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Data-Driven Online Health Assessment for Electronic Systems: A Portable Solution Exploiting Real-World Field Data

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Abstract

The field of Prognostics and Health Monitoring (PHM) for electronic systems is continually evolving to meet the growing demand for reliable and intelligent electronics, particularly in the context of the Internet-of-Things (IoT) and autonomous vehicles. This paper proposes a cost-effective and time-efficient approach to maintenance planning and monitoring of electronic systems through continuous real-time data analysis. By leveraging machine learning algorithms, the aim is to ensure the safety and reliability of electrical components without the need for permanent data storage. The degradation of solder contacts, caused by cyclic temperature loads, is identified as a primary cause of electronic failures. Finite Element Analysis (FEA) is commonly used for evaluating solder joint reliability but is not suitable for real-time monitoring due to computational resource requirements. Instead, FEA is employed to generate artificial data for training machine learning models. The paper presents a portable solution for online health assessment using a combination of real-world field data from an electric bike's power module and a synthetic database. The focus is on evaluating the Remaining Useful Lifetime (RUL) of solder joints without the need for a large temperature database. The methodology, including field data acquisition and machine learning model training, is described in detail. The results obtained demonstrate the potential of the proposed approach for practical implementation in electronic systems.

Keywords: Prognostics and Health Monitoring, Internet-of-Things, Maintenance planning, Electrical component reliability.

I. Introduction

The research field of Prognostics and Health Monitoring (PHM) for electronics systems has been evolving continuously over time. With the increasing demand for reliable and intelligent electronics, particularly in the context of the Internet-of-Things (IoT) and autonomous vehicles, the importance of PHM has grown. This field offers a cost-effective and time-efficient approach to maintenance planning and monitoring of electronic systems. Continuous monitoring of electronic systems generates a vast amount of data, which can be expensive to transmit, store, and analyze using external devices. Therefore, analyzing data in real-time is more advantageous for ensuring the safety and reliability of electrical components, without the need for permanent data storage. Machine Learning (ML) algorithms are well-suited for this purpose [1].

One of the primary causes of electronic failures is the degradation of solder contacts, primarily due to cyclic temperature loads [1]. When there is a thermal mismatch between a component and the substrate, such as a Printed Circuit Board (PCB), cyclic loads are induced in the solder contact. Over time, this leads to the accumulation of plastic strains, resulting in crack initiation, growth, and eventual failure of the solder joint. To determine and evaluate the reliability of solder joints, Finite Element Analysis (FEA) is considered the state-of-the-art method [2-4]. Physical FEA models are helpful for optimizing material selection and electronic package design. However, due to its computational resource requirements, FEA is not suitable for real-time health monitoring. Instead, FEA can be utilized to generate artificial data for ML models [5]. This

demonstrating the feasibility and effectiveness of the proposed approach for online health assessment of electronic systems.

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