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ScienceDirect

Procedia CIRP 132 (2025) 227–232

www.elsevier.com/locate/procedia

12th CIRP Global Web Conference (CIRPe 2024)

Integrative inspection methodology for enhanced PCB remanufacturing using artificial intelligence

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Abstract

Electronic waste (e-waste) represents one of the world's most significant environmental challenges, with over 50 million tons generated annually. A key component is the management of Printed Circuit Boards (PCBs), which are integral components of electronic devices and have an operational lifespan of 15 years. However, on average, electrical equipment is discarded after 5 years due to individual defects, prompting the EU to enforce regulations supporting the right to repair. Although industrial remanufacturing of PCBs could be a viable solution, it is not currently feasible due to the complex inspection process required. This paper presents a novel inspection process approach based on data fusion of thermography, current measurement and optical inspection using artificial intelligence. The result is intelligent diagnostics in less time and with lower investment costs. In addition to the concept, initial investigations with real industrial applications in the field of automation are presented.

Keywords: Sustainable Manufacturing; E-Waste Management; Artificial Intelligence; Printed Circuit Board (PCB)

1. Introduction

The rapid development and proliferation of electronic devices has led to a significant increase in electronic waste (e-waste), posing a major challenge to waste management systems worldwide. It is estimated that 53.6 million tons of e-waste is generated globally each year, and projections indicate that this figure could rise to 75 million tons by 2030 [1][2]. This increase in e-waste requires effective and sustainable disposal and recycling solutions due to the presence of hazardous materials and the potential for recovery of valuable metals and components [3]. In response to this growing e-waste problem, the European Union (EU) has introduced strict regulations through the Waste Electrical and Electronic Equipment (WEEE) directive. This directive mandates the collection, treatment and recycling of e- waste and promotes the responsible disposal of electronic equipment [4]. Despite these efforts, there are several significant obstacles to practical implementation [2]. One of the most important is the high labour costs associated with the manual inspection and disassembly. This labour-intensive process is essential to identify and separate different materials to ensure safe handling of hazardous components and efficient recovery of valuable materials. The high cost of labour, however, can make this process economically unfeasible, especially given the large volumes of e-waste [5]. The use of artificial intelligence for automated e-waste processing has become increasingly popular [6]. Automation has the potential to reduce labour costs and improve the efficiency and accuracy of inspection and disassembly processes. However, developing cost-effective and time- efficient automation systems for e-waste management is a complex challenge [5]. These systems need to handle a wide variety of electronic devices with different designs and material compositions, requiring sophisticated technologies and significant investments. Innovations in robotics, machine learning and sensor technology promise to address these challenges, but further research and development is needed to create viable solutions that can be widely adopted [6]. This paper focuses on printed circuit boards (PCBs), which are an integral part of many electronic devices. PCBs consist of a substrate to which various soldered components are attached. Due to their intricate structure, PCBs present significant challenges for inspection. The main objective of this paper is to implement a new method in the context of circular production for the inspection of PCBs. By focusing

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10.1016/j.procir.2025.01.038

on the reuse of functional electronic components, the aim is to significantly reduce waste and environmental impact [3].

2. State of the art of PCB inspection methods

Traditional inspection methods in PCB manufacturing face economic challenges. High-precision measurement technology (MT) requires large investments and long cycle times, making it costly to rework. Conversely, low-cost but less accurate MT systems fail to meet required standards, highlighting the industry's need for innovative solutions that balance cost and performance. This cost-accuracy trade-off highlights a critical challenge for the industry, requiring the development of innovative solutions that offer both economic feasibility and high technical performance.

2.1. Traditional PCBs inspection

Traditional methods of inspecting PCBs primarily involve manual visual inspection and the use of various non-destructive testing techniques. Manual visual inspection is carried out by trained technicians who examine the PCB to identify defects such as solder faults, component misplacement and physical damage. While this process is effective in detecting evident defects, it is labour intensive, time consuming and prone to human error, especially on complex boards with high component densities [5]. Another widely used method for in-circuit testing (ICT) of PCBs is the bed-of-nails tester [7]. This instrument uses spring- loaded pins to make contact with various test points on a circuit board, enabling tests like continuity checks and signal path analysis. While ICT is effective for large-scale production, it requires custom fixtures for each PCB design, making it unflexible, slow and more costly for small production runs or designs with high variability [7]. In contrast, the Flying Probe test method is particularly advantageous for small production runs and scenarios with high variability, such as remanufacturing. Unlike ICT, Flying Probe does not require custom fixtures, which significantly reduces setup time and costs. This flexibility makes it ideal for testing small batches of PCBs with diverse designs. However, the Flying Probe method has limited physical access to the board and complex interconnects can prevent full board testing [7]. Moreover, implementing a Flying Probe system, which can cost well above € 300.000, involves high capital costs and presents challenges related to setup time as well as cycle time for complete measurement of unknown PCBs [8].

2.2. Inspection based on imaging technologies

Non-destructive testing (NDT) methods such as automated optical inspection (AOI) and X-ray inspection are often used in addition to manual inspection. AOI being comparably cheap uses high-resolution cameras and sophisticated algorithms to capture and analyse images of PCBs, comparing them with predefined patterns to identify defects [8]. On the other hand, X-ray inspection is used to inspect hidden features such as solder joints under components and the inner layers of PCBs that are not visible to the naked eye [9]. Despite their widespread use, these conventional techniques have inherent limitations. AOI is challenged by the increasing miniaturisation and complexity of modern PCBs [8]. X-ray inspection, while very effective, is cost prohibitive and requires specialised equipment and expertise [9]. These limitations highlight the urgent need for more advanced and automated solutions to improve the efficiency, accuracy and cost effectiveness of PCB inspection processes. Another method of PCB inspection is thermal inspection. Thermal inspection uses infrared (IR) thermography to identify thermal anomalies that indicate defects or performance problems [10]. This non-contact method measures the temperature distribution across the surface of the PCB while it is powered on, capturing images that reveal hot spots and uneven heating. These patterns can indicate short circuits, faulty components, poor solder joints and inadequate heat dissipation. It can also detect hidden defects that are not visible by other methods, particularly those related to thermal management, which is critical to device reliability, and provides real-time, high-resolution images for rapid identification and localization of defects [10]. Thermal inspection is divided into two approaches: active and passive thermography lamps [11]. In passive thermography, the object of interest itself generates energy, and an IR-camera records the temperature distribution of objects over time, transforming this data into a tool for identifying defective objects. On the other hand, active thermography uses an external heat source to apply thermal stress to the object. This method can detect a wide range of defects in electronic components using a variety of thermal stress sources. Reported options for thermal stress include open flame, air steam, steam, voltage/current, and sunlight, as well as more complicated options such as acoustics, induction heating, pressure, microwave, mechanical torque, and man-made lighting such as lasers, strobe lights, and flash lamps [11]. However, thermography requires time for thermal saturation, which must be factored into any automation process. The time taken to reach thermal equilibrium is crucial for accurate defect detection and must be accounted for to ensure reliable results. By eliminating the need for physical contact, thermal inspection reduces the risk of damage to the PCB and allows for continuous monitoring without interrupting production [12]. Moreover, the effectiveness of the method can be affected by the thermal properties of PCB materials, and similar thermal characteristics between components can mask defects [13].

2.3. Current over time measurement techniques

Current over time measurement techniques, particularly I_{DDT} (transient current testing), are well-established inspection methods in areas such as deep sub-micron CMOS ICs and SRAMs. These techniques have been successfully used for defect detection in digital VLSI circuits, SRAMs, and complex integrated circuits [14][15]. In defect detection, I_{DDT} leverages its sensitivity to short- term current spikes caused by switching activities [1]. This method compares the current consumption over time with reference measurements to identify anomalies [14][15]. For example, the behavior of pattern-sensitive faults in

SRAMs is analyzed by monitoring dynamic current consumption, where significant current transients indicate faults [15]. This allows for precise and rapid fault identification, making I_{DDT} a valuable method for quality assurance [14]. By comparing current waveforms with reference measurements, deviations and defects can be detected at an early stage without requiring invasive procedures [15]. Although there is currently research being conducted using this method for PCB inspection, it could also be suitable for the remanufacturing of PCBs, as it enables fast and cost-efficient inspection. A precise current measurement device typically costs in the range of €10,000.

2.4. Comparison of PCB inspection methods

In summary, each inspection method has its own set of advantages and disadvantages. Visual inspection, while having a relatively low capital investment, often lacks the precision required for high-density PCB assemblies. Thermography offers a non-contact approach to detect thermal anomalies that indicate defects or performance issues. It provides real-time, high-resolution images for rapid identification and localization of defects. However, the MT requires time for thermal saturation, which can delay the inspection process. Additionally, the effectiveness of thermography can be influenced by the thermal properties of PCB materials, and similar thermal characteristics between components can mask defects. The Flying Probe test method is particularly advantageous for small production runs and scenarios with high variability, such as remanufacturing. Its flexibility, due to the lack of need for custom fixtures, significantly reduces setup time compared to a bed-of-nails tester. Nevertheless, it has a high capital cost and is difficult to set up. The economic dichotomy in metrology is evident across these methods: low-cost inspection techniques often lack the necessary accuracy, while high-precision systems are cost- prohibitive and not always profitable. It is evident that no single method can be successful in the context of remanufacturing. In order to be profitable, it is necessary to harness each method's individual strength. To date, there has been no work that combines several existing inspection methods to exploit the advantages of each method at the appropriate stages. This gap highlights the need to develop a hybrid inspection approach that optimizes both economic feasibility and technical performance in the remanufacturing context.

3. Methodology

The proposed methodology aims to combine the advantages of various measurement technologies to select the best MT combination for specific scenarios. By early estimation of the functionality of the components, PCBs that are likely to be functional can be screened out early from the inspection process, saving time and costs in the more precise identification of the conditions. The central concept is based on the high capital costs of precise MT and the relatively low costs of less accurate MT. This methodology is based on three main principles:

1. Sequential Measurement Technology Application: Measurement Technologies are chained according to their capital cost, starting with the least expensive and progressing to the most costly.
2. Data Fusion: Previous measurement data within the sequence and data from earlier PCBs are fused to maximize the information gained from the measurements of less expensive systems.
3. Value Focus: The main focus is on identifying valuable, functioning parts rather than precisely determining defects in the PCB.

The ultimate goal is to maximize profit per PCB, considering knowledge acquisition, data collection, and measurement costs.

3.1. Conceptual framework

Figure 1 visualizes the general concept. The y-axis represents the value of the PCBs, and the x-axis represents the measurement technologies and measurement time. The value of the device under test (DUT) is described by the green lines. The area between the green lines represents the uncertainty about the condition of the PCB. Initially, the PCB has minimal value as all components could be defective. As more information is gathered through measurements, the potential functionality of the DUT can be better assessed decreasing the uncertainty. With each additional measurement and technology, information about the specific DUT is collected and retrieved for recurring PCBs. This allows for faster and more cost- effective estimation of whether the PCB is functional. Measurement data within the sequence, as well as data from earlier boards, are fused to gain the maximum information about the PCB, thereby maximizing the Added Value (AV). This way a learning process carrying over data from one step to the next one is established. Consequently, for board n, the value curve increases more steeply due to the information gained from previous measurements, generating a greater value gain. The red curve, and thus also on the y axis, represents the cost curve of different measurement technologies, which scales with the value of the MT and the time it takes to inspect a DUT with said MT. Therefore, the MTs are ordered according to their capital costs per unit time, forming an efficient process chain. Based on the state of the art, the following MT sequence is derived, starting with the least expensive MT and progressing to the most expensive:

1. Visual Inspection, $(t_0 \leq t < t_1)$
2. Current-Time Analysis, $(t_1 \leq t < t_2)$
3. Thermography, $(t_2 \leq t < t_3)$
4. Flying Probe, $(t_3 \leq t < t_4)$

With each measurement, the uncertainty U decreases, narrowing the green corridor. This reduction is illustrated linearly but does not necessarily have to be linear in reality. If the process is halted at any point, only the minimum value can

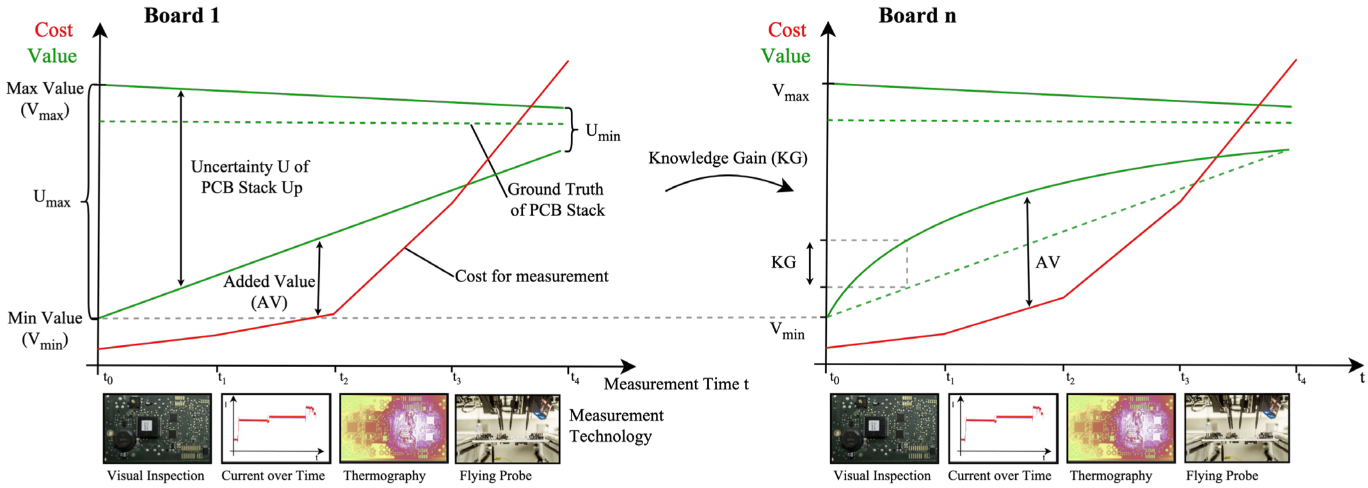

Fig. 1: Conceptual framework of sequential PCB inspection process

be achieved as it reflects the knowledge about working components. The condition of the other components remains unknown. The maximum value thus only represents an upper limit and the theoretically achievable maximum value. The main goal is to maximize AV, calculated as the difference between the minimum green curve and the red curve. Over time, the reduction in the uncertainty corridor accelerates as more knowledge is gained. Initially, a visual inspection is conducted to identify obvious defects, assess the condition of the components, and identify them. After processing the measurement data, an economic evaluation of the electronic components is performed, and it is decided based on the measurements whether further investigation of the PCB is necessary. If the data is sufficient, the PCB is removed from the process chain, and the most appropriate R-strategy (Reuse, Remanufacture, or Recycling) for the DUT is decided (see fig. 2). As described above, following the visual inspection, current-time analysis, thermography, and flying probe testing are performed based on the same evaluation principles.

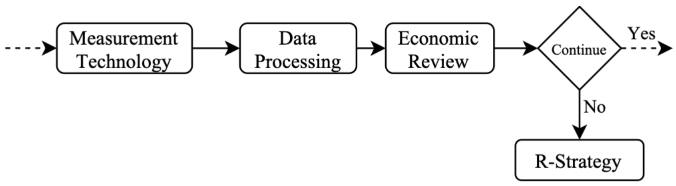

Fig. 2: Process description

3.2. Application of the concept

As a first step for a proof of concept, we choose to validate each MT of the sequence based on an industrial use case. An IO-Link Master is a common component in the industry, widely used for connecting various sensors and actuators via a standardized protocol to all kinds of control systems. We focused on the IO-Link Master of Balluff (fig. 3). This product is already designed for remanufacturing as it is encased in an ultrasonic welded plastic case which is different from other industrial components which often are cast into plastics. It is the perfect example of a product in the context of PCB remanufacturing.

Fig. 3: Use case: IO-Link Master from Balluff

3.3. Visual inspection and components recognition

The first stage of the proposed methodology is to accurately identify the electronic components on the PCB. This is critical as defects can result from either the omission or incorrect placement of certain components on the PCBs. To address this challenge, a neural network has been developed and deployed to accurately identify both the location and type of electronic components on the PCBs. The proposed approach integrates the YOLOv5 algorithm into WEEE management systems, exploiting its ability to detect and locate multiple objects in images. The application of YOLOv5 improves the efficiency of sorting processes by accurately identifying PCB components and their variable locations [16][17]. This component recognition phase is of critical importance for the subsequent PCB inspection phases, which using electrical signals and thermographic inspection (see 3.4 and 3.5).

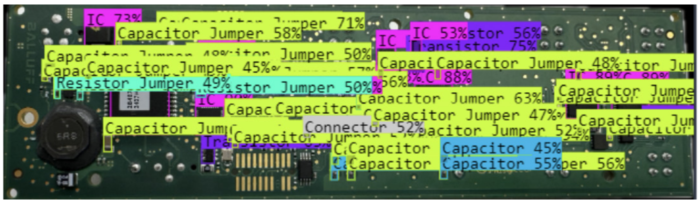

Fig. 4: Electronic components classification for Balluff BNI IO Link Master

The training dataset for YOLOv5 was generated using Roboflow, a widely used online resource for the training phase of neural networks [18]. The images were manually labeled to identify the different component classes and resized to 416x416 pixels, and data enhancement techniques such as flipping, rotating, saturating and zooming were applied to increase the original dataset size. The dataset was partitioned into 80% for training and 20% for validation and testing. Figure 4 shows the result of the network application on the Balluff BNI IO Link Master PCB. The product consists of 12 different components. The YOLOv5 network implementation processes and classifies an image every 0.72 seconds, demonstrating its suitability for production line applications. It should be noted that some components are not visible in the image because they are obscured by other labels. In addition, a 50% confidence threshold has been applied, which may result in certain components being excluded from the image.

3.4. Current-over-time curve

An essential and novel step of this work lies in analyzing the power consumption of the DUT during the boot process. Each active component has a specific energy consumption signature. Since the voltage is constant, this can be measured by the current consumption. If a component fails or does not work correctly, the consumption will fluctuate, which can be immediately detected. This method leverages the unique current signature of each DUT by comparing it with a reference measurement to identify possible defects. This step represents the second phase in the inspection process in Fig. 1. While the expected results may not be highly precise without additional metrology, the advantage of this method lies in its speed. With approximately 2 seconds, corresponding to the duration of the DUT's booting process, identification is possible in a very short time. The required measurement technology is also relatively simple and cost- effective compared to e.g. a Flying Probe tester. Thus, this method is particularly suitable for the remanufacturing of PCBs, as the DUT only needs to be powered on, and no investigations at the component level are required. To build a dataset, a Keithley SMU2461 was used. By programming a test script, we are able to build representative and repeatable dataset, which is essential for a direct comparison of signatures. For each DUT, 100 measurements were taken with 100,000 samples each, corresponding to 50,000 samples per second. In fig. 5, the current consumption of the BNI IO Link Master during the boot process is shown over time. Two PCBs were measured, one of which was manipulated. A component defect was simulated by removing a resistor and short-circuiting three pins of an IC. Our investigations revealed that these fault types exhibit distinct signatures compared to a fully functional state. Specifically, we observed that the two examined defect types do not behave identically in their signatures. This indicates that some fault types can be detected more effectively than others. Non-detectable fault types may include components that are not addressed during the boot process and therefore do not appear in the signature. Additionally, high-frequency signals pose a problem as they cannot be detected by our measurement technology due to an insufficient sample rate. Our primary interest lies in what is measurable, as these signatures provide a reliable basis for fault detection. In fig. 5, the blue curve represents the average of 100 measurements of the functional PCB, while the red curve represents the average of the defective PCBs.

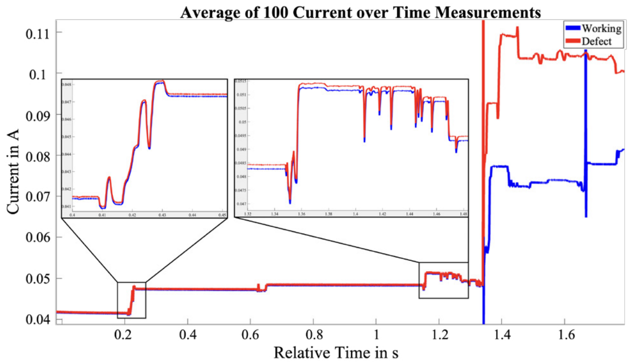

Fig. 5: Current over time curve for Balluff BNI IO Link Master

3.5. Thermography

As described in Section 2, numerous approaches and publications already exist on the use of thermography for PCB defect detection. However, the integration of data fusion remains largely unexplored. This is particularly intriguing as it enables the utilization of historical data from the same board type and previous processes, thereby facilitating faster decisions regarding the optimal R-strategy. During the powering of the PCBs, thermographic images were captured using the ImageIR 9400 infrared camera from Infratec. The operational duration for each measurement was 2 minutes, which, at a frame rate of 100 Hz, results in 12,000 snapshots per measurement. Active thermography was employed by applying the operating voltage to the DUT, activating the PCB and inducing current flow. This method is intended to detect potential defects in defective PCBs, as these defects would result in higher current flow compared to a functional DUT, making them visible with the IR camera. Figure 6 shows a comparison between a functional (a) and a defective (b) PCB. The defect is a short circuit of 3 pins of the IC, highlighted with the black box. The core temperature of the PCB is the same up to 0.43°C, with the defective IC having a temperature difference of 0.87°C. The IR-images allow us to visualize the heat distribution on the PCBs, identifying potential defects in electronic circuits. While visual inspection has so far enabled us to examine the external features of the PCB, using thermographic images makes it possible to visualize the heat distribution and identify potential problems or malfunctions in electronic circuits and differentiate between functional and defective DUTs. Thermography thus enhances the measurement technology pipeline for the remanufacturing process, providing a more comprehensive assessment of the DUT's condition.

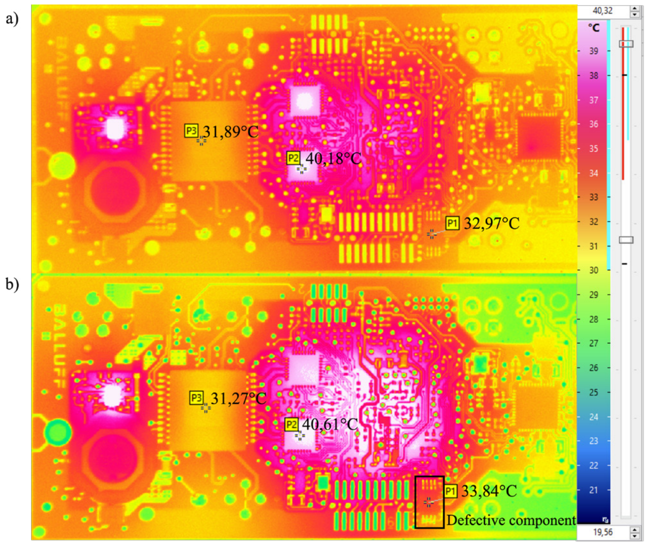

Fig. 6: Comparison of thermographic image: a) functional and b) defective DUT

4. Conclusion

This paper presents a novel inspection concept that leverages data fusion of visual inspection, current measurement, thermography, and FP using artificial intelligence to address the complex challenges in remanufacturing PCBs. By combining multiple measurement technologies, we aim to identify valuable, functioning components early in the inspection process, thereby reducing time and costs associated with more precise identification methods. The methodology proposes sequential measurement technology, data fusion and a value-based approach to optimize profit per board. The inspection sequence starts with visual inspection, followed by current-time analysis, thermography and FP testing, balancing economic and technical performance. The introduction of current-time analysis improves early defect detection by comparing the unique current signature of each DUT with reference measurements, allowing fast and cost- effective identification of functional discrepancies. This approach is a promising step towards a fully validated concept in industrial applications. The goal is to show the limits of the technology. In conclusion, this paper lays the groundwork for a hybrid inspection approach that combines the strengths of various measurement technologies and is therefore well suited for the remanufacturing of PCBs. While our focus has been on the conceptual development and initial validation of the methodology, future work will delve deeper into refining the process, exploring additional use cases, and optimizing the integration of advanced AI algorithms. In particular, the data processing of the current over time and thermography needs to be detailed. The core challenge will be the usage of the multi-modal data to select, improve and speed up measurements. For this purpose, a knowledge database will be necessary storing all measurements. In addition, it will be necessary to acquire product and market data for the technical and economic evaluation of the components of a PCB.

Acknowledgements

The authors would like to thank the Ministry of Science, Research and Arts of the Federal State of Baden-Württemberg for the financial support of the projects within the Innovation Campus Future Mobility (ICM).

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