experimental test samples. This study develops a prognostic approach by considering actual load conditions and life limiting factors, and utilises machine learning algorithms to build the model. The model also makes use of real-life test samples from lab ALT (Accelerated Life Testing). After development of the AI model to predict electronic board component maintenance, the test results revealed the predictive accuracy to have up to 95% correlation for the red/urgent category and 94% for the yellow/medium-urgency category.

KEYWORDS Electronic board life prediction AI; failure rate; railway maintenance; RUS Boost Ensemble machine learning; accelerated life testing

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1. Introduction

Traditionally, determining the optimised maintenance regimes for boards have depended solely on access to either experimental ALT (accelerated life testing) results and component datasheets that specify component life limits. Datasheets of components and their parameters add little value to life calculations due to the variances in operating usage rates on trains and complex electrical relationships between component and component and the electronic board substrate. On the other hand, ALT, which is an experimentation method for life prediction in regard to electronic board assembly, does provide a good start for estimating the lifespan of boards provided that the following real-world factors are accounted for (Yin and Wang, 2011):

(1) Temperature load variation. ALT uses a single temperature for acceleration testing and calculation of predicted life. However, in a real-world situation, components of the electronic equipment will operate within a different temperature profile and hence the acceleration rate of each component will be different from each other. In other words, the aging rate of each component needs to be calculated according to different acceleration rates of different operating temperature.

(2) Combined effects of internal and surface heat load. In most ALTs, the equipment under test is offline (powered off) as it is a part of an electronic system and cannot operate in a standalone configuration. Therefore, during ALT the core and surface temperatures of all components are equal to the acceleration temperature. However, in the real operating environment, the core temperature of a heat-generating component is different from its surface temperature while it is the core temperature that should be used for calculation of the acceleration rate.

(3) Limited test samples. Usually the numbers of samples sent for ALT are limited, and normally one or two pieces are permitted due to the expensive nature of these test samples.

A new approach, as determined by this study, aims to enhance the traditional ALT life prediction through taking account of operational real-world conditions as mentioned above and optimising/simplifying the process via machine learning algorithms so that it can be readily used and replicated for different railway electronic boards.

2. Maintenance goals and constraints in the railway industry

Elimination of teething issues prior to determining the maintenance regime. It is common practice for a maintenance organisation to first eliminate all teething issues or design related issues prior to establishing standardised maintenance regimes for an electronic asset/board. During the inception of a new electronic asset, boards commonly undergo a minimum of one year of operational trials on a full fleet of trains and the components are either replaced or modified depending on whether the root cause of failure was determined to be a manufacturing

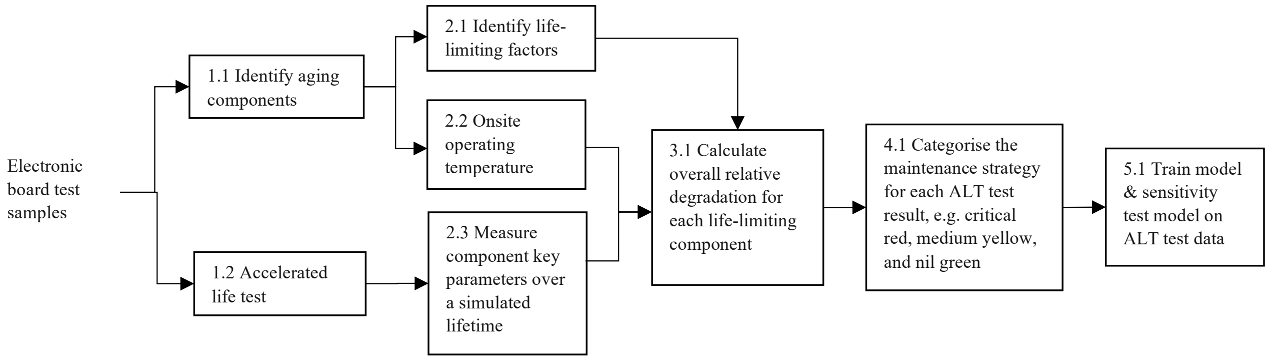


Figure 1. Process of electronic life modelling (ELM).

defect or a design-related issue. After these teething issues are resolved, determination of the maintenance periods is necessary so that better budgeting for fleet replacement of components can be planned in advance.

Prediction of board failure for the purpose of both early spare part planning and prevention of railway operating failures. The paradigm and approach to maintaining electronic boards in the railway industry are not run to failure, i.e. not replacing a component which has failed or is nearing the end of its life but rather minimising the occurrence of any failure affecting train operation while, at the same time, minimising maintenance cost as determined by component replacement frequency (which predetermines the manpower requirements, train booking costs, lost time in train stabling area, and spare part costs). In order to find the optimal replacement period without risking system failure, the ideal approach is to replace the board under a combination of proof load condition monitoring and hard time life prediction through lab experiments. This is known as the "hybrid method" that combines both real-world verification methods (i.e. condition monitoring) and estimated lab work predictions. However, it is not practical to undertake large-scale condition monitoring on a frequent basis due to its cost implication; thus, only sample checks and targeted checks are considered.

3. Assessment of a safety critical train-borne signalling electronic board

To demonstrate the application of the electronic life modelling (ELM) process shown in Figure 1, an electronic circuit board called CPS board of the Trainborne Signalling System of MTR South Island Line, which has operated for 2.5 years since December 2016, was used for this pilot project. The ELM comprises the following processes (Wei et al., 2014):

(1) A component survey to identify components which would be affected by aging, such as electrolytic capacitors, optocouplers, semiconductors and relays.
(2) A temperature survey on the operating temperature of the identified aging components.
(3) Four cycles of ALT of 188 hours each representing a nominal accelerated life of 20 years.
(4) Acceleration rate of each component is calculated based on the actual operating temperature.
(5) Components are measured and the board health is functionally tested using an OEM tester after each ALT cycle and the relative deterioration rate of each component is formulated.
(6) Determine the maintenance action to be taken prior to functional failure of the test board and categorise the maintenance action into three categories of severity (red, yellow, and green).
(7) Run the dataset through classification machine learning algorithms to build a predictive model of the three categories of severity.
(8) Validate the model using a confusion matrix and sensitivity analysis.

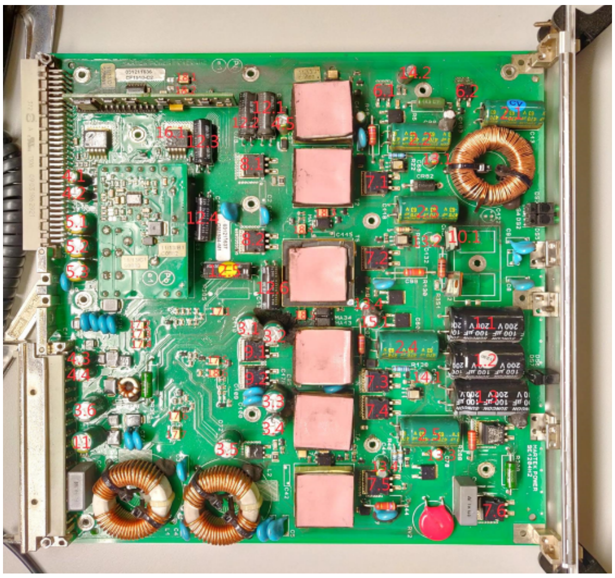


Figure 2. Photo of the CPS board used for electronic life modelling.

4. Selection of aging-susceptible components

Refer to Figure 1 block 1.1 “Identify aging-susceptible components”, components that are susceptible to aging were identified for the CPS board. These included power capacitors, power MOSFET transistors, power diodes, and optocouplers. The identification was largely determined through the categorisation of high-power components or components that are sensitive to timing variation (such as RC circuits) and susceptible to electro-static sensitivity. Furthermore, datasheets for each component were consulted in order to review the manufacturer recommendations on usage-life if they existed. The following were the final results of component selection:

Table 1. List of identified aging components.

Part no.	Type	Supplier	Specifications	Supplier part reference
C2	Capacitor	SunCon	63V, 470µF	63ME470AX
C3	Capacitor	SunCon	35V, 470µF	35ME470CA
C4	Capacitor	SunCon	25V, 100µF	25ME100AX
Q7	MOSFET	STMicro	Various, refer to datasheet	STB40NF20
D9	Diode	STMicro	Various, refer to datasheet	STTH2002CG
D10	Diode	STMicro	Various, refer to datasheet	STTH2002CT
C11	Capacitor	SunCon	35V, 220µF	35ME220AX
C12	Capacitor	Nichicon	16V, 1000µF	UHM1C102MPD3
C13	Capacitor	SunCon	35V, 33µF	35ME33AX
C15	Capacitor	SamWha	WB Series, 50V, 47µF	N/A
U17	Optocoupler	Toshiba	Various, refer to datasheet	TLP127

5. Experimental temperature testing results

Refer to Figure 1 block 2.2. In order to determine the operating temperature load of the CPS board for specific components versus time, a lab setup was constructed with a trainborne electronic rack (see Figure 4) in which the CPS board was subjected to realistic electrical loads continuously and temperature readings were taken at hourly intervals (both with thermal imaging equipment and with a high-resolution digital thermometer for validation). Sample thermal images are shown in Figure 3. The humidity was kept at a controlled level of 60% in order to emulate the actual controlled air-conditioning environment on trains.

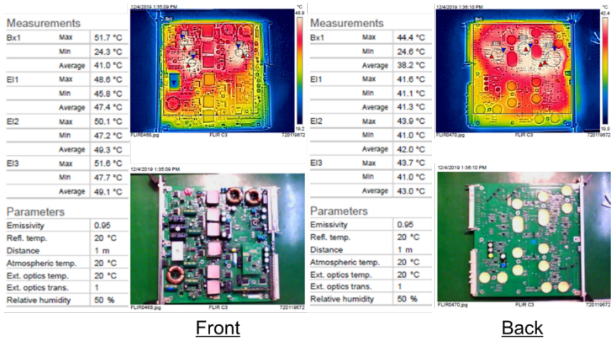


Figure 3. Sample thermal image results of the CPS board.

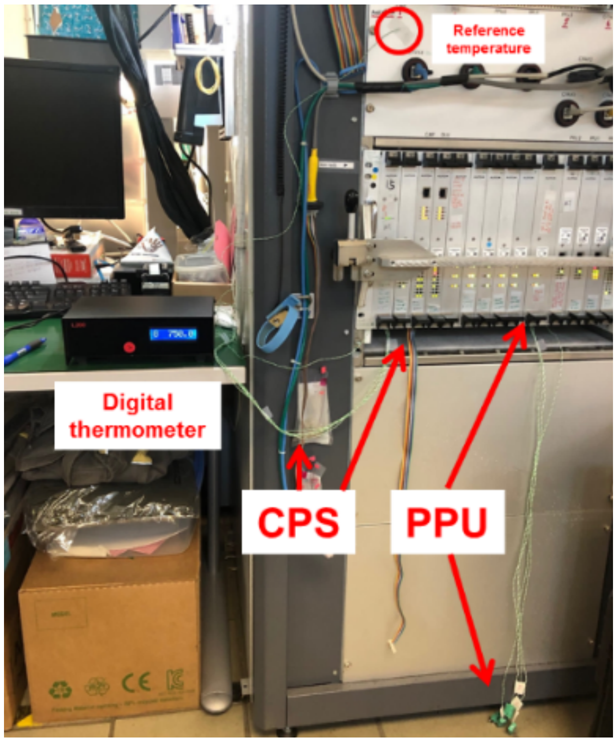
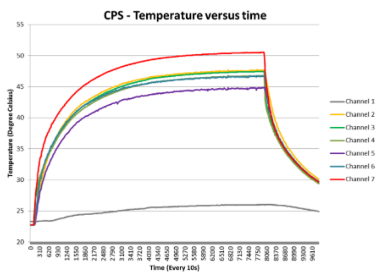


Figure 4. Temperature measurement setup.

Test results of selected components are plotted in Figure 5. It shows that the temperature of respective components reaching a steady state after a certain period of testing and drop off inverse-exponentially after the electrical load is removed.



Channel	Component	No.	Temp at steady state (approximately)
1	/	REF	
2	Capacitor, SunCon, 10x16, 35V, 470µF	2.4	47.4
3	MOSFET, STMicroelectronics, TO-263	7.3	46.8
4	Diode, STMicroelectronics, TO-263	9.1	45.4
5	Capacitor, SunCon, 5x11, 35V, 33µF	13	44.9
6	Capacitor, SamWha, 6.3x11, WB Series, 50V, 47µF	15.1	44.8
7	unable to identify	19	51

Figure 5. Temperature measurement results for selected components on the CPS board.

6. Accelerated life testing (ALT)

Due to the high cost of CPS test boards, only a few samples were available for destructive testing. As such, an additional 30 components of the same model/brand were separately acquired and placed in the same test chamber for the ALT testing. See Figure 6. ALT testing consists of the application of high temperature (85 degrees Celsius) and high humidity (85% R.H.) to simulate accelerated aging of the board with subsequent components in the same test chamber. In total four consecutive rounds of testing, each with a period of 188 hours, were carried out (an arbitrary value derived from past testing experience so that a full scale of around 50 years in total of equivalent aging period can be achieved).

Figure 6. Photo of the ALT test chamber.

Equivalent accelerated test life was calculated by estimating the equivalent acceleration factor as stipulated by the Arrhenius Model as shown below (Yu and Chen, 2009; Norris and Landzberg, 1969):

Table 2. Arrhenius Model.

Arrhenius Model	**Parameters used in CPS board testing**
$\boldsymbol{A = \left[\frac{RHa}{RHo}\right]^3 e^{\left[\frac{Ea}{R} x \left(\frac{1}{To} - \frac{1}{Ta}\right)\right]}}$ (1)	$A = \left[\frac{85}{60}\right]^3 e^{\left[\frac{0.9}{8.617x10^{-5}} x \left(\frac{1}{To} - \frac{1}{358}\right)\right]}$ (2)
A = Acceleration factor **Rha** = Acceleration Humidity **Rho** = Usage Humidity **Ea** = Activation Energy **R** = Boltzmann's constant **To** = Usage Temperature **Ta** = Acceleration Temperature	**A** = Acceleration factor **Rha** = 85% **Rho** = 60% **Ea** = 0.9 eV **R** = 8.62x10-5 **To** = Usage Temperature of boards/components as determined by the previous operating temperature measurements **Ta** = 358k Test condition: 85°C & R.H.: 85%

Applying the Arrhenius model (Eq. (2)) for each individual component (since their operating temperature is different as per the measurements conducted in section 5), this arrives at the equivalent aged life as tabulated in Table 3 which shows the aged life for the first round out of the total four rounds of testing (note that four rounds of testing is equivalent to four times the equivalent aged life period of the first round).

For each round of testing, the CPS board underwent comprehensive visual inspections and functional testing using our OEM's (original manufacturer) functional tester in order to check whether the board was still functionally normal after each ALT test round (in total there were four test rounds). It was found that the board failed with intermittent functional problems after the fourth round of ALT testing which indicated that some faulty component or degraded board substrate had occurred to an extent that had interfered with the board's health – somewhere between the third and fourth round of testing. This further suggests that component inspection, repair or replacement should occur between the third and fourth round as the functional problems posed a significant risk but were not regarded as causing a catastrophic board failure.

Table 3. Estimation of the equivalent test age of individual components on the CPS board after the first round of testing.

Part ref.	Test round (out of 4)	Usage temp (degC)	Usage humidity (%RH)	Acceleration temp: 85 degC	Acceleration humidity: 85% R.H.	Activation energy (eV)	Acceleration factor	Accelerated test duration (Hr)	Aged life calculated (year)
CPS 2	1	47.4	60	85	85	0.9	87.31	188	1.87
CPS 3	1	32	60	85	85	0.9	452.94	188	9.72
CPS 7	1	46.8	60	85	85	0.9	92.82	188	1.99
CPS 9	1	45.4	60	85	85	0.9	107.15	188	2.30
CPS 10	1	33	60	85	85	0.9	404.98	188	8.69
CPS 11	1	39	60	85	85	0.9	210.04	188	4.51
CPS 12	1	33	60	85	85	0.9	404.98	188	8.69
CPS 13	1	44.9	60	85	85	0.9	112.83	188	2.42
CPS 15	1	44.8	60	85	85	0.9	114.00	188	2.45
CPS 17	1	51	60	85	85	0.9	60.77	188	1.30

7. Categorisation of maintenance decisions for components on the CPS board

Refer to Figure 1 block 2.3. Each component that was regarded as a life-limiting component (refer to the categorisation review of section 4) was measured based on degradable life-limiting factors which could be measured using standard off-the-shelf equipment:

- For capacitors, measurement factors included capacitance (uF) and ESR (mΩ).
- For MOSFET power transistors, measurement factors included Vgs[on] (V), Id[on] (mA), Ig (μA), Vgs[off] (V), Id[off] (μA), gm (mA/V), and Rds[on] (Ω).
- For power diodes, measurement factors included Vf forward bias voltage (V), and If forward bias current (mA).

For each measured factor, the level of degradation after each round of ALT testing could be represented by the maximum change in value relative to the original set-point after normalisation (i.e. the highest change in value was represented by 100%):

Let ka be one of the measurement factors for a specific component for N number of observations. For the case of capacitor components, ka_n can be either the measured capacitance (uF) or the ESR (mΩ).

Then Ka_n, the normalisation of ka_n, results in:

$$Ka_n = \frac{ka_n}{\max(ka_n)} \ . \tag{3}$$

Similarly this is applied for kb_n, kc_n, kd_n, etc. which are subsequent other measurement factors specific to the type of component.

Thus, K_total_n which is the total degradation of the component of observation n can be described as the highest normalised life-limiting value out of Ka_n, Kb_n, Kc_n, Kd_n …:

$$K\_total_n = \max(Ka_n, Kb_n, Kc_n, Kd_n \ldots) \tag{4}$$

Next a maintenance decision needs to be applied to each observation in the ALT dataset. Ideally, the decision should be based on whether a functional failure occurred after each round of testing, and whether or not K_total exhibited a significant value compared with the entire population of test samples of the same component type, i.e. three categories are proposed below:

- Red category (critical) = board functional failure occurred and the component exhibited relative degradation of K_total_n >66%.
- Yellow category (medium) = board functional failure occurred and K_total_n<66%.
- Green category (low) = board with no functional failure.

As shown above, each category represents normalised severity as calculated by the relative degradation formula. The categorisation was deliberately formulated such that the red category represents that a board failure is likely and is measurable by a value of the component, and for our case of ALT testing, functional failure occurred after the fourth round of ALT testing. The yellow category represents a medium level of degradation and failure occurred during testing and hence was regarded as a medium risk, while green represents low risk, i.e. no failure occurred no matter the degradation amount of the component.

Maintenance planning. Ideally, components with red categorisation will undergo high-priority inspection and replacements. Components categorised as yellow will trigger a fleet inspection activity or sound alarm for early procurement of spares to cater for potential train fleet replacement/renewal in the future. Components categorised as green are of low risk and do not require immediate action to be taken.

Table A1 shows the category labels for a component 13 capacitor for the CPS board (for demonstration only). All life-limiting components tested in the ALT underwent the same category labelling approach.

8. Machine learning assisted modelling

Principle component analysis (PCA) was performed for each type of component prior to building the machine learning model to remove any overlapping derived factor or factors that did not exhibit significant change such that it could be safely omitted from the model altogether.

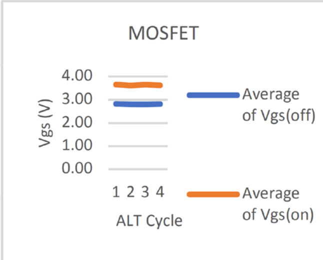
After viewing the change in key parameters for each component, it was found that only capacitors exhibited significant changes after four rounds of ALT aging tests:

Figure 7 demonstrates that capacitors were the only viable component that exhibited significant variation during the ALT testing which is reasonable since power capacitors contain electrolyte that gradually degrades each time it undergoes internal heat loads. Therefore, the final input predictors used in the machine learning model include four factors of all power capacitors used in the CPS board, which are: simulated aged life (years), component designation number, measured capacitance (uF), and measured ESR (mΩ).

Selection of the supervised learning algorithm. The ensemble method was selected as it utilises multiple learning algorithms to produce better predictive performance than could be obtained from any other constituent learning algorithm alone (such as SVM). Ensembles combine multiple hypotheses to form a better hypothesis. However, this method does entail significantly higher computation power during training as compared with other machine learning algorithms. Out of the ensemble-type algorithms, Random Undersampling Boosting (RUS Boost) was selected as it is especially effective at classifying imbalanced data, meaning that some classes in the training data have many fewer members than others

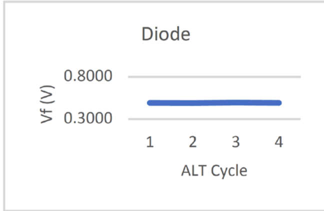
(a)

ALT Cycle	Average of Vgs(off)	Average of Vgs(on)
1	2.81	3.65
2	2.80	3.61
3	2.81	3.65
4	2.81	3.62
Grand Total	**2.81**	**3.63**



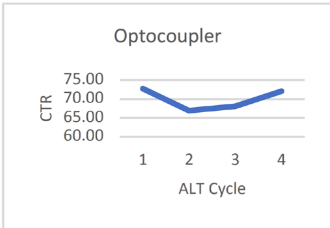
(b)

ALT Cycle	Average of Vf
1	0.4937
2	0.4900
3	0.4947
4	0.4926

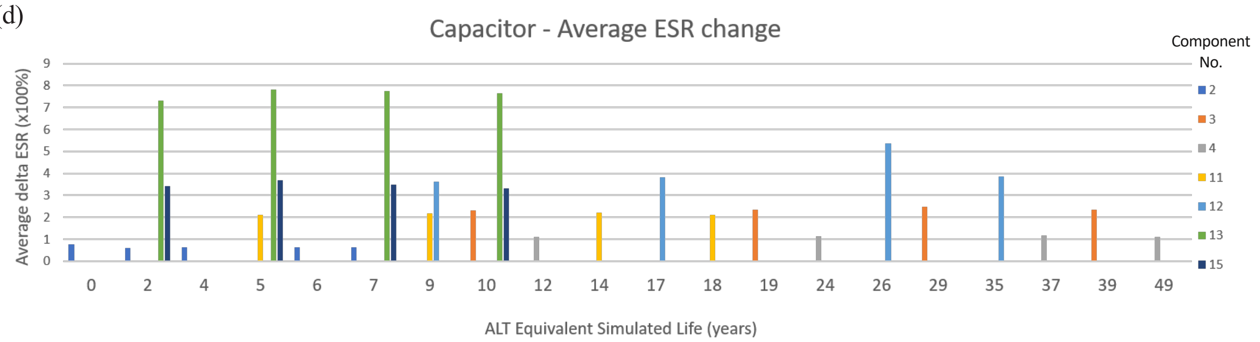


(c)

ALT Cycle	Average of CTS
1	72.68
2	66.88
3	68.06
4	72.09



(d)



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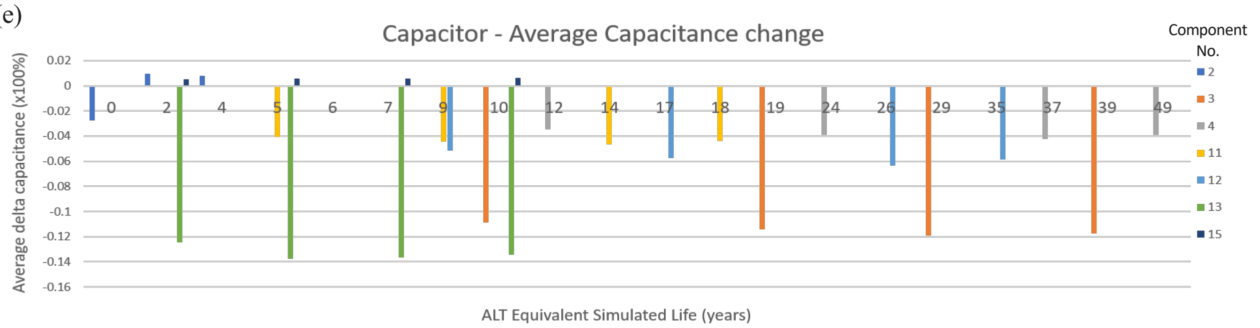


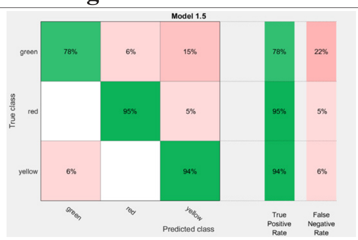
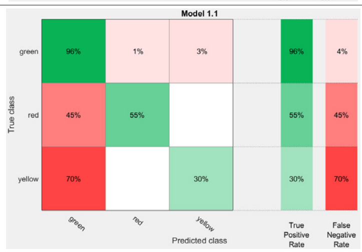
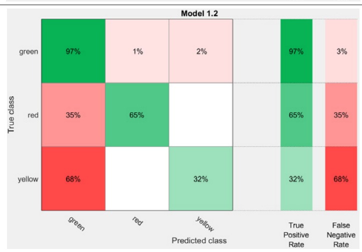
Figure 7. Plots of the variance in measured key parameters of specific components after four rounds of ALT testing. Capacitances and ESR graphs are shown in equivalent years for clarity of representation for each board component designator.

which is the case for our ALT data. The algorithm takes N, the number of members in the class with the fewest members in the training data, as the basic unit for sampling. Classes with more members are under sampled by taking only N observations of every class. This procedure makes use of Adaptive boosting named AdaBoostM1. The algorithm trains learners sequentially. For every learner with index t, AdaBoostM1 computes the weighted classification error as (Freund and Schapire, 1997; Friedman, 2001; Friedman et al., 2000; Bartlett et al., 1998):

$$\varepsilon_t = \frac{1}{2}\sum_{n=1}^{N}\sum_{k\neq y_n} d_n^{(t)} F(y_n \neq h_t(x_n)) \,, \qquad (5)$$

where:
x_n is a vector of predictor values for observation n;
y_n is the true class label;
h_t s the prediction of learner (hypothesis) with index t;
F is the indicator function; and
$d_n^{(t)}$ is the weight of observation n at step t.

The results of training the dataset arrives at the following validation results in the form of a confusion matrix. Other ensemble algorithms with comparatively high accuracy rates were compared with the preferred RUS Boost algorithm:

Model type	Training result confusion matrix
Model Type Preset: RUSBoosted Trees Ensemble method: RUSBoost Learner type: Decision tree Maximum number of splits: 20 Number of learners: 30 Learning rate: 0.1	
Model Type Preset: Boosted Trees Ensemble method: AdaBoost Learner type: Decision tree Maximum number of splits: 20 Number of learners: 30 Learning rate: 0.1	
Model Type Preset: Bagged Trees Ensemble method: Bag Learner type: Decision tree Maximum number of splits: 838 Number of learners: 30	

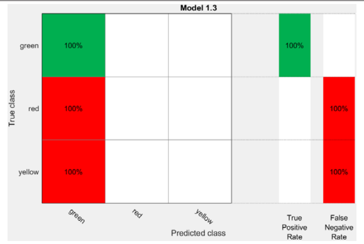
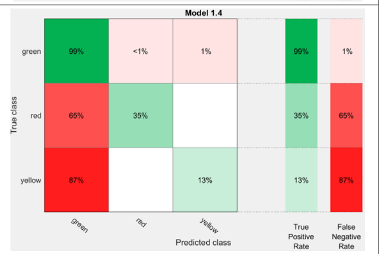
Model Type Preset: Subspace Discriminant Ensemble method: Subspace Learner type: Discriminant Number of learners: 30 Subspace dimension: 2	
Model Type Preset: Subspace KNN Ensemble method: Subspace Learner type: Nearest neighbors Number of learners: 30 Subspace dimension: 2	

Figure 8. Machine learning validation results using ensemble algorithms.

As can be observed from the above figure, the RUS Boost performed the best as compared with other listed algorithms, achieving 95% accuracy in identifying the red category, 94% accuracy in identify the yellow category, and 78% accuracy in identifying the green category. While the green category accuracy was relatively low (as 6% and 15% of the data fell into the red and yellow categories erroneously), it is not a major concern from the maintenance engineer's perspective which favours conservativeness in identifying red and yellow for safety critical electronic board maintenance.

9. Sensitivity analysis and review

Graphically, the simulated life (in years) versus the overall degradation is shown in Figure 9. The colour red represents the capacitors that require urgent attention such as replacement, the colour yellow represents the medium level attention needed such as early purchasing of spares and component inspections, while the colour blue (green category) represents that no action is required. This shows evidently that intermittent capacitor failure, resulting in functional failure of the CPS board, can occur anywhere between the third year and 10th year of life of the board. Translated into layman terms this means that some (not all) capacitances and ESR may degrade due to operating temperature usage; while if the capacitors can outlive 10 years of usage, it is likely not to fail due to the relatively good manufacturing or installation quality of the component/board for that particular batch of CPS boards which will outlive its intended life. However, some capacitors will exhibit early failure, which calls for periodic inspections and replacement activities to occur within the component's lifecycle.

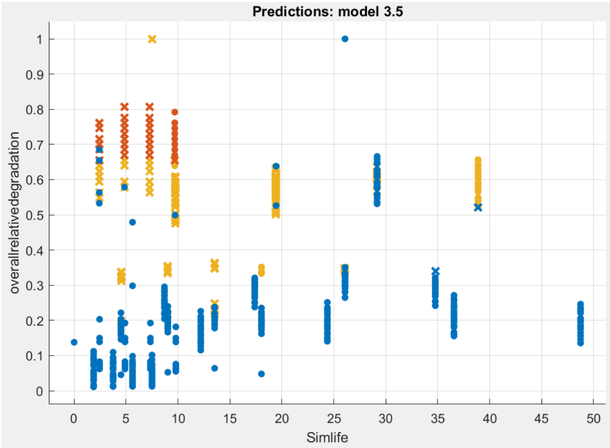


Figure 9. Simulated life (in years) versus the overall relative degradation *K_total* (%) along with red, yellow, blue (which is green category) categorisations.

The usefulness of the AI model that was built ensures that maintenance engineers can determine whether or not a component should be replaced based on the capacitor's measured values (part number, operating period, capacitance, and ESR). These four pieces of information can be fed directly into the AI model and the corresponding risk category of red, yellow, and green will be outputted to precisely guide the engineer towards the correct maintenance decision to be taken based on risk level.

For further testing of the model using sensitivity analysis, we selected the following extreme values for assessment:

Table 4. Sensitivity test results.

Test cases and expectation	Input parameters	Output results
1. Expected red category – high loss in capacitance	Cap 13, 10 years of operation, 6 uF loss in capacitance, 3 ohm increase in ESR	Red
2. Expected red category – high increase in ESR	Cap 13, eight years of operation, 0 uF loss in capacitance, 100 ohm increase in ESR	Red
3. Expected yellow category – long usage but no value change	Cap 13, 50 years of operation, 0 uF loss in capacitance, 0 ohm increase in ESR	Yellow
4. Expected green category – 10 years usage but no value change	Cap 13, 10 years of operation, 0 uF loss in capacitance, 0 ohm increase in ESR	Green
5. Expected green category – short usage and no value change	Cap 13, one year of operation, 0 uF loss in capacitance, 0 ohm increase in ESR	Green

As observed, the test results for extremity test parameters matched the expected results for all five cases.

10. Application in industry

The developed AI model can used to help prioritise the replacement of CPS boards as an initiative for planning the replacement prioritisation for other electronic boards. Through regular preventive maintenance inspections, the component values measured can be entered into the AI model inputs to derive the category urgency (red/yellow/green) as described in previous sections. These will help determine whether an immediate replacement (red) or procurement of backup spares (with a long lead time) is required. Compared with traditional hard time replacement regimes or "run to failure" models, this AI-based method is advantageous for reducing frequent scrap replacements and preventing failure on a running train through early failure-prediction/anticipation strategy.

11. Conclusion

Here we present an AI model to model the asset life and maintenance decision for components on the CPS board. By use of ALT testing and Arrhenius' equation (Eq. (1)), we derived the accelerated life vs. relative degradation factor from life-limiting components such as capacitors, diodes, MOSFETs, and optocouplers. Each ALT test result for each component was classified by risk level colour (red, yellow, and green) which corresponded to the level of maintenance decision to be made (i.e. respectively: immediate replacement, purchasing of spares and undertaking inspections, and no action to be taken). After performing PCA analysis, only the factors resulting in significant change variation were used for feature building in the AI model which resulted in the selection of capacitors and their values of capacitance and ESR. The highest-accuracy AI model found from running various Ensemble machine learning algorithms was the RUS Boost model. Testing results using sensitivity analysis showed that the model was accurate in regard to expectations and achieved an accuracy factor of up to 95% for red category detections and 94% for yellow category detections according to confusion matrix evaluation.

The results derived from this study demonstrate the feasibility of machine learning in aiding the development of maintenance decision models for railway electronic components. They also suggest that a process (see Figure 1) for achieving the goal using a top-down process could be achieved by using standard electronic measuring equipment and only a few ALT test samples; and this process can be applied to any form of electronic board in the railway industry.

Appendix

Table A1. Excerpt of training data with category labels for the component 13 capacitor for the CPS board (for demonstration purposes only, other component data are omitted).

Sim life (years)	Component designation no.	Measured capacitance (uF)	Measured ESR (mΩ)	ΔC/C (uF)	ΔESR (mΩ)	Overall relative degradation (calculated) K_total_n	Categorisation label
2.42	13	28.3	4	-14.24%	852.38%	71.55%	green
2.42	13	28.5	3.3	-13.64%	685.71%	68.51%	green
2.42	13	28.4	3.5	-13.94%	733.33%	70.03%	green
2.42	13	28.7	3.5	-13.03%	733.33%	65.46%	green
2.42	13	28.4	3.9	-13.94%	828.57%	70.03%	green
2.42	13	28.3	3.6	-14.24%	757.14%	71.55%	green
2.42	13	28.5	3.8	-13.64%	804.76%	68.51%	green
2.42	13	29	3.5	-12.12%	733.33%	60.90%	green
2.42	13	29.1	3.6	-11.82%	757.14%	59.38%	green
2.42	13	29.5	2.84	-10.61%	576.19%	53.29%	green
2.42	13	28	3.87	-15.15%	821.43%	76.12%	green
2.42	13	28.4	4	-13.94%	852.38%	70.03%	green
2.42	13	29.3	3.4	-11.21%	709.52%	56.33%	green
2.42	13	28.7	3.5	-13.03%	733.33%	65.46%	green
2.42	13	28.4	3.5	-13.94%	733.33%	70.03%	green
2.42	13	28.7	3.9	-13.03%	828.57%	65.46%	green
2.42	13	29.3	3	-11.21%	614.29%	56.33%	green
2.42	13	28.9	3.5	-12.42%	733.33%	62.42%	green
2.42	13	28.8	3.35	-12.73%	697.62%	63.94%	green
2.42	13	28.4	3.6	-13.94%	757.14%	70.03%	green
2.42	13	28.3	3.5	-14.24%	733.33%	71.55%	green
2.42	13	28.7	3.5	-13.03%	733.33%	65.46%	green
2.42	13	28.1	3.7	-14.85%	780.95%	74.60%	green
2.42	13	28.9	3.7	-12.42%	780.95%	62.42%	green
2.42	13	28.8	3.4	-12.73%	709.52%	63.94%	green
2.42	13	29.4	3.3	-10.91%	685.71%	54.81%	green
2.42	13	28.8	3.5	-12.73%	733.33%	63.94%	green
2.42	13	28.7	3.7	-13.03%	780.95%	65.46%	green
2.42	13	28.8	3.6	-12.73%	757.14%	63.94%	green
4.84	13	28.1	4.2	-14.85%	900.00%	74.60%	green
4.84	13	28.2	3.5	-14.55%	733.33%	73.08%	green
4.84	13	28.1	3.7	-14.85%	780.95%	74.60%	green
4.84	13	28.5	3.6	-13.64%	757.14%	68.51%	green
4.84	13	28.2	4	-14.55%	852.38%	73.08%	green
4.84	13	28.2	3.7	-14.55%	780.95%	73.08%	green
4.84	13	28.3	3.9	-14.24%	828.57%	71.55%	green
4.84	13	28.7	3.6	-13.03%	757.14%	65.46%	green
4.84	13	28.8	3.7	-12.73%	780.95%	63.94%	green
4.84	13	29.2	3.1	-11.52%	638.10%	57.85%	green
4.84	13	27.7	4	-16.06%	852.38%	80.69%	green
4.84	13	28.1	4.1	-14.85%	876.19%	74.60%	green
4.84	13	29.2	3.5	-11.52%	733.33%	57.85%	green
4.84	13	28.5	3.7	-13.64%	780.95%	68.51%	green
4.84	13	28.1	3.7	-14.85%	780.95%	74.60%	green
4.84	13	28.4	4.1	-13.94%	876.19%	70.03%	green
4.84	13	29.1	3.1	-11.82%	638.10%	59.38%	green
4.84	13	28.7	3.6	-13.03%	757.14%	65.46%	green
4.84	13	28.6	3.5	-13.33%	733.33%	66.99%	green
4.84	13	28.2	3.7	-14.55%	780.95%	73.08%	green
4.84	13	28	3.6	-15.15%	757.14%	76.12%	green
4.84	13	28.5	3.7	-13.64%	780.95%	68.51%	green
4.84	13	27.9	3.9	-15.45%	828.57%	77.64%	green
4.84	13	28.6	3.8	-13.33%	804.76%	66.99%	green
4.84	13	28.7	3.5	-13.03%	733.33%	65.46%	green

4.84	13	29.2	3.4	-11.52%	709.52%	57.85%	green
4.84	13	28.5	3.6	-13.64%	757.14%	68.51%	green
4.84	13	28.4	3.9	-13.94%	828.57%	70.03%	green
4.84	13	28.4	3.8	-13.94%	804.76%	70.03%	green
7.26	13	27.9	4.3	-15.45%	923.81%	77.64%	green
7.26	13	28.3	3.4	-14.24%	709.52%	71.55%	green
7.26	13	28.1	3.7	-14.85%	780.95%	74.60%	green
7.26	13	28.5	3.6	-13.64%	757.14%	68.51%	green
7.26	13	28.2	3.9	-14.55%	828.57%	73.08%	green
7.26	13	28.1	3.7	-14.85%	780.95%	74.60%	green
7.26	13	28.3	3.9	-14.24%	828.57%	71.55%	green
7.26	13	28.7	3.6	-13.03%	757.14%	65.46%	green
7.26	13	28.9	3.7	-12.42%	780.95%	62.42%	green
7.26	13	29.2	3.1	-11.52%	638.10%	57.85%	green
7.26	13	27.7	4	-16.06%	852.38%	80.69%	green
7.26	13	28.2	4.1	-14.55%	876.19%	73.08%	green
7.26	13	29.1	3.5	-11.82%	733.33%	59.38%	green
7.26	13	28.4	3.7	-13.94%	780.95%	70.03%	green
7.26	13	28	3.7	-15.15%	780.95%	76.12%	green
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7.26	13	28.8	3.6	-12.73%	757.14%	63.94%	green
7.26	13	28.6	3.4	-13.33%	709.52%	66.99%	green
7.26	13	28.3	3.7	-14.24%	780.95%	71.55%	green
7.26	13	28.1	3.5	-14.85%	733.33%	74.60%	green
7.26	13	28.1	3.8	-14.85%	804.76%	74.60%	green
7.26	13	28.7	3.8	-13.03%	804.76%	65.46%	green
7.26	13	28.7	3.8	-13.03%	804.76%	65.46%	green
7.26	13	28.9	3.4	-12.42%	709.52%	62.42%	green
7.26	13	29.3	3.3	-11.21%	685.71%	56.33%	green
7.26	13	28.6	3.6	-13.33%	757.14%	66.99%	green
7.26	13	28.5	3.8	-13.64%	804.76%	68.51%	green
7.26	13	28.5	3.7	-13.64%	780.95%	68.51%	green
9.69	13	28.1	4.3	-14.85%	923.81%	74.60%	red
9.69	13	28.4	3.4	-13.94%	709.52%	70.03%	red
9.69	13	28.1	3.6	-14.85%	757.14%	74.60%	red
9.69	13	28.5	3.6	-13.64%	757.14%	68.51%	red
9.69	13	28.3	3.9	-14.24%	828.57%	71.55%	red
9.69	13	28.2	3.7	-14.55%	780.95%	73.08%	red
9.69	13	28.5	3.8	-13.64%	804.76%	68.51%	red
9.69	13	28.8	3.6	-12.73%	757.14%	63.94%	yellow
9.69	13	29	3.6	-12.12%	757.14%	60.90%	yellow
9.69	13	29.3	3	-11.21%	614.29%	56.33%	yellow
9.69	13	27.8	4	-15.76%	852.38%	79.17%	red
9.69	13	28.4	4.1	-13.94%	876.19%	70.03%	red
9.69	13	29.3	3.4	-11.21%	709.52%	56.33%	yellow
9.69	13	28.6	3.6	-13.33%	757.14%	66.99%	red
9.69	13	28.2	3.7	-14.55%	780.95%	73.08%	red
9.69	13	28.6	4	-13.33%	852.38%	66.99%	red
9.69	13	29.2	3.1	-11.52%	638.10%	57.85%	yellow
9.69	13	28.8	3.6	-12.73%	757.14%	63.94%	yellow
9.69	13	28.7	3.4	-13.03%	709.52%	65.46%	yellow
9.69	13	28.4	3.6	-13.94%	757.14%	70.03%	red
9.69	13	28.1	3.5	-14.85%	733.33%	74.60%	red
9.69	13	28.6	3.6	-13.33%	757.14%	66.99%	red
9.69	13	28	3.8	-15.15%	804.76%	76.12%	red
9.69	13	28.7	3.8	-13.03%	804.76%	65.46%	yellow
9.69	13	28.8	3.4	-12.73%	709.52%	63.94%	yellow
9.69	13	29.3	3.3	-11.21%	685.71%	56.33%	yellow
9.69	13	28.6	3.6	-13.33%	757.14%	66.99%	red
9.69	13	28.6	3.7	-13.33%	780.95%	66.99%	red
9.69	13	28.5	3.7	-13.64%	780.95%	68.51%	red

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