A value-driven approach to printed circuit board inspection: Strategic use of inspection technologies to reduce waste

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A value-driven approach to printed circuit board inspection: Strategic use of inspection technologies to reduce waste

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Abstract. Electronic waste is an escalating global challenge that requires innovative and sustainable strategies to mitigate its environmental impact. This paper presents a decision model designed to identify the most effective inspection processes for printed circuit boards (PCBs) to enable their reuse, recycling or remanufacturing. The goal is to maximise the recoverable value of PCBs while minimising waste. By systematically analysing inspection processes, the model provides a structured framework for determining the sequence of measurement technologies that balance cost effectiveness with the potential for value recovery. This methodology improves resource efficiency and minimises environmental impact, in addition to supporting the principles of a circular economy. Through an illustrative case study, the approach shows how targeted inspections can significantly extend the life of electronic boards, improve economic value recovery and promote environmentally friendly manufacturing practices.

Introduction

As the digital age advances, the management of electronic waste (e-waste) has become a critical environmental and economic challenge. Projections indicate that global e-waste volumes could increase from 53.6 million tonnes to 75 million tonnes by 2030, highlighting the urgent need for effective recycling and disposal methods [1]. The European Union has introduced strict measures to regulate the collection, treatment and recycling of e-waste through the Waste Electrical and Electronic Equipment (WEEE) Directive [2]. Despite these regulatory measures, the practical application of these directives is fraught with challenges, in particular the high cost of labour required to manually inspect and disassemble e-waste. This necessary but labour-intensive process of separating materials and safely disposing of toxic components is becoming economically unsustainable as the volume of e-waste increases.

The volume of discarded electronic equipment has increased dramatically as a result of accelerating technological progress and the rapid obsolescence of electronic equipment [3]. This growth in e-waste affects ecosystems and human health due to the hazardous substances it contains, and represents a significant loss of valuable materials and resources [4]. It raises critical concerns about efficient collection, treatment and recycling processes. The escalating crisis underlines the urgent need for innovative solutions and policies aimed at promoting sustainable management practices, improving recycling technologies and encouraging the development of environmentally friendly products [5].

This paper addresses the challenges of inspecting printed circuit boards (PCBs), which are essential components in many electronic devices. It proposes advanced methods to optimise PCB inspection and reuse strategies, improving inspection effectiveness to maximise the recovery of valuable components. Through a systematic analysis of inspection processes, this approach establishes a structured framework for determining the optimal sequence of measurement

technologies, balancing cost effectiveness with potential value recovery. The discussion then reviews the most commonly used methods before presenting a novel methodology that improves inspection efficiency. An illustrative case study demonstrates this methodology, using numerical data to highlight its effectiveness. The paper concludes by summarising key findings, addressing limitations and suggesting future research directions.

Literature review

Traditional PCB inspection techniques are challenged by the high cost of advanced inspection tools and the inaccuracy of the more affordable alternatives. These limitations highlight the need for innovative solutions that balance cost effectiveness and accuracy while maintaining technical excellence. This section analyses the main techniques currently used to inspect PCBs and outlines their advantages and disadvantages.

Manual visual inspection is the most basic form of PCB inspection, in which trained technicians identify defects such as solder faults, component misplacement and physical damage, as shown in Fig. 1(a). While effective at detecting visible defects, this method is time-consuming, labour-intensive and prone to error. To address these limitations, neural network-based automated visual inspection systems have been developed to significantly reduce human error and labour costs, while improving inspection speed and accuracy [6].

Current over time testing is another technique for defect detection in PCBs; a qualitative output is shown in Fig. 1(b). It identifies defects by monitoring transient current spikes during device switching. This method is non-invasive, fast and capable of detecting defects early in the production process, making it ideal for both manufacturing and remanufacturing applications [7]. However, the equipment for current over time techniques costs several thousand euros, which can be a problem for small and medium-sized enterprises.

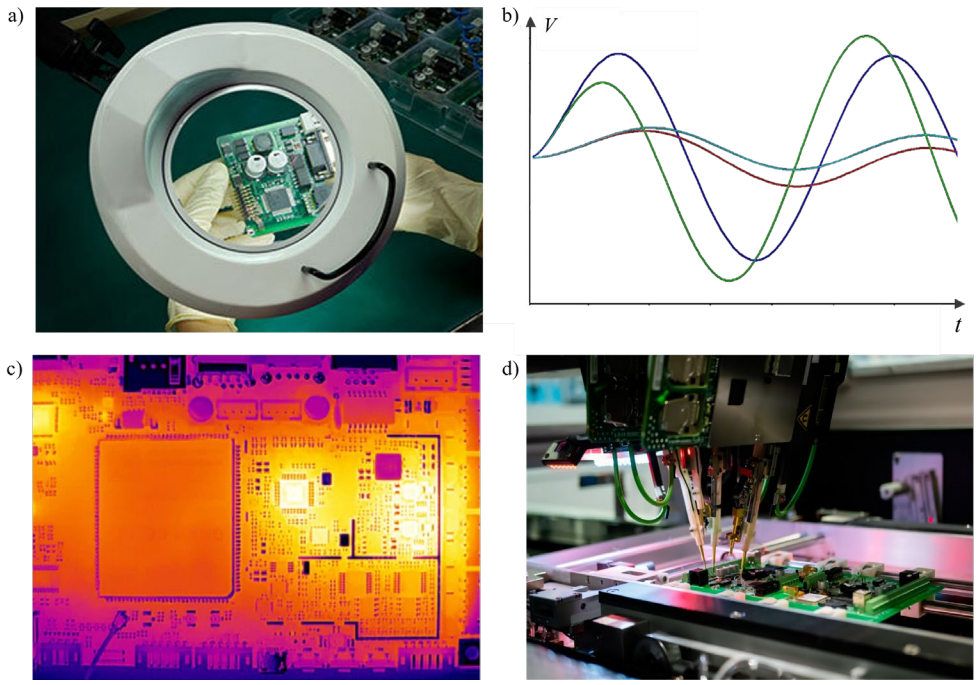

Fig. 1. *Some representative images of conventional PCB inspection methods: (a) visual inspection, (b) current over time analysis, (c) thermography and (d) flying probe test.*

Another widely used technique is thermal inspection, shown in Figure 1(c), which uses infrared thermography to detect thermal anomalies on the PCB. This technique identifies the temperature distribution of the board during operation, highlighting problems such as short circuits or inadequate heat dissipation [8]. It is particularly effective at identifying hidden defects that are

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critical to device reliability, providing real-time, high-resolution images for rapid defect location. However, for accurate results, the PCB must reach thermal equilibrium prior to analysis [9].

The last technique worthy of mention in this paper is the flying probe test (FPT), shown in Fig. 1(d). FPT uses moving probes that contact specific points on the PCB to test interconnects without the need for custom fixtures. While FPT is slower than other tests, advances in probe technology have improved its speed and accuracy, making it a cost-effective choice for low-volume production [10]. However, FPT has limitations in terms of physical access to the board, and complex interconnects can prevent comprehensive testing of the entire board. In addition, implementing a flying probe system can be costly in terms of setup and cycle times, making it less feasible for certain applications [10].

Other widely used PCB inspection techniques, such as X-ray and bed-of-nail inspection, are not covered in this paper. X-ray inspection is effective at detecting hidden defects but it is expensive and used primarily in high-volume production [11]. In contrast, the bed-of-nails test provides accurate measurements but it requires bespoke PCB designs, resulting in higher costs [12].

Proposed methodology

The proposed approach integrates multiple inspection technologies to determine the optimal R-strategy - reuse, remanufacture or recycle - for each PCB [13]. It uses a sequential process that leverages the strengths of different inspection techniques, starting with low-cost methods such as visual inspection and progressively applying more advanced techniques such as flying probe testing to maximise resource efficiency. By consolidating data from different stages of inspection, this approach prioritises the identification of valuable components over exhaustive fault diagnosis, ensuring a cost-effective, streamlined process that balances accuracy and efficiency. Fig. 2 illustrates the basic concept of the proposed inspection methodology.

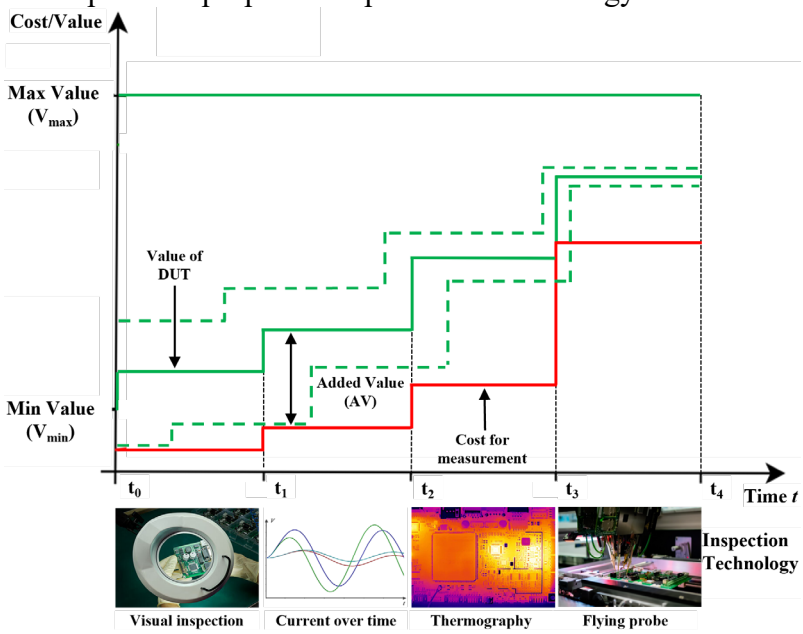

Fig. 2. *Schematic of the proposed methodology.*

The y-axis represents the value of the PCBs, while the x-axis represents the inspection techniques used and the time taken to make these measurements. For simplicity, the graph assumes equal inspection times, although in practice these times may vary for different PCBs. The value of the device under test (DUT) is represented by green lines with dashed uncertainty bands, which also include the measurement uncertainty and indicate the maximum and minimum values that can be obtained from the measurement. As more measurements are taken, these bands narrow,

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reducing the uncertainty and ambiguity about the value of the board and emphasising the dynamic nature of the assessment process over time.

The red curve on the graph illustrates the cost of different inspection techniques, which correlates with both the value of the inspection technique and the time required to inspect a DUT. In this framework, a step function is adopted to model both cost and information gain, reflecting the fact that each inspection stage involves a fixed operational cost - such as equipment setup, test execution and data processing - and yields a discrete, measurable increase in knowledge (e.g. defect identification or pass/fail classification). Although continuous models offer mathematical tractability, they do not adequately represent the inherently staged and event-driven nature of real-world inspection workflows. As a result, the use of a step function provides a more realistic abstraction that captures the incremental structure of inspection processes [14].

Initially, PCBs are assumed to be of minimal value, with remanufacturing for raw material recovery serving as the baseline, as all components are assumed to be defective. However, as inspections progress and new technologies are introduced, data is collected to refine the understanding of the condition of each PCB. This iterative learning process improves the extraction of valuable information and optimises the value-added (AV) by balancing value and cost. With each inspection step, the uncertainty about the device under test (DUT) decreases, visually narrowing the green dashed corridor. If the process is stopped prematurely, only the minimum known value is retained, as the condition of untested components remains uncertain. However, as more data is collected, the uncertainty decreases at a faster rate, accelerating knowledge acquisition and improving the efficiency of the overall test sequence. The decision to proceed with subsequent inspection steps is guided by predefined cost-benefit analysis. After each inspection phase, the cumulative inspection costs are compared with the estimated value added. The process continues only if the expected recoverable value exceeds the incremental inspection cost by a pre-determined margin, thus ensuring cost-effective operations.

The inspection sequence begins with a visual inspection to identify evident defects and assess the overall condition of the board. Following the preliminary and subsequent data analysis, a cost-benefit evaluation of the components is carried out. If the collected data is sufficient, the board is removed from the test sequence. This process is repeated at the end of each inspection. The gathered information plays a critical role in determining the most appropriate R-strategy for the DUT. For example, if only a few components are defective, it may make more sense to replace them and reuse the entire board. Conversely, if a significant number of components are faulty, it may be preferable to salvage only the functional parts.

It is important to note that as the system analyses more boards, the methodology learns to identify the optimal R-strategy for each board type. Consequently, as the number of boards analysed increases, the value derived from each board also increases due to this learning effect [14]. In this context, Fig. 3 provides an example of this process through the logistic regression curve, which effectively illustrates the learning process across different inspection stages.

This learning effect can be expressed using the logistic regression in Eq. (1) [14]:

$$V = \frac{L}{1+e^{-k(n-n_0)}} + \varepsilon \tag{1}$$

where L is the maximum achievable value of V, indicating the saturation limit of the response. The parameter k controls the steepness of the curve and determines how quickly V approaches this maximum as n, i.e. the number of boards, changes. The inflection point n_0 is where V is equal to half of L plus a variability error, marking a critical threshold in the response. The term ε is an error included to capture the variability of the data, including measurement inaccuracies and external disturbances, which enhances the realism and applicability of the model to empirical data. These parameters can be adapted to specific industrial contexts. The integration in the model of learning

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effect allows the model to estimate the probability of a successful inspection outcome as a function of the number of boards n. Importantly, this model can be adapted to different inspection scenarios by adding the subscript i for each parameter to reflect the specific inspection type analysed [14].

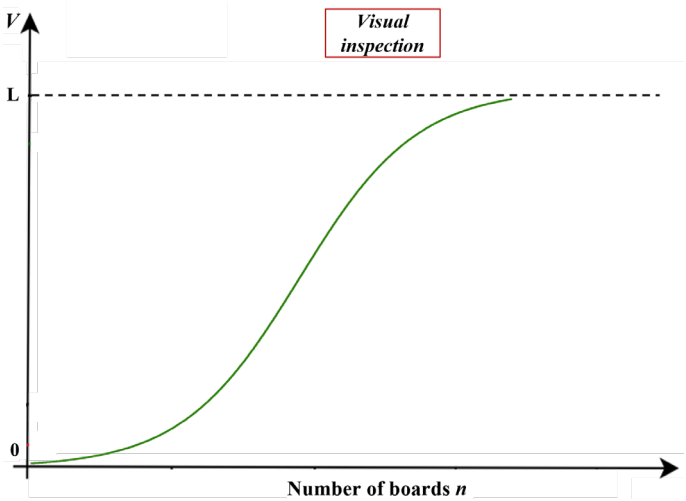

Fig. 3. *Logistic regression trend learning for examined inspection technologies (visual inspection example).*

Applying the logistic learning effect model to the scenario shown in Fig. 2 produces the revised model shown in Fig. 4, which incorporates learning effects across different inspection methods.

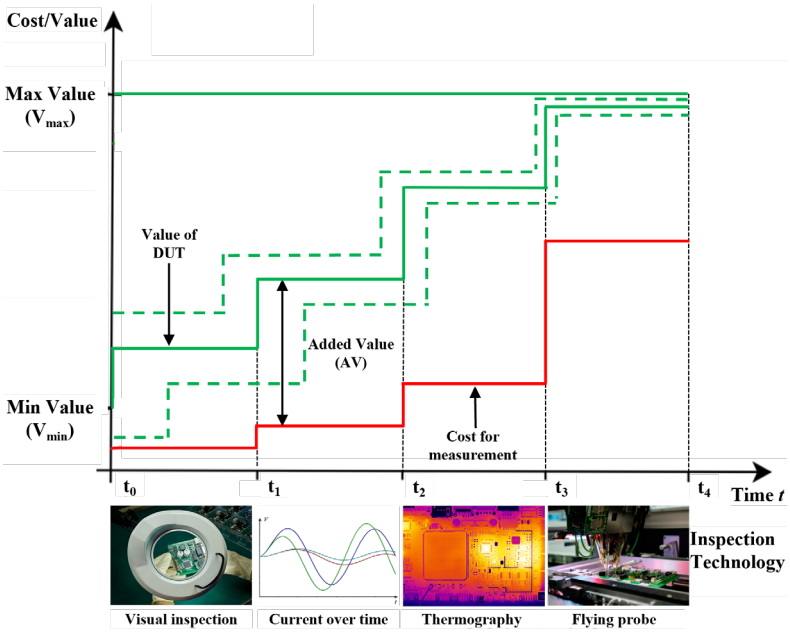

Fig. 4. *Learning effect on the proposed methodology.*

This change is evident in the graph, as the AV in Fig. 4 is significantly higher than in the previous model, reflecting the improved recoverable value from each PCB due to accumulated historical data on similar PCB types. In addition, the uncertainty associated with the recoverable value from each PCB is reduced, as indicated by the lower variability in the dashed lines of Fig. 4. This reduction in uncertainty results from the systematic integration of historical data, which increases the accuracy and effectiveness of the model in predicting the recoverable value of each PCB. Consequently, this improvement strengthens decision making in resource recovery strategies.

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An illustrative case study

The proposed model takes a structured approach to PCB inspection, sequentially integrating multiple inspection techniques to determine the most effective recovery strategy. The aim is to optimise cost, efficiency and value recovery by applying increasingly detailed inspections only when necessary. Initial experimental testing on a simple RLC circuit, commonly used in communications system control, together with cost analysis, provided the basis for the values reported in the illustrative example below (see Fig. 5). Although simplified for illustrative purposes, these values reflect realistic scenarios and can be refined through detailed cost analysis and further market data collection.

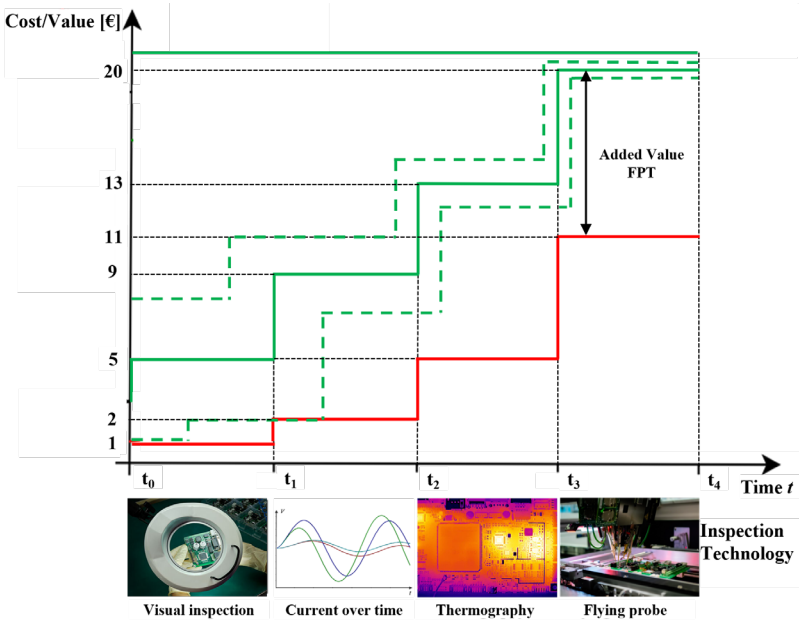

Fig. 5. *Application of the proposed methodology to real-world data.*

An initial visual inspection of a discarded board identifies evident damage such as burns or missing and broken components. The visual inspection costs approximately 1 € per board and can add approximately 5 € in recoverable value, with an uncertainty of ±3 € reflecting the variability in assessing the visible condition of the board. This first step is crucial as it sets the baseline for determining subsequent inspections and potential R-strategies.

Following the visual inspection, the board is subjected to a current over time test, which assesses the electrical integrity of the circuits and detects non-visible defects. The current over time test costs approximately 2 € per board and adds an estimated recoverable value of 9 €, with an uncertainty of ±2 €. This reflects the variability in the detection of minor electrical faults that may not immediately affect the functionality of the board but could lead to future failures.

If electrical discrepancies are not found, the board is subjected to thermography to identify problems such as localised overheating or hidden faulty connections. Such problems may be indicative of deeper electrical problems that cannot be detected by simple visual inspections or current tests. The thermography test costs on average 5 € per board and adds 13 € in recoverable value, with an uncertainty of ±1 €. This step is essential to ensure that boards with internal defects not visible to the naked eye are correctly diagnosed and directed to the appropriate action.

Boards that still show problems after thermography are then subjected to a flying probe test, a more advanced diagnostic method. This test costs approximately 11 € per board and can add 20 € in recoverable value, with an uncertainty of ±0.5 €, as it enables precise fault detection that may have been missed by earlier tests. This last step is critical as it ensures the highest level of defect

detection and assessment, providing valuable data for the final decision on the board's destination. It also contributes to the value added as shown in Fig. 5 (Added Value FPT).

At the end of the inspection process, the choice of the most appropriate R-strategy depends on a detailed analysis of the test results and the recoverable value added at each stage. This decision-making process carefully balances inspection costs against potential recoverable value to maximise the economic return for each board inspected. In addition, by analysing a larger number of boards, the learning effect can be observed, improving the efficiency of the inspection process over time. This continuous learning refines the understanding of common defects in specific board types, leading to more informed decisions about the most effective R-strategy.

Conclusions

The increasing volume of electronic waste requires innovative strategies for efficient resource recovery. This study presents a decision model that optimises PCB inspection processes to determine the most appropriate R-strategy through a cost-effective, sequential evaluation approach. By integrating multiple inspection technologies, the methodology improves resource efficiency, minimises costs and maximises recoverable value.

The proposed approach starts with low-cost visual inspections to identify major defects, followed by advanced techniques such as current over time, thermography and flying probe testing. This structured, step-by-step strategy enables effective decision-making while reducing unnecessary testing costs. The model also incorporates a learning effect where accumulated inspection data improves predictive accuracy, leading to better repair outcomes over time.

A key finding is that a sequential inspection approach optimises the trade-off between cost and information gain. By progressively reducing uncertainty about PCB condition, the methodology enables early identification of functional components while minimising resource waste on non-recoverable boards. The logistic regression model further explains the learning effect, demonstrating that as more boards are analysed, the framework becomes increasingly efficient in identifying high-value recovery opportunities.

Systematic data transfer between inspection stages refines the PCB classification and informs future inspections, strengthening the decision-making process. This adaptive learning mechanism enhances the model's ability to determine the most appropriate recovery strategy, ensuring cost efficiency and environmental sustainability. As more boards are inspected, the methodology uses historical inspection data to improve its predictive accuracy, resulting in a more refined, effective and sustainable assessment framework for e-waste management.

This research has significant implications for sustainable electronics management, supporting regulatory compliance and improving the feasibility of e-waste recovery. The proposed decision model provides a scalable, adaptable solution that balances economic viability with environmental responsibility. Future research will focus on the extensive application of the proposed inspection methodology to real and more complex industrial case studies. This will allow detailed validation of the approach through quantitative data analysis, providing practical insights into its effectiveness, scalability and economic feasibility in real-world manufacturing environments.

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