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FAILURE PREDICTION SYSTEMS IN AUTOMATIC TELLER MACHINES

2024

INSTITUTO POLITÉCNICO
DE VIANA DO CASTELO

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Rita Antunes Peres

Escola Superior de Tecnologia e Gestão

Instituto Politécnico
de Viana do Castelo

Failure prediction system in Automatic Teller Machines

Autor(a)

Rita Antunes Peres

Trabalho orientado por

Professor Doutor João Paulo Magalhães

Mestrado em Cibersegurança

07 de Fevereiro de 2024

Mestrado em Cibersegurança
Master in Cybersecurity

Failure prediction system in Automatic Teller Machines

a master's project authored by

Rita Antunes Peres

and supervised by

Professor Doutor João Paulo Magalhães
Professor Adjunto, ESTG - Politécnico do Porto

This project was submitted in partial fulfillment of the requirements for the Master's degree in Cybersecurity at the Instituto Politécnico de Viana do Castelo

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07 of February, 2024

Abstract

Automatic Teller Machines (ATM) are a form of access to banking services widely used by end customers. The fact that they are available to users 24 hours a day and 7 days a week (24x7) makes these devices one of the most used services in the banking world. Therefore, the availability of ATMs is essential for evaluating service quality. Like all computer equipment, these machines have hardware and software failures. These incidents have the direct consequence of the non-availability of functions to the end customer, leading to service degradation and user dissatisfaction. These failures can also give rise to ATM security flaws, since human intervention is normally required to repair the equipment, giving third parties access to data on banking transactions that have taken place and/or the cash present on the equipment.

This project focuses on predicting failures in this equipment, consequently increasing the security of the equipment and the network in which it is inserted. Through Data Analysis methodologies, decision support tools were created to predict and increase Mean Time Between Failures (MTBF), thus contributing to reducing Mean Time to Repair (MTTR) and consequently maximizing uptime. A Preventative Maintenance approach was also used on the equipment, which contributed to a positive percentage increase in equipment availability.

Keywords: ATM; Availability; MTBF; MTTR; Uptime.

Resumo

As Automatic Teller Machines (ATM) são uma forma de acesso a serviços bancários amplamente usada pelo cliente final. O facto de estarem disponíveis aos utilizadores 24 horas por dia e 7 dias por semana (24x7), torna estes equipamentos num dos serviços mais utilizados do mundo bancário. Assim, a disponibilidade das ATM é fundamental para a avaliação da qualidade de serviço. Como todos os equipamentos informáticos, estas máquinas têm falhas a nível de hardware e de software. Estes incidentes, tem como consequência direta a não disponibilidade de funções ao cliente final, originando a degradação do serviço e a insatisfação dos utilizadores. Estas falhas podem também dar origem a falhas de segurança do ATM, uma vez que para reparação do equipamento é, normalmente, necessária intervenção humana, originando acesso de terceiros a dados de transações bancárias ocorridos e/ou ao numerário presente no equipamento.

Este projeto incide na previsão das falhas nestes equipamentos, aumentando consequentemente a segurança do equipamento e da rede em que o mesmo está inserido. Através de metodologias de Análise de Dados, foram criadas ferramentas de apoio à decisão para prever e aumentar o Tempo Médio entre em Avarias (MTBF), contribuindo dessa forma para a redução do Tempo Médio de Reparação (MTTR) e consequentemente maximizando o uptime. Foi também usada uma abordagem de Manutenção Preventiva nos equipamentos, o que contribuiu para um aumento percentual positivo da disponibilidade dos mesmos.

Palavras-chave: ATM; Disponibilidade; MTBF; MTTR; Uptime.

Aknowledgements

Having reached the final phase of this project, I want to thank all the people who contributed to it, directly or indirectly. To Professor João Paulo for his support, help and dedication in monitoring this project, providing guidance in order to finalize its requirements.

To the company, which kindly provided access to the data that served as the basis for this project, whose name, for reasons of anonymity, will not be mentioned in this document, and to the entire operational team that daily produces the data used in this work.

To António, a companion and mentor for more than a decade.

To my mother, Fernanda, my father José Manuel and my sister Filipa, for their support in all the ups and downs along the way.

To everyone else, whose names were not directly mentioned, but who in some way contributed to the completion of this project.

Thank you all.

"Blame it on the stars. Always."

Rita

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List of Abbreviations

ATM Automatic Teller Machine

DG Data Governance

DIS Cash dispensing

ETV Cash Transport Company

FAT Technical Assistance Suppliers

FLM First Line Maintenance

FS Free Standing (Lobby)

MCyber Master in Cybersecurity

MTBF Mean Time Between Failures

MTTR Mean Time to Repair

OEE Overall Equipement Effectiveness

RUL Remaining Useful Life

SLM Second Line Maintenance

TPM Total Productive Maintenance

TTW Through the wall

Chapter 1

Introduction

This document presents the project developed by the author, within the scope of the Cybersecurity masters degree at the Escola Superior de Tecnologia e Gestão de Viana do Castelo under the supervision of Professor Doutor João Paulo Magalhães. This work focuses on the development of a system that responds efficiently to the need for anticipation of failures in Automatic Teller Machines (ATM) towards their proactive maintenance, maximizing its availability and uptime.

1.1 Context

The availability of Automatic Teller Machines is a crucial aspect of service quality. Maximizing availability is done using multiple techniques. The adoption of redundant systems capable of tolerating failures, as well as reducing the Mean Time to Repair (MTTR) are widely used for this purpose. An extra step towards maximizing availability, which is intend to work on in this project, has to do with the ability to predict failures, thus allowing proactive maintenance operations on equipment to avoid failures, maximizing its availability. In this project, starting from a set of historical data relating to failures of types of equipment, the objective is to create a system that, uses the available data to predict, with a high accuracy rate which equipment may suffer from a failure in short time. Forecasting capacity is extremely important as it will allow adapting the way the Technical Assistance Suppliers (FAT) teams work. By predicting what equipment may fail is possible to do proactive maintenance rather than acting only when the equipment is out of operation.

McCollough et al. in [15] refer that *companies today are generating considerably more data than ever before and at a much finer granularity. Using analytical approaches and capable technologies, companies can infer useful knowledge and gain insights from large stores of collected data, increasing the efficiency of their organizations supply chain and providing a competitive advantage. Predictive modeling helps organizations move from "Reactive" Maintenance to "Predictive" Maintenance paradigm by helping them predict future demand for parts needed for maintenance in advance.* Silpasree et al. in [25], state that *failures of field units provide the most valuable source of data for the company.*

This document presents a research project that aims to predict failures in ATM. It makes use of data already existing regarding failures and makes use of prevision/forecasting algorithms to model the Mean Time Between Failures (MTBF). By predicting possible failures, it becomes possible to promote proactive maintenance, reducing the downtime of these systems, thus increasing equipment safety, as well as promoting team coordination towards efficiency.

1.2 Problem and Motivation

In the area of service companies, regardless of the type of equipment, a top priority is service availability. Surulivel et al. [26] refers that *the services provided are aimed at ensuring comfort, convenience and security of the customer, expressed in varied forms from mechanical to electronic, to ensure fast and rapid delivery of services intending at satisfying the customer.* Within the scope of this project, availability refers to the fact that the system has banking functions available to its users. Considering the global use of systems and user demands, the objective is to guarantee the highest possible availability of the ATM. Surulivel et al. [26] affirms that *customer satisfaction is critical in banking services. The level at which customers are satisfied with the services of the banks, extrapolate the future status of the banks.*

Guaranteeing such availability is a complex and challenging task. Adopting techniques and tools to maximize the availability is of utmost importance. Parab et al. in [20] refers that *ATMs are not attested by banks rather from acquiring to keeping up the machines and* *this results in an increased amount of ATM anomalies occuring for the past few years.*

Nowadays, within the scope of the data on which this project is based (ATM failures), it is a difficult task to predict in a timely manner which equipment is most likely to fail, as referred by Parab et al. in [20] *accurate recognition of anomalous behaviour at a point in time is the most challenging problem for systems.* The FAT team works based on failure incidents that arise daily, taking a reactive approach to them. This work is motivated and based on this daily need to transform reactive into preventive and proactive maintenance operations, guaranteeing better performance of the teams in their evaluation parameters, as well as, increasing the availability of the systems leading to better user satisfaction.

1.3 Objectives

In order to improve the availability of ATM and change the paradigm from reactive to proactive intervention, this work explores the use of prediction/forecasting techniques and algorithms to model and predict the occurrence of failures. More specifically, the objectives to be achieved by this project are:

- Calculate the Mean Time Between Failures (MTBF) of each equipment and rank it among its peers;
- Develop a decision support tool for coordination teams;
- Reduce the downtime and the Mean Time to Repair (MTTR);
- Maximize the uptime and availability of each ATM;
- Promote the resources optimization (involved teams).

1.4 Contribution

The main contribution of this project is the development of a system that can be used daily by coordination teams so that they can make effective decisions based on relevant information regarding the ATM possible failures, thus allowing the increase in MTBF, so maximizing the availability and uptime of these equipments. Another point to which this project aims to contribute is the evidence that equipment maintenance combined with a preventive approach can be a more effective alternative than a reactive approach, increasing the availability of equipment and its respective functions.

1.5 Project Structure

This project is organized into chapters. Chapter 2 presents the preliminary study for preparing the state of the art, presenting the work already done in the area as well as some existing solutions. Chapter 3 presents the study carried out on the topic of this project as well as the characterization of the various data available to carry out this work. Chapter 4 describes the requirements specification and the implementation steps. Chapter 5 presents the analysis of the results. Finally, Chapter 6 presents a conclusion about the project.

Chapter 2

State of the art

This chapter presents the state of the art regarding the proactive maintenance of systems. It starts by presenting a methodology used to find the most relevant works in the scope. Then a contextual history regarding the ATM is presented and finally, reliability concepts are described with a focus on the ones that promote the availability of the systems.

2.1 Literature Review

This subsection presents the methodology used to conduct a systematic literature review and the most significant works achieved in the field.

2.1.1 Bibliometrix - PRISMA Methodology

The PRISMA method is a systematic review of the existing bibliography. In other words, it is a study that has the phases of research, selection, analysis, and data synthesis, with the objective of responding to a topic and reducing possible methodological biases [22].

For the literature review, several libraries were used, available through the B-ON Library, with the IEEE repository standing out in the research, which had a greater number of articles on this topic. Initially, the keywords defined for the literature study were “ATM”, “Automatic Teller Machines”, “Availability”, “MTBF”, “MTTR”, “ATM failure prediction”, “ATM network improvement solutions”, “Bank customer satisfaction”. A second search, more extensive so as not to condition the theme of the results obtained in the first search, was carried out for this project, and the following search strings were defined: “Increased equipment availability”, “Impact of preventive approach”, “Equipment Failure Prediction”, “Increased uptime”, “Preventive maintenance”, “Reactive maintenance vs Preventive maintenance”.

During the stages of the research, the works that emerged in the research on the topic were organized into a *.ris*[1] file. This option was taken because the .ris format is used as an input source in the Rayyan and VOSViewer tools, which were also used in this phase of the project.

Then, using the online tool Rayyan [23], the articles were reviewed and selected based on the Prisma method. This systematic review method uses search, selection and analysis methods, helping to synthesize research from preliminary studies, with the aim of achieving structured research and reducing possible methodological biases. The Rayyan tool allowed a structured classification of the articles obtained in the two research phases that were carried out for this project, originating the result illustrated in Figure 2.1.

The exclusion criteria are also shown in Figure 2.1. The article selection criteria for this project were the scope of the topic under study and evidence of improvements obtained in the results presented.

[1]A RIS file is a bibliographic citation file saved in a format developed by *Research Information Systems* (RIS)

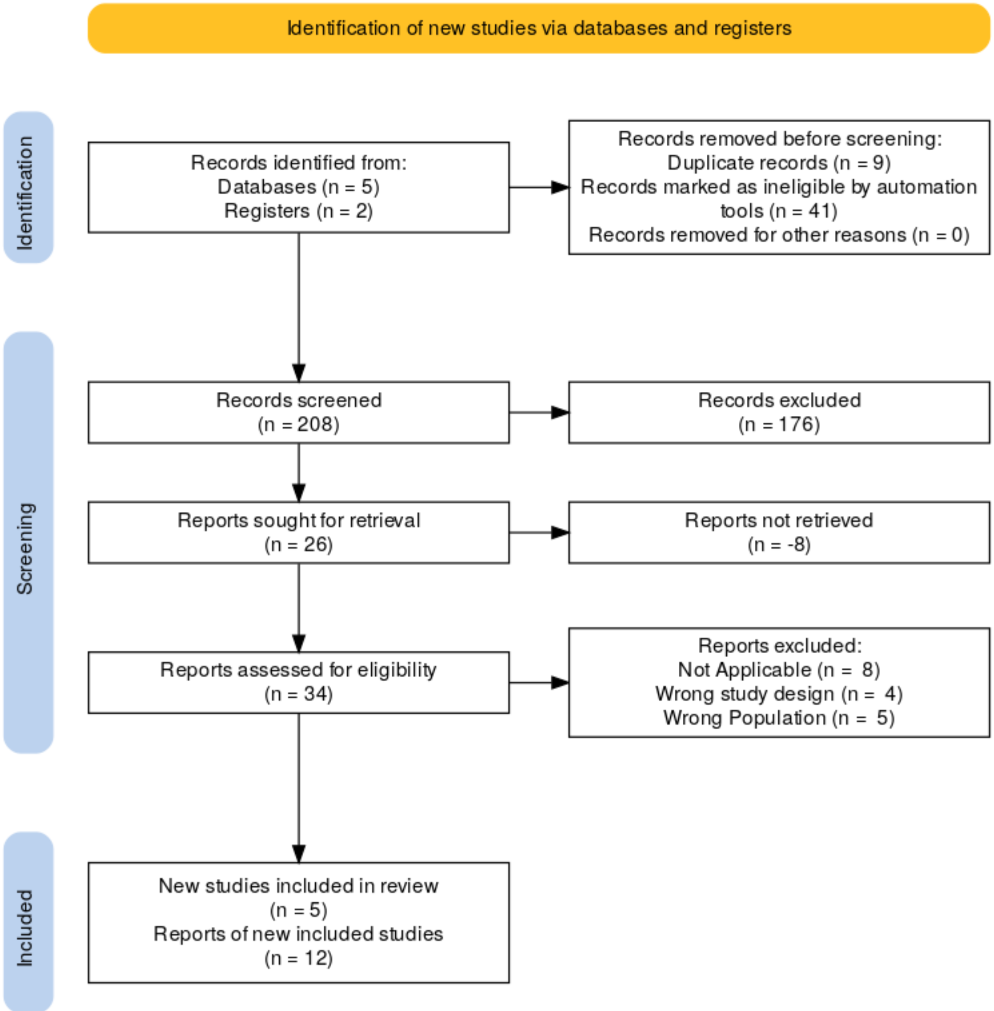


Figure 2.1: Methodology Prisma - Rayyan

2.1.2 VOSviewer

To complement the systematic review, the VOSviewer [31] software was used. This software allows to build and visualize bibliometric networks. The same file *.ris* referred to in 2.1.1 was used as input for VOSviewer. The decision to use the VOSViewer tool was to visually clarify the interconnections between the keywords and search strings used in article selection. This tool, through the refinement of the clusters, allowed a clearer view of the connection and importance between the keywords and search strings used.

The first time VOSviewer was run, the network graph shown in Figure 2.2 was created. The initial cluster, still without any refinement of the analysis, presents numerous nodes, each with several available paths that connect to each other. However, it is clear that the terms “reliability”, “availability” and “maintenance” are terms that are intrinsically linked to the terms MTBF and MTTR, as they stand out among the others.

These five terms correspond to the five strongest clusters present in the initial analysis, which will be refined into the clusters generated subsequently.

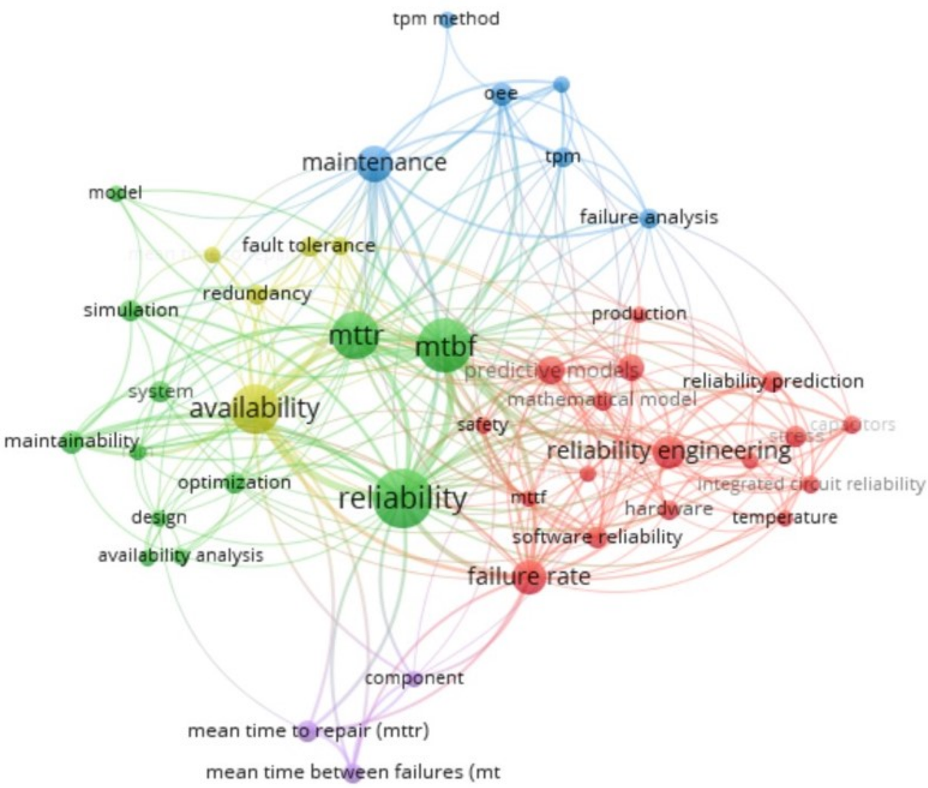


Figure 2.2: Initial Bibliometric Network with 5 Clusters

Analyzing in detail the two main clusters observed in Figure 2.2, is visible that the reliability main links are the average time between failures, the average resolution time, the analysis and failure rate, and also the term maintenance. These links are illustrated in Figure 2.3. In turn, the cluster related to availability (Figure 2.4) refers to the same terms mentioned above and combines redundancy and fault tolerance.

The next step in the systematic review was to refine the clusters. In this step, the same .ris file was used, but a .txt file was also created containing the VOSviewer thesaurus. This file is optional but aims to unify the keywords used in the papers.

Considering that in the resulting papers, there may exist some spelling variations it becomes necessary to proceed with a uniformization of terms. In Figure 2.2 the reference to the term MTBF and the term *mean time between failures* is observed. In practice, the term is the same. In short, the VOSviewer thesaurus file allows to predict and group these

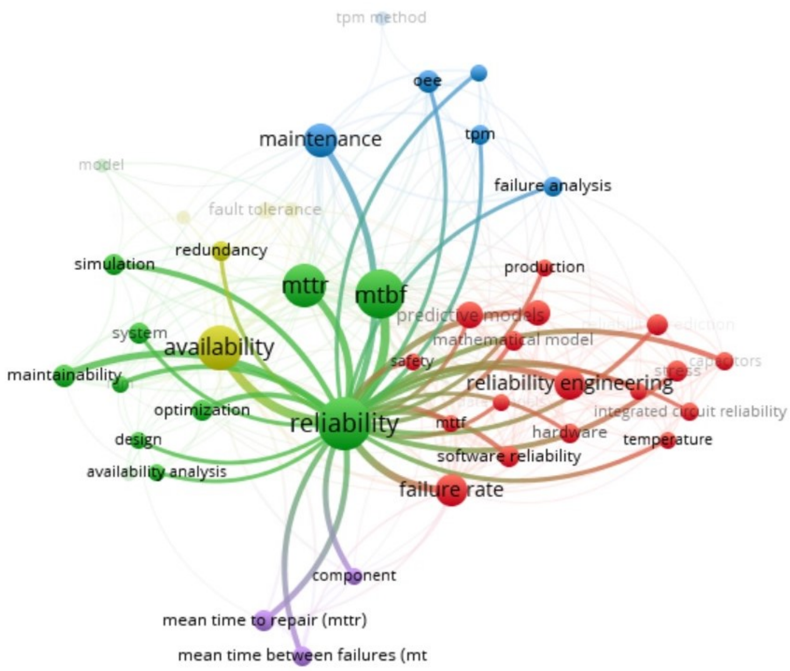


Figure 2.3: Bibliometric Network with 5 Clusters - Reliability

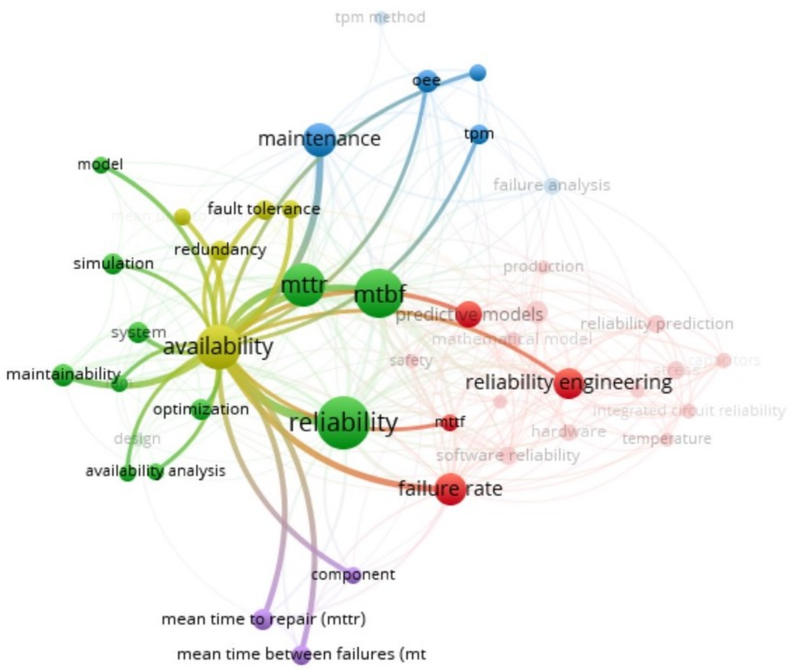


Figure 2.4: Bibliometric Network with 5 Clusters - Availability

variations by clarifying the cluster connections. The file used in this analysis is presented in Appendix A.

The initial bibliometric network had five clusters (Figure 2.2), each represented by a different color. Using the aforementioned .txt file, the network graph illustrated in Figure

2.5 was obtained. It contains three clusters, highlighting the most important keywords in this research. These keywords by cluster are:

- Red Cluster - ***Reliability*** - Key Terms: predictive models, failure rate, hardware reliability and software reliability.
- Green Cluster - ***Availability*** - Key Terms: MTBF, MTTR and error tolerance.
- Blue Cluster - ***Maintenance*** - Key terms: TPM and OEE.

Once again, it is widely visible, in refining the initial cluster from five clusters to three, it is visible how the terms "maintenance", "reliability" and "availability" highlight their importance, showing which subterms are most considered to maximize each cluster node .

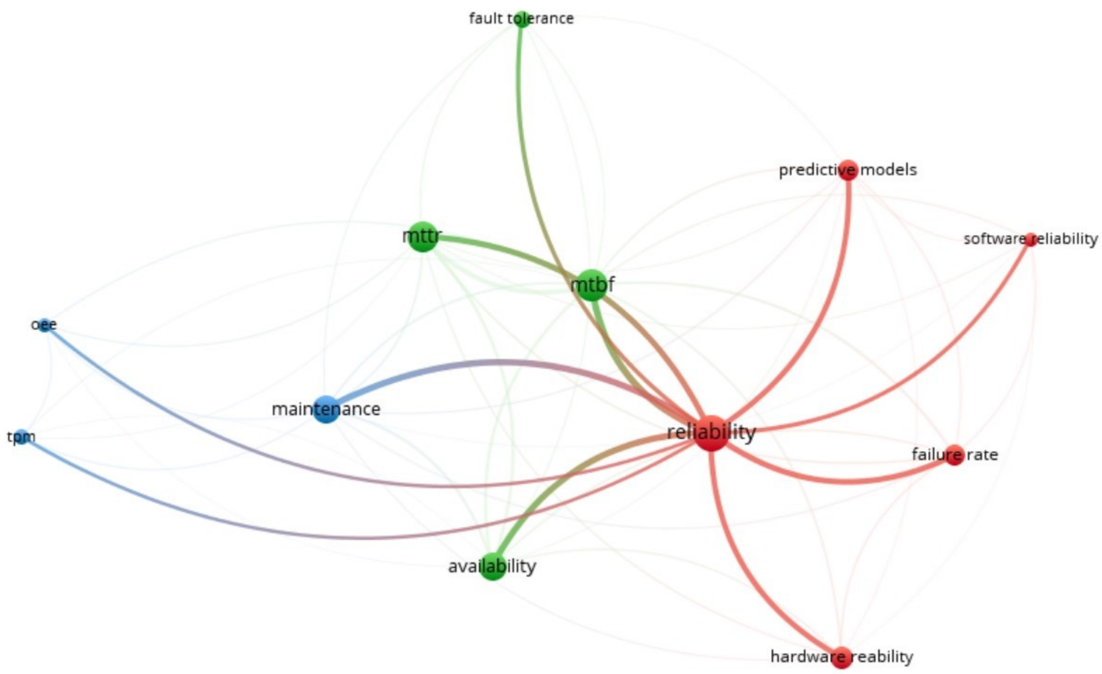


Figure 2.5: Bibliometric Network with 3 Clusters

At this stage of the study, the cluster obtained was improved again, going from three to two final clusters. The *.ris* file and the *.txt* file already mentioned above were used again, but forcing, through the VOSviewer software, the creation of only two clusters. As a result, the frequency of reference to key terms was increased and the network shown in Figure 2.6 was generated, representing the two strongest clusters (group of keywords).

It is therefore concluded, based on the bibliometric network illustrated in Figure 2.6,

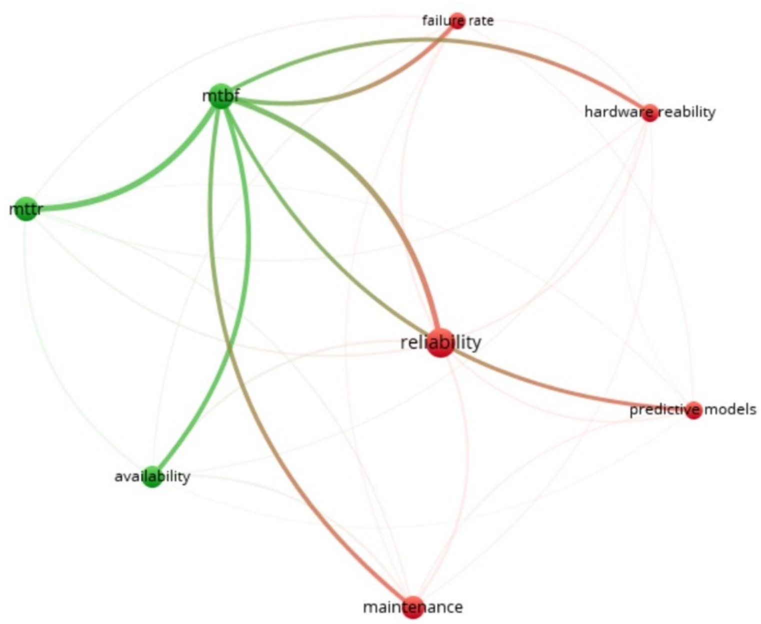


Figure 2.6: Bibliometric Network with 2 Clusters

the availability of computer equipment is intrinsically linked to MTBF and MTTR and that its reliability is directly linked to its maintenance.

At this stage of the project, as a result of the systematic literature review, the opportunity to classify incidents was found. This classification did not exist in the available data of the original dataset and was implemented in point 4.1.2 of this project. The article that most contributed to this decision was the article written by Avizienis et all. [2] and the article [3], also written by the same author.

2.2 History and Operation of the ATM

The first reference to equipment similar to the ATM is know today is from 1939 [10]. Luther Simjian had the idea of creating a machine that would allow customers to make financial transactions and this idea was put into practice, by installing equipment at CitiCorp in New York. The *Bankmatic Automated Teller Machine* was withdrawn just six months later due to a lack of interest from users.

Years later, in June 1967, the first ATM was installed in a branch of Barclays Bank in Enfield, north London. This process was led at the time by John Shepherd Barron, who worked at the company *De La Rue Instruments*. At this time, this equipment was called the acronym DACS - *De La Rue Automatic Cash System* [10].

In Portugal, the first ATM were installed in 1984 in the internal network of Montepio Geral [8]. The network that is now known in Portugal as the *multibanco* network, started on September 2, 1985, with nine equipments in Lisbon and Porto.

Nowadays, these devices are available 24 hours per day, every day, but this was not always the case. Initially the ATM *were not available between 01:00 and 07:00 in the morning and only allowed the user to make cash withdrawals, consultations and PIN changes* [14]. Today the main objective of an ATM is to be always available to the user and to let him do most of the bank operations in a self-service approach.

Being always available is a complex and daunting task. Computer equipment, regardless of its purpose of use and the function for which it is designed, is in itself equipment that can suffer from faults, errors, and failures, thus compromising its availability. In a theoretical approach, Avizienis et al. in [2], identify reliability, availability, security, and integrity as important characteristics of a system. Equipment failures and errors pose a threat to these characteristics.

An *Automatic Teller Machine* is *a computer equipment, used by people, mainly to carry out financial transactions and/or access financial information* [20]. As with any other computer equipment, ATM are subject to failures that compromise their normal function, leading to unavailability and user dissatisfaction. Reactive repair is used to bring these equipments back into operation. In practice the first line of incident resolution is carried out directly by the banking institution to which they belong, most of this service is outsourced to cash transport companies. The second line of maintenance is outsourced to technical assistance providers. The reactive approach is necessary, but there is room for improvement if a proactive approach is adopted. Such, a proactive approach can be very efficient if it is combined with predictive analysis to know in advance which ATM require maintenance first. Nita Hivarekar et al. in [11], refers that *predictive maintenance is used to identify failures based on past failure trends. Predictive modeling improves the life of the system by performing condition-based maintenance activities.*

In this context, Parab et al. [20] define that *accurate recognition of anomalous behavior is the most challenging problem of all systems.* When predicting ATM failures, there are several factors that can influence the occurrence of errors/incidents. Perera et al.

[21], argue that *atmospheric conditions, the day of the week and the approach to salary payment day are preponderant factors that influence the use of this equipment, increasing or decreasing the transactions carried out.*

Since one of the main purposes of using an ATM is to withdraw money, the condition of the cash note can also lead to failures. Teranishi et al. [27] in their work argue that *the level of use/spending of cash note in a load of ATM values can influence the proper functioning of the equipment.* Kongprasert et al. [12], suggest a Support Vector Machine model to classify whether a given cash note is suitable for circulation or not. These are some of the variables that can contribute to the occurrence of failures, but it is also important to distinguish the approaches that authors propose for solving the failure prediction problem.

The main objective in using *Machine Learning* algorithms in a failure prediction system is the fact that the system can respond in a timely manner and with a high success rate to which equipment should be given greater attention in order to minimize the existence of failures. Avizienis et al. in [2], it is mentioned that one of the greatest advances in technology was *the recognition of security as a composite of the attributes of confidentiality, integrity and availability.* In [2], Avizienis et al., argue that:

- *A system is an entity that interacts with other entities, that is, other systems, including hardware, software, humans, and the physical world with its natural phenomena. These other systems are the environment of the given system.*
- *The system boundary is the common boundary between the system and its environment.*
- *The function of such a system is what the system is intended to do and is described by the specification in terms of functionality and performance.*
- *The behavior of a system is what the system does to implement its function and is described by a sequence of states.*
- *The total state of a given system is the set of the following states: computation, communication, stored information, interconnection, and physical condition. The structure of a system is what allows it to generate behavior.*

- *The service delivered by a system (in its role as provider) is its behavior as perceived by its user(s); a user is another system that receives a service from the provider. The part of the provider's system boundary where service delivery occurs is the provider's service interface.*

2.3 Definition of Reliability

The reliability of a piece of equipment is its ability to perform a certain function or set of functions.

Memon et al. in [16], define that the *"Reliability of a product is the measure of its ability to perform its function, when necessary, for a specified time in a particular environment"* and that *"Reliability is the probability that a designed system or equipment will perform and complete the mission without failure, provided that the system operates within prescribed conditions*". They also mention that *"Reliability analysis plays an important role in the acquisition of a project from the customers point of view, as well as in the conception of a project from the designers point of view."*

Avelar et al. in [28] states that, "*reliability is the ability of a system or component to perform its required functions under stated conditions for a specified period of time [IEEE 90]*".

Within the scope of this project, it is assumed that the reliability of an automatic teller machine is its ability to guarantee the availability of its functions to its end user, in order to increase their satisfaction.

2.4 Definition of Availability and Uptime

According to Memon et al. in [16], *availability is the probability that the system will be in its operational state when it is requested for a mission. The availability performance of a system is evaluated by predicting the time between two consecutive failures.*

Using a comparison between these two articles again, Avelar et al. refer in [28], that "*availability, is the degree to which a system or component is operational and accessible when needed for use [IEEE 90].*"

Availability can be determined by evaluating the MTBF and the MTTR. The equation to determine it is:

$$Availability = \frac{\text{MTBF}}{(\text{MTBF} + \text{MTTR}))}$$

This equation effectively shows that MTBF and MTTR have a major impact on the availability of equipment. The availability of a system is directly proportional to the MTBF when the MTTR is constant. On the other hand, availability is inversely proportional to MTTR when MTBF is constant.

Edmondson in [29] refers that "*uptime and availability are distinct concepts that need to be understood to measure system realibility accurately. Uptime is a measure of the amount of time that a system or service is available and operational without any unplanned downtime. Availability measures the proportion of time that a system or service is accessible and usable by its intended users. It take into account the system's uptime and any planned or unplanned downtime that might impact a user's ability to acess the system.*"

2.5 Failure Definition - Incident

Before getting into the concrete definition of the MTBF and MTTR formulas, it is important to define what an incident is. An incident is a failure to perform the function requested by the user of the equipment or a failure of the equipment system without human intervention at the time of the error, i.e, Avizienis et al. in [2], the authors state that *all failures that can affect a system during its lifetime are classified, leading to classes of elementary failures.* Authors consider the following main failure classes:

- ***Natural failures*** *are physical failures (hardware) that are caused by natural phenomena without human participation.*
- ***Interaction Failures***, *made by man, resulting from human actions* - this class is further subdivided into three particularities:
  - **Omitted Faults** - the absence of actions when the actions should be performed, that is, simply omissions.

  - **Malicious Faults** - introduced during system development with the aim of causing damage to the system during its use
  - **Non-Malicious Faults** - introduced by the user without malicious intent

- ***Service failures*** - *an event that occurs when the delivered service deviates from the correct service.*

After highlighting this classification, it is important to make clear the possible reasons for the human factor to introduce failures into the system. These can be to:

- Interrupt the service, resulting in its denial;
- To access confidential information;
- Improperly modifying the system.

It is also important to clarify that service failures, which are characterized by an incorrect service delivered to the user, can have different levels of severity. These can be vary according the:

- The fault domain;
- Fault detectability;
- The consistency of failures;
- The consequences of failures on the environment.

It has already been mentioned in this chapter that in [2], it is considered that *most internal failures circulate between their inactive and active states*, however, it is also essential to clarify that a failure may not compromise the entire system itself. A failure may render the equipment as a whole unusable or may render only a specific functionality of the equipment in question unusable.

Particularizing the specific topic of automatic teller machines (ATM), Reddy et al in [24], define that there are two types of failures in an ATM:

1. **Inconvenience Failures** - when the failure is inconvenient for the operator or user, but does not prohibit the use of the module in practice;

2. **Critical Failures** - when the failure renders the module unusable until the failure is repaired by FLM or SLM.

Silpasree et al in [25], consider the main objective of the ATM to be the withdrawal of cash and add yet another type of failure to the topic:

- **Operation Failures** - operation failures occur when money is not received by the customer due to internal component failures.

2.6 Failure Rate, Fault Tolerance and Failure Prevention

Memon et al. in [16], state that *failure can be defined as a condition in which a system is not fulfilling the desired objective or is a transition from a functional state to a non-functional state as a result of a defect in any part of the system.* Thus, the authors define that "*the failure rate is defined by the number of failures per unit of time, which implies the determination of the occurrence of the number of failures per unit of time*".

Avizienis et al. in [2], consider that dealing with faults may prevent the occurrence of errors and failures. Faults can be handled using different approaches:

- **Fault prevention** means preventing the occurrence or introduction of faults;
- **Fault removal** means reducing the number and severity of faults;
- **Fault tolerance** means avoiding service failures in the presence of faults;
- **Fault prediction** means estimating the present number, future incidence, and likely consequences of faults that may result into failures.

Fault prevention and tolerance seek to enable equipment to increase its ability to provide a service that can be reliable, while fault removal and prediction aim to achieve confidence in this equipment capacity.

It is therefore considered that failure prediction is one of the main means of achieving the necessary trust and security in a system. Avizienis et al. in [2], refer that *failure prediction is carried out by evaluating the system behavior in relation to the occurrence of failure or its activation.* This assessment has two aspects:

- **Qualitative Assessment** - or ordinal - which aims to identify, classify and hierarchize failure modes, or combinations of events (component failures or environmental conditions) that would lead to system failures;
- **Quantitative Assessment** - or probabilistic - which aims to evaluate in terms of probabilities the extent to which some of the attributes are satisfied; these attributes are then viewed as measurements.

2.7 Definition of MTBF

MTBF stands for *mean time between failures.* It is given by the formula:

$$MTBF = \frac{\text{Total Time - Stopping Time}}{\text{Qty. Stops}}$$

Torell et. all in [28] refers that *MTBF affects reliability and availability.* "*The difference between reliability and availability is often unknown or misunderstood. High availability and high reliability often go hand in hand, but are not interchangeable terms*". It is also mentioned that *MTBF, or mean time between failures, is a basic measure of the reliability of a system. It is normally represented in units of hours. The higher the MTBF number is, the greater the product reliability is.*

Wood et al in [32], state that MTBF is an important parameter in maintenance planning because *being able to approximate expected field reliability from reliability predictions allows to do a better job of estimating contract prices appropriate service stations, plan spare parts stocks, and estimate the number of service personnel required to support the product.*

2.8 Definition of MTTR

MTTR means *mean time to repair*, and this parameter is given by the formula:

$$MTTR = \frac{\text{Total Repair Time}}{\text{Qty. of Incidents}}$$

Torell et. all in [28], refers that "*MTTR, or mean time to repair (or recovery), is* *the time expected to recover a system from a failure. This may include the time required to diagnose the problem, the time required to get a field technician on site, and the time required to physically repair the system. Similar to MTBF, MTTR is represented in units of hours. MTTR impacts the availability, not reliability*".

2.9 Definition of Maintenance

When the topic is a set of equipment available 24/7 to the user, one of the keywords is maintenance. Memon et al. in [16], divide this important concept, stating that *maintenance of a system is broadly classified into two categories: preventive actions and corrective actions.* Authors further state that *maintainability analysis plays an important role in increasing system efficiency as well as security and also reducing system maintenance cost.*

In [33], Zonta et al. also mentions that *data is the key to generating information that can anticipate or collaborate in making predictive decisions*, and introduce the concept of predictive maintenance. For these authors, *predictive maintenance (PdM) is based on historical data, models, and domain knowledge. They can predict trends, behavior patterns, and correlations by statistical or machine learning models to anticipate pending failures in advance to improve the decision-making process for maintenance activity, mainly avoiding downtime.*

Avizienis et al., in [2], define that *the term maintenance, following common usage, includes not only repairs but also all system modifications that occur during the use phase of the systems useful lifetime. Therefore, maintenance is also a development process.*

Within the scope of this project, it is assumed that maintenance is all corrective and planned actions carried out on the set of equipment under study and which aim to ensure the proper functioning and availability of ATM so that end users can perform banking functions intended.

2.10 Definition of OEE

The acronym OEE stands for *Overall Equipment Effectiveness.* Chong et all [5], state that OEE reflects the effectiveness of *Total Productive Maintenance* (TPM) implementation.

Chong et al., in [5], refer that *OEE is the most important crucial metric that focuses on maximizing equipment effectiveness by reducing equipment downtime*. Failure Mode and Effects Analysis (FMEA) is considered a form of measurement for the improvement of this parameter.

In [18], authors mention the main advantages of OEE:

- Improved ROI (*Return of Investment*);
- Support in identifying the causes of production losses;
- Streamlining the work of all profiles related to production activity;
- Reduction in machine repair costs;
- Increased competitiveness;
- Process optimization;
- Improvement of monitoring and decision-making processes.

Liao et. all in [13], go a little further and propose "*a concept of Predictive Overall Equipment Effectiveness (POEE) to evaluate and monitor the future effectiveness*" of a piece of equipment. Making use of *comparison with the deterministic effectiveness defined in OEE and based on prior information*. In other words, the authors state that this data is crucial information about the analyzed system, which in turn, *"can be obtained from fault detection and classification data"*.

2.11 Definition of TPM

The acronym TPM stands for *Total Productive Maintenance*. In practice, this measure seeks to involve the entire organization, regardless of its function or level, to maximize the overall effectiveness of the equipment. This process seeks to adjust existing processes, reducing errors and incidents.

Molefe et al. in [17] further clarify that each word of the acronym must be governed by:

- **Total:** all employees of the organization are involved, from the field technician to administration;
- **Productive:** in other words, no other activity or service is carried out other than in favor of customer expectations and satisfaction;
- **Maintenance:** always keep the equipment and its modules in good working order, that is, always in conditions that are as good or better than the original condition.

The main motivation for implementing these methods is to maximize the effectiveness of the equipment or set of equipment maintained by the organization in favor of end customer satisfaction.

The pillars of this method are [19]:

1. Autonomous maintenance;
2. Focus on improvement;
3. Planned maintenance;
4. Quality maintenance;
5. Early management of equipment;
6. Education and training for teams;
7. Environmental health and safety conditions;
8. Administration (Data must be shared transparently between departments, such as operations and maintenance).

All these pillars refer to proactive and preventive techniques to improve equipment reliability.

In [6], Conwat et al., state that *an important element of the implementation strategy is to analyze and improve equipment productivity. A second important element is to increase the level of knowledge and flexibility of employees.*

In turn, in [4], Braglia et al., state that *nowadays, the growing demand for productivity and equipment availability, combined with decreasing profit margins, require increasing* *reliability and increasing performance, keeping operating costs at a low level. In a scenario where the cost of maintenance can be decisive for the success or failure of a business, the development of a Total Productive Maintenance (TPM) plan and/or the use of Preventive Maintenance (PM) should be considered as a promising solution. In fact, PM makes it possible to minimize maintenance costs and failures by scheduling standard maintenance activities immediately before a failure occurs. To achieve this, a reliable estimate of the risk rate of equipment is required, but unfortunately, understanding the underlying failure processes and predicting when equipment may fail is challenging.*

2.12 Reliability Estimation and Prediction Methods

Torell et al., in [28], refer, among others, to three methods for predicting and estimating the reliability of a group of equipment.

1. **Similar Items Prediction Method:** this method provides a quick means of estimating reliability based on historical reliability data for a similar item. The effectiveness of this method depends primarily on the similarity of the new equipment to the existing equipment for which field data is available. There must be similarities between manufacturing processes, operating environments, product functions, and designs. For products that follow an evolutionary path, this forecasting method is especially useful as it leverages previous field experience.

2. **Field Data Measurement Method:** the field data measurement method is based on the actual field experience of the products. This method is perhaps the most used method by manufacturers, as it is an integral part of their quality control program. These programs are often called Reliability Enhancement Management. By tracking the failure rate of equipment in the field, a manufacturer can quickly identify and resolve problems, thus eliminating product defects. Because it is based on actual field failures, this method accounts for failure modes that prediction methods sometimes miss. The method consists of tracking a sample population of products and collecting failure data. After the data is collected, the failure rate and MTBF are calculated. The failure rate is the percentage of a population of units that are expected to "fail"

in a calendar year. In addition to using this data for quality control, it is also used to provide customers and partners with information about the reliability of products and quality processes. Given that this method is widely used by manufacturers, it creates a common point for comparing MTBF values. These comparisons allow users to evaluate the relative differences in reliability between equipment, which provides a tool for making specifications or purchasing decisions. As with any comparison, it is imperative that the critical variables are the same for all systems being compared. When this is not the case, it is likely that poor decisions will be made which can result in a negative financial impact.

3. **FMEA / FMECA:** Failure Mode and Effects Analysis (FMEA) is a process used to analyze the failure modes of equipment. This information is then used to determine the impact each failure has on the user. The analysis can go a step further, assigning a severity level to each of the failure modes, in which case it would be called FMECA (Failure Mode, Effects and Criticality Analysis). FMEA uses a bottom-up approach, i.e., it analyzes a piece of equipment or group of equipment and generalizes to a whole.

Chapter 3

ATM failure prediction - Motivation and Approach

Genevois et. all, in [9], state that *automated teller machine (ATM) management is one of the crucial management issues for banks in order to ensure sustainable profitability and customer satisfaction in nowadays competitive environment. On the other hand, ATM management is a very complex issue, as the process is related to a large number of agents and variables.*

In fact, the management of an ATM park involves several departments and people specialized in each area of activity. This is due to the fact that the park management process involves several processes, from ATM management and its use, to equipment security, as well as its maintenance, and remote monitoring.

This entire project is based on real equipment data that is collected from the various ATM, distributed across districts of Portugal. It is important now to define the term "data" and its importance within the scope of this work.

This chapter is divided into three sections. What data are and their importance is defined and a study carried out on the specific topic that gave rise to the motto of this project is presented.

3.1 Section 1 - Data and Data Governance

Côrte-Real in [7], defines data as *"a representation of unprocessed or unrelated facts and constitutes the raw material for building pieces of information. Making good decisions at the right time is something that happens when companies manage the data they have well. Data should be seen as a fundamental instrument that allows companies to leverage their value with decision strategies, risk control, cost minimization, and greater knowledge deep part of your business."* and in the same article, Côrte-Real [7], defines Data Governance itself as *a transversal management program that considers data a business asset. It is considered a set of corporate policies, standards, processes, people, and technologies essential for managing critical business data. Data governance is considered a strategic competence and a pillar for organizations with the sole aim of leveraging the business through correct information management.*

Vial, in [30], states that *data governance seeks to achieve two objectives: 1 - maximize the value of information for the organization, ensuring that information is reliable, secure and accessible for decision making; 2 - protect information so that its value to the organization is not diminished by technology or human error, loss of timely access, inappropriate use, or misadventure.*

In this sense, data is considered a source of information that adds value to the company, helping to support decisions, and can provide clear information on the path towards improving services and operations.

3.2 Section 2 - Base Context

The *dataset* used in this project refers to a set of around 2000 ATM devices. The analyzed set consists of six main families of models, with twenty-three different sub-models. They are installed in various areas of the country and for a better comparison they were grouped into five zones so that their equipment has a similar population ratio between them.

Every month, service performance is evaluated based on four parameters:

- Uptime - Availability of the equipment for the user;

- Number of incidents;
- Number of recurrences;
- Incident resolution time.

Briefly, an ATM that does not have any incidents in a given period of time is said to have an uptime of 100%. An incident is a failure that occurs in equipment, causing the unavailability of a function, or a set of functions, on that same equipment. When a failure occurs, an incident is opened, and this incident is only closed when the ATM is able to return to performing the function that caused the failure. The time count, between opening and closing, is linear and without interruption. Although there are some cases in which the equipment can recover on its own, in most cases, an incident results in human intervention on the equipment. The intervention can be carried out by first-line actors (FLM - bank operator or cash transport company operator) or second-line (SLM - specialized technical team). ATM are computer equipment that, in addition to having cash inside, provide and carry out monetary transactions. Whenever there is a need for human intervention, this can be a factor in reducing the safety of the equipment, as it can be vulnerable to third parties. For example, in the case of a failure caused by software, the ATM can no longer be monitored by the central system, which creates a gray area in terms of physical occurrences with the equipment. Clarifying this example, in practice, an ATM with a software anomaly is unable to inform the central system that its cash cassettes have been removed.

Some key concepts to remember, for the maintenance of the ATM there are two types of teams.

1. The FLM team (*First Line Maintenance*) includes incidents that do not require a tool or part, but are necessary to develop the ATM or infrastructure to adequate operational conditions. FLM interventions include consumables, that is, loading cash cassettes and placing paper rolls. - The FLM of the ATM network are the bank operators and the cash transport company operators.

2. The SLM team (*Second Line Maintenance*), where the remaining incidents fall. In this case, you already require advanced support from experienced service technicians

or technical support teams. These repairs typically involve diagnostic tools and assessments, as well as on-site equipment repairs. - the SLM are the Technical Assistance Providers.

In addition to the previous explanation, is important to consider the following premises regarding this topic:

- The ATM can send automatic incidents through the central system 24/7;
- Each incident is related to an ATM module which in turn is responsible for a function or set of functions;
- Each incident has an OPEN (start time) and a CLOSED (end time) status;
- The incident can be automatic (reported directly by the ATM) or manual (requested when the 1st line is unable to put the equipment into service);
- The incident ID is unique;
- CLOSED is sent by the ATM when the central system considers the ATM is repaired and working;
- The ATM can recover without the need for technical intervention, thus generating an automatic CLOSE through a transaction from the module that reported the failure;
- The incident time count depends on the weight of the module it corresponds to (Figure 3.1);
- The downtime of an incident is the time elapsed between the start time of the incident and the close of the incident;
- The time it takes SLM to resolve an incident is the downtime of that incident. ATM uptime is the time that the ATM is available for the end customer to use;
- SLM, when it needs to intervene in modules inside the ATM vault, or in the case of the ATM being within an alarmed infrastructure, needs FLM to give it access to the equipment – in this case a prior appointment is made between the two entities.

A point that is important to draw attention to right away is that the MTTR – Mean-Time-To-Repair – has its main influencing factor on whether or not the SLM has direct access to the ATM module to which the incident refers. In this context, the MTTR is analyzed differently for incidents that require scheduling with FLM and for incidents with direct access – the MTTR worsens considerably when the SLM team needs the FLM team to access the equipment. This data, which in practice is relevant to the results of the SLM team, was taken into consideration in the tool implementation chapter, and a segmentation field was created to choose data whether from incidents with a schedule or not.

3.2.1 Characteristics of an incident

Clarifying the previous section, the incidents have the following characteristics:

- It is a unique identifier and has an associated a unique ticket;
- Automatic or Manual;
- Has an OPEN and a CLOSE;
- Is relative to a module;
- With or without the need for intervention from the FLM;
- The weight of an incident in the ATM uptime count is given by the table 3.1.

Module	**Description**	**Weight**
PRR	Receipt Printer	25
DEP	Deposit Module	25
CDM	Cash Dispenser Module	50
BDG	Badge Reader	100
(...)	Others	100

Table 3.1: ATM Module Weights

3.2.2 Concept of a repeated incident

If an ATM has several incidents in the same period of time, its availability is affected and this is directly reflected in the degradation of its uptime. However, when the same module, after technical intervention, again causes an incident that requires new intervention on the equipment, the equipment is considered a repeat offender.

3.3 Section 3 - Typology of an ATM

The type of ATM is determined by the location of its installation and the functions it provides to the user. There are mainly two types of equipment:

- The simplest - allows cash withdrawals, balance checks, movements, and PIN changes;
- The most complex - they allow you to deposit notes, coins, and checks, as well as carry out more complex banking transactions.

In terms of their location, ATM that are inside banking facilities or commercial areas are called indoor ATM (*on premise*). ATM that are installed on a wall, facing the outside for access by customers are considered (*off premise*).

3.3.1 Existing Families and Models

As previously mentioned, the analyzed park is made up of six main families, twenty-three models in total. Since the data used in this project is real, the models and sub-models were anonymized to guarantee the privacy and security of the set of equipment. The models are designated as follows:

- Family A - Models A1, A2 and A3
- Family B - Models B1, B2, B3 and B4
- Family C - Models C1, C2, C3, C4 and C5
- Family D - Models D1, D2 and D3
- Family E - Models E1, E2, E3, E4 and E5
- Family F - Models F1, F2 and F3

Their typologies and age ranges are presented in the table 3.2.

Family	Model	Typology	OS	Age
A	Model A1	Lobby	XP	10 to 15 years
	Model A2	Lobby	XP or W10	10 to 15 years
	Model A3	TTW	XP or W10	10 to 15 years
B	Model B1	TTW	NT4	25 to 30 years
	Model B2	TTW	NT4 or XP	20 to 25 years
	Model B3	Lobby	NT4	20 to 25 years
	Model B4	Lobby	NT4	20 to 25 years
C	Model C1	TTW	XP	15 to 20 years
	Model C2	Lobby	XP or W10	10 to 20 years
	Model C3	Lobby	XP or W10	10 to 15 years
	Model C4	TTW	XP or W10	10 to 20 years
	Model C5	TTW	XP or W10	15 to 20 years
D	Model D1	Lobby	W10	4 to 6 years
	Model D2	TTW	W10	0 to 5 years
	Model D3	TTW	W10	0 to 5 years
E	Model E1	TTW	XP or W10	10 to 15 years
	Model E2	Lobby	W7 or W10	5 to 10 years
	Model E3	TTW	W7 or W10	0 to 5 years
	Model E4	TTW	W7 or W10	3 to 10 years
	Model E5	TTW	W10	5 to 10 years
F	Model F1	TTW	W7 or W10	0 to 5 years
	Model F2	TTW	W10	0 to 5 years
	Model F3	TTW	W10	0 to 5 years

Table 3.2: Table of ATM Families and Models

3.3.2 Geographic Distribution District/Model

Since one of the prediction methods is the evaluation of similar equipment, (*previously discussed in 2.12*), it is also important to visualize where each of these models is physically located. This is because, taking into account that the equipment fleet is spread across mainland Portugal, it is normal for equipment in more populated districts to behave differently than equipment in lower population density districts and vice versa.

In this sense, for better visualization of the equipment park, an interactive map was created in Power-BI, Figure 3.1, in order to group the equipment by family and/or models.

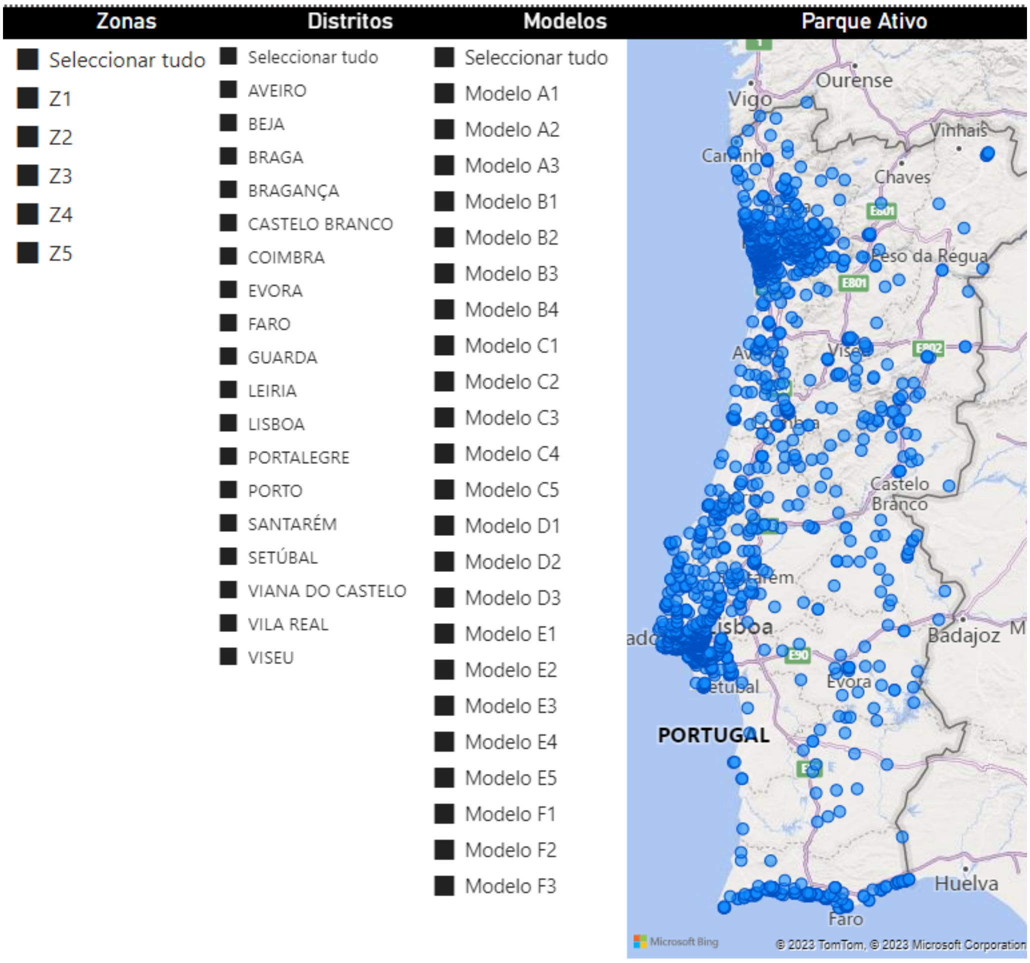


Figure 3.1: ATM Park - Geographic Distribution

The equipment was segmented into five areas of the country and was also segmented by model.

Taking into account that the data that supports this project are real and reflect the incidents caused by the set of equipment under study, which until this project had a corrective maintenance approach, the main reason for this project is to respond to the need of the SLM team in being able to effectively analyze the available data, being able to group them by zones and models. This need exists due to the fact that the same equipment model may experience greater component wear in denser population areas, since the number of transactions is significantly higher than in less dense population areas. Another need identified was the fact that a tool is needed that allows checking the type of incidents. For example, the cash dispenser module may have several associated sub-errors and the fact that the initial dataset was not organized did not allow it to be easily identified which models most give rise to certain types of sub-errors.

This project aims to solve this team's need, increasing the visibility of available data and modeling it, in order to provide the MTBF parameter as a new analysis method that will help plan equipment that needs a planned intervention, introducing thus, a predictive maintenance approach, in order to maximize resources and increase equipment availability and consequently the reliability of each ATM.

Chapter 4

ATM failure prediction - Practical Implementation

This chapter presents the tools developed to respond to the needs identified in the previous chapter. The tool is made up of two parts. The first part is a program executable in a Windows environment, which receives an Excel file with data from the current park. This file is sent monthly by the main client and represents the park for which the company is responsible for the maintenance and proper functioning of the equipment. The application developed for this project connects directly to the company database, accessing the incidents caused by the equipment referred to in the Excel file. The data is processed and the application transforms this data into two Excel files that are placed in the company internal cloud, thus feeding the Power-BI template that constitutes the second part that is available to SLM team coordinators.

The pratical implementation of this project was divided into two distinct phases, each divided into subphases. The implementation of the phases will be presented and explained in detail below.

4.1 Phase 1 - Development of the Data Extraction and Manipulation App

4.1.1 Initial Development

Based on the active park and taking into account the objectives of this project, a program was initially created, in WinForms C#, which receives the park's Excel file (*available monthly by the customer with active ATM*) and, taking into account counts this information, accesses the database and fills in the list of incidents received between two chosen dates, relating to equipment in force between two chosen dates as shown in Figure 4.1.

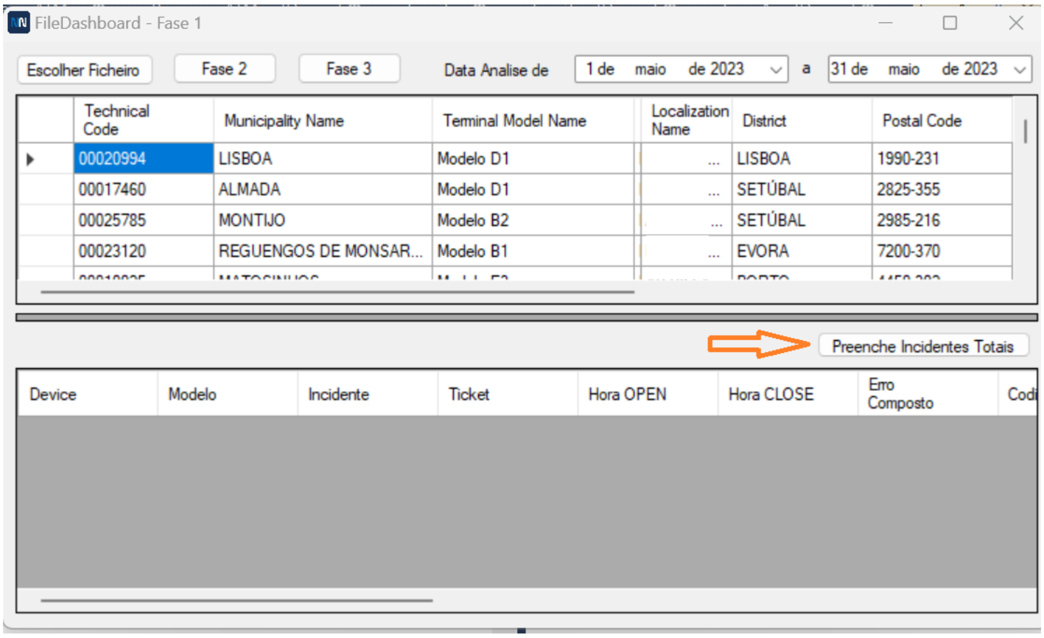


Figure 4.1: Winforms C# Incident Extraction

When filling *datagridview* with incidents, the program decomposes some fields in the database and organizes the information for each incident line as described in the table 4.1.

Field Name	Description	Field Type
Device	ATM identification	DB Field
Model	ATM model	DB Field
Incident	Unique incident identifier	DB Field
Ticket	Ticket to which the incident belongs. A Ticket can have N incidents.	DB Field
OPEN Date	Incident opening date and time	DB Field
CLOSE Date	Incident closing date and time	DB Field
Compound Error	Composite error consisting of code and corresponding text	DB Field
Error Code	Error code	APP Field
Error Text	Text description of the error code	APP Field
Module	Composite module of the ATM to which the error refers	DB Field
Final Module	Specific module the error refers to	APP Field
Incident Type	Incident type - (Automatic or Manual Opening)	APP Field
Scheduling	Whether or not an appointment with the FLM was necessary	DB Field
Time Minutes	Time elapsed in minutes between the date the incident was opened and the incident closed	APP Field
Zone	Zone to which the ATM belongs	DB Field
District	District in which the ATM is physically installed	DB Field
Municipality	Municipality in which the ATM is physically installed	DB Field
FLM	First Line Entity ATM Maintenance	DB Field

Table 4.1: Table of Database Fields and APP Generated Fields

The team's performance assessment, by decision of the company, is carried out on a monthly basis, although the program developed allows the introduction of a time interval of the user's choice if necessary.

Therefore, on a monthly basis, the application receives the file of equipment under maintenance and generates the first excel file, which, as explained in table 4.1, contains all incidents generated by ATM in the corresponding month. With this data, the application calculates the equipment's downtime, its uptime, the number of incidents generated, as well as the equipment's MTTR and MTBF for the month in question. This calculated data is then saved in the second excel file generated by the application.

Here it is important to highlight that the calculation of downtime, uptime, MTTR and MTBF is done in two ways. The first way is in real time, considering that each ATM module has the same weight. The second way is time weighted, based on the time weighted table weights 3.1.

The time measure used is minutes, as this is the measure used by the team.

To calculate MTTR, MTBF and uptime values, the following formulas were used:

$$MTTR = \frac{\text{Total Repair Time}}{\text{Qty. of Incidents}}$$

$$MTBF = \frac{\text{Total Time - Stopping Time}}{\text{Qty. Stops}}$$

$$Availability = \frac{\text{MTBF}}{(\text{MTBF + MTTR}))}$$

After compiling the initial information, in terms of data, it was concluded that there is a lot of data available. However, the way they were stored was somewhat isolated and not organized. For example, when the technician goes to the site to carry out an intervention, he fills out an intervention report in which he writes, in free text, the comments relating to the intervention carried out. There was no classification as to what led to the incident, nor was there a cross-check as to whether or not the technician spent material on repairing the equipment. The job sheets[1] are created independently and were not linked to any equipment itself. That is, the field technician, when repairing equipment, if he replaced an ATM part, would return the damaged part to the company's laboratory for repair, but there was no field in the database that would automatically inform the team coordinator that parts had been replaced. In practice, coordinators were unable to visualize how many field interventions were made to replace parts.

4.1.2 Data Improvement

Recalling some concepts learned and based on the article [2], two levels of classification were proposed.

- Incident with on-site technician (*when FAT intervention is required to repair the equipment*)
- Incident without technician on-site (*when CLOSE is received in the system without there being a FAT SLM intervention*)

Within the case ***Technician on site*** the following main reasons are proposed:

[1] The job sheets refer to the parts used in interventions.

- Module OK on arrival;
- Incident with a cause external to the ATM;
- Incident caused by hardware failure;
- Incident caused by software failure;
- Incident caused by dyeing system.

In the case of an incident ***No Technician on site*** the following main reasons were proposed:

- Incident canceled without intervention;
- Resolved by phone;
- Canceled appointment (either by FAT or ETV);
- Duplicate incident;
- Canceled by Equipment Network Management.

These reasons were proposed to the field services coordination team and technical coordination and after approval, they were implemented in the application for closing technician interventions, which came into force on March 20, 2023. At the request of technical coordination, One more field was also added to help you know how to obtain CLOSE in a field. Another point, which took the opportunity to make at this stage, was the fact of starting to relate the worksheets generated with the equipment on which the technician completes the intervention, so that this information can also easily be seen on *dashboards* designed for the phase 4.2 of this project.

4.1.3 Final Development

As mentioned previously, for this project a monthly assessment of incidents was carried out, although at any time this assessment could be made based on two dates of choice.

Considering that the incident data set for a month is created from the monthly file of the current ATM fleet, this avoids generating data from uninitialized ATM.

At this stage, with the new version of the technical intervention closures application, referred to in the previous point, being already in force, the application developed in the 4.1.2 phase has changed, and the classification fields of each occurrence (based on in the technician's diagnosis carried out at the repair site) were also removed, as well as the field relating to the existence or not of replacement of material for repairing the ATM. This data gave rise to a third file generated by the application and which was also used in phase 2 of this project. This file proved to be very useful and effective in identifying and clarifying the reasons for incidents and the resulting *modus operandi* of the field team.

4.2 Phase 2 - Development of Power-BI Template

With the first phase completed, and based on the files generated in the application developed in the previous phase, a template was created in Power-BI, so that this tool can add new data visualization dimensions, helping to clarify the variables present in the day-to-day field work and consequently improve the information available to support decision-making. Power-BI was used, as the company has licensing available for all users of its domain, making it easy to share information between the different teams. At this point, access security has not been forgotten because within domain sharing, the administration panel allows the choice of whether a given report can be seen by everyone within the domain or only by specific people. These reports are also easily shared as a tab via Microsoft Teams, a tool also used in the company in question.

The developed template was designed based on the need felt by the operational coordination team. The objective is to quantify and group incidents and observe their evolution by comparing the different models and areas where the equipment is physically installed.

The template report created is made up of ten tabs, each with a schematic type of information. The table 4.2 presents a brief description of these separators and each of them will be explained in more detail below.

Power-BI Tab	**Description**
General Incidents	Dashboard with general data on incidents caused by active ATM
Model Incidents	Dashboard relating to incidents generated by ATM model
Uptime by Zone Model	Dashboard relating to the uptime of each model by zone
MTBF by Zone Model	Dashboard relating to the MTBF of each model by zone
MTTR by Zone Model	Dashboard relating to the MTTR of each model by zone
Analysis by Device	Dashboard relating to the detailed analysis of data available about each ATM in the park
Type Incidents Module	Dashboard relating to the analysis of the type of incidents per module
Type Incidents Model	Dashboard relating to the analysis of the type of incidents by model
Incident Classification	Dashboard related to data analysis by classifying the origin of incidents
MTBF to Check	Dashboard relating to the analysis of the MTBF parameter of each ATM equipment

Table 4.2: Table of Dashboards Available in Power-BI

Monthly, on the first business day of each month, the incident base from the previous month is added to this report. To do this, it is just necessary to run the tool mentioned in the 4.1 phase. In the various tabs, data segmentation was placed in all of them so that the analysis can be carried out by Zone, by module and model.

4.2.1 General Incidents

In this tab is possible to see a general overview of the incidents received. The quantity and type of incident (manual or automatic) are displayed, as well as the number of total incidents and percentages for each module. In this data segmentation, views can be chosen depending on the area to be evaluated and the data can also be evaluated on a monthly basis (Figure 4.2).

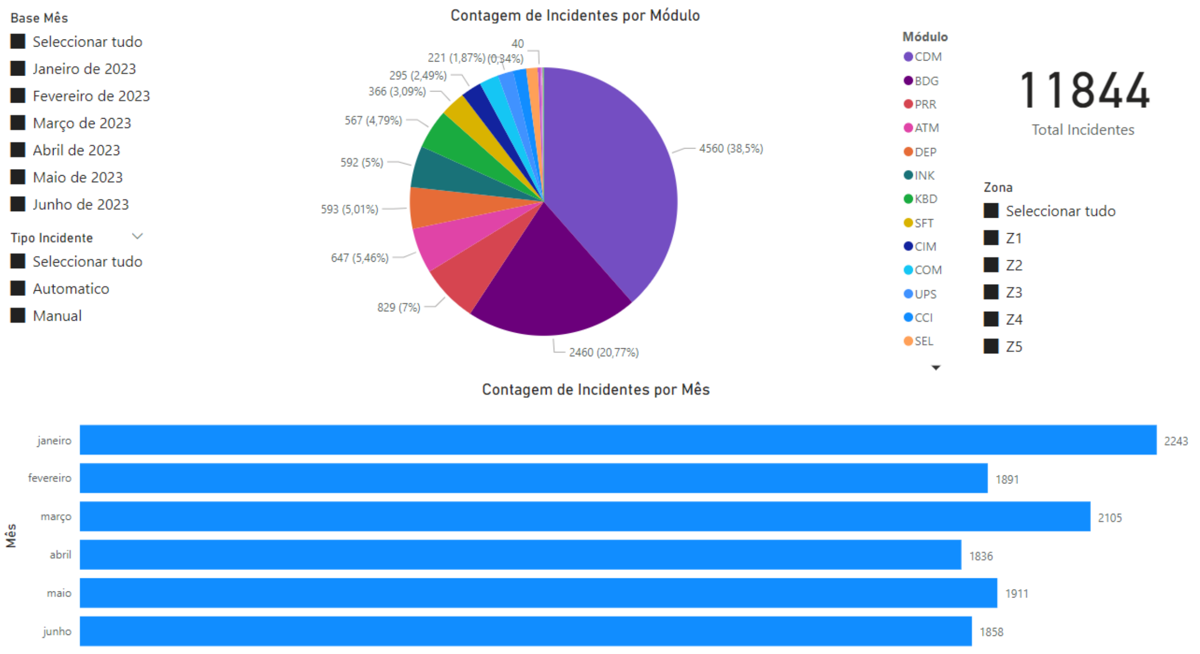


Figure 4.2: General Tab Incidents

4.2.2 Model Incidents

Since the equipment fleet has several different models, it is important to easily visualize which equipment has the most incidents and which model. In this tab, a funnel chart was created that highlights this issue and which modules generate the most incidents in each model (Figure 4.3).

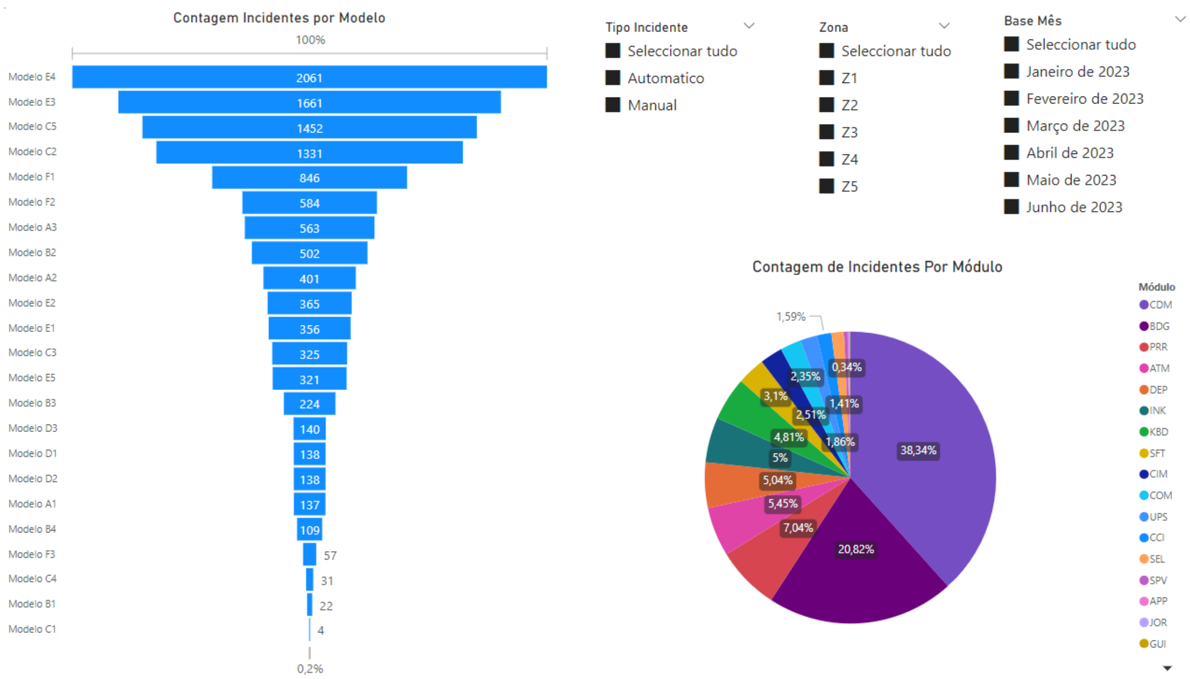


Figure 4.3: Tab Model Incidents

4.2.3 Uptime by Zone Model

In this tab (Figure 4.4) Is possible see uptime data by zones and model. It is also possible to view data segmentation by the number of incidents related to the chosen equipment model.

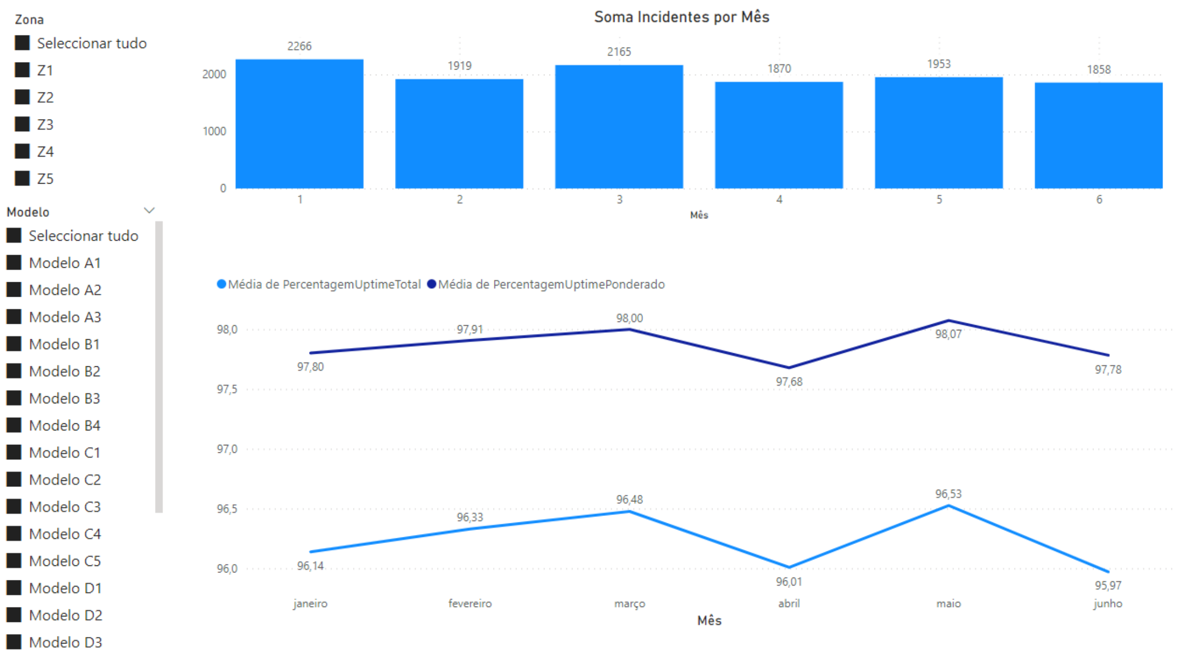


Figure 4.4: Uptime Tab by Zone Model

One point that is easily visible in this tab is that, as shown in Figure 4.5, having fewer incidents is not directly proportional to greater uptime. This is due to the fact that some incidents have a higher MTTR because it is necessary for the FLM team to provide access to the equipment.

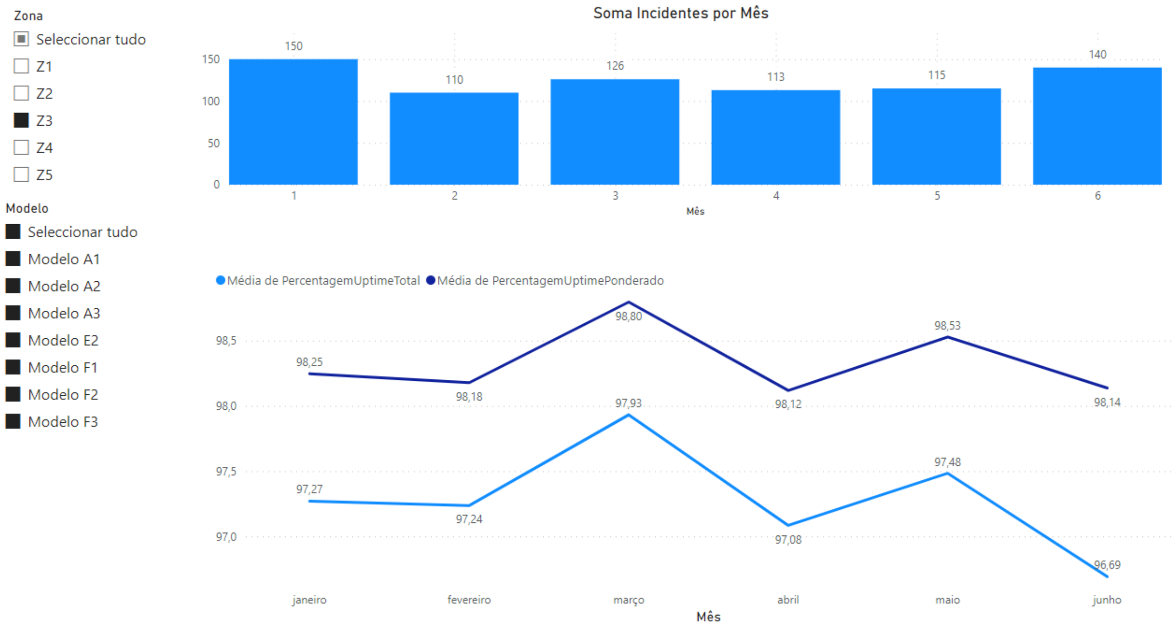
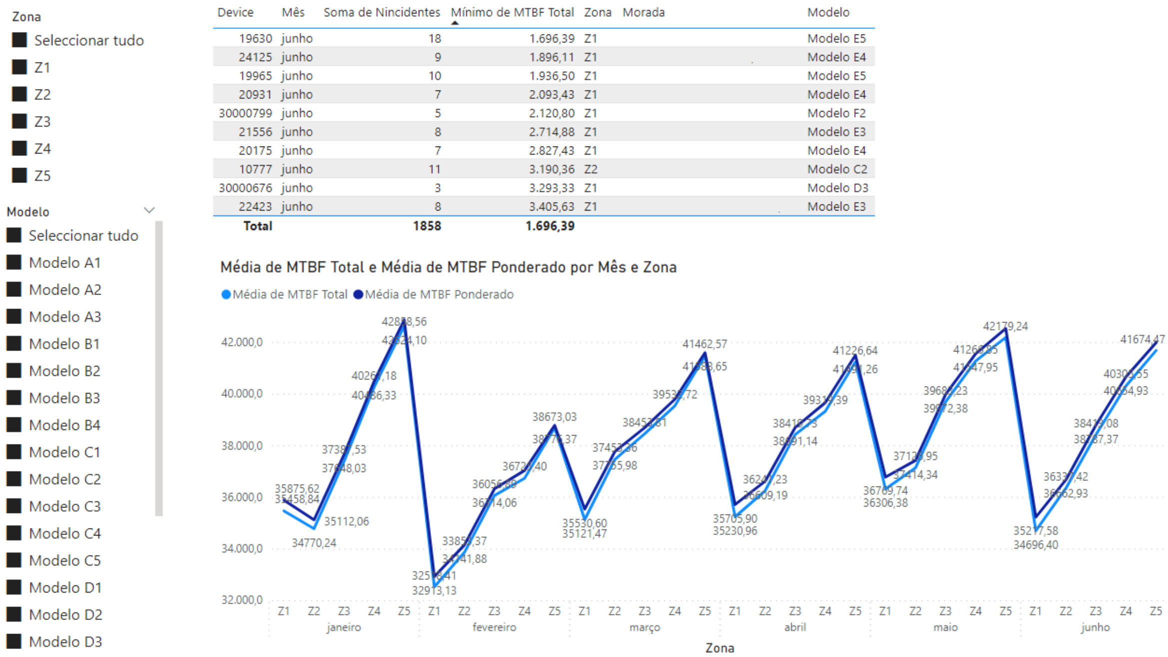


Figure 4.5: Uptime Tab by Zone Model - Detail Z3

4.2.4 MTBF by Zone Model

The tab represented by the Figure 4.6 highlights the MTBF of the areas based on the last month (see segmentation table) and also represents the average MTBF in the past months. It is possible to see all zones at the same time or by choosing just one zone. Here the evolution of this parameter over the months is easily visible, as shown in Figure 4.7 for example.



Device	Mês	Soma de Nincidentes	Mínimo de MTBF Total	Zona	Morada	Modelo
19630	junho	18	1.696,39	Z1		Modelo E5
24125	junho	9	1.896,11	Z1		Modelo E4
19965	junho	10	1.936,50	Z1		Modelo E5
20931	junho	7	2.093,43	Z1		Modelo E4
30000799	junho	5	2.120,80	Z1		Modelo F2
21556	junho	8	2.714,88	Z1		Modelo E3
20175	junho	7	2.827,43	Z1		Modelo E4
10777	junho	11	3.190,36	Z2		Modelo C2
30000676	junho	3	3.293,33	Z1		Modelo D3
22423	junho	8	3.405,63	Z1		Modelo E3
Total		1858	1.696,39			

Figure 4.6: MTBF Tab by Zone Model

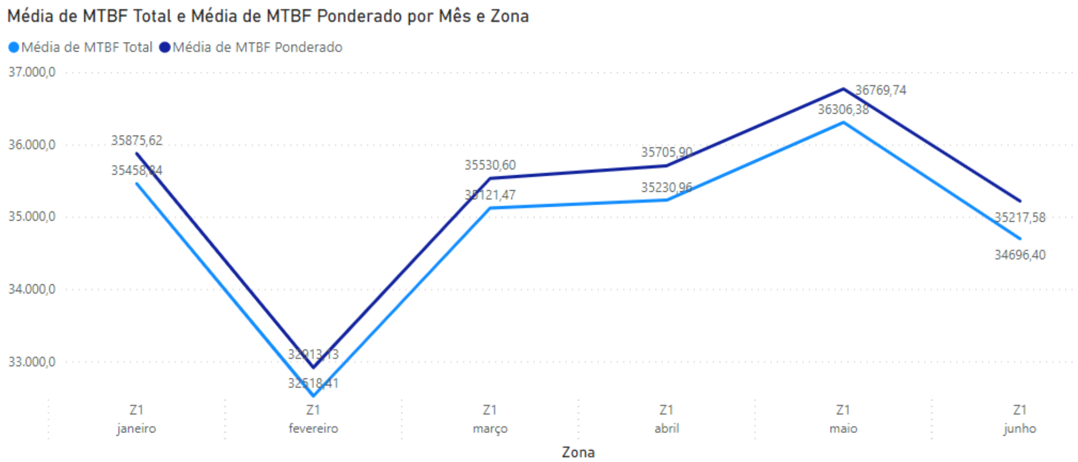


Figure 4.7: MTBF Separator by Zone Model - Detail Z1

This tab is important as it allows you to view and evaluate the average MTBF for a given area/model and see which equipment has an MTBF below the average value.

4.2.5 MTTR by Zone Model

Although the increase in MTBF and uptime parameters are the central point of this project, it is also important to evaluate the MTTR, so that it is possible to improve the response capacity of the field team. The increase in incidents and the fact that it is necessary for a third party to give access to the equipment to repair it, may lead to the MTTR increasing.

In this tab is possible see the number of incidents per model/zone, as well as the respective MTTR, as shown in Figure 4.8.

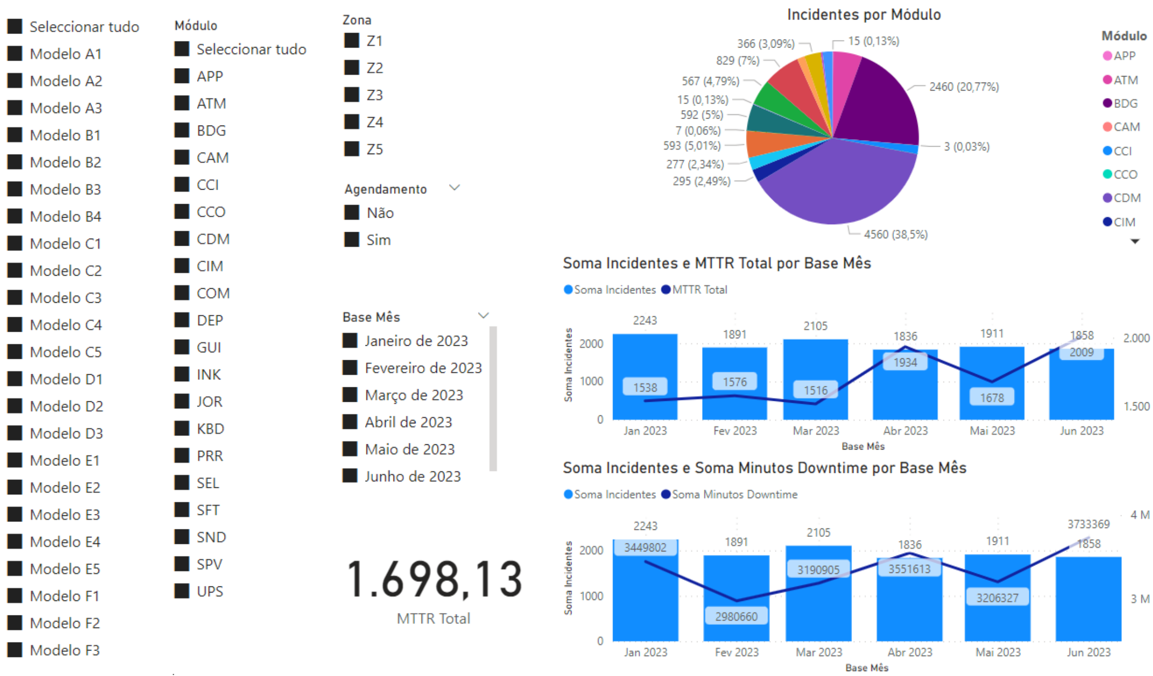


Figure 4.8: Tab MTTR by Zone Model

In the analysis of this tab, stands out the fact that the MTTR analysis must be carried out using the available segmentation regarding whether the incident is scheduled or not, so that the conclusions are as effective as possible.

4.2.6 Analysis by Device

In this tab, illustrated by Figure 4.9, is possible to choose any ATM that is part of the assisted park and have a visual procession of the evolution of the chosen equipment, as well as its uptime in previous months, as well as the average MTBF and MTTR that it had in previous months.

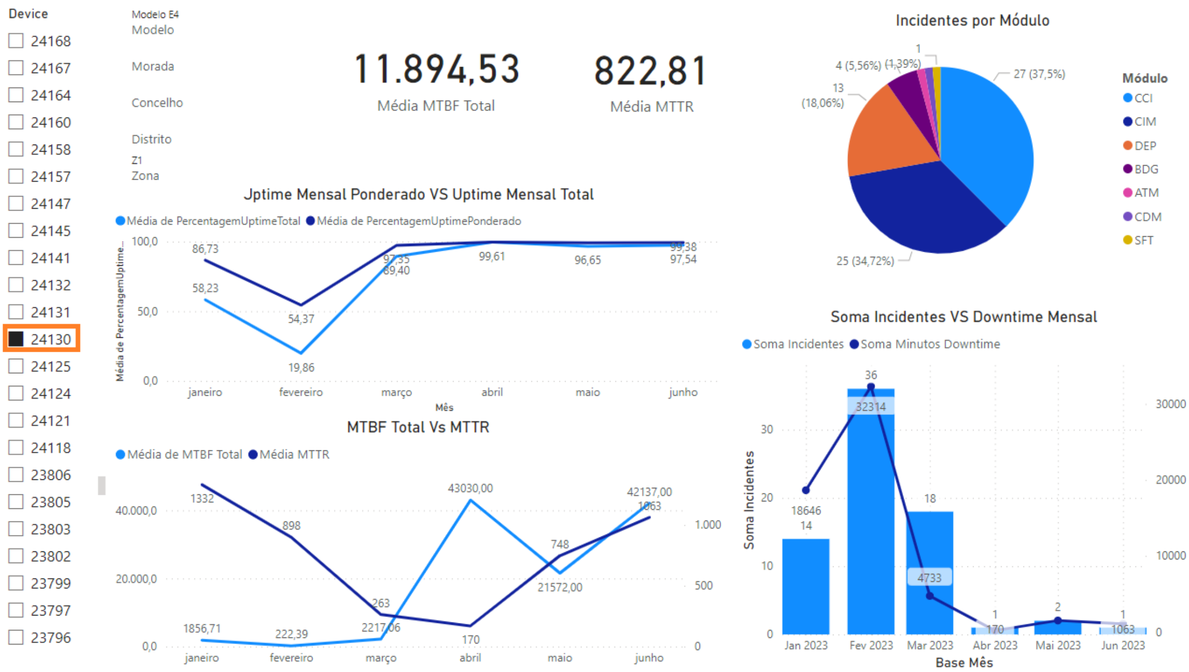


Figure 4.9: Tab Analysis by Device

It is also possible to see which modules cause the most incidents. This analysis allows to take a deeper look at the real problem affecting the ATM in question. For example, in Figure 4.10, choosing the percentage module that is being analyzed from the Pie Chart, the segmentation below shows the number of incidents and downtime that this module represented in the last few months of equipment operation.

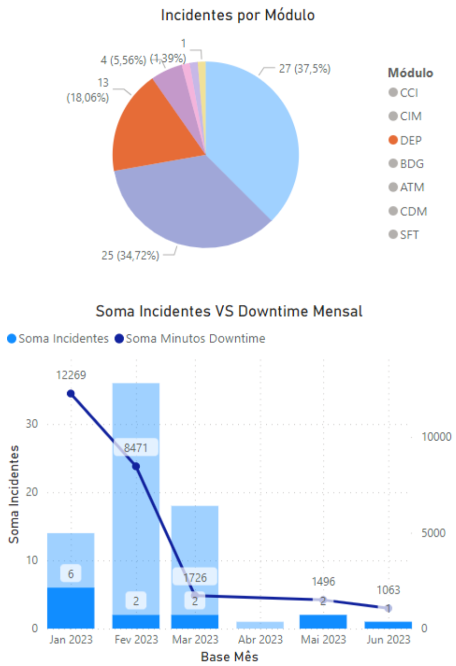


Figure 4.10: Analysis by Device - Detail 1

4.2.7 Type Incidents Module

In this tab is provided the visibility of all incidents by model/module, as shown in Figure 4.11. Is possible analyze by automatic incidents or manual incidents. Recapitulating the previous chapter, manual incidents are requested, for some reason, by those responsible for FLM or by the Network Management that manages the ATM. Automatic incidents are generated, as the name suggests, automatically by the equipment. In this tab is possible analyze which models generate the most incidents and what type. Also noteworthy is the possibility of, in each model, it is possible to analyze the error code itself. In this tab there is only data after April 2023, as this is one of the changes in the application of field technicians, which allowed the classification of these incidents.

For example, looking at the Figure 4.12, choosing the module CDM module, the funnel chart shows the number of incidents of that module that each model in the park had.

But if with this choice, combine the choice, for example of the code of the error code CDM22140302, as shown in Figure 4.13, the funnel graph will show the representativeness of this error code in the universe of CDM incidents, as well as the Pie Chart will show the total number of errors and their representation in the park.

The information presented in this tab, in addition to being important for evaluating

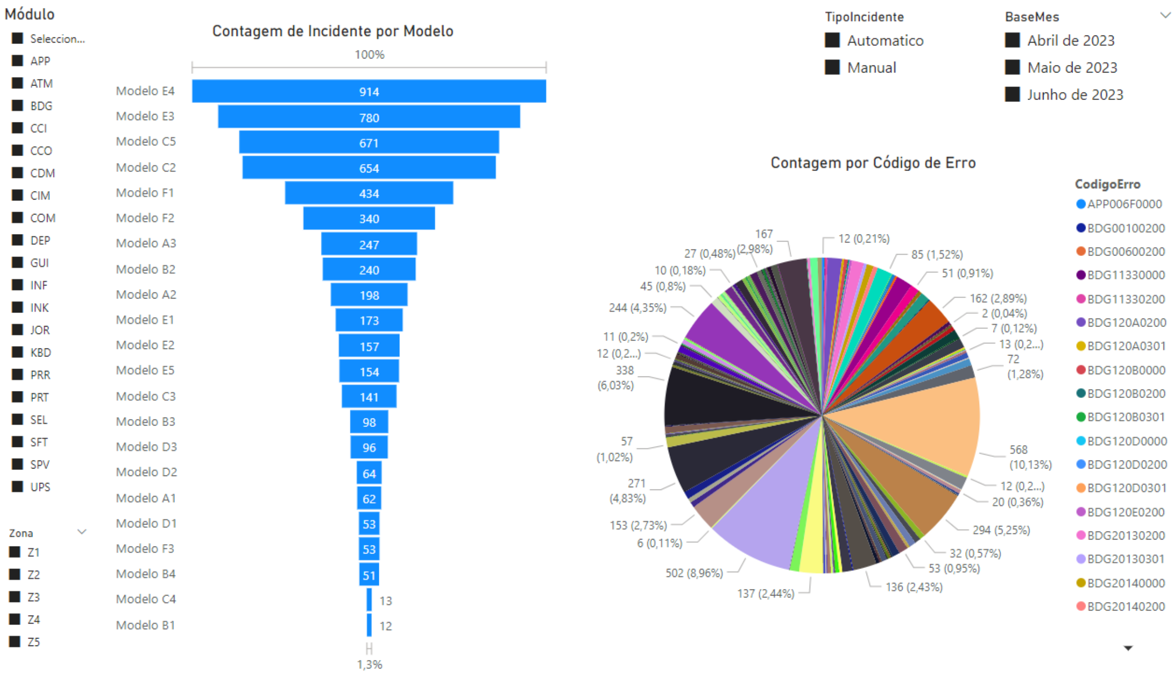


Figure 4.11: Tab Type Incidents Module

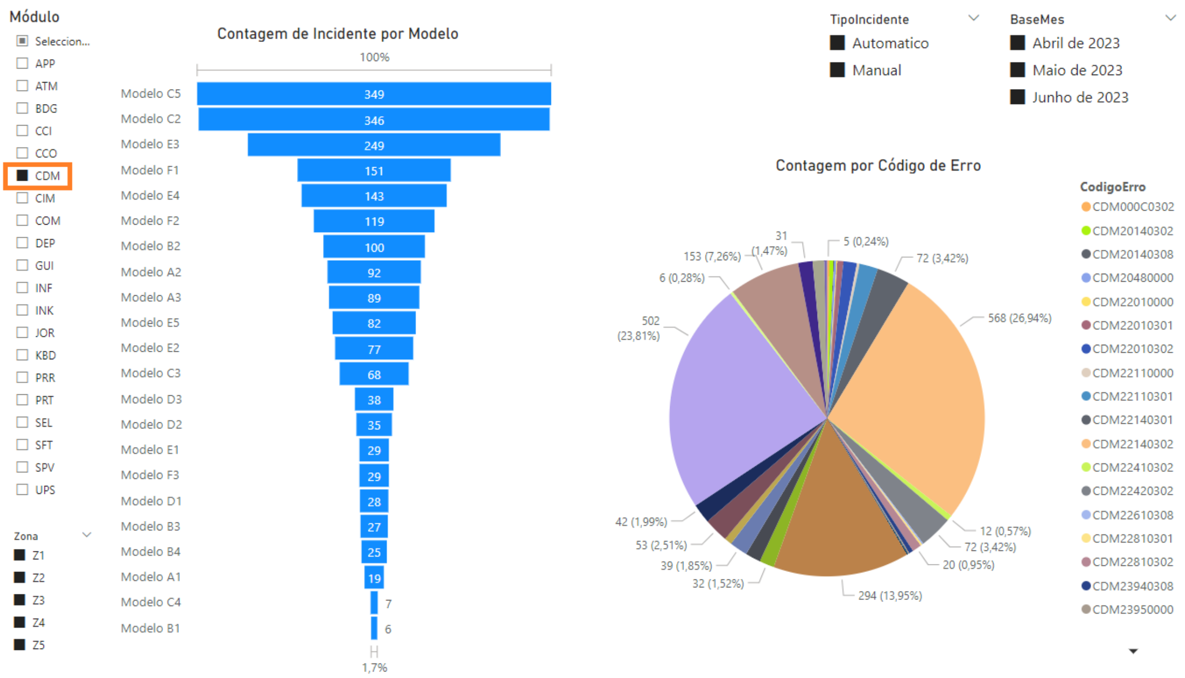


Figure 4.12: Module Incident Type - Detail 1

what happens in the field, is also important information for the laboratory department. This is because the parts replaced in the equipment are repaired in the laboratory. Therefore, if the laboratory also knows which errors ATM generate most in the field, the more effective the laboratory repair becomes as each error code is generated by a component

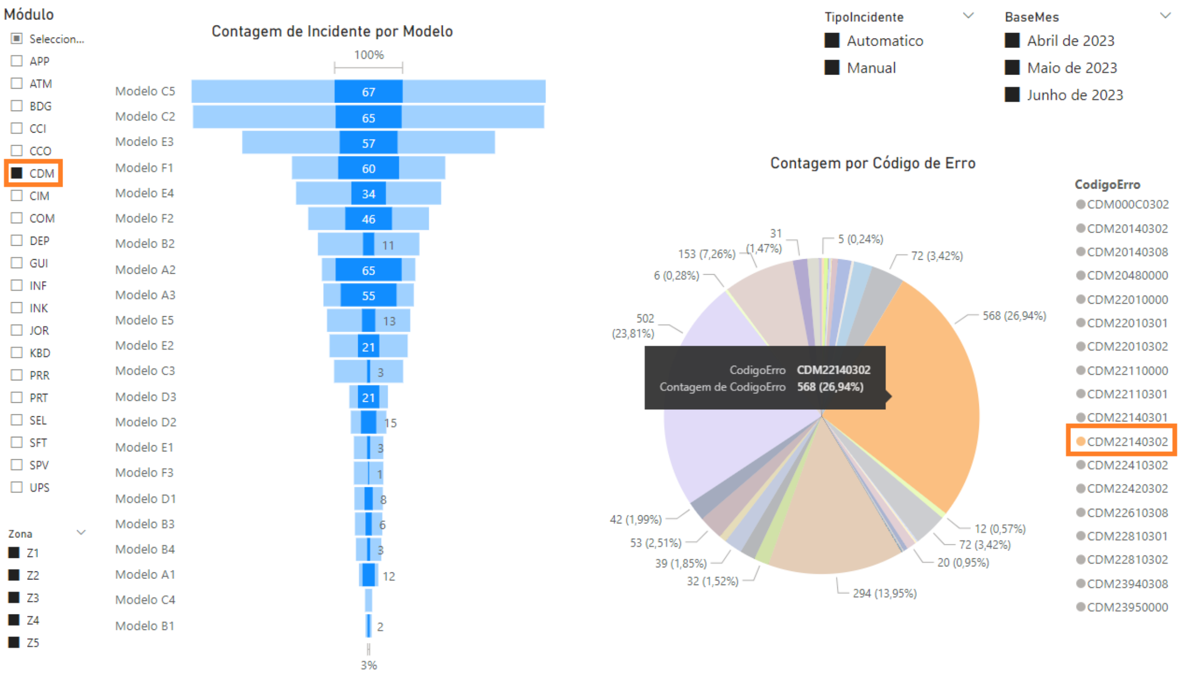
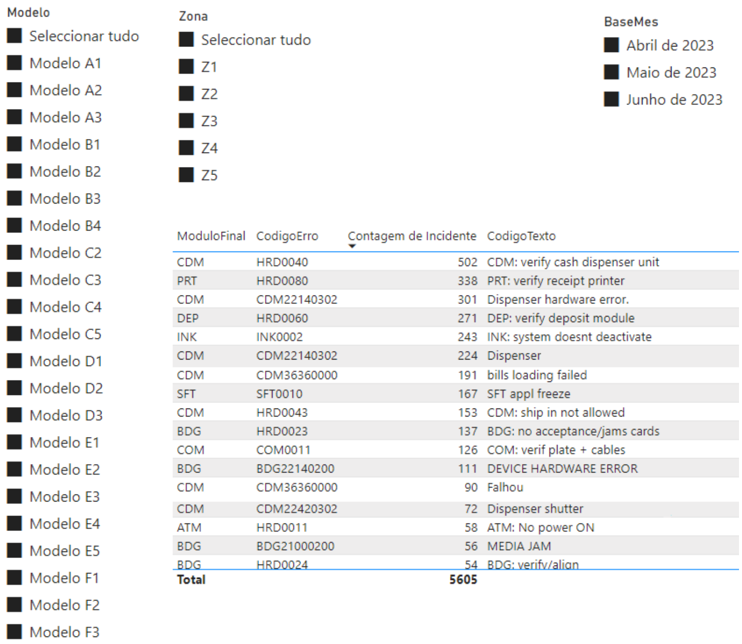


Figure 4.13: Module Incident Type - Detail 2

of the main module itself. For example, the acronym CDM refers to the Cash Dispenser Module, and the module itself has several different components. Clarifying the error code also allows the repair team to be more aware of the repair of a specific component of the main module and to more quickly and effectively detect anomalous error patterns generated by ATM.

4.2.8 Type Incidents Model

This tab is similar to the one explained in the previous point. However, this presents a model/zone approach. In Figure 4.14, referring to this tab, there is a segmentation in which it is possible to choose to carry out the analysis by model or choose to check in which area a model causes the most errors and what type. As in the previous one, this tab shows the type of errors but also adds the Text Code that corresponds to that same Error Code in order to facilitate the understanding of the data.



ModuloFinal	CodigoErro	Contagem de Incidente	CodigoTexto
CDM	HRD0040	502	CDM: verify cash dispenser unit
PRT	HRD0080	338	PRT: verify receipt printer
CDM	CDM22140302	301	Dispenser hardware error.
DEP	HRD0060	271	DEP: verify deposit module
INK	INK0002	243	INK: system doesnt deactivate
CDM	CDM22140302	224	Dispenser
CDM	CDM36360000	191	bills loading failed
SFT	SFT0010	167	SFT appl freeze
CDM	HRD0043	153	CDM: ship in not allowed
BDG	HRD0023	137	BDG: no acceptance/jams cards
COM	COM0011	126	COM: verif plate + cables
BDG	BDG22140200	111	DEVICE HARDWARE ERROR
CDM	CDM36360000	90	Falhou
CDM	CDM22420302	72	Dispenser shutter
ATM	HRD0011	58	ATM: No power ON
BDG	BDG21000200	56	MEDIA JAM
BDG	HRD0024	54	BDG: verify/align
Total		5605	

Figure 4.14: Tab Template Incident Type

4.2.9 Incident Classification

In this tab, referring to the Figure 4.15, it possible see the classification carried out by field technicians when they are carrying out an intervention. This tab reflects the results of the implementation referred to in 4.2. Segmentation by ATM model, by zone or module is also available in this tab for analysis. This tab is important because it clarifies and quantifies the reason that led to the incident, how it was resolved and whether or not the technician was on site.

In this same tab, by choosing the “Yes” option, as illustrated in Figure 4.16, it is quantified in which incidents parts were replaced and the reasons that led to these incidents

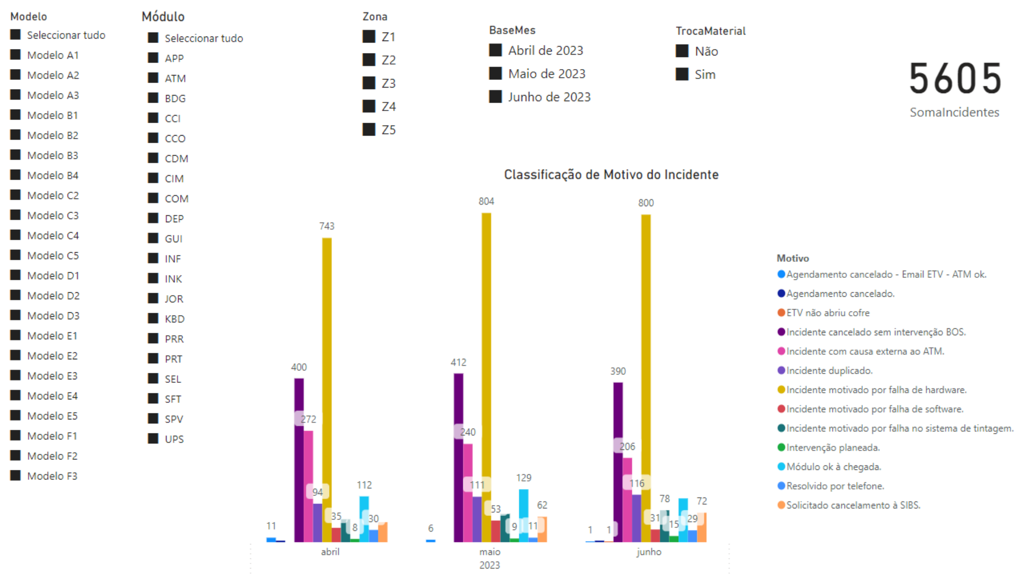


Figure 4.15: Tab Incident Classification

where material was replaced. The reasons for the incidents presented in this tab are those defined and referenced in the section 4.1.2.

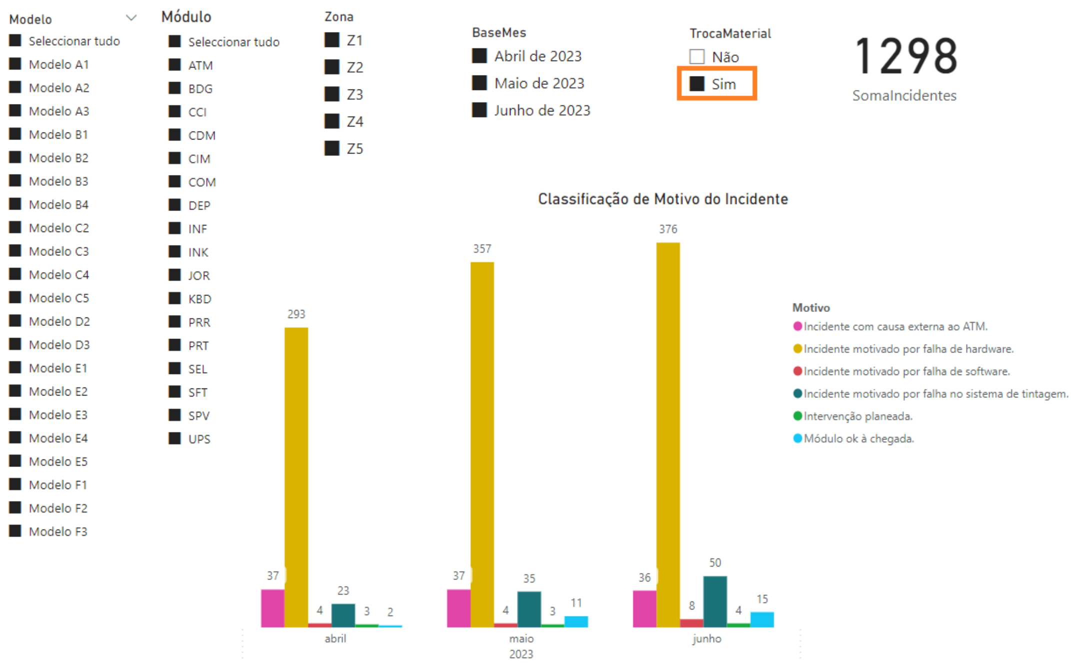


Figure 4.16: Incident Classification Detail

4.2.10 MTBF to Check

This tab reflects the average MTBF parameter of all equipment being maintained by the team. Three segmentations are available: by model, by district and by municipality and the three segmentations can be used together or separately. This is one of the main tabs of the Power-Bi template created for this project, because it allows the visualization of the MTBF parameter, showing which devices have the lowest MTBF, as shown in Figure 4.17. In the table shown, it is possible to sort this parameter in ascending or descending order, depending on the analysis desired by the user.

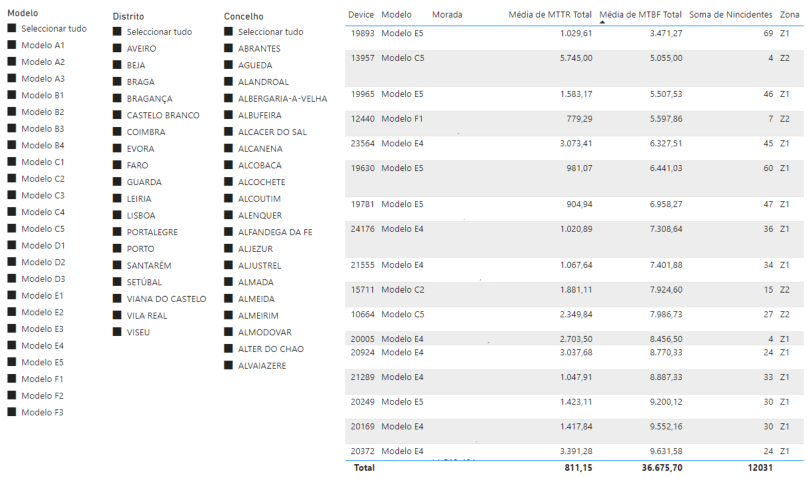


Figure 4.17: MTBF Tab to Check

When the user goes over the list of equipment, on each device a sub-graph is displayed relating to the uptime of the ATM in question. So whoever uses this tab can quickly analyze whether the ATM, despite having the lowest MTBF, has already been resolved or not based on uptime evolution (Figure 4.18).

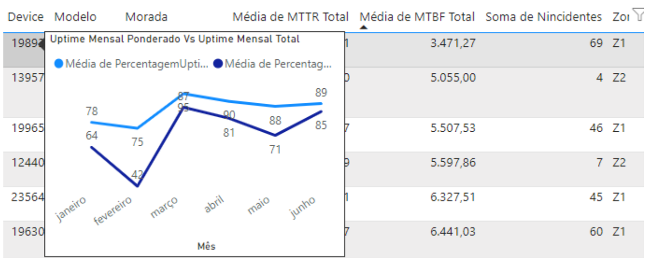


Figure 4.18: MTBF Uptime Detail to Check

The ten tabs designed in the Power-BI template aim to give a new view of the maintenance processes for the set of equipment in place. As previously mentioned, phase 1 of this chapter resulted in the technicians' closing application being changed to allow the classification of incidents. The template developed in phase 2 of this chapter was made available to the field coordination team at the beginning of April 2023. Based on the results presented and their evolution, it was possible to choose six pivot ATM to carry out preventive maintenance. The results of this pivot are presented in the results analysis chapter.

Chapter 5

Results analysis

As previously mentioned, the data used in this project refers to a set of ATMs physically installed in several districts of Portugal. The initial data set is made up of incidents generated, since the beginning of 2023, by these equipment. Based on the art study presented in the chapter 2, in March incident classification methodologies were introduced and incident resolution metrics were added. This data began to be included in the original data set from April 2023. The fact that incident classification began to exist allowed operational teams to have information on what caused equipment failures.

This results analysis chapter is divided into two sections. The first section refers to a data analysis on the final data set obtained and the second section to the pivot of preventive maintenance interventions carried out within the scope of this project.

In total, seven months of data from the equipment fleet were processed and analyzed. The first three months with the original data set and the last four months with the complete data set, which allowed greater knowledge about the incidents that occurred during that period, namely their classification, as well as the consumption of repair material. The implementation of the tools explained in 4.2 and the data analysis that will be referred to in 5.1, allowed six pivot equipment to be chosen to carry out preventive maintenance and to be able to analyze the behavior of the equipment before and after this intervention planned. This equipment was chosen, based on the previous study that was carried out in chapter 2.12, as these six ATM, among their peers, were the ones with the lowest value of the MTBF parameter.

5.1 Data Analytics Google Collab

One of the analyzes carried out within the scope of this project was a general analysis of incidents to increase knowledge about the park's behavior. The *Google Collab* tool was used, using the two main *datasets* of this project, the file *BaseIncidentes7Meses.xlxs* and the file *BaseClassificacaoIncidentes4Meses.xlxs*. The language used was the Python language, as it is widely used in data analysis. The *sweetviz* library [1] was installed, which allowed obtaining the results that will be presented in this section.

The exploratory analysis that resulted from the files is presented in the following points of this section.

5.1.1 General Park Data - Correlation Maps

Figure 5.1 illustrates the quantity of equipment per model, regardless of the geographic area of installation. It is easily visible that the F1, E3 and F2 models are the ones with the greatest representation in the park.

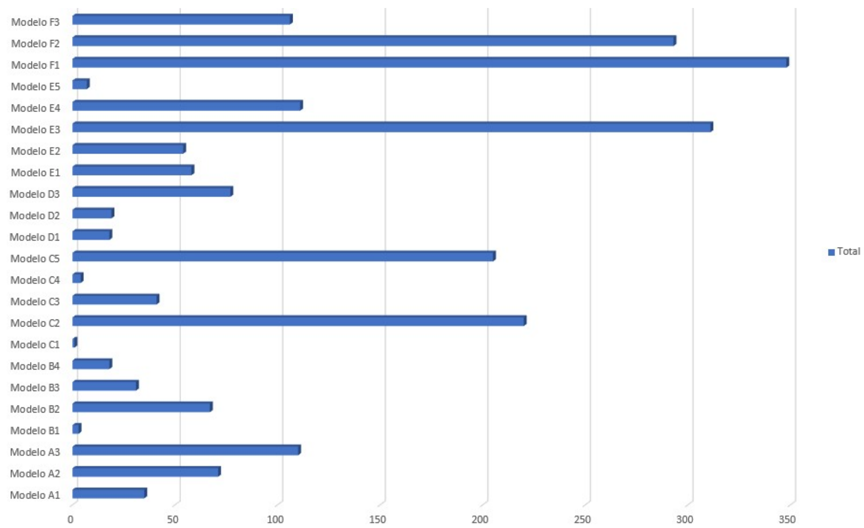


Figure 5.1: Quantities Vs Models

However, as can be seen from the Figure 5.2, the models that, in percentage terms, are responsible for more incidents are models E4, E3, C5 and C2. Together, these four models caused 54% of the park's failures. This is an analysis that did not exist before the

[1]Sweetviz is an open-source Python library that generates high-density exploratory data analysis (EDA) visualizations. The data is generated and gives rise to an HTML file.

practical implementation of this project, as incidents were not quantified in a clear and grouped way.

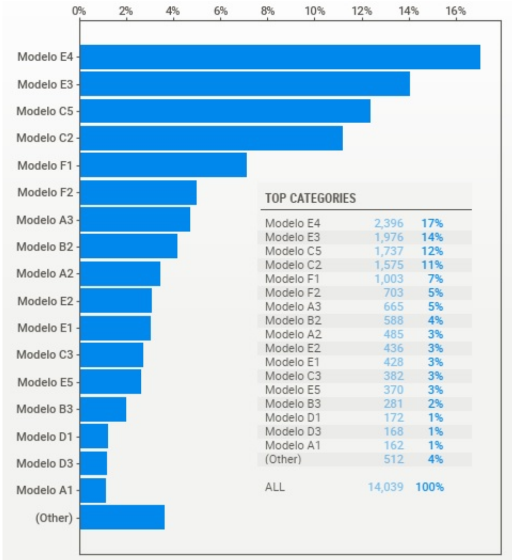


Figure 5.2: Incidents Vs Models

Observing Figure 5.3, it is possible to conclude that the two most critical modules in terms of incidents are the CDM (Cash Module Dispenser) and the BDG (Badge Card Reader), these two modules are responsible for 60% of incidents generated by the set of equipment analyzed.

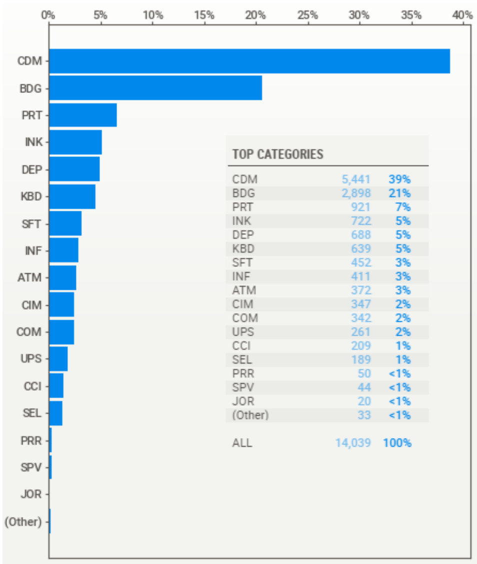


Figure 5.3: Modules with the Most Incidents

From the Figure, 5.4, is possible to see that the incidents are mostly automatic, however, these are not a numerical increase in relation to the number of manual incidents, requested by the FLM. As explained previously, automatic incidents are generated, as the name indicates, automatically by the ATM. Manual incidents are incidents that are required by FLM teams. The fact that, after introducing the classification of the reason for the incidents, the origin of the incidents is clarified and cross-referenced this information with the classification of the reason, is an added value because knowing the origin of the cause, it is possible to effectively plan its resolution and minimize downtime caused by incidents.

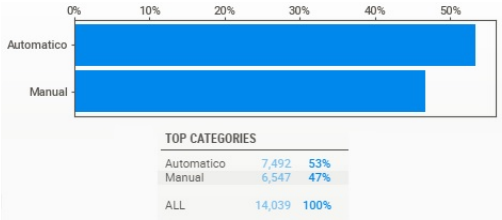


Figure 5.4: Typology of Incidents

Still in relation to incidents, from Figure 5.5, is possible to see that for the most part, to intervene in an incident, it is not necessary to schedule an appointment with a third entity to repair the equipment.

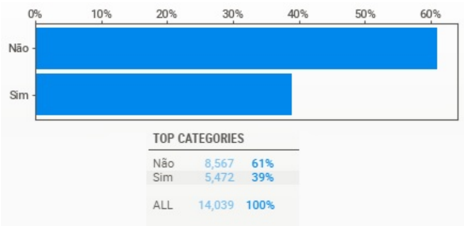


Figure 5.5: Intervention Typology

The fact that it is not necessary to schedule a time for intervention is a factor that directly affects the availability of equipment, and causes an increase in MTTR.

Figure 5.6 represents the correlation map of the *features* analyzed.

It is possible to conclude that the model has a strong correlation with typology and age, just as the geographic zone has a strong correlation with the geographic districts. It should be highlighted the fact that the type of incident has a strong correlation with the module that originates the incident, and it should also be noted, once again, that the average repair time, in minutes (MTTR), has a strong correlation with the 'Scheduling'

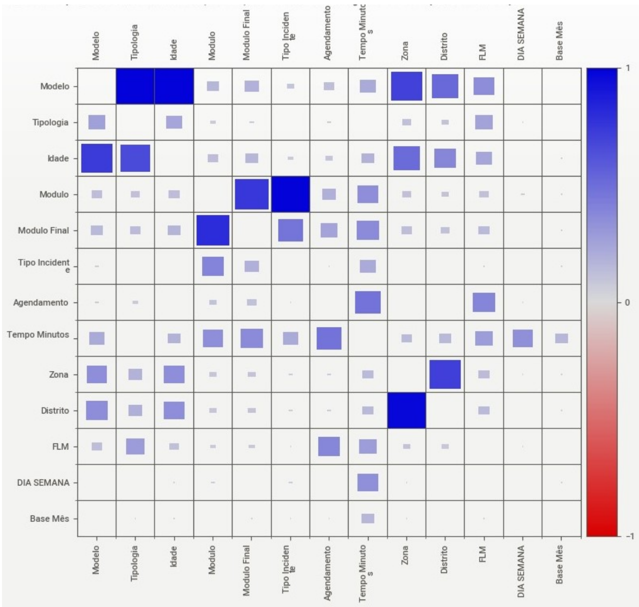


Figure 5.6: HeatMap - Correlation Features Incidents - 7 Months

feature, that is, whether or not it is necessary to request access to third parties to carry out a repair. The day of the week on which the incident occurs also has a high correlation with the MTTR of that same incident.

From the graph, illustrated in Figure 5.7, It is also possible to conclude that during the week, the day on which fewer incidents occur is Thursday and that there is a decrease in incidents at the weekend.

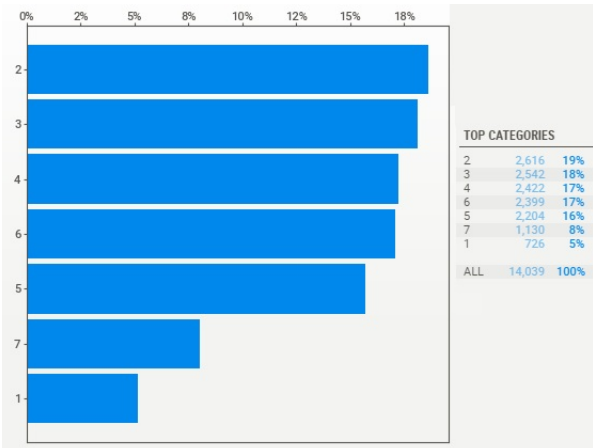


Figure 5.7: Input Incidents Vs Day of Week

As previously mentioned, in the last four months after the developed tool was put into effect, it was concluded that, as can be seen in the Figure 5.8, only in 67% of the incidents, there was a need for the SLM team, intervene locally on the equipment.

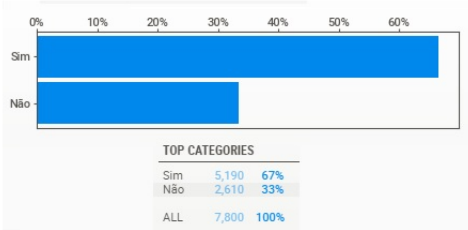


Figure 5.8: Incidents vs Go to Site

And in the universe of these 67% incidents, in 76% of cases, the ATM was repaired without the need to change parts. In 24% of cases, parts needed to be replaced.

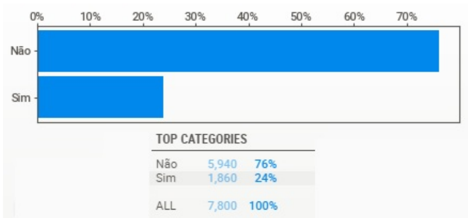


Figure 5.9: Histogram Incidents Vs Visits to the Site Vs Material Exchange

Figure 5.10 refers to the classification of incidents, clarifying the field diagnosis and how the Automatic Teller Machine was recovered.

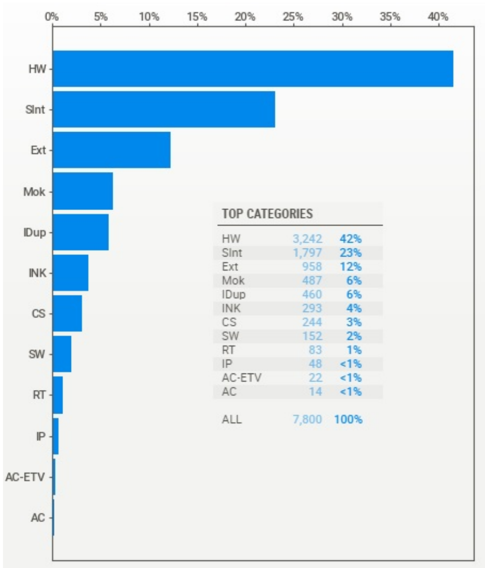


Figure 5.10: Incident Classification

As can be seen in Figure 5.10, it is clear that incidents caused by hardware failure are the most significant (42%), which contrasts directly with incidents caused by software (2%). In terms of classification, in 23% of incidents it was reported that the ATM recovered without any intervention from the team and 1% of incidents were overcome remotely. It should also be noted that 12% of the incidents were classified as having their origin in external causes, these being caused by human factors. For example, such as inappropriate use of the equipment either by the end-user or by the FLM team. The human factor is considered here to be the third biggest factor in the failure of this equipment, thus causing its unavailability.

Analyzing the Figure 5.11, referring to the incident classification correlation map, the FLM feature is correlated with the equipment typology. In addition to the correlations already mentioned in Figure 5.6, it is evident here that the reason for the incident is correlated with the SLM team going to the location to carry out the repair of the ATM, as well as this parameter, it is an influencing parameter in the classification of the incident and obtaining a close-up of the incident and consequently, the recovery of the equipment.

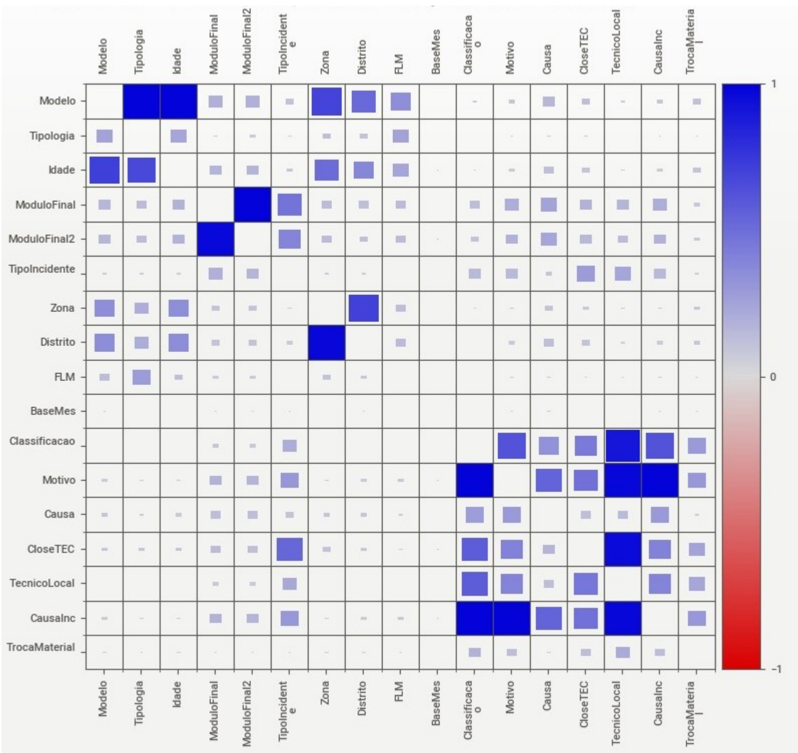


Figure 5.11: HeatMap - Correlation Features Incidents Vs Reasons - 4 Months

Prior to this implementation, the analysis of results carried out by the coordination team was only carried out on a monthly basis based on the client's assessment. The fact that they began to use available internal data in an organized and grouped way was an added value in supporting day-to-day decisions.

5.2 Pivot ATM

The main objective of this project is to increase equipment uptime. The increase in uptime, in addition to increasing the level of ATM user satisfaction, also increases the security of the equipment as no human intervention is required in its ecosystem.

On a practical level, with the kind collaboration of the company's technical team, from April 2023, using as a basis the data presented by the Power-Bi template described in section 4.2 of this project, two machines were chosen per month, to be the target of a preventive technical intervention. The objective, as already mentioned, was to increase the uptime of the equipment as a result of this maintenance. In other words, two preventive maintenance were carried out in April, May and June 2023. These equipment were considered the pivot equipment of this project and were chosen based on the previously calculated MTBF parameter.

In total, six pieces of equipment were chosen. These ATM are installed in a denser population area and had a lower MTBF compared to their counterparts in the same conditions. A preventive maintenance intervention was carried out in each of them, with the objective and focus of increasing the availability of the equipment.

Tables 5.1, 5.2 and 5.3 show the data obtained by the tool developed before and after maintenance on pivot equipment. The value of the MTBF parameter presented in the tables is in minutes.

An important point to mention is that this pivot lasted four months (from April 2023 to July 2023), which explains the fact that the ATM intervened in April have three months of data to analyze results after the intervention of maintenance, the pivot ATM in May have two months of data after the intervention and the last two ATM to enter this pivot only have one month of data for analyzing results. The results of the MTBF and uptime parameters are visible in the respective tables presented below.

5.2.1 Pivot ATM - April

In table 5.1 presents the results of the two ATM that underwent intervention in April. It is possible to see the date of the intervention, as well as data relating to MTBF and uptime in the months before and after the intervention. To make the result of the intervention clearer, the average of the MTBF and uptime parameters before and after the intervention was also calculated. The last line of the table highlights the difference found in each parameter.

Month	**ATM Pivot 1**		**ATM Pivot 2**	
	Model E4		**Model E3**	
	MTBF	**Uptime**	**MTBF**	**Uptime**
jan/23	1857	58.23 %	7960	71.33 %
feb/23	222	19.86 %	8700	86.31 %
mar/23	2217	69.40 %	10553	94.56 %
Apr/23	4303	99.61 %	20035	92.75 %
Maintenance Date	**13/04**		**20/04**	
Previous Average	**2149.75**	**61.78 %**	**11812**	**86.24 %**
may/23	21572	96.65 %	44540	99.78 %
jun/23	42137	97.54 %	40772	94.26 %
jul/23	44640	100 %	39978	97.29 %
Average After	36116.33	98.06 %	41763.33	97.11 %
Difference	33966,58	**+36,29 %**	29951,33	**+10.87 %**

Table 5.1: Pivot ATM - April Maintenance

5.2.2 Pivot ATM - May

In table 5.2 presents the results of the two ATM that underwent intervention in May. As in the previous table, it is possible to see the date of the intervention, as well as data relating to MTBF and uptime in the months before and after the intervention. To make the result of the intervention clearer, the average of the MTBF and uptime parameters before and after the intervention was also calculated. The last line of the table highlights the difference found in each parameter.

Month	ATM Pivot 3 Model E2		ATM Pivot 4 Model C3	
	MTBF	**Uptime**	**MTBF**	**Uptime**
jan/23	6231	83.75 %	44640	100 %
feb/23	3283	48.86 %	12568	95.56 %
mar/23	2691	60.28 %	44133	98.86 %
apr/23	4603	53.27 %	8602	79.65 %
may/23	16593	74.34 %	17911	80.24 %
Maintenance Date	**12/05**		**19/05**	
Previous Average	**6680.20**	**64.10 %**	**25570 .80**	**90.86 %**
jun/23	40492	93.73 %	40618	97.01 %
jul/23	44640	100 %	44511	99.71 %
Average After	42566.00	96.87 %	42564.50	98.36 %
Difference	35885,80	**+32.77 %**	16993,70	**+7.50 %**

Table 5.2: Pivot ATM - May Maintenance

5.2.3 Pivot ATM - June

Table 5.3 presents the results of the two ATM that underwent intervention in June. As in the previous tables, it is possible to see the date of the intervention, as well as data relating to MTBF and uptime in the months before and after the intervention. To make the result of the intervention clearer, the average of the MTBF and uptime parameters before and after the intervention was also calculated. The last line of the table highlights the difference found in each parameter.

Month	ATM Pivot 5 Model A3		ATM Pivot 6 Model E4	
	MTBF	**Uptime**	**MTBF**	**Uptime**
jan/23	44640	100 %	43779	98.07 %
feb/23	40271	99.88 %	39213	97.25 %
mar/23	44640	100 %	39645	93.21 %
apr/23	8738	80.91 %	9847	91.18 %
may/23	7187	80.50 %	7804	87.41 %
jun/23	6561	91.12 %	5069	82.14 %
Maintenance Date	**28/06**		**30/06**	
Previous Average	**25339.5**	**90.07 %**	**24226 .17**	**91.54 %**
jul/23	44640	100 %	43638	97.76 %
Average After	44640.00	100%	43638.00	97.76 %
Difference	**19300,50**	**+7.93 %**	**19411 .83**	**+6.22 %**

Table 5.3: Pivot ATM - June Maintenance

Analyzing the line of differences in each table, it is demonstrated that after preventive maintenance, all equipment had a positive increase in the uptime parameter. Considering the entire set of six ATM, there was an average improvement of 16.93% in pivot equipment. This increase in availability, in addition to being a satisfactory factor for the user since they have all the functionalities at their disposal, is also a factor in increasing the security of the equipment and the network in which it is inserted. A flawless ATM, in addition to being available, is an ATM that does not require human intervention. When there is human intervention, as previously explained, physical and remote attacks on the network can occur, since each piece of equipment is an access point. In Figure 5.10, it is mentioned that 2% of incidents were motivated by software failures. These failures, although small, are the most serious failures that can occur as they cause a gap in movements in real time. Thus, increasing the uptime of a device increases the physical security of the device (*as well as the cash inside it and banking transactions carried out on the network*).

Chapter 6

Conclusion

The present project made it possible to reach a set of conclusions about the work carried out. It was possible to understand the impact that Data Analytics tools can have in the maintenance area.

The data used within the scope of this project already existed in the company, however it was stored in the company's database and served as history whenever a new incident related to an ATM appeared. The approach used in the company's day-to-day operations was a corrective approach. Over the years, this type of approach, although having some effectiveness, has shown to be an approach that exhausts the teams involved, not helping to maximize results.

Alpaydin in [1] says that *data starts to drive the operation; it is not the programmers anymore but the data itself that defines what to do next.*

Increasingly, this is an undeniable fact. Nowadays, having a lot of data does not mean having useful information about it. The tools developed within the scope of this project filled an existing need in the team's daily life. More than giving the coordination team a tool, it also allowed the beginning of a change in mindset, from a modus operandi of just corrective maintenance, to the evolution towards a mentality in which data analysis in conjunction with maintenance predictive analysis takes place because the team itself felt that having a clearer and deeper knowledge of the data allows error patterns to be identified more effectively and the classification of incidents allows them to work in a direction of improvement, minimizing the impact on day-to-day operations.

It is worth highlighting the fact that the equipment park analyzed over these months is a park of Automatic Teller Machines. This equipment allows its user to withdraw money, deposit cash and access sensitive banking information. Their critical functions mean that these equipment, when they fail, can create shadow areas, in which, at times, the network administration area does not know what is happening with the equipment that failed, especially if the reason that caused the incident was at the software level. It is in these time intervals, which translate into the MTTR time, that the ATM is most likely to suffer external attacks. The equipment repair intervention itself involves, in most cases, human intervention, thus introducing yet another unsafe factor into the system. It then becomes vitally important to address a path that allows failures and incidents to be minimized, thus increasing availability and consequently increasing the security and reliability of ATM.

According to Avizienis et al., in [2], the *relationships between the means for Reliability, Security and all the "howtos" that appear in the definitions of failure prevention, failure tolerance, failure removal, prediction of failures, are, in fact, goals that can rarely if ever be fully achieved, because all design and analysis activities are human activities, and therefore imperfect. These imperfections bring relationships that explain why only the combined use of the above activities can lead to a reliable and secure computing system.*

The same article reinforces that, *despite failure prevention, through development methodologies, failures can occur. Therefore, there is a need to remove them. Fault removal is itself imperfect (i.e., all faults cannot be found, and other fault(s) may be introduced when removing a fault) and commercially available components - hardware or software - of the system may contain faults; Here lies the importance of failure prediction (in addition to analyzing the likely consequences of operational failures).*

More important than the model used is the quality of the data that feeds the model. It was demonstrated in this project that the incorporation of information obtained through continuous data is an added value for reliability analysis, as it allows a more assertive and concrete identification of the most critical equipment, that is, the equipment that fails most often, leaving unavailable to the user.

It was also concluded that it is essential to clarify the most critical modules and qualitatively define the reason that caused the failure, as only in this way is it possible to identify the problem effectively, in order to act on it, minimizing future failures.

Solving a problem, data analysis with Power-BI, more specifically in the area of failure prediction, is specific from the beginning, until the data classification stage. The use of these models is inevitable in the future, as the use of evaluation metrics and practical demonstrations of predictive success help the decision-making process.

The objectives defined for this project were: calculate the MTBF of equipment and its evolution, reduce equipment downtime and the respective MTTR, maximize uptime and promote resource optimization involving teams.

The calculation of the MTBF parameter was carried out and allowed the identification of the six target ATM used in the pivot. In all cases, it was proven that after preventive maintenance, equipment uptime increased, which resulted in an average of 16.93% in maximizing equipment uptime. A direct consequence of increasing uptime is reducing downtime, also reducing MTTR.

The classification of incidents and the quantification of how they were resolved allowed greater sensitivity of the teams involved as it was possible to reorganize resources in terms of parts available for replacement in order to minimize further trips to the site in the event of a recurrence.

As future work, it is suggested to increase the number of pivot equipment and verify the impact that the increase in pivot equipment has on the general uptime of the entire equipment fleet. Assertive monitoring of the park in question must be continued, always with a view to continuously improving its availability and uptime.

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Appendices

Appendix A

File VOSviewer thesaurus.txt

label replace by

mean time to repair (mttr) MTTR

mean time between failures (mtbf) MTBF

mean time to repair MTTR

reliability engineering Reliability

oee OEE

maintainability maintenance

tpm TPM

tpm method TPM

fault tolerant systems fault tolerance

capacitors hardware reability

integrated circuit reability hardware reability

hardware hardware reability

component hardware reability

maintenance engineering maintenance

simulation fault tolerance

mathematical model predictive models

reliability prediction predictive models

integrated circuit reliability reliability

reability reliability

stress usage fee