

Lifetime Prediction of Optocouplers in Digital Input and Output Modules based on Bayesian tracking approaches

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ABSTRACT

In recent years, reliability of DIO modules has been drawing much attention from manufacturing companies under the growing complexity of automation systems for smart factory establishment. In manufacturing systems, DIO modules have been widely used to pass sensor measurements and configuration input signals for controlling actuators. Because sensor measurement and control signals pass through DIO modules, the faults of DIO modules would cause malfunctions or failures of the smart manufacturing systems and eventually lead to unexpected downtime in the manufacturing process. For predictive maintenance of DIO modules, this paper proposes a method of predicting the remaining useful life of a critical component in DIO modules based on the Bayesian tracking approaches. Optocouplers are one of the critical components in DIO modules that uses a short optical transmission path including light sources and photo-sensors to transfer an electrical signal. The performance of optocouplers may be degraded overtime with damages in a light source or a photo-sensor and eventually cause the faults of control systems. Extended Kalman Filter and Particle Filter are used in nonlinear degradation modeling to predict the lifetime of optocouplers, evaluating those filters by accuracy-based prognostic metrics and showing the effectiveness of Bayesian tracking approaches for lifetime prediction of optocouplers.

1. INTRODUCTION

In recent years, automation systems including digital input and output (DIO) modules are getting complicated with a move to establish the smart factory that optimizes the flexible manufacturing process itself. In manufacturing systems, DIO modules have been widely used to pass sensor measurements and configuration input signals for controlling actuators. Typically, the sensors are pressure, temperature, flow, and

level sensors, and the actuators are motors, pumps, and solenoid valves.

Under the growing system complexity, safety, reliability and availability of DIO modules have been getting much attention. Because sensor measurement and control signals pass through DIO modules, the faults of DIO modules would cause malfunctions or failures of the smart manufacturing systems and eventually lead to unexpected downtime in the manufacturing process. Therefore, prognosis of DIO modules is becoming a key to self-maintenance to reduce downtime in smart factory.

Reliability of digital systems inclusive of DIO modules has been studied by many researchers in consideration of dynamic interactions between electronic components. Especially, in the field of nuclear power plants, researchers have concentrated on assessing the reliability of digital systems because failures of safety-related digital systems may lead to catastrophic failures of nuclear power plants. To model common failure causes between components in digital systems, traditional probabilistic safety assessments (PSA) methods have been presented by the U.S. Nuclear Regulatory Commission (NRC) (Chu, Martinez-Guridi, Yeu, Lehner, and Samanta, 2008). The PSA methods have been applied to model reliability of the digital system of feedwater control systems (Chu, Yeu, Martinez-Guridi, Mernick, Lehner, and Kuritzky, 2009) and nuclear safety-related digital instrumentation and control systems (Shi, Enzinna, Yang, and Blodgett, 2010, Authen and Holmberg, 2012, Bjorkman, Lahtinen, Tyrvaainen, and Holmberg, 2015, Lee, Jung, and Yang, 2016). In addition to the conventional approaches to model reliability, prognosis of DIO modules is emerging to predict the reliability of complex automation systems accurately based on systems' conditions. Predictive maintenance of DIO modules should be available along with a prognostic method of applying the probabilistic system evolution in time.

The objective of this paper is to prognosticate the remaining useful life (RUL) of DIO modules based on Bayesian tracking approaches. Failure mode, effects, and criticality analysis (FMECA) is used for deriving critical components having high failure risk priorities. For an experimental verification, this study conducts an accelerated life test of the critical component. Bayesian tracking algorithms including Extended Kalman Filter (EKF) and Particle Filter (PF) are applied to predict the lifetime of the components for failure prognosis of DIO modules.

2. FMECA

FMECA is often used to analyze faults and symptom relations, and criticality of faults for each failure mode of components. FMECA approach was utilized to derive critical components in DIO modules that have the highest risk regarding probability to occur and effects of failures. It was assumed that the faults of the most critical components significantly affect failures of DIO modules, and that failure of the critical components would determine the lifetime of the entire digital DIO module systems.

2.1. Failure modes, effects, and causes

The DIO modules analyzed in this study are used in the semiconductor manufacturing systems and adopt EtherCAT technology for network connections with other modules. The DIO modules consist of 60 kinds of components that are in charge of power convert, signal isolation, signal transformation, and EtherCAT protocol processing. Table 1 shows the possible failure modes and failure causes of main functional components.

Table 1 Failure modes and causes of main functional components

Component	Failure mode	Failure cause
EtherCAT BGA	Solder joint crack	Thermal cycling
	Brittle fracture	Mechanical shock (drop)
	Die crack	Elevated temperature testing, vibration, bending stress
Electrolytic capacitor	Capacitance reduction	High voltage, ripple current, high temperature
	Short	
	Open	

	Crack	
Optocoupler	Reduction of LED brightness	High temperature
Surge killer	Puncture	High current
	Crack	non-uniform heating

2.2. Critical components

The criticality rank was analyzed by calculating risk priority number (RPN) for each failure mode. The RPN is typically the multiplication of the likelihood of detection, likelihood of occurrence, and severity of failure. In this study, only the likelihood of occurrence and severity of failure were considered because there is no established technique for detecting the degradation of component faults in the current control system. Likelihood of occurrence was determined based on the operating conditions of the controller systems and the historical data of significant fault cases.

The results indicated that optocouplers are the most critical components that have the high RPN value. Optocouplers are one of the optoelectronic devices that use short optical transmission paths, including light sources and photo-sensors to transfer an electrical signal. We found that aluminum electromigration in the light emitting diode (LED) is caused by the high temperature that is led from light sources in optocouplers and environment conditions. And the electromigration consequently reduces LED brightness. The performance of optocouplers may be degraded overtime with LED wear-out damage and may eventually cause the faults of the control systems.

3. PROGNOSTICS APPROACH

To predict failure of DIO modules, time to failure of optocouplers was predicted by applying three processes: data collection and pretreatment, reliability prediction, prognostics and verification. Figure 1 shows the overall prognostic approach based on Bayesian tracking approaches. In the first step of data collection and pretreatment, degradation data was collected by measuring failure precursors of the optocouplers while they were under the accelerated life test. Secondly, several randomly selected degradation datasets were used as explicit knowledge data for training the initial system models of EKF and PF. Performance EKF and PF algorithms for predicting the lifetime of the optocouplers were verified by using the rest dataset.

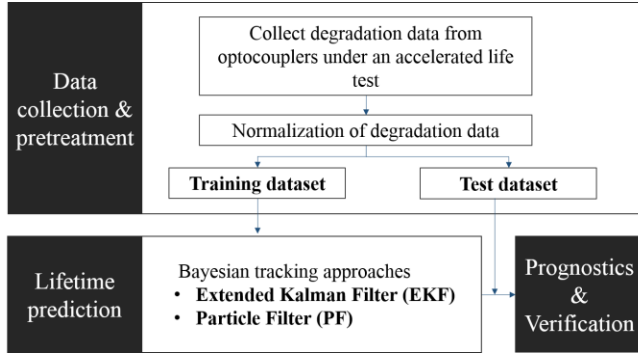


Figure 1 Lifetime prediction of optocouplers for DIO modules prognosis

3.1. Data collection and pretreatment

This section presents the failure precursor of optocouplers used in this study to predict the life of optocouplers and the setup of accelerated life test to collect the failure precursor.

A dominant optocoupler's wearout phenomenon is current transfer ratio (CTR) degradation as time goes on. CTR is a ratio between the collector and the forward current in percentage. CTR is defined as shown in equation (1).

$$\text{CTR}(\%) = \frac{I_C}{I_F} \times 100 \quad (1)$$

where I_C is collector current and I_F is input forward current. Because the input forward current was controlled constantly, the degradation of light source means the reduction of CTR. Initial CTR of optocouplers is different from input forward current. Before the saturation mode of transistors in optocouplers, initial CTR increases as input current increases.

A preliminary test was conducted for finding proper input forward current conditions because the difference of initial CTRs would show different CTR degradation rates even in a damaged optocoupler. In related studies (Slama, Helali, Lahyani, Louati, Venet, and Rojat, 2008, Shi, Lu, Chen, and Feng, 2014), the CTR drift after the ageing tests was highlighted at certain measurement conditions that are low input forward current operation outside of saturation mode. In the preliminary test, the input forward current was swept from 0.1mA to 50mA which are within the absolute maximum input forward current rating of the tested optocouplers to get the conditions presenting high degradation rates.

After finding an input forward current condition, the accelerated life test of optocouplers was conducted using 32 optocouplers. The optocouplers were connected in series, and constant current flowed in all optocouplers equally regardless to different characteristics of LED because of variation in optocouplers' quality. To measure the output current for calculating the CTR, 1Ω resistors were connected to all output terminals of the optocouplers in series and the output

current was obtained from the measurement of voltage across the resistors. Figure 2 shows the schematic of the experimental study, including 32 optocouplers, a power supply, a data logger, and a laptop for instrumental control of the power supply and the data logger.

The device under test optocouplers were Toshiba TLP291-4 which has 4 transmission paths in a single chip, and they were operating in a chamber for accelerating the test conditions. The power supply was used to control the input forward current for lighting LEDs, voltage across collectors and emitters for sensing the light in the optocouplers. To accelerate the failure mechanism that showed the high risk, ambient temperature and input forward current were controlled at 110°C and 200mA, which were the operating margin of the samples. The voltage across collectors and emitters was controlled as 5V.

The data logger was used to collect the surface temperature, collector current and input forward current to get CTR. In measurement, the input forward current was swept from 200mA, which is the accelerated stress condition to a proper input forward current condition determined in the preliminary test. The sweep rate was 0.25s and the measurement period was 1hr. Input forward current change does not have a significant effect on the overall stress level because the sweep rate is short compared to the overall test time.

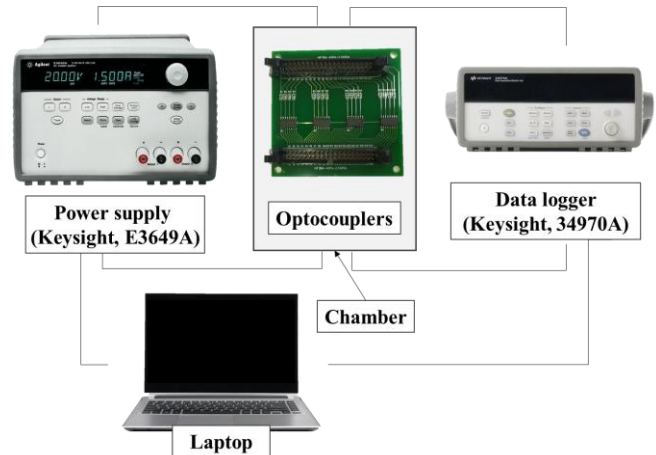


Figure 2 Schematic of the accelerated life test of optocouplers

3.2. Lifetime prediction

Since the failure mode of optocouplers is reduction in LED brightness, the LED exponential lumen degradation model (Fan, Yung, and Pecht, 2014) was applied for the measurement model as shown in equation (2).

$$z_k = A_k \times \exp(-B_k \times 1000 \times t_k) + n_k \quad (2)$$

where z_k is CTR, A_k is a measurement model parameter, B_k is a measurement model parameter, t_k is time, n_k is measurement noise, and k is measurement cycle. The parameters of the degradation model are seen as the states. Because degradation trajectory doesn't change, measurement model parameters are constants. The states model is shown in equation (3)-(5).

$$x_k = \begin{bmatrix} A_k \\ B_k \end{bmatrix} \tag{3}$$

$$A_k = A_{k-1} + v_{k-1}^A \quad v_{k-1}^A \sim N(0, Q_v^A) \tag{4}$$

$$B_k = B_{k-1} + v_{k-1}^B \quad v_{k-1}^B \sim N(0, Q_v^B) \tag{5}$$

Where x_k is state parameters, v_k is state noise, Q_k is covariance of state noise.

4. RESULTS

First, the CTR degradation's trajectory was analyzed to identify which input forward current conditions make the high CTR degradation rate. Secondly, the optocouplers' lifetime was predicted by EKF and PF. Prognostic performance of EKF and PF was evaluated by residuals of predicted CTR. And then root mean square error (RMSE) of CTR prediction was calculated for each prognostic algorithm. And RUL of optocouplers was predicted and verified based on true time to failure of optocouplers.

4.1. CTR degradation

Not only the initial CTR but also the degradation rates were different from the input forward current conditions. Measured CTR was normalized to compare the degradation rates regardless of the initial CTR. Figures 3, 4, and 5 show the normalized CTR as time goes on when the input forward current is 0.1mA, 1mA, and 20mA, respectively. The normalized CTR showed large variations when the input forward current is 0.1mA because of the measurement error and the resolution limit of the equipment. When the input forward current was 20mA, CTR degradation rate was low. The CTR of all training samples was higher than 90% even after 528hrs. On the other hand, when the input forward current is 1mA, the CTR showed small variation and the highest degradation rate. The reason is that optocoupler output transistors operated in saturation mode when the input forward current was over 1mA in the preliminary test. 1mA input forward current, which showed the high degradation, was used in the measurement of the accelerated life test because the high degradation rate means that it clearly reflects the degraded conditions of optocouplers.

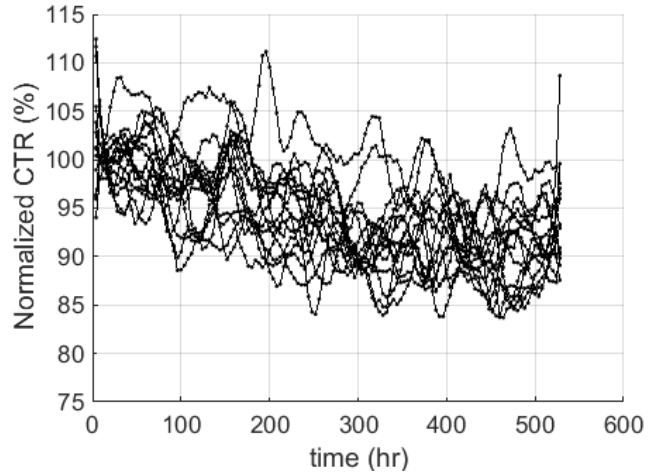


Figure 3 Normalized CTR vs. time when I_F is 0.1mA

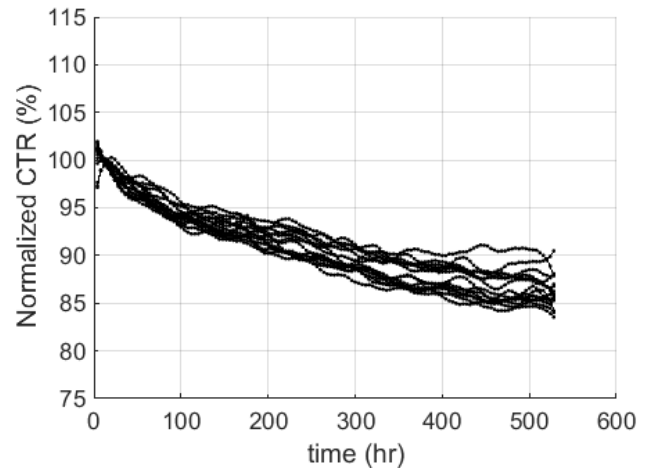


Figure 4 Normalized CTR vs. time when I_F is 1mA

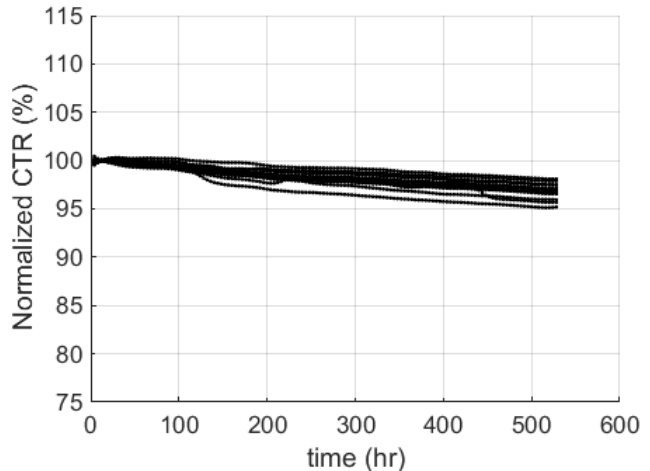


Figure 5 Normalized CTR vs. time when I_F is 20mA

4.2. CTR degradation prognosis

Out of the 32 optocouplers in total, 16 optocouplers were used to train the initial states, which are the parameters of degradation model. The rest of the optocouplers, excluding the training dataset, were used to predict the CTR degradation. Figures 6 and 7 show the estimated curve and predicted curve of the normalized CTR obtained by EKF and PF, respectively, for the tested optocoupler. The estimation curves followed close to the true CTR in both of EKF and PF algorithms. However, the prediction curve after 200hr presented residuals with the true values.

Figure 8 shows the averaged absolute value of residuals for all optocouplers. In the estimated curve, PF showed faster initialization error recovery with respect to EKF. But EKF and PF showed similar prognostic performance after 200hr. Table 2 shows the RMSE of CTR estimation and prediction. EKF and PF showed similar accuracy in predicting the CTR and had small RMSE compared to the normalized CTR.

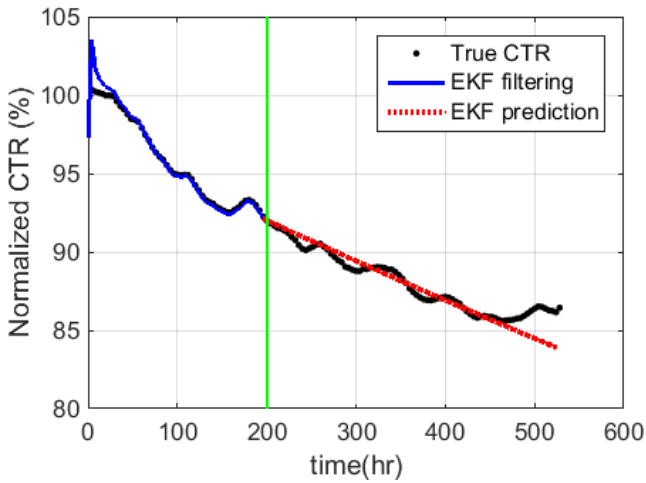


Figure 6 EKF prediction results for optocoupler #8

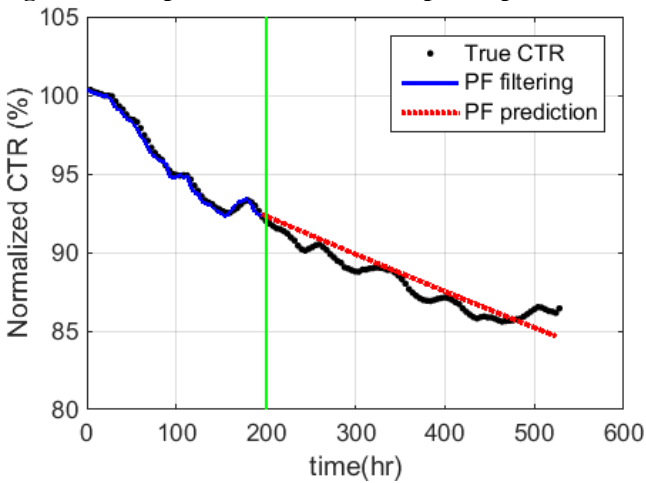


Figure 7 PF prediction results for optocoupler #8

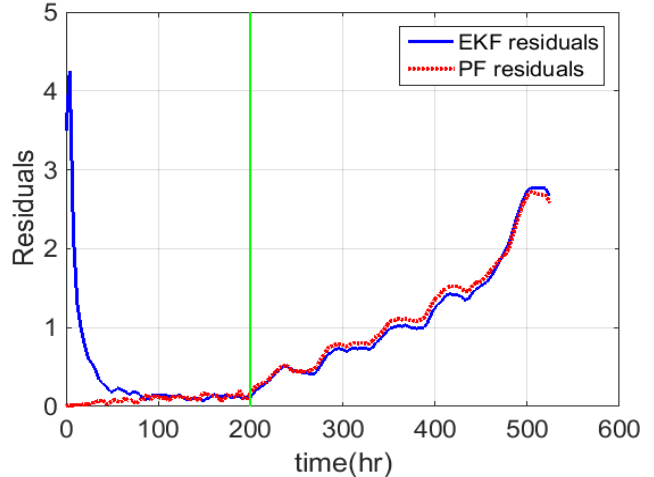


Figure 8 Residuals of EKF and PF prediction

Table 2 RMSE for estimation and prediction by EKF and PF

RMSE	EKF	PF
CTR Estimation (%)	0.92	0.13
CTR Prediction (%)	1.50	1.53
Total (%)	1.21	1.10

RUL for each optocoupler was predicted, assuming that the time to 85% CTR is the time to failure of optocouplers. The accuracy of RUL prediction was evaluated by RMSE calculation for RUL of all optocouplers. Table 3 shows the RMSE of RUL prediction results. EKF showed fewer errors than PF. But the percentage of RMSE compared to the true CTR was 22% and 23% for EKF and PF respectively. Therefore, the difference between RMSE of EKF and PF was not significant.

Table 3 remaining useful life RMSE

RMSE	EKF	PF
RUL (hr)	41.94	43.55

5. CONCLUSION

This paper presented lifetime assessment of DIO modules based on Bayesian tracking approaches including EKF and PF for prognosis. FMECA was used to derive the most critical items in the DIO modules in terms of failure probability and effects of failure. The most critical item was optocouplers, and optocouplers were weak to thermal and electrical stress, and they induced electromigration on LEDs in optocouplers. As a result of experimental verification, EKF and PF indicated that the Bayesian tracking algorithms are proper in estimating the nonlinear state of optocoupler degradation. EKF and PF showed accurate performance of estimation and prediction of optocoupler degradation. The

RMSE of prediction was lower than 2% in the normalized CTR.

The results show that the FMECA analysis enabled us to concentrate on components which have high probability and risk of failure and make a lifetime prediction of the entire DIO module systems. Moreover, the proposed prediction method based on Bayesian tracking approaches with EKF and PF is proper in estimating the degradation states of optocouplers. Using this approach, health of DIO modules is managed by the optocouplers' life prediction in real-time in consideration of system evolution in time. Consequently, malfunctions and failures of the automation systems are prevented by detecting the faults of DIO modules.

Our future work on this topic includes further accelerated life tests of optocouplers to obtain CTR degradation data until the optocoupler failures. In addition, the DIO modules will be under accelerated life tests to compare the lifetime of DIO modules and optocouplers.

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BIOGRAPHIES

Insun Shin received the bachelor's degree in system design and control engineering at the Ulsan Institute of Science and Technology (UNIST), Republic of Korea, in 2015. Since 2014, She is with IoT based System Reliability (ISR) laboratory at the UNIST. Her research focuses on prognostics and health management of electronic systems. She is currently involved with development of core technologies for fault prognostics and management of smart manufacturing systems.

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