# POLITECNICO DI TORINO

**Laurea Magistrale in Ingegneria Gestionale**
**percorso ICT e data analytics per il management**

# Reducing Waste in Electronic Components: A Circular Economy Decision Model Using Graph Neural Networks and Reinforcement Learning


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**April 2025**

# Abstract

This work stems from the need to find a solution to mitigate one of the problems that characterizes most the environmental impact of the modern era: e-waste management. After analyzing its relevance in the context of environmental sustainability, the thesis discusses different types of tests used to study the defects in printed electronic boards and the recovery strategies that can be implemented. The thesis proposes a decision-making model modelled in the form of a Markov Decision Process characterized by uncertainty. The information space of PCBs, consisting of varying numbers of components that may have different defects, was represented through the use of graphs. These main aspects lead to a resolution through the implementation of a simulation algorithm developed in Python based on Reinforcement Learning and the use of Graphical Neural Networks. Through the use of simulated data from the use of historical data and test and recovery strategies, the aim of this model is to identify the optimal test sequence required to understand the defective state of electronic boards and the appropriate subsequent recovery strategy, balancing cost and profit.

# Acknowledgements

I would like to express my sincere gratitude to Professor Maurizio Galetto from Politecnico di Torino and Professor Gisela Lanza from Karlsruhe Institute of Technology (KIT) for giving me the opportunity to carry out this thesis project.

A special thank you goes to Stefano Puttero, whose constant support, availability, and valuable advice greatly contributed to the development of this work. His dedication and willingness to share his knowledge made a significant difference and provided continuous support throughout the project.

I am also very grateful to Florian Stamer at KIT for his availability, collaboration and hospitality during my time in Germany. Working alongside him has been a real pleasure and has given me the opportunity to learn new skills and deepen my knowledge.

Finally, I would like to thank my family and friends for their continuous encouragement and support throughout my studies.

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# Acronyms

**IoT**
: Internet of Things

**WHO**
: World Health Organization

**PCB**
: Printed Circuit Board

**AI**
: Artificial Intelligence

**LCT**
: Life Cycle Thinking

**LCA**
: Life Cycle Assessment

**AOI**
: Automated Optical Inspection

**ICT**
: In-Circuit Test

**FPT**
: Flying Probe Test

**TI**
: Thermographic Inspection

**COT**

Current Over Time

**MDP**

Markov Decision Process

**UML**

Unified Modeling Language

**BPMN**

Business Process Model and Notation

**RL**

Reinforcement Learning

**GNN**

Graph Neural Network

# Chapter 1

# Sustainable Management of Electronic Devices

## 1.1 The spread of electronic devices: an opportunity and a challenge

The expansion of electronic devices has become a defining feature of economies, industries, daily life, and the modern world in general. Recent decades are distinguished by technological advances, fueled by globalization, that have accelerated the adoption of digital systems that have made electronics an integral part of both consumer and digital applications. This transformation represents from one point of view a major opportunity but at the same time it brings considerable challenges.

History sees a close link between economic development and technological progress. After World War II, industrialization and modernization drove economic expansion in which the technological innovation played a key role in productivity growth [1]. Industry 4.0 with digital transformation has emphasized the importance of electronics. Modern manufacturing systems are intrinsically linked to automation, IoT (Internet of Things) and the latest artificial intelligence. These, along with the adoption of PCBs (printed circuit boards) and other electronic components in various industries, highlight their importance in the process that leads to improved efficiency, translated into the reduction of operating costs and optimization of production time that characterize global competitiveness [1].

Playing a key role in economic and social development is information and communication technology (ICT) investment. As of 2011 data, global ICT investment had reached $ 3.5 trillion, encompassing most sectors, such as finance, manufacturing, and healthcare [2]. This major expansion of electronics represents an opportunity for innovation, productivity and sustainability. Smart manufacturing systems offer the possibility of moving to circular economy models, greatly reducing waste and optimizing resource use in industrial settings [1]. Among the benefits of automation and artificial intelligence, considerable results are mentioned by several studies, such as a 20% increase in productivity in manufacturing and logistics [3], as well as a decrease in occupational accidents by more than 15% through the use of collaborative robots (cobots), improving worker safety [4].

Among the various fields, the medical field is one in which excellent results have been achieved. The implementation of telemedicine systems has increased by 60% in the past 5 years, allowing patients residing in remote areas easier access to specialized care [5]. In addition, the use of AI has improved the accuracy of diagnoses by 25% by reducing the expected time to diagnosis and improving clinical outcomes [6].

However, the spread of technology and electronic devices leads to several challenges. Productivity gains at the aggregate level have not always materialized. This is a phenomenon referred to as the "productivity paradox." While technological advances are growing by leaps and bounds their diffusion across firms and the economy is uneven, creating major productivity and efficiency gaps [7].

Among the most important challenges related to this phenomenon, such as cybersecurity, digital inequalities, and access to technology, one issue that assumes significant importance is the pollution and environmental impact of e-waste, which will be discussed in the following section.

## 1.2 Electronic waste and its environmental impact

Electronic waste, referred to as e-waste, represents a wide variety of products, including smartphones, computers, household appliances, or tools of industrial use. Recent years have seen, in conjunction with the expansion of electronic devices, a proportional increase in e-waste. By 2022, 62 million tons of e-waste was counted globally, an 82% increase from 2010, and continued growth has been predicted [8]. The rapid growth is attributed to higher consumption and shorter product life cycles with limited opportunity for repair.

To give examples, lead in batteries and printed circuit boards can accumulate in the soil to the point of making it unusable for agriculture and damaging the food chain, with harmful effects on ecosystems [9]. In Figure 1.1 it's possible to see the main hazardous substances and the e-waste from which they originate.

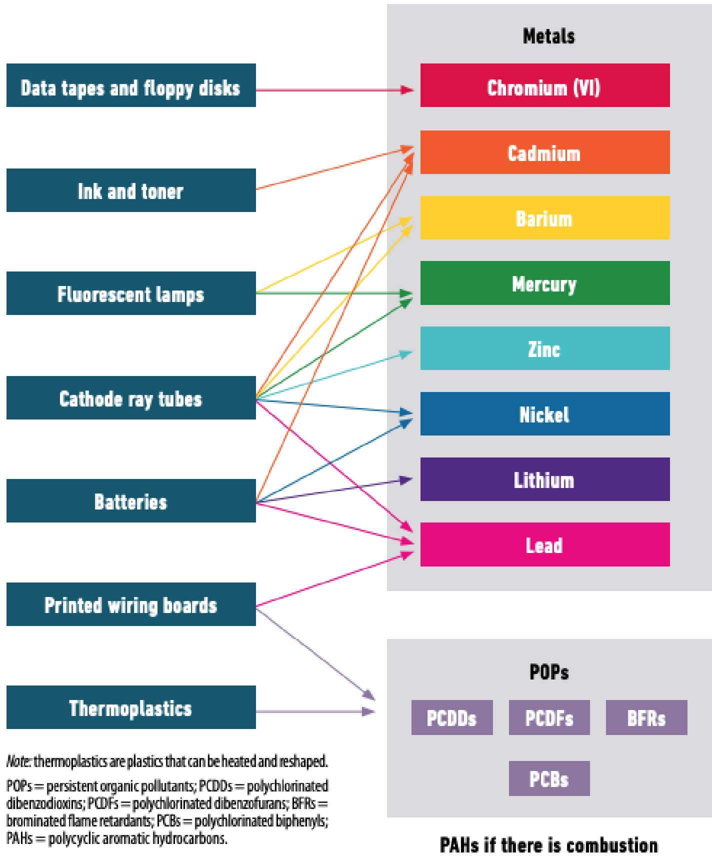


**Figure 1.1:** Common toxicants released from unsound waste management activities [10].

A World Health Organization (WHO) study highlights how e-waste is a source of exposure to toxic substances that lead to neurological disorders, kidney disease, and even cancer, especially in vulnerable individuals [9].

The e-waste problem also sees exploitation in developing countries, which are often subject to illegal imports of waste from wealthier countries. One example is the Agbogbloshie landfill in Ghana, which receives thousands of tons of waste every year. In fact, as can be seen in Figure 1.2, the disparity between countries in the subsistence of subsistent regulations to administer the disposal and management of e-waste is not insignificant.

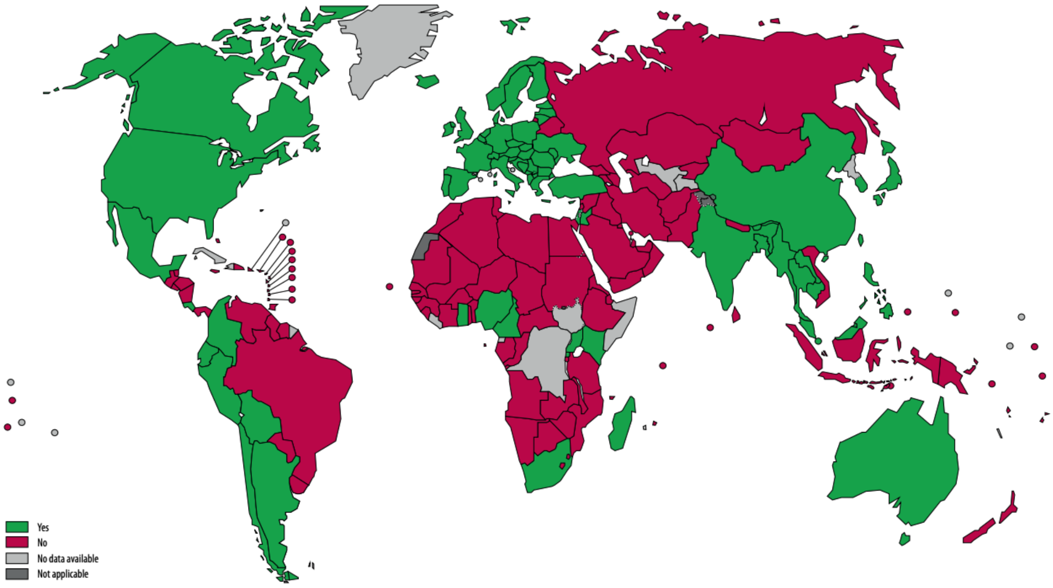


**Figure 1.2:** Countries with national e-waste legislation, policy or refulation in place, 2019 [10].

Another issue related to the e-waste context is the disposal costs. This is a particularly relevant issue in countries without adequate infrastructure. It is estimated that more than 90% of e-waste in Africa is mismanaged with dangerous practices [11].

These materials are destined to be burned in the open to extract precious metals resulting in the release of pollutants and cangerogens into the air. A process that therefore not only damages the environment, but also affects the lives of workers, often children, at very serious risk, as documented by the 2021 WHO report [10].

The model of electronic device management mainly adopted over time has been the linear model, which sees the achievement of the stages of production, use and waste creation. The linear model has been the prevailing model adopted in the last decades of industrialization. Over time, however, it has proven to be environmentally and economically unsustainable. As can be seen from an OECD report [12], the linear model contributes to the generation of more than 53.6 million tons of e-waste each year. This is a system that fuels pollution, worsens environmental conditions and results in a major waste of valuable resources, such as gold, silver and rare earths.

In this context finds its foundation the importance of implementing a circular economy model, discussed in the next section.

## 1.3 The role of circular economy in electronics

The circular economy model aims to reduce waste by maximizing resource efficiency. The cornerstones of this model are reuse, recycling and sustainable design aimed at extending the life cycle of electronic devices [13].

The shift to this type of model is crucial in the electronics sector, which we have discussed in previous sections, characterized by millions of discards each year. The implementation of circular economy principles in electronics, such as eco-design, the use of recyclable materials, and the development of product that are easy to repair and dispose of, could generate a 50% reduction in e-waste by 2030 [14].

In order to develop products that reflect these principles, it is important to rely on Life Cycle Thinking (LCT) approaches. It consists of conducting analysis and evaluation, applying standardized methodologies, to assess the environmental impacts generated throughout the life cycle of the product and service in order to reduce their overall impact. Through it comes a shift from the separate study of individual elements of the product life cycle to a global view whose fundamental goal is the reduction of environmental impact. The LCT philosophy is applied through Life Cycle Assessment (LCA). This is a methodology dealt with by the International Organization for Standardization, which provides guidelines for its proper implementation. The objective is the study of the product's life cycle aimed at identifying critical points to be followed by appropriate decisions to improve its environmental aspects [15].

In evaluating the adoption of the circular economic model in the context of e-waste, its main strengths and limitations can be represented in the following main points.

Main benefits include:

- Reduction of e-waste: Possible through reuse, repair and recycling, decreasing the amount going to landfills and mitigating environmental impact [16];
- Conservation of natural resources: The need to extract new resources is reduced by recovering valuable materials such as gold, silver and copper [16];
- Energy conservation: Recycling and reuse placed in comparison of electronics manufacturing demonstrates lower energy consumption resulting in lower greenhouse gas emissions; [16]

However, the following limitations must be considered:

- High Upfront Costs: Infrastructure and technology adoption of strategies such as recycling and reuse require large investments [17];
- Technological challenges: Recovery of materials, especially rare or hazardous materials, requires complexity in implementing appropriate technologies [17];

- Regulatory barriers: The difficulty in formulating uniform regulations across the globe makes adoption of the circular model uneasy [17];

A key challenge in implementing this model is the management of defective products. This is possible through the key practices of reuse, repair and recycling. These are discussed in more detail in the next section to highlight their characteristics.

## 1.4 Managing faulty components: reuse, repair, and recycling

In the context of the circular economy, the sustainable handling of electronic components is an important topic and can be managed through reuse, repair and recycling. These strategies are adoptable depending on the contexts and products under consideration, below we show a comparison of them to understand their implementation and feasibility trying to highlight their main challenges with particular regard to printed circuit boards.

### 1.4.1 Reuse

Reuse is one of the fundamental operations adopted to reduce environmental impact, but the possibility of being able to practice it efficiently involves dealing with several challenges. The disassembly of electronic components is one of the aspects that needs particular attention. Devices are becoming increasingly complex and intricate as technology advances, making the extraction of reusable parts technically challenging. This is what emerges from a study published in RSC Sustainability, in which is considered the issue of disassembling components from discarded printed circuit boards (WPCBs), defining how this is the most critical step in the reuse process [18]. Another problematic aspect is the quality assurance of reused components. Indeed, it is necessary to assess their satisfaction of performance and safety standards in order to consider them acceptable [19].

Various solutions have been used and considered. One of these, in the field of printed circuit boards, is the use of vitrimeric materials for their production. This type of material offers good resistance and allows them to be attached or detached several times, facilitating disassembly. In this way, it allows printed circuit boards to be reused without directly compromising their performance [20]. Also emerging in the range of solutions is the concept of solderless PCBs. This is a practice whereby 3D-printed housings are used to assemble electronic components without the use of solder. Research shows that adopting this method simplifies the assembly and disassembly of components, making them more easily reusable [21]. However, the adoption of this type of operation still leads to many difficulties in successfully reusing electronic boards, as the lack of standardization of dimensions and specifications of individual products complicates the process.

### 1.4.2 Repair

It is one of the most important techniques to combat planned obsolescence and consequently reduce the generation of electronic waste. In the field of PCBs, repair needs to interface with the miniaturization of components. Electronic components are becoming increasingly smaller and densely placed on boards, resulting in more complex repair operations. Tools such as fine-point soldering irons and microscopes are used for this purpose in order to avoid damage to surrounding traces and components by aiming for the most efficient precision possible [22]. Repair also requires an accurate diagnosis of possible faults in the boards. Figuring out what may be the cause involves visual inspections and instrumental tests, which we will adequately cover in the following sections. There are several solutions that are used, and it is conceivable to find a way to fulfill these needs. It is worth mentioning the study of maze-solving automatisms for the self-repair of open interconnections. This approach is explained in the integration of self-repair mechanisms in PCBs in which fractured interconnections are physically repaired by means of conductive particles dispersed in an insulating fluid. The result offers a methodology for self-repair of broken PCB paths at a rate of 10 um/s [23].

It is important, in addition to post-damage action, to adopt preventive maintenance practices. This means periodically overhauling and updating the electronics of devices and timely replacement of worn components that could damage surrounding components.

### 1.4.3 Recycle

It is the practice par excellence for the recovery of materials from electronic waste. PCBs contain many substances such as gold, silver, copper or glass resins and fibres. This type of materials, if properly treated, can be extracted and reused to make new products or for other general purposes, while reducing the amount of waste going to landfills.

It is mainly implemented through mechanical, pyrometallurgical and hydrometallurgical methods. The former involve the crushing of PCBs followed by separation of the components by material type, but this is usually not a very efficient approach and results in the creation of fine dust that is harmful to humans. Pyrometallurgical methods use temperatures to melt metals and this involves high energy consumption and is likely to result in toxic emissions. Hydrometallurgical methods, on the other hand, are more selective and consist of dissolving metals with chemical solutions, enabling their subsequent recovery. This method has a good selective capacity but involves the use of toxic chemical reagents [24]. An approach that is becoming increasingly popular in the modern context is also the use of artificial intelligence, constituting machine learning-based methodologies to classify and identify PCB components independently by improving component disassembly [25].

In general, this is not an easy process to apply in the context of PCBs because it involves the management of hazardous substances and constitutes environmentally sustainable processes that require appropriate research and technological development.

### 1.4.4 Comparing the three strategies

Comparing the three types of strategies, it is useful to ask when and if it is possible to define a criterion to determine when one may be preferable to the other. In general, it can be said that reuse and repair are preferable to recycling because they are less energy-intensive and allow for more valuable outputs, since it would be possible to obtain 'ready-made' products. At the same time, however, they are two methods that necessarily require data acquisition in order to establish with adequate accuracy when they can be practiced. There are cases where it is not possible to understand how to implement them because they are too complex and one has to resort to recycling, which is nevertheless a good strategy to deal with the ever-increasing waste generation. It can therefore be said that reuse and repair are preferred to recycling but depend on the context.

# Chapter 2

# Testing Methodologies for Identifying PCB Defects

## 2.1 Introduction to PCB testing

Printed circuit boards, or PCBs for short, are components of modern electronics, consisting of conductive paths cut from copper foil and laminated to a conductive substrate, that have the primary function of providing mechanical support and electrical connections in various electronic contexts. An example is shown in Figure 2.1.

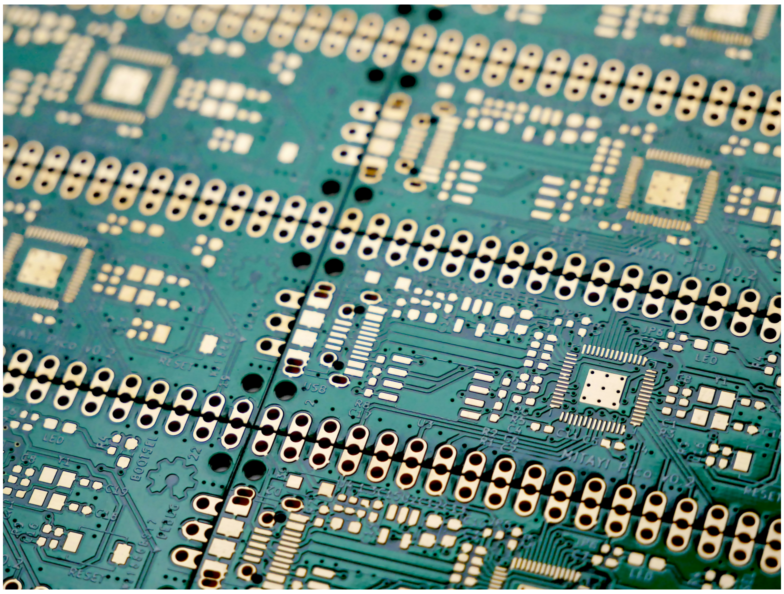

**Figure 2.1:** Example of Printed circuit board (PCB).

They were invented in the early 20th century by a German inventor, Albert Hanson, who introduced ‘Printed Wires’. Later in history, they were used for various purposes, including as proximity fuses by the United States during World War II. Coming to the present day, PCBs are now used for all kinds of electrical devices [26]. To be usable, a printed circuit board must be well designed to ensure the electrical integrity and durability of the final device. Reliability is therefore a fundamental requirement and can be verified using test methodologies.

There are several types of tests that can be adopted to recognize the status of PCBs. Generally, however, it is possible to distinguish them into two subcategories, **electrical** and **non-electrical** tests. An overview of the main types of testing used is shown below, which will be discussed in more detail in later sections [27].

### 2.1.1 Non-electrical inspection

These are testing methods that do not involve the use of electrical signals at the PCB and are oriented towards a physical analysis of the boards.

1. **Visual inspection** is a type of test that can be performed manually or by automated systems (Automated Optical Inspection, AOI), through the use of artificial intelligence. It is very effective and suitable for identifying surface defects, including cold welds, missing or misplaced components, or even interrupted tracks. Implementation is possible through the use of cameras controlled by image processing algorithms [27].

2. **X-ray inspection**, also known as Automated X-ray Inspection (AXI), finds its usefulness in inspecting internal structures of PCBs, to analyse non-visible parts such as components below the Ball Grid Array (BGA). it is a suitable type of test to check for defects such as porosity in solder, internal short circuits and missing connections [28].

3. **Thermography** is a type of non-destructive inspection using a thermal imaging camera to measure temperature distribution on surfaces. It is therefore aimed at identifying thermal anomalies that result in the identification of defects, such as faulty connections and others. It therefore allows identification without direct contact and is suitable for those defects that are difficult to see.

### 2.1.2 Electrical inspection

These are testing methods involving the use of electrical signals to check the condition of PCBs. This means that the circuit board is monitored when connected to power, in order to study its operational characteristics.

1. **In-Circuit Testing (ICT)** is a type of testing that uses probes to measure electrical characteristics of PCB by testing individual components. For its implementation is required an expensive equipment for low volumes.

2. **Flying Probe Test (FPT)**, on the other hand, is a method that adopts the use of flying probes without the need of a fixed bed of nails. This type of testing method is characterized by flexibility and adaptability for small series or prototypes.

3. **Current Over Time test (COT)** is a type of test technology that analyzes changes in electrical consumption during the operation of an electronic device. Thus, the current value over time is monitored to identify defects such as intermittent short circuits, unstable connections, or even deteriorating components.

## 2.2 Testing methods

The various tests differ in a number of aspects. In general, they are used to identify defects that may be different or the same, but operating from different points of view. The choice may depend on different factors, such as the cost related to the accuracy required and the quantity of components to be tested. In the following subsections, a more precise analysis of each type of test method is presented to understand whether a specific test can be chosen depending on the context.

### 2.2.1 Automated X-Ray Inspection (AXI)

The Automated X-Ray Inspection is an advanced PCB inspection technique whose operation is based on the emission of X-rays from an X-ray tube. The rays pass through the PCB and, absorbed to varying degrees by the materials of which the board is made, exploit data on density and atomic number. Areas with denser materials (such as solder) absorb more X-rays and are visualized darker through the images as output, as it is possible to see in Figure 2.2. The images are created by a detector on the opposite side that captures the rays passing through the PCB and converts them into visual signals that are processed [29], [30].

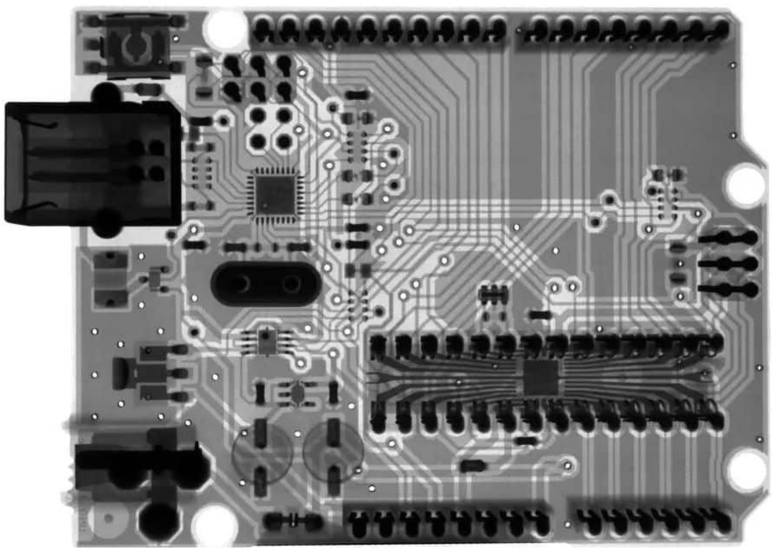

**Figure 2.2:** X Ray Inspection of a PCB [31].

This technique is therefore useful for identifying hidden defects such as cold solder, which are characterized by weak electrical junctions and can lead to intermittent and permanent faults. Hidden electrical bridges are also identified, which occur when excess solder unintentionally connects several nearby conductive tracks.

It is a technique suitable for the evaluation of high-volume production contexts, i.e. in high-consumption electronics such as aerospace and automotive where non-destructive and highly accurate evaluation methods are required. It therefore offers a solution for the inspection of electronic components with a complex surface structure [29], [30].

### 2.2.2 Visual inspection

Visual inspection is a technique that can be performed manually or through systems called Automated Optical Inspection (AOI). Automated AOI is a computer vision-based method for automatically examining PCBs in order to acquire images of the components. It is made possible by high-resolution cameras, as can be seen in Figure 2.3, that are then processed by specialized software to recognize the characteristics of the boards and the different component types.

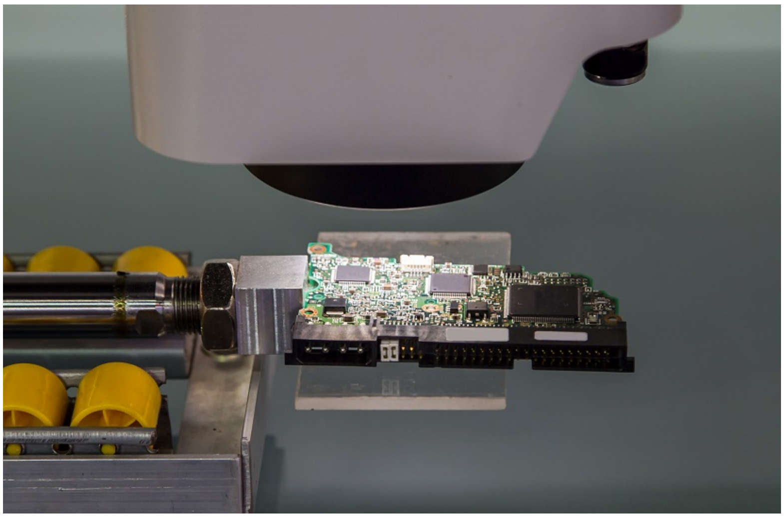

**Figure 2.3:** Example of an Automated Optical Inspection (AOI) system inspecting a printed circuit board (PCB) [32].

The software uses the images to compare them with previously analyzed visual information based on reference models with predefined parameters to identify any discrepancies. This practice can be adopted in various cases, such as the inspection of bare boards or their evaluation at different stages of production [33].

The defects for which it is prepared are superficial ones. To give some examples, some of these are possible defective soldering, thus insufficient or excessive soldering, which are often the cause of short circuits, damaged traces, which include cuts, breaks or even corrosion in the conductive tracks that can hinder electrical continuity, or even simply for components that are missing or that are incorrectly positioned, thus such as resistors and capacitances that are incorrectly positioned, compromising the functionality of the PCB [34].

It is very efficient when very clear images of the analyzed cards are available and especially when an adequate database is available to refer to in order to detect potential differences.

The main characteristics of this method, when the prerogatives that make it efficient are fulfilled, are the rapidity in acquiring information, the fact that it is very economical since it mainly involves obtaining images as input, the repeatability that allows the analysis of large volumes and furthermore it is a methodology that can be easily integrated into production lines.

### 2.2.3 In-Circuit Testing (ICT)

The In-Circuit Testing (ICT) is a technique used in the inspection of PCBs that is based on the use of a device called a ‘bed of nails’, as can be seen in the Figure 2.4, it consists of a matrix of spring-loaded pins positioned according to a certain logic designed to make contact with specific points to be tested. The board is placed on this bed and the pins, which simultaneously make contact with the nodes of the circuit, allow the measurement of parameters associated with the various components, such as resistance, capacitance and continuity. [35].

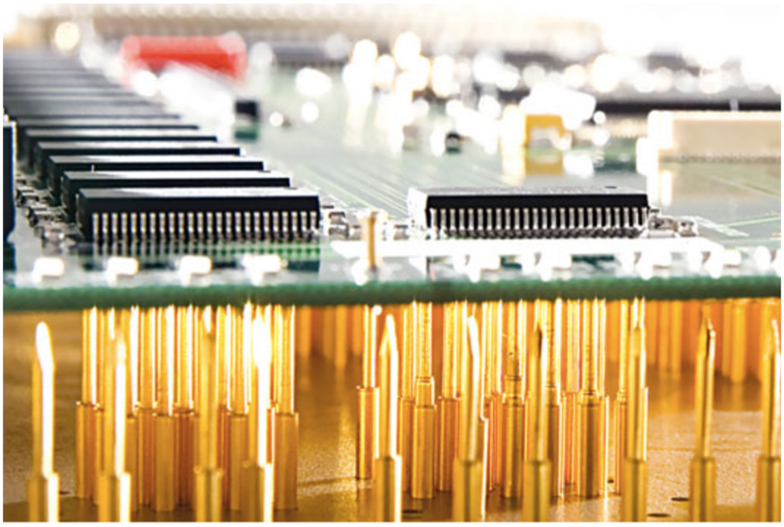

**Figure 2.4:** Test of a PCB using Bed of nails [36].

This technique is very useful for identifying faults such as short circuits or open circuits, uncovering unwanted connections or interruptions, poorly positioned components by verifying the presence of all components whose orientation is viewed, or incorrect component values by measuring parameters that must be within certain design specification limits.

It is also characterized by a very high degree of accuracy due to an individual study of each component on the boards. In order to be feasible, however, the board under consideration must be suitably designed to provide complete access to its components. In this sense, its implementation is particularly costly as it often involves the creation of a customized bed of nails.

### 2.2.4 Flying Probe Test (FPT)

Flying Probe Test (FPT) is an advanced technique that uses flying probes to check board connections, making the use of dedicated fixtures unnecessary. It adopts a series of mechanically controlled probes that move above the surface of the PCB, as shown in Figure 2.5, to make contact with specific points to be monitored, usually following programmed sequences.

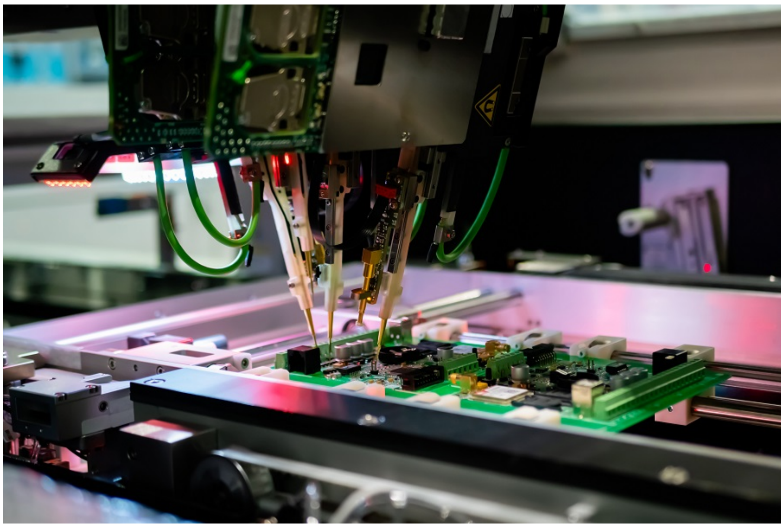

**Figure 2.5:** Flying Probe Testing [37].

Specifically, the probes apply electrical signals by measuring their responses and making possible to identify faults such as short circuits, open circuits or malfunctioning components.

As mentioned earlier, unlike the traditional 'bed of nails', it does not require customized fixtures, making this testing phase more flexible and more adaptable to the different configurations that boards may have. In this sense, the FPT is suitable and used mainly for prototypes and small series, since it offers cheaper testing than that proposed by the ICT, and for boards whose design may undergo frequent modifications, since it is easily adaptable to possible changes in component configuration [37].

The effectiveness of the FPT is a consequence of the accuracy of the probes, which is highly dependent on the quality of the control system. It is somewhat less fast than the application of bed-of-nails, once it is ready, but modern tests of this type have improved in speed and accuracy [38].

### 2.2.5 Thermographic Inspection (TI)

Thermographic Inspection (TI) is a non-destructive technique that is applied by detecting infrared radiation emitted by electronic components to identify anomalies. The components of a PCB generate heat when it is in operation, and it is the use of these heat differences in their distribution that can indicate various faults such as cold soldering, short circuits or others [39]. In particular, to use this advanced testing technology, the PCB must be powered and brought to normal operating conditions. A high-resolution thermal camera is then used, which is placed above the board to capture real-time thermal images, such as the one shown in Figure 2.6.

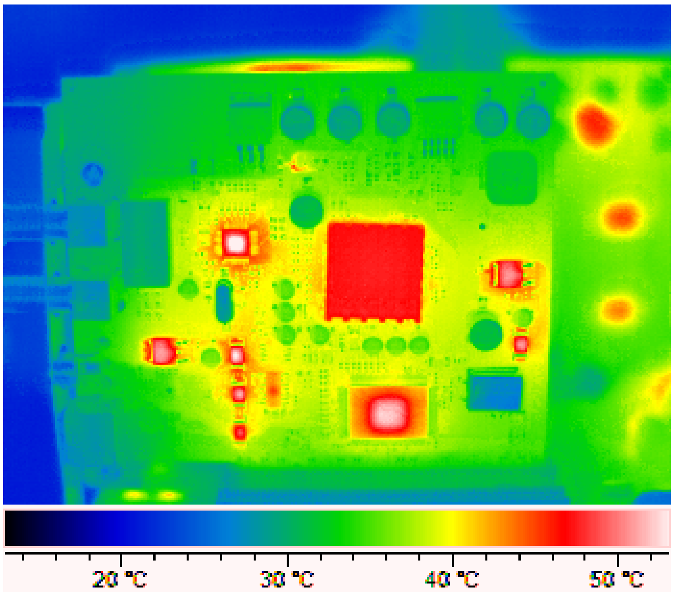


**Figure 2.6:** Example of an image from a thermal camera [40].

By analyzing these images, an attempt is made to detect the manifestations of temperature variations from the board's normal thermal profile. To give examples, a cold solder might have a lower temperature than the correct connections, or a short circuit might result in localized overheating. In general, temperature differences in the order of 1−2°C can be a sign of significant defects [41]. Furthermore, thermographic analysis can generally be practiced in two different ways, the active and the passive one. The so-called passive methodology simply monitors the thermal distribution during normal board operation, while the active one is conducted through the application of controlled electrical stimuli aimed at highlighting specific anomalies. The accuracy of this technique varies depending on the sensitivity and resolution of the thermal imaging camera used, as well as experience in interpreting the data correctly under the most appropriate conditions [39].

### 2.2.6 Current Over Time (COT)

Current Over Time (COT) is a testing technique based on electrical diagnostics used to detect current variations during the operation of a board. By analyzing the current over time, it is possible to visualize faults such as intermittent shorts, unstable connections and other types of defects [42]. Fault manifestations are translated as spikes, dips or fluctuations in the current profile, indicating potential faults. We can observe a graph showing the current trend from Figure 2.7, which shows the presence of short circuits corresponding to the two peaks.

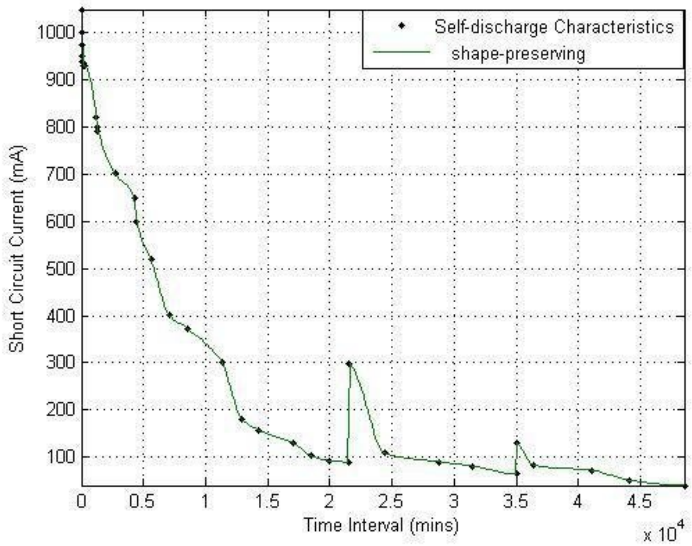


**Figure 2.7:** Current development in the presence of short circuits [43].

For its implementation, the PCB is powered and brought to standard operating conditions. At these conditions, high-precision current sensors are connected to the critical circuits to measure the current flow in real time. Specialized software collects and analyses the data and compares them with current profiles corresponding to expected values or reference models. To give examples, a gradual increase in current may suggest that the component in question is degrading, while sudden fluctuations may be a sign of instability. The quality and thus the accuracy of the COT test is derived from the quality of the sensors used and the time data acquisition system. The costs are quite high given the initial investment in the acquisition of the necessary equipment and software [44], but in the long term, due to the ability to detect defects early, its use leads to a reduction in costs.

## 2.3 General Comparison of Test Methods

The technical choice depends on the requirements of the production system, thus on the volumes to be analyzed and also on the type of defect to be investigated.

If we compare the accuracy of the various tests, it appears that ICT offers a higher level of accuracy for electrical tests, while X-ray is an advisable choice for identifying internal structural defects. AOI, on the other hand, is very effective for visible defects and FPT adequately covers electrical tests without using fixtures. Thermographic inspection (TI) proves very useful for PCBs characterized by high density, which can be analyzed by improper heat dissipation. The current over time test (COT), on the other hand, is suitable for detecting the progressive degradation of components that cannot be detected by static analysis.

From a cost point of view, ICT and X-ray testing are more expensive, while AOI and FPT are generally cheaper, especially for small batches in the case of FPT. ICT on the other hand has a moderate cost by requiring specific cameras but not physically coming into contact with the board for the testing phase. COT can be a variable cost test, depending on the accuracy of the sensors.

Considering the applicability of the various tests, AOI is suitable for large-scale production to identify visible defects, ICT is very good for large volumes that are uniform in board structure and with easy access to PCB nodes, FPT is suitable for testing prototypes and small production runs, while X-ray testing is necessary for PCB components whose density variability is well identifiable. The TI is useful for identifying components whose overheating indicates faults while the COT, by evaluating current over time, is useful for detecting reliability and diagnosing faults under dynamic operating conditions.

We can say that it is not possible to define a general scale of tests to define which one might be the best. Since each meets different needs, it would be possible to identify which tests are better than others based on the characteristics of the boards and the production system under consideration.

In order to give an overview of the testing methods main features, we can collect the data analyzed in the subsections discussed above by means of the Table 2.1. In this way, it's possible to observe a simplified analysis of the advantages and disadvantages depending on the accuracy, cost and applicability of the individual test methods.

**Table 2.1:** Comparative Summary of Testing Methods for PCB Defects, Including Advantages and Disadvantages.

| Test Method | Advantages | Disadvantages |
|---|---|---|
| **AOI** | Fast and cost-effective; effective for surface defects (defective soldering, missing components, broken traces). | Limited to visible surfaces; AOI may generate false positives/negatives. |
| **X-Ray** | Detects internal defects (hidden soldering, BGAs, electrical bridges); does not require physical access to PCB nodes. | Expensive; requires specialized equipment and skilled operators. |
| **ICT** | High accuracy in testing individual components; direct identification of incorrect values and defective connections. | Expensive for small batches; requires accessible test points in the PCB design. |
| **FPT** | Flexible and suitable for prototypes and small productions; does not require dedicated fixtures. | Slower compared to ICT for large volumes; lower accuracy for high-frequency tests. |
| **TI** | Non-invasive and suitable for high-density PCBs; detects thermal anomalies without direct contact. | Sensitive to environmental conditions; complex image interpretation. |
| **COT** | Identifies intermittent faults and degradation issues over time; useful for reliability monitoring. | Requires high-resolution data acquisition tools; complex analysis of collected data. |

## 2.4 Analysis of the level of sustainability of traditional testing

Considering the choice of the various types of tests undertaken, it is of interest to assess their environmental impact according to three main criteria: energy consumption, waste production and environmental impact. waste production and environmental impact.

### 2.4.1 Sustainability of each test

#### 2.4.1.1 In-circuit testing (ICT)

From an energy point of view, ICT testing, being highly automated, requires a considerable amount of energy to operate the specialised electrical devices and instruments. Its implementation tends to require high operating costs, especially in high-volume production contexts.

As far as waste generation is concerned, it can be stated that, in the case of ICT testing, it comes mainly from test devices and any boards that are determined to be defective during testing. The increase in material waste is proportional to the complexity of the devices used.

The resulting environmental impact is related to the use of heavy machinery that involves considerable energy consumption and potential emissions, especially if these are not powered through the use of renewable energy [45].

#### 2.4.1.2 X-ray inspection

X-ray testing systems, from the point of view of energy consumption, require a lot of energy to allow X-rays to be used and imaging systems to operate, which also results in high electricity consumption.

In the context of waste generation, on the other hand, since it does not involve the physical destruction of PCBs, waste can be said to be minimal. However, consideration must be given to the disposal of obsolete or malfunctioning X-ray equipment, which may contribute to the disposal of e-waste.

The overall environmental impact is not high, but is still present given the use of hazardous materials such as lead in the manufacture of some X-ray tubes. Therefore, proper protocols for their disposal and recycling must be employed [46].

#### 2.4.1.3 Automated optical inspection (AOI)

The energy consumption associated with this type of inspection is in the lighting and camera operations. It therefore does not involve as much consumption as X-ray and ICT, but one can also add the use of operating systems managed by artificial intelligence or other means to manage image selection.

Even in the generation of waste, AOI produces much less because there is no need for devices that have to be replaced frequently or modifications to PCBs in order to inspect them, nor is the use of particular substances required.

In assessing its environmental impact, it may be asserted to be very low, as it is not a destructive test and does not require any specific consumption for its use [47].

#### 2.4.1.4 Flying Probe Test (FPT)

It is very similar to the ICT test, since being automated it requires the use of considerable energy. However, as it does not require customised devices, it requires less energy, but more, again comparing it to ICT.

The rejects generated by this type of test are minimal because it does not alter the structure of the PCBs and the main ones, as with the other tests, come from the rejects of the PCBs identified as defective.

All in all, it is possible to say that FPT does not produce a great environmental impact and is preferable for small batches and prototypes as it does not consume a lot of energy and is not very fast [48].

#### 2.4.1.5 Thermographic inspection (TI)

It uses infrared cameras to detect faulty components practicing the test requires electricity to operate the sensors and image processing systems. Compared to other techniques its energy consumption can be said to be relatively low.

In the context of waste generation, as it is also a non-destructive technique and without the need for physical contact with the board, thermographic inspection produces no physical waste during the analysis process.

It is a type of test that does not require the consumption of solvents or chemical agents. The absence of these chemicals and hazardous waste, combined with good energy efficiency, allows this type of test to be defined as having minimal environmental impact [49].

#### 2.4.1.6 Current Over Time (COT)

Involves the continuous monitoring of electric current using sensors and data acquisition systems. These devices involve variable energy consumption depending on the duration of the tests and the complexity of the equipment. In general, however, it is reasonable to conclude that compared to the other tests, the consumption associated with the latter is moderate.

From the point of view of waste, being a non-destructive technique, it can be said to produce no direct physical waste during its implementation. The only associated waste is the obsolescence of the sensors and equipment used [50].

Overall, COT has a relatively low environmental impact. It does not involve the use of chemicals or hazardous waste, and the associated energy consumption is moderate, not indirectly contributing to greenhouse gas emissions [51].

### 2.4.2 Sustainability comparison

The Table 2.2 shows the information on the various tests in the context of sustainability in comparison. It is reasonable to conclude that, as they all have their advantages and disadvantages depending on the contexts considered, they have different environmental impacts by differing in consumption and waste generation. Therefore, when choosing which tests to use, it may also be useful to consider this aspect.

**Table 2.2:** Comparative Summary of PCB Testing Methods Based on Energy Consumption, Waste Generation, and Environmental Impact.

| **Test Method** | **Energy Consumption** | **Waste Generation** | **Environmental Impact** |
|---|---|---|---|
| **AOI** | Moderate | Low | Moderate energy consumption, no additional waste impact. |
| **X-Ray** | High | Low | Generates hazardous waste (lead shielding, X-ray tubes). |
| **ICT** | High | Moderate | High energy consumption and potential emissions. |
| **FPT** | Low | Minimal | Minimal environmental impact. |
| **TI** | Low | Minimal | No use of chemicals, low environmental impact. |
| **COT** | Moderate | Minimal | Limited impact, requires responsible e-waste management. |

# Chapter 3

# Problem definition and approach

## 3.1 Introduction to the decision-making problem

As discussed in the first chapter of this thesis, e-waste management is a major problem today. This problem continues to grow exponentially with the increasing adoption of electronic devices. Among the e-waste that is generated, printed circuit boards are one of the types that require the most attention

In order to manage their waste, it has been explored the different strategies of recovery, reuse, repair and recycling strategies, but from what the study shows, it is not always easy to be able to practice them and understand which is the most appropriate to choose. Whether it is possible to implement them depends primarily on the type of electronic boards, but also on the types of defects they may be affected by. For this reason, it is essential to be equipped with useful tools to derive the information needed to understand how best to manage e-waste.

In the second chapter, we addressed the main types of tests that can be used to study the state of PCBs. These included Automated Optical Inspection (AOI), X-Ray inspection, In-Circuit Testing (ICT) and Flying Probe Testing (FPT). From the study and subsequent comparison of these types of tests, it emerged that it is not always easy to understand which is the best one to use for the study of defects. What can be done is to try to understand their main characteristics related to cost, accuracy, the prerogatives necessary for their implementation and other aspects that are more generally related to the context in which they have to be used. For the study of high-volume production systems, some tests may be more suitable, while others may be more suitable for low numbers of controls.

The objective of this thesis is to develop an automated decision-making model for the study of defective PCBs aimed at reducing waste through the use of the above-mentioned recovery strategies and tests. The challenge is therefore to be able to understand for each individual board which is the best test sequence and the consequent most suitable recovery strategy, with the aim of reducing the waste of electronic devices. The best test sequence is the one that maximizes the information on board defects with the best possible accuracy while minimizing costs and consequently maximizing the profit from any board recovery.

## 3.2 Proposed decision-making model

The decision-making model, in order to select what we have defined as the 'best' sequence of tests, consists of a step-by-step evaluation of the selection of individual tests based on the probabilities of their individual outputs. At each step, therefore, the possibility of selecting a particular test by simulating its results is assessed. It is thus a sequential process that develops results dynamically, based on the data obtained in real time.

The question that arises is: how is it possible to consider that a certain test is better than another at a certain step in the sequence? What must be taken into account when comparing tests?

The challenge is mainly the variability of the characteristics of the components tested, which often have different types of defects. First and foremost, a factor to be taken into account is the ability to interpret with the best accuracy the probabilities associated with each board and, in particular, each defect from which a component may be affected.

Another factor to be taken into account is the profit that would be generated by the sequence indicated. It is therefore appropriate to take into account the costs necessary to use the individual tests and, in relation to these, the economic value of the output of the process, which must be linked to the value of the PCB, therefore, its overall value and that of the components and materials of which it is made.

By taking these factors into account, the system aims to achieve a balance that can make it sustainable and scalable for e-waste management.

This type of decision-making model can be modelled as a Markov Decision Process (MDP) characterized by uncertainty [52]. This is a mathematical model that is used to represent sequential decisions, the results of which are characterized by both randomness and a decision maker who controls their development. An MDP is defined by a set of states, a set of actions and a function that allows the transition by describing with which probability the transition between the different states is possible depending on the action taken and the defined reward. The latter serves to numerically define the different outcomes given by the action-state pair. Introducing the concept of uncertainty brings to consider several aspects. First of all, uncertainty characterizes transition rates, as these are not always known precisely, and the sensitivity of decisions to these uncertainties is analyzed by assessing how the resulting variation may influence the best decisions. The uncertainty of the models must also be taken into consideration, as the observation probabilities are not certain but may be partially known. In addressing this problem, a partially observable Markov decision process (POMDP) with uncertain transitions and observations can be introduced. Finally, the robustness of the control must be taken into account by investigating control methods to handle the uncertainties of the system in order to be able to say that time specifications are met in the presence of parameters affected by uncertainty.

To model our problem in the form of an MDP, a state was represented as the knowledge of the state of a PCB in terms of the probability of knowing the defects from which each component may be affected. Actions, on the other hand, correspond to the choice of a specific test or recovery strategy. Determining the transitions between one state and another are the output probabilities from the actions, which reflect the uncertainty of detecting a certain fault. We can observe a graphical representation of the MDP for our case in Figure 3.1.

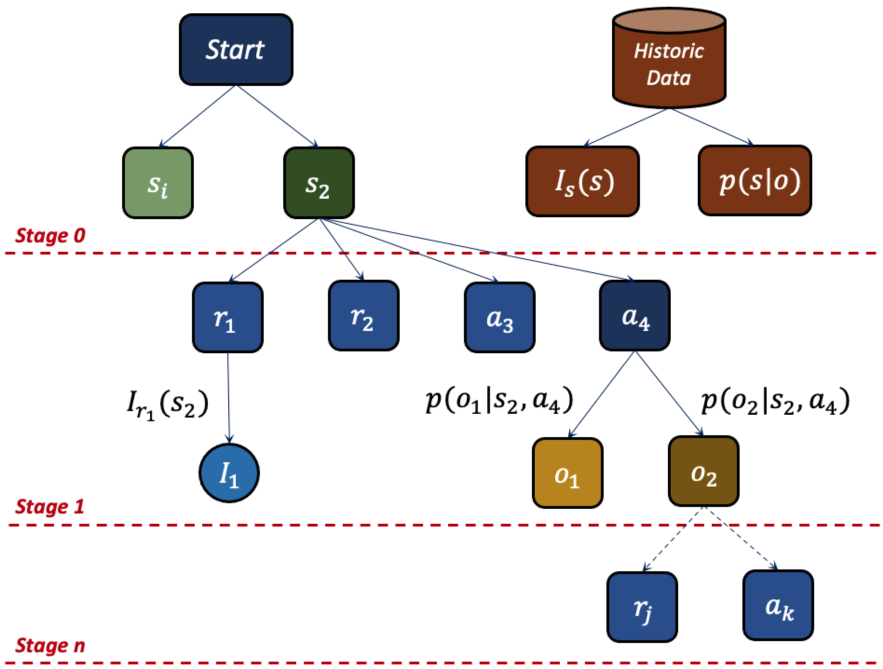


**Figure 3.1:** Graphical representation of the proposed decision model.

The process begins at *Stage* 0 with state $s$, which represents the 'real state' of the PCB, i.e. the set of characteristics of a given PCB, which will contain certain defects for certain components of which it is composed. Then, moving on to *Stage*1, there is the possibility of selecting a certain generic action $a$. This may represent, as we have said, a recovery strategy $r$ or the use of a certain test. When a strategy is selected the decision system stops, as it is not considered to select another test, the consequence is that an income $I_1$ will be obtained after a certain $r_1$. This is derived through the historical data on which the decision system is based, so a certain actual state $s_2$ will correspond to income $I_{r_1}(s_2)$ based on the historical data. If the decision system chooses to select a test (in the case of the picture, action $a_4$), this will be followed by various observed states or which will be calculated according to the probability of having certain defects depending on the test used. So, for example, we will have an observed state $o_2$ with a certain probability given an initial real state $s_2$ and having chosen the action $a_4$, then $p(o_2 \mid s_2, a_4)$. Iteratively the process will move to *Stage n* until the last action selected is a recovery strategy $r$.

In calculating the probability $p(o_2 \mid s_2, a_4)$, the probability of having a certain real state $s$ given a certain observed state $o$, derived from the use of a certain test, will be taken into account from the historical data. To better understand the meaning of this probability, it is useful to see Figure 3.2.

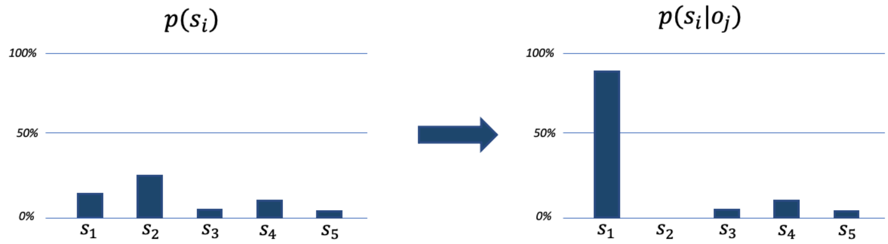


**Figure 3.2:** Probability of a state s given a certain observed state.

The idea is that initially, given a certain PCB, we will have probabilities $p(s_i)$ based on historical data to have different types of real states $s_i$, which we remember represent the probabilities that the components of the PCB have a certain defect. When we use a PCB test, we will result in certain defects being found with a certain uncertainty through the observed state $o_j$. This, combined with the generic probability of having a defect, will increase the likelihood of a component having certain defects to $p(s_i \mid o_j)$, making the other types less likely and getting closer to achieving an increasingly accurate level of information. In the case in Figure 3.2, therefore, the test would have detected faults corresponding to the real state $s_1$ increasing the probability that this is indeed the case.

This type of problem can be solved by using Reinforcement Learning (RL) [53]. In the next section, we will analyze how to implement it and adapt it to the problem. First, it is necessary to define some key aspects that precede its use, i.e. to define in which form it is most appropriate to represent the data space on the PCBs, which are made up of different types of components that in turn may have different interconnected defects.

In this regard, the proposed solution is to represent the space of PCBs through the use of graphs. A PCB, represented as a graph, will have the components as nodes and their interconnections are the arcs. The observed state thus refers to a single component of the PCB and is linked to a predefined set of faults. Figure 3.3 shows the representation of the PCB, modelled as a graph, in a mathematical set form.

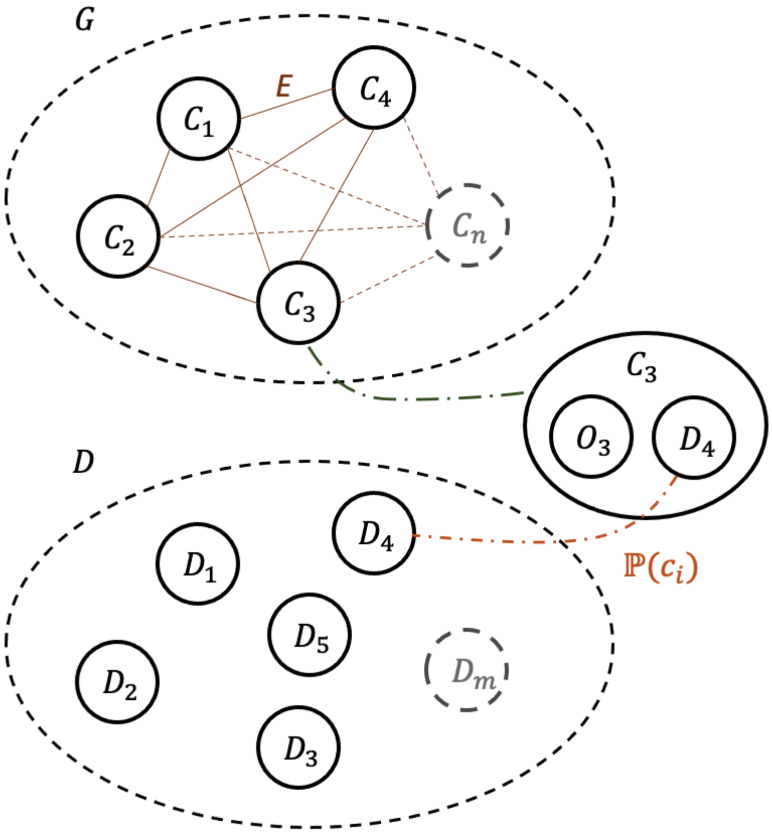


**Figure 3.3:** Mathematical representation of a PCB.

- $G = (C, E)$: Set representing the graph, i.e. the PCB, having the components $C_n$ as nodes and their electrical connections $E$ as arcs;
- $P(c_i)$: Probability distribution that associates each component $c_i$ with a defect $D_m$. We will have $P(c_{im}) = \{p_{i1}, p_{i2}, ..., p_{im}\}$;
- $D$: Set of potential defects, $D = \{d_1, d_2, d_3, ..., d_m\}$;
- $O$: Observed state associated with a component, representing the probability of the real state of the components.

## 3.3 Proposed algorithm

In order to describe the logic and implementation of the proposed approach to solving the problem, an overview of the data structure used is first proposed, using a Unified Modeling Language (UML class diagram), followed by a broad description of the process using a Business Process Model and Notation (BPMN), and then the logic of using reinforcement learning and its implementation in Python.

### 3.3.1 Data Structure Representation: UML Class Diagram

The Unified Modeling Language (UML) Class Diagram is a tool for visually representing the structure and relationships between data, which is why it is very useful and used for modelling databases. Class diagrams allow entities, their attributes and associations to be defined in a structured manner. Its main function, therefore, is to ease the transition from conceptual design to database implementation [54]. The UML diagram shown in Figure 3.4 represents the architecture of the PCB testing system based on reinforcement learning. It is organized around nine main classes that interact with each other to structure the decision-making model. Below is a brief description of the classes and their responsibilities:

- **PCB**: It is the class that represents a printed circuit board, with attributes such as its identifier, type and associated current profit. It contains a collection of components and has methods for initializing its actual state, obtaining the representation in the form of a graph and cloning its class instance.
- **Component**: Used to model a single component constituting the board, it maintains the observed and actual state of the component together with the probabilities of the different types of faults. The associated method, in addition to that for initialization, is that for feature extraction used by the neural network model.
- **DQNAgent**: Represents the reinforcement learning agent based on Deep Q-Network. It maintains the two neural networks, policy and target, to stabilize learning and a buffer for storing experiences. It contains methods for selecting actions, optimizing the model and updating the target network.
- **GNNModel**: Class defining the architecture of the neural network with graph convolution used by the DQN agent. It contains two graph convolution layers and a final fully connected layer that aims to map the extracted features into Q-values.
- **ReplayBuffer**: Represents the double-ended dequeued data structure to store the agent's experience transitions.

- **Action**: This is the class that represents the generic action that can be taken for a certain PCB, that could be a test or a strategy, keeping the cost and duration information of the action.
- **Measurement**: Class used to model a specific test, which in our case can be one of the X-Ray, Visual Inspection or Flying Probe Test. It associates cost, accuracy and duration with them. The methods it contains are aimed at performing the test and obtaining the resulting new information on the probability of defects.
- **Strategy**: It is the class that represents a recovery strategy for PCBs between reuse, repair and recycling. It associates the relevant costs and revenues with these.
- **Decision_System**: It is the class that coordinates the decision-making process by selecting actions via the DQN agent and available actions.
- **DatabaseManager**: This is the class that manages the storage of the results of the sequence of actions taken for a given PCB. In general, a PCB is created with its components, then the Decision_System, via DQNAgent, selects the next action to be taken. The selected action is executed on the components of the PCB and the results of the action are used to update the agent model and choose the next action. Data are also collected via the DatabaseManager and the process continues until a recovery strategy is selected.

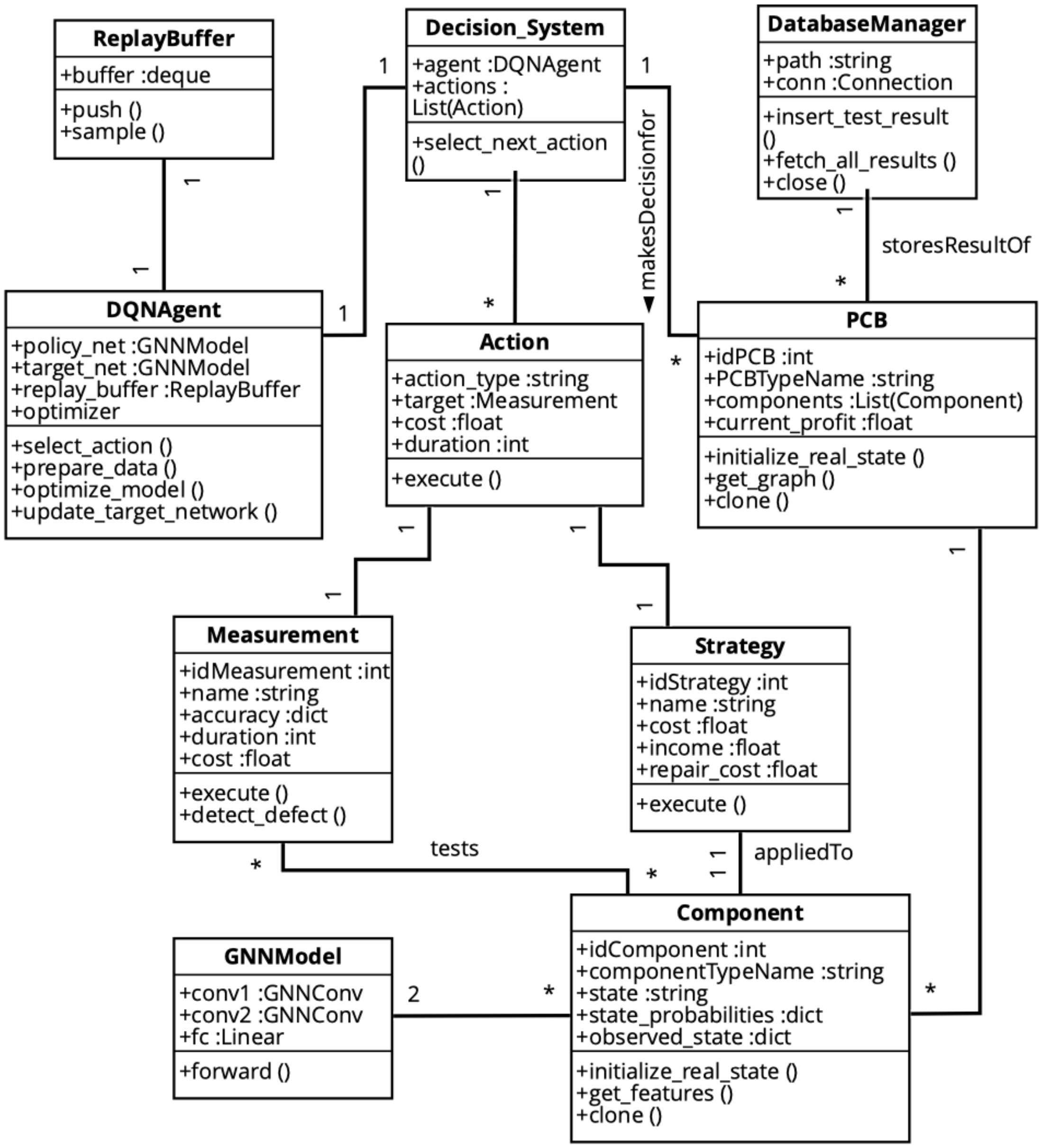


**Figure 3.4:** UML class diagram.

### 3.3.2 Process Workflow Representation: BPMN Diagram

The Business Process Model and Notation (BPMN) is a modeling and analysis tool for business processes. It makes it possible to graphically represent the different stages of processes by distinguishing the different workflows to enable an analysis of the individual activities of which they are composed. One of its peculiarities is that it is able to include a level of detail of information that allows the distinction of activities by type and enables a consequent automation of processes [55].

The Business Process Diagram visible in Figure 3.5 represents the complete operational flow of the process, highlighting the main interactions between the different actors and components of the system. The standard adopted is BPMN 2.0 and illustrates the collaboration of classes in implementing the decision-making process.

The general structure of the process is divided into four lanes constituting the PCB testing System, which represents the entire process domain. Each lane represents an actor or functional component of the system.

The process flow begins with the initialization phase via the *Initialization* lane. Here, the process sees the configuration of the SimPy simulation environment, the setup of the set of 100 PCBs per training episode, the creation and configuration of the reinforcement learning agent and the preparation of the SQLite database to store the results. At the end of initialization, the flow connects the hyperparameter optimization phase by means of a message. In this phase, managed by the *ParameterOptimization* lane, the process configures the Optuna optimization study, runs a complete training trial with a specific set of hyperparameters and evaluates the performance of the model with the correct parameters. The process is iterated through an exclusive '*MoreTrials?*' gateway that determines whether to continue with another trial or conclude the optimization by saving the best parameters found. The process then connects to the main training cycle phase which takes place in the *Environment* lane. In this lane, the PCB batch for the current episode is generated and the action to be taken is requested via the DQN Agent. In parallel, then, via the *DQNAgent* class, the neural network is used to select the optimal action which is stored in the replay buffer, after which a batch of 128 random PCBs is extracted from the buffer and the neural network weights are refreshed and the target network is updated every 10 episodes. The action taken is then sent from the agent class to the environment class, which goes on to execute the action by calculating the new observed state and determining the reward based on the action performed.

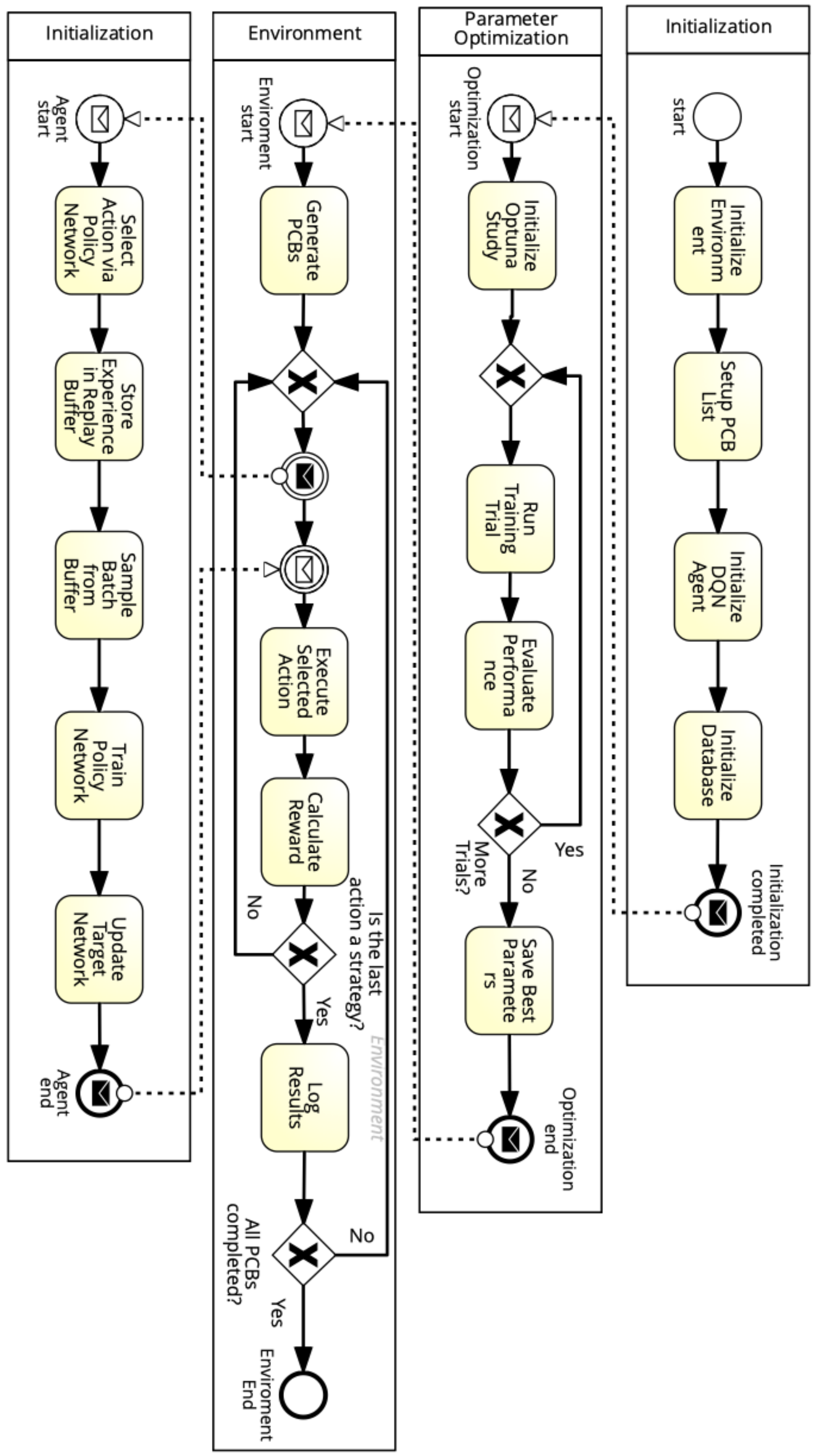


**Figure 3.5:** Business Process Diagram and Notation.

### 3.3.3 Logic and implementation of the algorithm

As defined in the previous section, it was possible to manage the logic of the algorithm using the RL agent. Traditional agents, however, use neural networks that require fixed-length inputs, whereas in our case, PCBs are characterized by significant variability, given the number of components and the number of faults each of them may have. Using the mathematical representation of PCBs in the form of a graph, as described in the previous section, a Graph Neural Network (GNN) can be used to interface with the variability of the graph [56]. This is a type of neural network designed to process data processed as graphs. Their operation is based, by considering the relationships between nodes and adding information from adjacent nodes, on the generation of compact representations of individual nodes, which in our case are the components.

The GNN processes the PCB, then the graph, in order to obtain the node embeddings. As the literature states, node embeddings consist of using vector data of the nodes in the graph designed to contain information on the structural characteristics and relationships of each node within the graph. Node embeddings are the tool needed to transform complex unstructured data into a form that allows easier operability for machine learning algorithms [57]. Mathematically, we can define them as follows:

$$h_v = GNN(S) \tag{3.1}$$

- $h_v$: node embeddings;
- $S$: is the representative state of the graph $G$ representing the PCB;
- $GNN()$: the Graph Neural Network function that processes the $S$ graph to obtain the $h_v$;

In order to make proper use of the PCB information contained in the node embeddings, it is necessary to link it to the possibility of choosing a certain action. The actions, as we defined above, can be a test, thus one between ICT, AOI, FPT or a recovery strategy between repair, reuse or recycle. To do this, the following function is used:

$$a_t = \pi(h_v) \tag{3.2}$$

- $a_t$: is the action chosen at time $t$;
- $h_v$: node embeddings;
- $\pi()$: aggregation function between actions $a_t$ and node embeddings $h_v$;

The $\pi$ function has the role of linking a chosen action $a_t$ a certain time to the probability of choosing the possible actions available. The objective that is realized through this function is to select the option that maximizes the expected outcome based on learned experience and expected reward.

In the sequence of the iterative algorithm, in fact, after choosing a certain action $a_t$, the system collects the new data updates the new observed state or, switching to the state of the graph $S'$. The reward by which the expected result is maximized is defined via the $Q - function$, which is the core of the reinforcement learning algorithm. The $Q - function$ is defined as follows:

$$Q(h_v, a_t) \leftarrow Q(h_v, a_t) + \alpha \Big[ r_t + \gamma \max_a Q(h'_v, a) - Q(h_v, a_t) \Big] \tag{3.3}$$

- $Q$: is the $Q - value$ associated with the action $a_t$ in the state defined by the embedding $h_v$;
- $\alpha$: is the learning rate, which determines how new information affects previous information;
- $r_t$: is the reward obtained after the execution of the action $a_t$;
- $\gamma$: represents the discount factor, i.e. the weight of future rewards compared to those obtained;
- $\max_a$: is the maximum expected reward value corresponding to state $S'$, i.e. the best value of the $Q$ calculated with all possible actions available;

Iterating the process, this approach allows for a dynamic search for action strategies and, based on the information obtained, allows for a progressive improvement of decisions by making the PCB inspection process more efficient.

#### 3.3.3.1 Code implementation

The system's code architecture is organized around a simulation aimed at reproducing a realistic PCB testing environment, which may present different faults for each component. The Simpy framework was used to implement the simulation, enabling the temporal modelling of the testing process. Each PCB is generated with a random number of components, set by default between 3 and 10, and each component can have one of the following defects: soldering problems, connection problems and burnt components. Three types of tests (X-Ray, Visual Inspection and Flying Probe) and three types of recovery strategies (Reuse, Repair, Recycle) were considered in the system. Information on accuracy, cost and duration characteristics was assigned to each of these actions.

The training of the network takes place in the main loop function (Figure 3.6), through the run of 200 episodes in which a batch of 100 PCBs is generated.

```
def main_function():
    for episode in range(1, NUM_EPISODES + 1):
        agent.logging_data = {key: [] for key in agent.logging_data.keys()}
        progress = (episode - 1) / (NUM_EPISODES - 1)
        pcb_list = setup_pcb()
        env = simpy.Environment()

        episode_rewards = []
        finished_pcb_list = []

        for pcb in pcb_list:
            env.process(pcb_process(env, pcb, actions, db, decision_system, agent,
                                    episode_rewards, progress=progress,
                                    finished_pcb_list=finished_pcb_list))
```

**Figure 3.6:** Main loop function.

Simulation is instead handled by a 'simulation' class that contains two of the most relevant methods. The 'pcb_process' method simulates the testing process for each individual PCB in which the logic for selecting actions and calculating rewards is implemented. The second is defined by the 'select_action' class, which is used by the 'pcb_process' to operate the greedy policy of the RL agent.

The centre of the system is implemented in the class 'DQNAgent', the main structure of which is shown in the Figure 3.7.

```
class DQNAgent:
    def __init__(self, node_feature_dim, hidden_dim, output_dim, writer=None,
                 lr=1e-4, gamma=0.99, buffer_capacity=1000, batch_size=128,
                 epsilon_start=1.0, epsilon_end=0.01, epsilon_decay=15000):
        self.device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        self.policy_net = GNNModel(node_feature_dim, hidden_dim, output_dim).to(self.device)
        self.target_net = GNNModel(node_feature_dim, hidden_dim, output_dim).to(self.device)
        self.target_net.load_state_dict(self.policy_net.state_dict())
        self.replay_buffer = ReplayBuffer(capacity=buffer_capacity)
```

**Figure 3.7:** class DQNAgent.

To stabilize the learning, as can be seen from the code in the figure, a target network was implemented which is structurally identical to the policy network. Its role is to keep the configurations of the hidden layers constant and to control the propagation of errors in the estimation process.

Exponential decay takes place from $\epsilon = 1.0$, i.e. full exploration, to $\epsilon = 0.01$, where exploitation is almost complete, over 15000 steps. The values were chosen to allow a wide exploration of the action space by the agent in the initial stages of training and to concentrate later on those actions that prove to be most 'effective'.

In addition, the system uses a replay buffer of 1000 transactions and a batch size of 128 for training. The replay buffer refers to the maximum number of 'transitions' or experiences that can be stored at the same time. The transitions are tuples of state, action, reward, next state and boolean value 'done', and represent the individual iteration steps.

When the buffer is full, subsequent experiences replace older ones. The batch size, on the other hand, refers to the number of actions randomly extracted to update the network. The values for these, 1000 and 128, were chosen to find a trade-off between computational efficiency and training stability. On the other hand, the gamma discount factor is set to 0.99, a standard value that allows the consideration of future rewards without sacrificing training stability.

The RL Agent, as we mentioned earlier, uses a neural network with graph convolution to process the state of the PCB, which is therefore suitable for handling the chosen graph structure. The init implementation of the GNN class 'GNNModel' can be seen in Figure 3.8.

```
class GNNModel(nn.Module):
    def __init__(self, node_feature_dim, hidden_dim, output_dim):
        super(GNNModel, self).__init__()
        self.conv1 = GCNConv(node_feature_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = nn.Linear(hidden_dim, output_dim)

    def forward(self, data):
        x, edge_index, batch = data.x, data.edge_index, data.batch
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = global_mean_pool(x, batch)
        x = self.fc(x)
        return x
```

**Figure 3.8:** class GNNModel.

The neural network consists of two graph convolution layers, ReLU activation functions and a fully connected layer. This is a fairly simple architecture but sufficient to be effective in capturing PCB features through convolution on the graph while the final layer maps this information into Q-values for possible actions. Before the final layer, a global pooling is performed to add the information from the graph and the ReLU activation functions are applied as non-linear activations.

By means of the Optuna framework, a Bayesian optimization process is practiced in order to find the best configuration in optimizing the hyper-parameters. Amongst these, the way in which the rewards associated with actions, and thus tests and strategies, are optimized is very important. In fact, they are implemented as linear trait functions, which the agent can be the one to the most suitable choices in the learning phase by modifying the associated rewards in the training phase. It's possible to see an example of hyper-parameters assignment in Figure 3.9. In the development of the code, it was chosen to run this process for 4 sessions, being suitable for obtaining initial indications of optimal metrics.

```python
OPT_STEPS = int(os.getenv("OPT_STEPS", 4))

def objective(trial):
    xray_zero = trial.suggest_float("xray_bonus_zero_progress", 0.01, 0.9)
    xray_end_prog = trial.suggest_float("xray_bonus_end_progress", xray_zero + 0.01, 1.0)
    hidden_dim = trial.suggest_int("hidden_dim", 8, 128)
    # ... altri parametri ...
    average_reward = main_function()
    return average_reward

study = optuna.create_study(direction="maximize")
study.optimize(objective, n_trials=OPT_STEPS)
```

**Figure 3.9:** Example of hyper-parameters assignment (X-Ray).

A TensorBoard system is used to track the various metrics in the training phase, which is able to track the progress of the training by means of the total profit per episode, the average length of the test sequences, the average rewards for each type of action and other parameters. This optimizes the testing process and enables detailed analysis of performance and learned behaviour in the network.

It's also necessary to mention that the results of the simulations were saved using a SQLite database, managed by a class called DatabaseManager, that keeps track of the tests performed and the results of the sequences associated with the PCBs. In this way, it is possible to analyze the system's performance even after the event, and to self-provide useful data for further improvements.

# Chapter 4

# Results and Analysis

The following chapter presents an analysis of the results obtained through training process of the algorithm in the optimization of test sequences and strategies for PCBs. The training of the algorithm was conducted on batches of 100 PCBs for 200 episodes. The choice was dictated by the available computational power limits, in particular the use of the free version of Google Colab [58]. Despite the limitations, the chosen values show significant results that made it possible to assess the effectiveness of the optimization model.

The analysis is carried out on the basis of the study of graphs representing different coloured curves representing individual trainings. In order to generate these graphs, it was deemed sufficient, given the calculation limitations, to consider 10 different trainings in order to consider the trend of the various parameters. The analysis begins with an evaluation of the performance of the algorithm, assessed on the basis of the performance of the rewards adopted, followed by an evaluation of the behaviour of the relevant parameters in the training phase through to economic considerations with regard to the profits obtainable. Finally, in the last section, a comparison is made of the algorithm's behaviour in handling larger batch sizes in order to consider the scalability of the model and compare its performance.

## 4.1 Performance evaluation of the algorithm

As a basic metric commonly used for an evaluation of the algorithm, the reward obtained during training episodes was considered [59]. Reward summarizes the algorithm's ability to select an optimal sequence of tests to detect defects present in PCB components. It is thus a key indicator of the model's effectiveness in assessing the balance between testing costs and board recovery value.

The analysis is divided into two subsections, the first in which the reward performance over time is analyzed to understand the learning process and the stability of the model while the second sees a comparison of the reward performance for different strategies in order to verify the effectiveness of the decision choices practiced.

### 4.1.1 Reward evolution during training

The graph in Figure 4.1 shows the reward trend during the 200 training episodes of the algorithm using batches of 100 PCBs for each iteration. This analyzes how the agent learns over time and how the quality of the test sequences and recovery strategies employed varies.

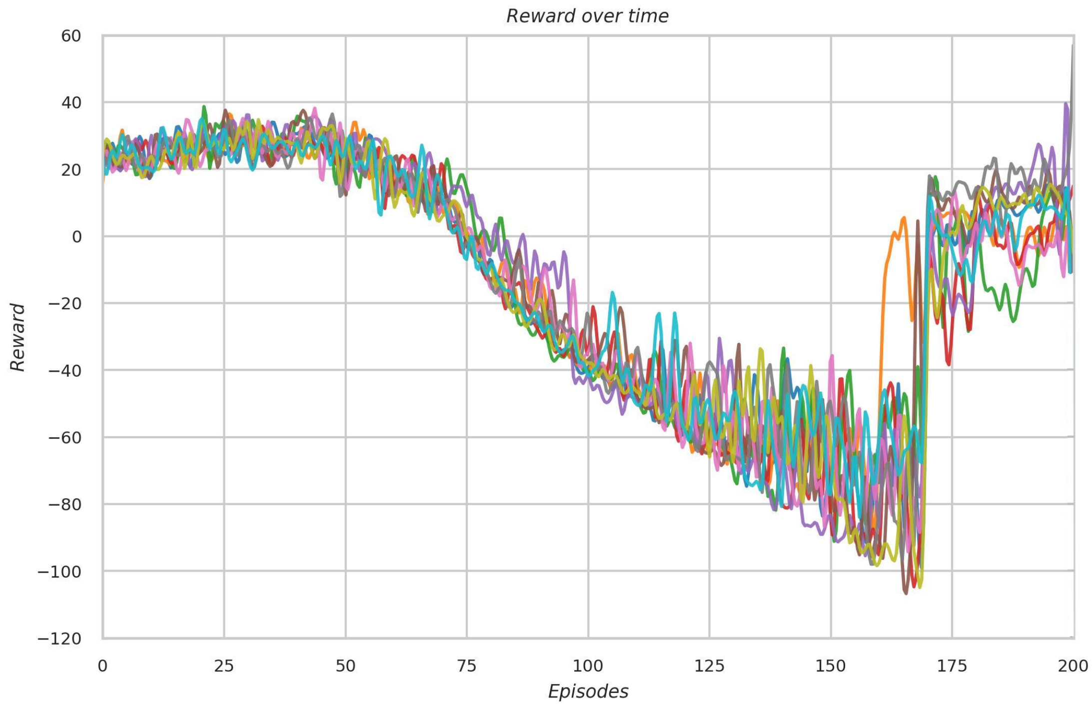


**Figure 4.1:** Reward trend over time - 100 PCBs, 200 episodes.

As can be seen in Figure 4.1, in the early stages of training, a relatively stable reward is observed around positive values close to those initially set. This indicates that even in the early iterations the algorithm succeeds in selecting test sequences that lead to recovery decisions with positive impact. Later, however, around the interval of episodes 50-100, a decreasing trend in reward is denoted, which becomes increasingly negative. This trend indicates the agent's exploration in trying new strategies and tests to evaluate alternatives in decision making.

After episode 175 there is a sharp increase in reward, which then stabilizes at positive values. The behavior translates into the ability the algorithm had in identifying more effective and consistent strategies in balancing test costs with payback values. The increase in reward stability in the final phase translates into the identification of a more robust policy that sees a reduction in exploration in favor of more established strategies.

### 4.1.2 Comparative Analysis of Reward Across Strategies

After analyzing the performance of the reward over time overall for the algorithm, it may also be useful to consider its performance for the three different recovery strategies separately, which are remembered to be reuse, repair, and recycle, since they have different economic and operational implications.

The significance of this comparison is to assess the different impact each strategy gives on the reward obtained in training and thus which approach is more beneficial. In this way it can be evaluated a thorough study of the optimization of the model in balancing costs according to the type of strategy to be favored.

Considering the reward trend graph for the reuse strategy, as can be seen in Figure 4.2, in the early episodes the reward remains stable on positive values indicating a tendency to select test sequences that lead to beneficial reuse decisions.

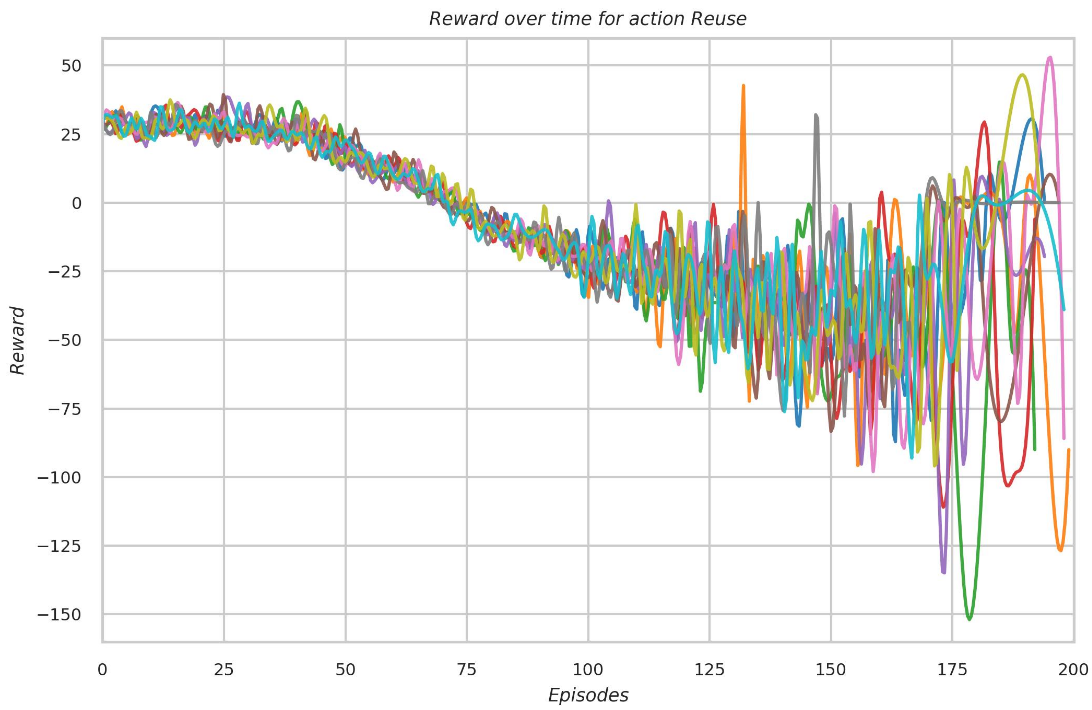


**Figure 4.2:** Reward trend over time for Reuse strategy - 100 PCBs, 200 episodes.

From episode 50 onward, however, we see a decrease in reward, which coincides with the exploration phase of the model. In the middle phase, between episodes 100 and 175, the reward is on average negative denoting attempts to apply reuse in less favorable contexts, probably related to the possibility that relevant defects make reuse an unviable choice. In the final stage, on the other hand, there is a strong instability in rewards with more pronounced fluctuations. This indicates that the model has difficulty selecting this strategy as the one to adopt, making it less predictable than the other alternatives.

Continuing with the analysis of the recovery strategies adopted, the graph in Figure 4.3 represents the trend of the reward in the Repair case. In the first training phase, it is possible to see that the reward, in addition to being positive, tends to increase slightly, denoting how it turns out to be a convenient strategy to apply in the first iterations.

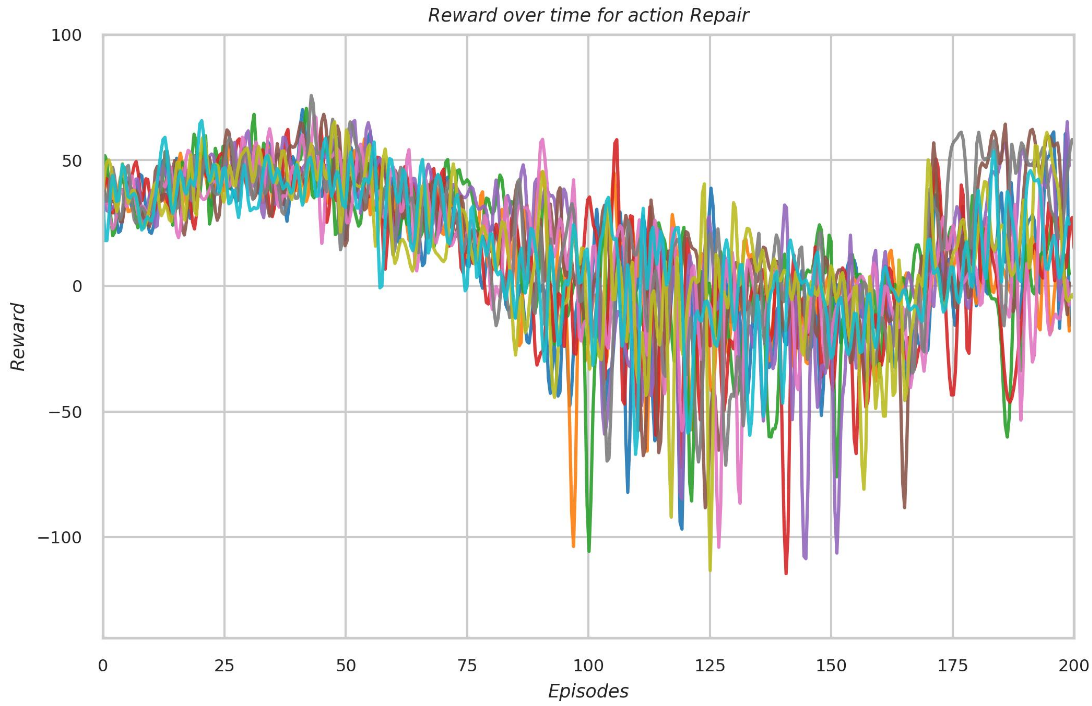


**Figure 4.3:** Reward trend over time for Repair strategy - 100 PCBs, 200 episodes.

In the middle part, after about 50 episodes, however, a descent begins that sees a very significant increase in variability. Indeed, several negative peaks are seen followed by positive values, indicating little predictability in the choice of this strategy. Despite this however, again in the central training phase, it can be denoted how the mean values are closer to zero than negative. This behavior is consistent with the Repair strategy, as having significant costs, if applied inefficiently it leads to a worsening of the reward.

In the last phase of training, from about 175 episodes, the reward trend sees an ascent characterized by less variability and settling mostly in the positive quadrant of the graph. This indicates that the algorithm has been able to better identify the contexts in which repair is most cost-effective by selecting it more precisely. However, the variability remains quite high, indicating how although it turns out to be an effective strategy it is still not well delineated in the various situations, making the choice not enough predictable.

The last strategy to be evaluated is Recycle, in Figure 4.4 we see the graph showing the reward trend along the 200 episodes. The trend in the early phase remains fairly stable for positive reward values, suggesting how scenarios are identified in which recycling is an economically viable choice.

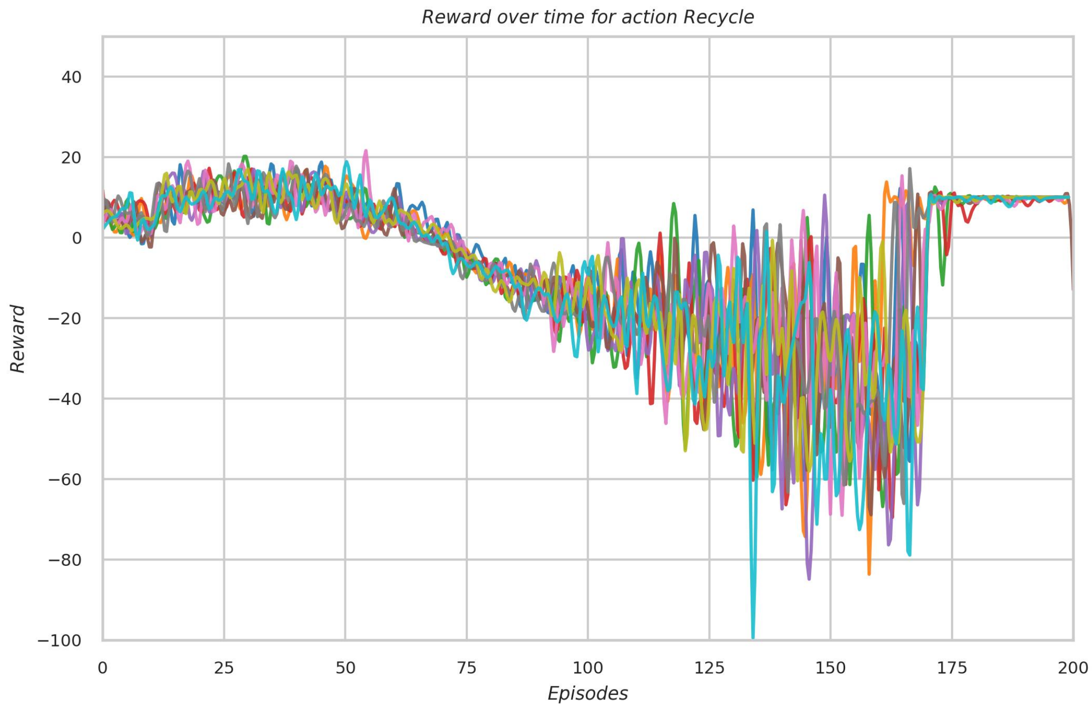


**Figure 4.4:** Reward trend over time for Recycle strategy - 100 PCBs, 200 episodes.

As training progresses, in the middle phase between episodes 50 and 100 the variability decreases and the trend is decreasing, indicating how the algorithm explores different strategies to identify sequences of actions. This is followed by a phase prior to episode 160 in which the variability increases dramatically, indicating how the model fails to define when to consider selecting Recycle, probably because the return value of this strategy does not adequately compensate for the costs of the testing phase. After that, however, there is a marked improvement in reward values, which stabilise with very little variability. This suggests that recycling is a cost-effective option compared to the other strategies that guarantee positive positive results.

#### 4.1.2.1 Comparative analysis of decision strategies

Looking overall at the performance of the three graphs, some significant differences emerge that reflect the characteristics of the different options and how they were handled by the algorithm.

The Repair strategy, as can be seen in Figure 4.2, initially shows the highest reward compared to the others, suggesting how it turns out to be the most advantageous option initially. As training progresses, however, the curve has considerable variability, indicating how unclear the scenarios in which to consider it are. This behavior is reflected in the nature of Repair, which can incur high costs depending on the flaws in the boards.

The graph in Figure 4.1 of the Reuse strategy, on the other hand, shows a different trend. After an initial stability, the reward undergoes a gradual reduction that results in variability that is higher than in the other strategies, indicating how it is the strategy characterized by low predictability and on which attention should be paid.

The Recycle strategy is the one to have a more regular trend than the other two, as seen in Figure 4.3. It sees an initial positive phase followed by a decrease characterized by less variability that increases thereafter. The most relevant result is different is the level of stability that is achieved in the final stages, which balances the variability present in the Reuse graph, proving to be a cost-effective strategy.

In summary, then, the algorithm deals differently with the three strategies, with repair characterized by greater exploration phase uncertainty, reuse with the highest fluctuations in the final phase, and recycling instead stabilizing more sharply. This model then, through this comparison, suggests how the most reliable strategy is Recycle, which is what we would expect since it does not need high accuracy in detecting defects. Despite, this however, attention should be paid to the other two strategies that require higher accuracy but are more profitable. For this reason, it is appropriate to analyze the economic efficiency of the model, which is deepened in the next section.

## 4.2 Economic impact

In order to carry out an appropriate analysis of the results obtained through the use of the algorithm, after evaluating its effectiveness through the study of its performance in terms of reward over the course of the episodes, it is appropriate to analyze the economic impact obtained.

The objective of this section is therefore to understand the variation in the overall profit of the PCB recovery process and how the decisions made by the algorithm have influenced it, balancing the cost of the tests with the income derived from the different recovery strategies chosen.

This analysis is conducted through two perspectives, the first sees an analysis of profit over the course of episodes, in order to assess and understand whether and how the model adjusts choices optimizing earnings during training. The second perspective sees an examination of the relationship between profit and the length of the sequence of actions chosen by the algorithm, to understand how a greater number of actions actually affects profit and whether it leads to more profitable decisions or whether, instead, excessive exploration leads to reduced earnings due to additional costs.

The aim is thus to allow an evaluation of effectiveness and of its ability to generate economic value, which is the key element for a practical application in the context of circular economy.

### 4.2.1 Profit trend over episodes

In order to evaluate the economic effectiveness of the algorithm, it is very important to analyze the evolution of profit over time during the learning process, which can be considered as a primary indicator for measuring its performance. Profit is calculated by subtracting the cost of the measurements used in the selected sequence and repair costs from the revenue generated by the recovery strategy adopted. As training progresses, the evaluation of profit allows one to tell whether the model is indeed able to select profitable decisions by optimizing the balance between cost and income.

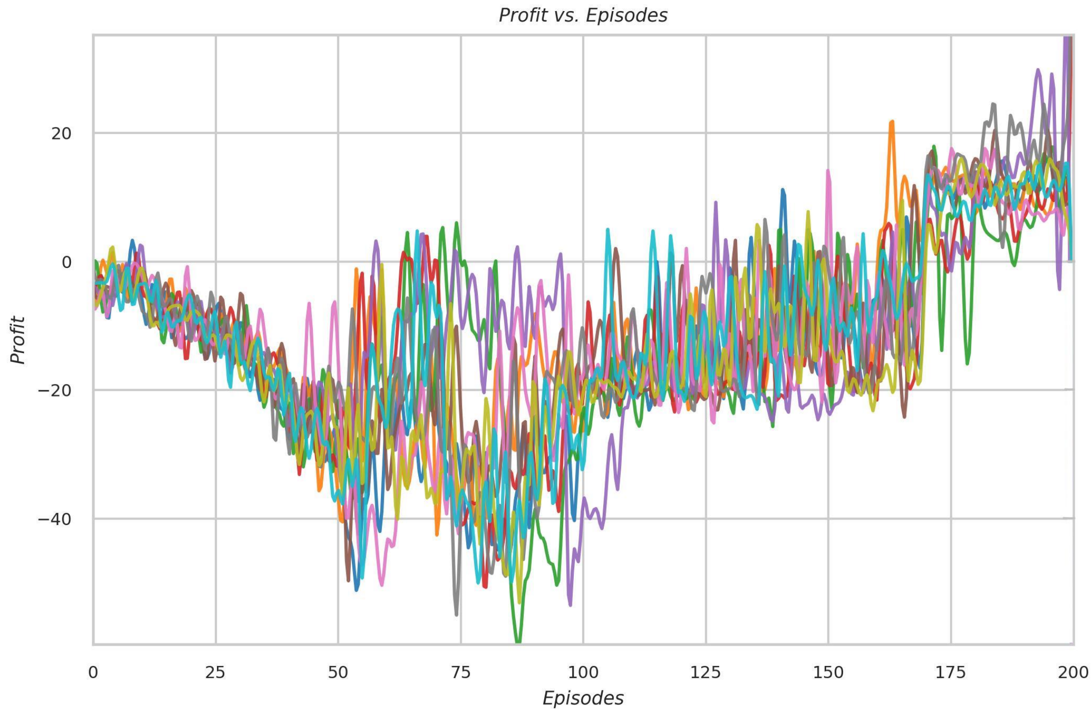


**Figure 4.5:** Profit trend over time - 100 PCBs, 200 episodes.

Looking at the graph in Figure 4.5, it can be seen that in the early stages of training, profit begins with values close to zero and continues with a marked decline in profit, suggesting how the algorithm is performing exploration of possible solutions to consider. Immediately after the initial phase of exploration, after about 50 episodes, it is possible to see that there is a strong variability across training, reflecting the typical behavior of Reinforcement Learning algorithms, in which the agent explores the wide range of possibilities.

After about 100 episodes, although remaining considerable, the variability decreases indicating how the algorithm is narrowing the range of solutions tending to improve its economic results and acquiring greater stability by identifying more efficient strategies.

In the final phase of the training, from about 175 episodes onward, it can be seen that the profit of the different trainings is almost entirely characterized by positive values, with a reduction in variability that still remains present although of a smaller magnitude. This result is very important and indicates how the model has learned a more robust policy for maximizing economic value, making more informed decisions and improving the selection of the sequence of actions taken to recover PCBs.

### 4.2.2 Profit analysis by test sequence length

The idea of this analysis is to assess the correlation between the length of the selected testing sequence and the profit that is made. This allows to understand whether the length of the sequence has a correlation with the profit due to the increased testing costs, balanced with the income from the recovery strategies.

The graph in Figure 4.6 shows the distribution of profit as a function of the number of tests performed to evaluate the status of PCBs. Looking at the general trend in the graph, a negative trend can be seen as the number of tests increases. As the length of the sequence increases, it can be seen that the average profit tends to decrease with a greater presence of negative values for longer sequences.

This result makes it possible to define how the execution of a large number of tests can tend to lead to more negative profit values as the additional costs may outweigh the benefits of decisions characterized by greater accuracy in detecting defects in PCB components.

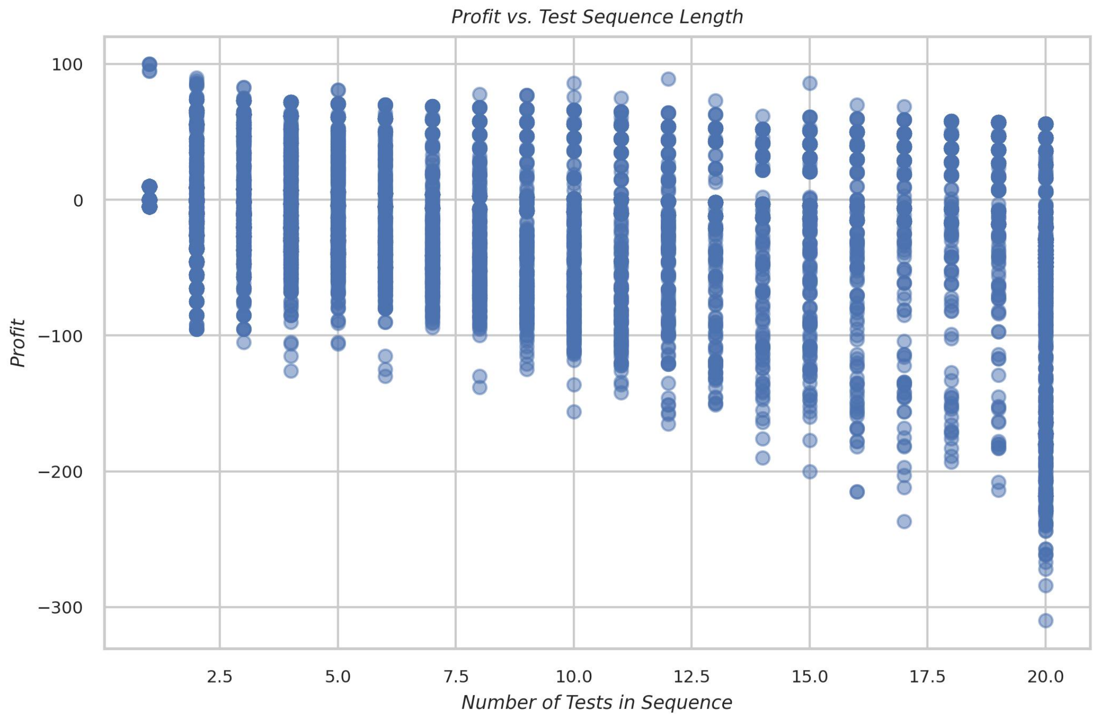


**Figure 4.6:** Profit as a function of the length of the test sequence - 100 PCBs, 200 episodes.

Another interesting aspect that emerges from looking at the graph is the variability of profit for each value of test sequence length. It is visible that for smaller values, where the number of tests is lower, both high profits and low losses are observed, indicating that in some cases little information may be sufficient to make cost-effective decisions. As the number of tests increases, however, the dispersion of the profit values grows and it data indicates that the maximum profit values obtained are slightly lower than the initial values, while the minimum profit values are more frequently negative, reaching values that are not small and far below zero. This suggests that sometimes the algorithm selects tests that are not necessary or that provide an accuracy that is not justified in relation to the benefits obtained.

Through these results, it can be argued that a trade-off between exploration and testing cost is necessary, so that although more tests lead to better accuracy for PCB state knowledge, too much investigation leads to a significant reduction in profit margins, making decision-making inefficient.

To better understand the results obtained in the profit analysis in relation to the length of the test sequence, it is useful to examine the distribution of the final strategies adopted according to the number of tests performed. The graph in Figure 4.7 shows how the frequency with which the three different strategies are chosen according to the number of tests run, allowing to assess whether there is a correlation between strategy choice and the drop in profit observed above.

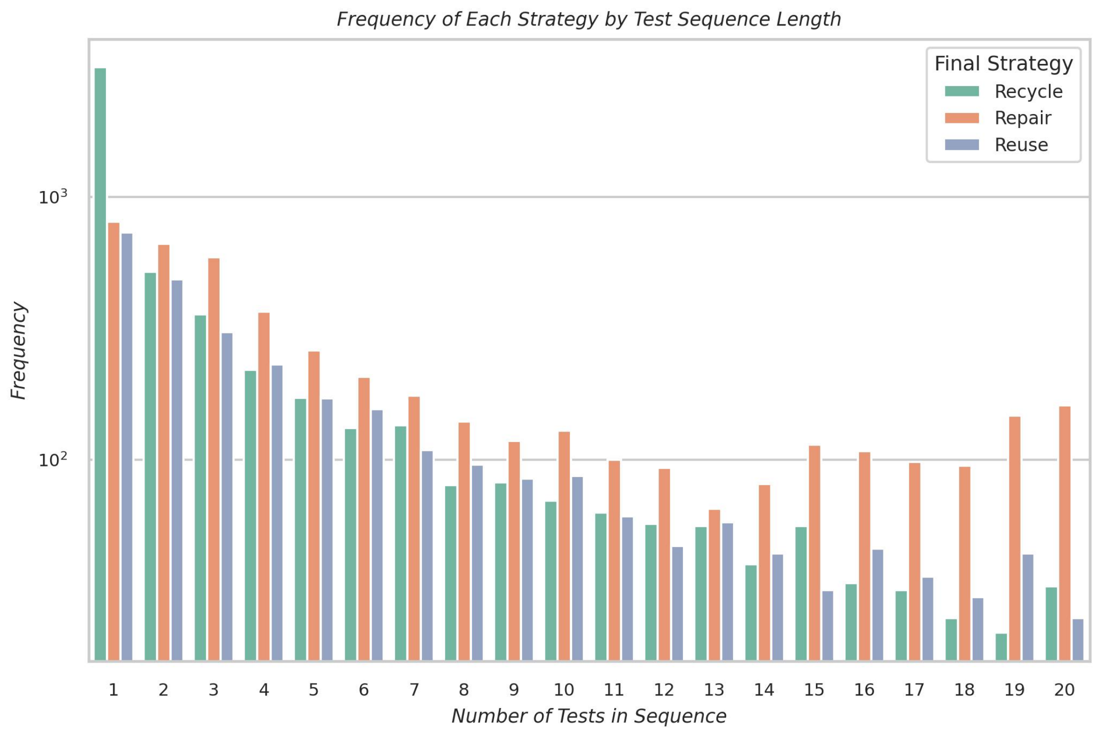


**Figure 4.7:** Distribution of final strategies according to the length of the test sequence - 100 PCBs, 200 episodes.

Looking at the overall trend, it is possible to note that, for the shortest test sequences, the Recycle strategy initially appears to be the most adopted, followed later by Repair and Reuse, with a balanced distribution among the three strategies. This is a consistent finding considering that through few tests the option best suited to the low accuracy in information is Recycle. However, it can be seen that from the number of tests equal to two, the predominant strategy over the others is Repair. In general, this is a trend that finds significance in the fact that having more information at one's disposal allows one to understand when and how to repair a PCB. This finding indicates how the algorithm attempts to support more profitable strategies to achieve positive profits, but this can be risky for less long test sequences considering that there is greater uncertainty in defining what the faults are. Continuing with the analysis, the graph shows that Reuse is the least adopted, tending to be preferred to Recycle for the central values of the number of tests in the chosen stock sequences.

Overall, the graph confirms the interpretation of the economic results, as the number of tests selected increases, card repair becomes predominant, the algorithm then demonstrates that it chooses more profitable strategies for longer sequences of tests characterized by higher costs. The problem that seems likely to contribute to the decline in profits for longer test sequences can be found in cases where although a higher level of accuracy has been achieved, for large numbers of tests there are instances where the frequency with which Recycle is chosen is greater than that of Reuse, leading to scenarios where the cost of testing may not have been balanced by Recycle's income.

## 4.3 Decision patterns and testing behavior

In order to better understand the algorithm's decision-making behavior, it may be interesting to analyze the frequency with which each strategy is chosen during the training process. The graph in Figure 4.8 shows the number of times the algorithm opted for Reuse, Repair or Recycle, providing a clear overview of the preferences developed.

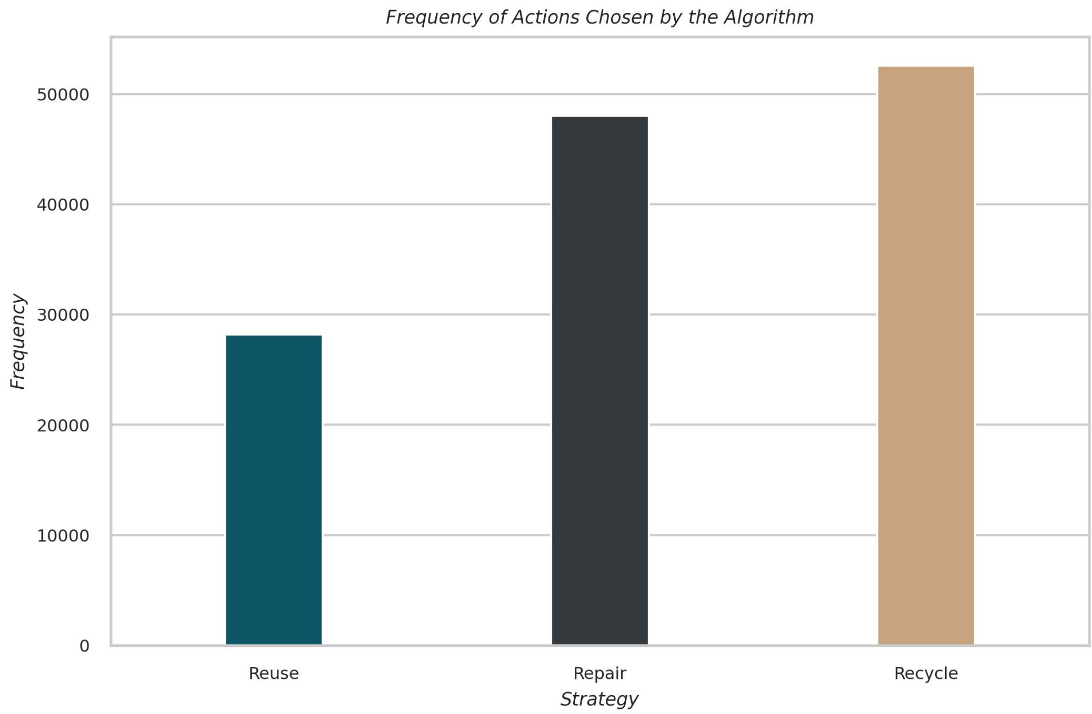


**Figure 4.8:** Distribution of strategies adopted by the algorithm - 100 PCBs, 200 episodes.

Observation of the graph shows that the Recycle strategy was adopted with the highest frequency, followed by Repair and Reuse, which is the least used. Overall, this distribution suggests that on the whole the algorithm favors Recycle as the final solution for PCB recovery. This behavior may stem from the possibility that recycling, while having a lower recovery value than reuse or repair, is the safest choice from a decision-making perspective, as it does not require extensive testing or expensive repairs.

Repair, which is the second most frequent, indicates how the algorithm identified enough economic value in many cases to justify the additional cost of testing to acquire greater accuracy. This is a result consistent with previous economic analysis, which showed Repair as a widely explored strategy, especially for longer test sequences.

Finally, Reuse turns out to be the least adopted one, this could be due to the fact that in order to reuse the PCB components without intervention, the algorithm has to obtain a very high accuracy of the defects present which requires a consequent higher use of tests.

Therefore, in general, the algorithm prefers safer strategy, i.e. Recycle, but balancing the costs with the recovery values of the other two strategies that it still manages to implement while trying to minimize test costs and at the same time trying to achieve higher accuracy in order to implement them.

In order to better understand how the algorithm makes these decisions and why it is led to choose the strategies with these frequencies, it is important to perform an analysis of the average length of the test sequence over the course of the training, so that it's possible to see if and how the algorithm adjusts the number of tests to obtain more reliable information before selecting the appropriate strategy.

The graph in Figure 4.9 shows how the number of tests performed in order to make a final decision varied over the course of the training episodes, providing insight into the ways in which the algorithm improved its decision making.

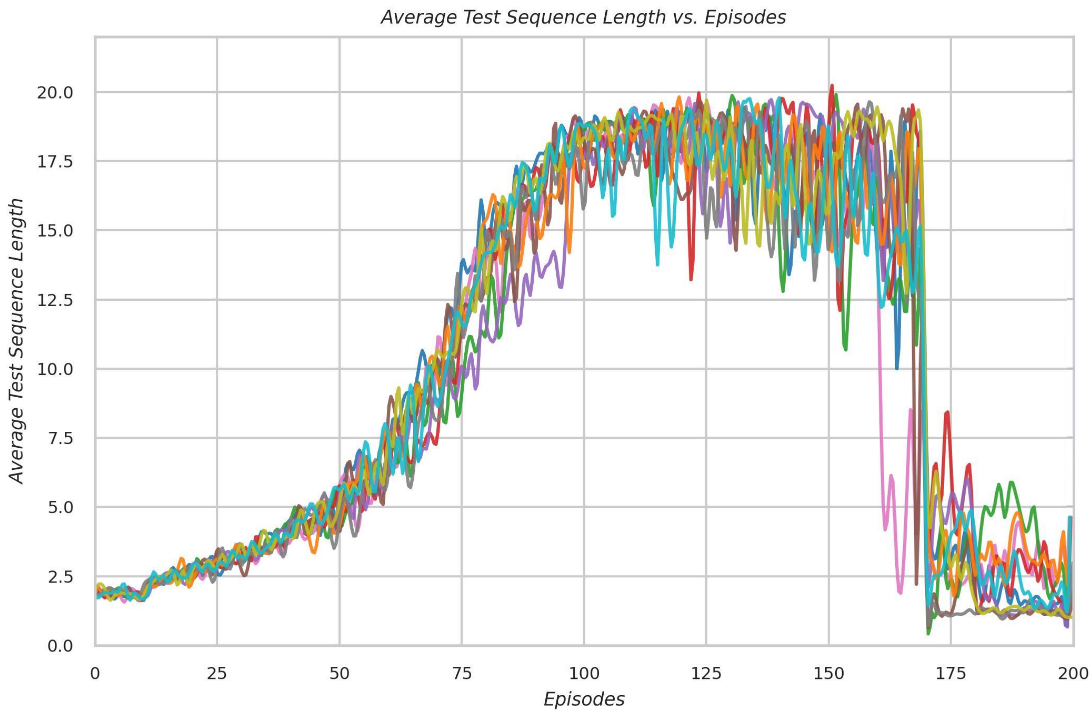


**Figure 4.9:** Evolution of the average length of test sequences over time - 100 PCBs, 200 episodes.

From the graph, it can be seen that in the early stages of training the average number of the test sequence is initially low, with values hovering between two and three tests per sequence. This behavior is typical of the early stages of learning in which the algorithm has yet to explore possible actions and makes quick decisions without gathering much information.

As the episodes progress, between episode 25 and episode 100, there is a clear upward trend in the number of tests per sequence in all trainings, reaching average values around 17,5 tests. This phase reflects the increased propensity of the algorithm to explore possibilities where greater accuracy in recognizing PCB component defects is achieved to choose the final strategy.

In the final phase, on the other hand, after about 160 episodes, there is a sharp drop in the number of tests, which for some trainings returns to about two tests per sequence, while for others it remains higher on average, between 2,5 and 5 tests. This variation indicates how the algorithm has learned that in order to achieve a reduction in exploration cost it is appropriate to use only a necessary number of tests without compromising the quality of the final decisions.

The results of the graph in Figure 4.9 are consistent with the previous economic analysis, as in the middle stages of training the model explores a large number of tests which explains the reduction in the economic values analyzed, while in the final stages we see that shorter test sequences correspond to cheaper economic results.

## 4.4 Scalability Analysis: comparison between small and large batches

The purpose of this section is to subject the model to an analysis aimed at assessing its effectiveness in maintaining its performance even when the size of the input data varies, with the aim of making considerations on its scalability for applicability in contexts characterized by higher volumes of PCBs to be retrieved.

The scalability analysis is relevant in the real industrial context, where the volumes of PCBs to be processed may be higher and the need may arise to batch in larger sizes. It is also interesting to observe how the increase in batch size affects the performance of the algorithm and its decision stability in generating an overall economic impact, and to see if any criticalities emerge.

In the specific case of this thesis, the algorithm was initially evaluated on batches of 100 PCBs, whereas an analysis conducted on batches of 400 PCBs will follow. The choice of this batch size is linked to the computational limitations for training the algorithm, which was possible on trainings of 100 episodes, instead of the initial 200. Therefore, although it would be more appropriate to evaluate a comparison on an equivalent number of episodes, it is still possible to obtain significant indications on the behavior of the model under conditions of greater complexity.

The next sub-sections will compare the performance of the model and the economic impact between the two scenarios, highlighting any differences and discussing the adaptability of the algorithm.

### 4.4.1 Performance comparison

As described in previous sections, training of the algorithm was initially conducted on batches of 100 PCBs for 200 episodes, showing, as it is possible to see in Figure 4.1, a behavior characterized by stable reward values along the episodes followed by a decrease during exploration that saw in the final phase a progressive stabilization on positive values.

To assess the scalability of the model, training was performed on batches of 400 PCBs limiting for 100 episodes for computational reasons. In the graph presented in Figure 4.10, it is possible too see that the reward trend presents an initial dynamic similar to that obtained for smaller batches, which sees an initial phase with positive rewards followed by a negative trend due to the exploration of alternative strategies.

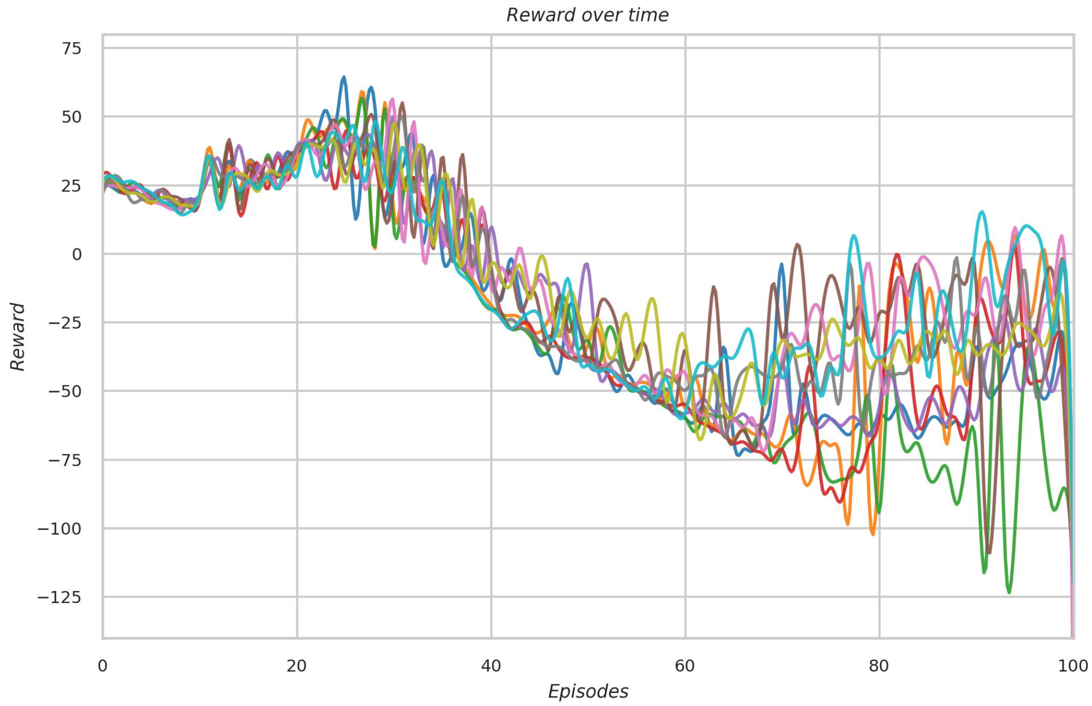


**Figure 4.10:** Reward trend over time - 400 PCBs, 100 episodes.

However, in this case it can be seen that at the end of the 100 episodes most of the values of the different trainings remain negative and a clear stabilization trend is not yet observed. In fact, the trend appears to be characterized by a strong variability that denotes an attempt of the model to obtain values close to zero, denoting how the model has failed to be effective in defining an efficient policy to be adopted for decisions regarding the recovery strategy to be undertaken.

To further explore this observation, it is useful to pose a direct comparison of the reward trend in the first 100 episodes for the 100 PCB case as well. From the results that emerge from the graph in Figure 4.1, in the first 100 episodes, again the reward is characterized by instability and remains around negative values, and only in the second half of the training the model shows a convergence toward cost-effective strategies.

Consequently, it can be hypothesized that the behavior observed in the case of batches consisting of 400 PCBs is influenced more by the small number of available episodes than by the increase in volumes. It is plausible that with a sufficient number of episodes the algorithm could have consolidated more effective strategies. However, based on the data collected it is not possible to definitively state this possibility, as resources would be needed to allow for more robust training.

### 4.4.2 Economic impact comparison

The other key aspect of evaluating the scalability of the model is the analysis of the profit obtained during training. After an analysis of the reward, we need to observe how the profit evolves in the case of batches of 400 PCBs to compare the results with what emerged from the training conducted on batches of 100 PCBs.

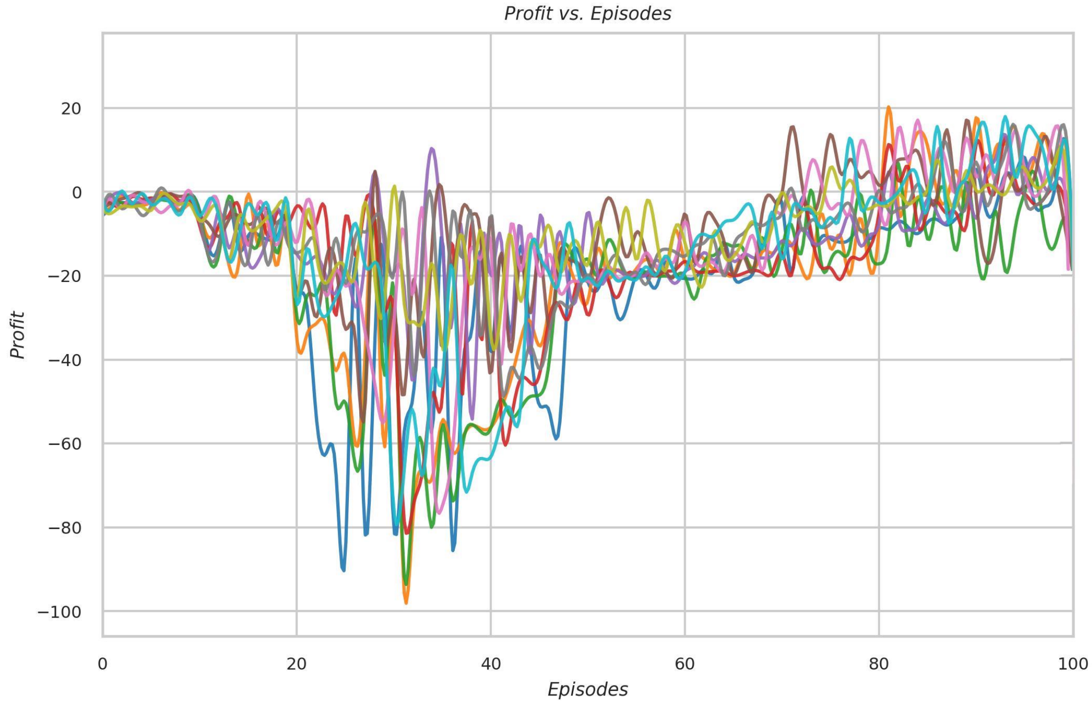


**Figure 4.11:** Profit trend over time - 400 PCBs, 100 episodes.

As can be seen from the graph shown in Figure 4.11, in the first few episodes the profit fluctuates around values close to zero and then undergoes a sharp drop in results. In the phase between episodes 20 and 50 there is a marked drop in profit with training reporting largely negative values. This phase is characterized by strong variability that is the result of exploring the different solutions tested by the model. As can be seen from the Figure 4.5 on the results obtained for batches of 100 PCBs, the profit values in the exploration phase were less negative than those obtained here. Whereas for batches of 100 PCBs, values close to -60 were reached, in this case the profit drops to values close to -100. This behavior reflects the difficulty of handling larger volumes, which can lead to greater losses in proportion to the amount of PCBs analyzed. After about 50 episodes the profit gradually begins to improve and although some level of variability is noted, the trend remains positive with average values positive or close to zero.

In order to properly evaluate the effectiveness of the model, it is worth taking into account how, in the case of 100 PCBs, profit showed similar behavior after 100 training episodes, characterized by strong variability and average values that turned out to be negative. It is only in the second half of the training that there is a well-defined growth in results to clearly positive mean values.

From this comparison it is possible to infer how the increase in batch size leads to an increase in computational complexity, which sees greater variability in economic results, in which the small number of training episodes must always be taken into account. Again, in fact, it is reasonable to assume that the algorithm could have consolidated better strategies, especially considering how from the comparison within 100 episodes training on larger batch sizes seems to get better results.

In conclusion, it is possible to say that the model seems to maintain a good fit even on a larger scale, but to ensure a positive economic impact, it is necessary to have adequate computational resources to achieve prolonged training.

### 4.4.3 Model scalability considerations

The analysis conducted on batches of different sizes reveals some significant considerations regarding the model's ability to adapt to more complex scenarios. Comparison of the results of batches of 100 and 400 PCBs show that increasing batch size introduces more variability in decision making due to the need to handle a larger number of defective components.

Although, in the case of batches of 400 PCBs, the reward and profit are still unstable and negative on average at the end of the 100 training episodes, the graph shows an improving trend, with signs of stabilization in the final stages. The comparison shows that even in the case of smaller batches, dwelling on the first 100 episodes, the model required a higher number of episodes to consolidate the effectiveness of the strategies undertaken. This leads one to consider the difficulties encountered in the case of larger batch sizes as an aspect related to the number of training episodes.

Overall, however, the results suggest that the model has the potential to maintain a consistent learning structure even in the more complex cases with which large-scale industrial scenarios are characterized.

# Chapter 5

# Conclusions and Future Works

Nowadays, the growing problem of electronic waste and inefficient management of discarded electronic components is one of the most important environmental challenges. The amount of waste generated has increased due to rapid technological development and the consequent frequent use of electronic devices. These, of which PCBs are an important one, contribute to the depletion of available resources and to pollution, especially when reuse and recycling practices are not properly implemented.

In this context, the following work rappresents an innovative approach to address the problem of e-waste generation and specifically in the recovery of PCBs. By optimizing the sequence of testing methods used to get informations about the condition of electronic board components, the model aims to identify defective parts and identify the most appropriate recovery strategy, balancing the costs associated with testing and the potential revenues obtained from component recovery.

Through the application of a reinforcement learning (RL) algorithm based on a GNN architecture, the results demonstrate the stability and effectiveness of the proposed approach confirming its ability to support decision-making policies for electronic device management. In this way, through its adoption, it is possible to contribute to sustainable practices that are cost-effective within the broader framework of circular economy principles

However, it is important to note that the model study was conducted with several limitations. First, three types of testing and three recovery strategies were considered. Secondly, one aspect to pay attention to is that the complexity of PCBs was limited in the number of components they can be composed of and defects they can be affected by.

Future work should lead to considering more types of testing and recovery strategies, as well as representing configurations of PCBs that more closely match their complexity. Indeed, in this work, a representation of them has been proposed through graphs whose nodes are all interconnected. For this purpose, the next step could be to define how the components of the PCBs are related to each other, thus, how the defects may be related, so that a more efficient algorithm can be developed that can take into account more detailed information. To ensure completeness, it would also be appropriate to conduct trainings of the proposed algorithm with more adequate computational resources in order to establish a more robust assessment of the scalability of the model. In conclusion, in order to obtain truthful data, future work should involve integrating market prices related to the costs and gains of the various factors considered, i.e. test methods, recovery strategies, and PCBs, to further improve decision making by providing information relevant to production needs.

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