

We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900

Open access books available

186,000

International authors and editors

200M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com



Computational Intelligence to Estimate Fault Rates in Power Transformers

Danilo Spatti, Luisa H.B. Liboni, Marcel Araújo, Renato Bossolan and Bruno Vitti

Abstract

Asset management in power transmission systems is one of the significant practices carried out by power companies. With the aging of the devices, the development of optimized tools, capable of considering failure rates, regulatory scenarios, and operational parameters, is increasingly mandatory. The purpose of this work is to present a statistics-based tool for optimized asset management. For such an objective, we have developed a computational method based on database processing and statistical studies that can support decision-making on preventive maintenance in the equipment of the electric sector. The final system interface is Business Intelligence-based.

Keywords: computational intelligence, failure rates, power transformers

1. Introduction

In this chapter, we will describe a software, based on Business Intelligence, that has health data (test data, inspections, and operation) of assets as inputs, as well as their technical and constructive characteristics [1, 2]. The software has as outputs the possible categorization of assets into families, the calculation and analysis of failure rates, and the detection of current or incipient anomalies. Therefore, the software includes relational graphs, statistical analysis, and machine learning tools.

In **Figure 1**, the central conception of the system, which is named as the ISA CTEEP Asset Management Support System (AMSS), is shown. Thus, data from critical assets, such as power transformers, will also be considered as inputs to the software. In addition to making trend and relational graphs, the output module for anomaly identification and failure rate calculation, by analyzing test and inspection data, indicates the probability of a particular asset to needing special care. The software architecture was developed so that both input and output modules are easily accessible to the users through a graphical interface [3].

The algorithms that perform the relational and critical analysis of the health of an asset and calculate its failure rate are hosted within the program called Analysis Engine.

Input data may be made available manually by the user or may be directly acquired at the ISA CTEEP database. The software should query the database

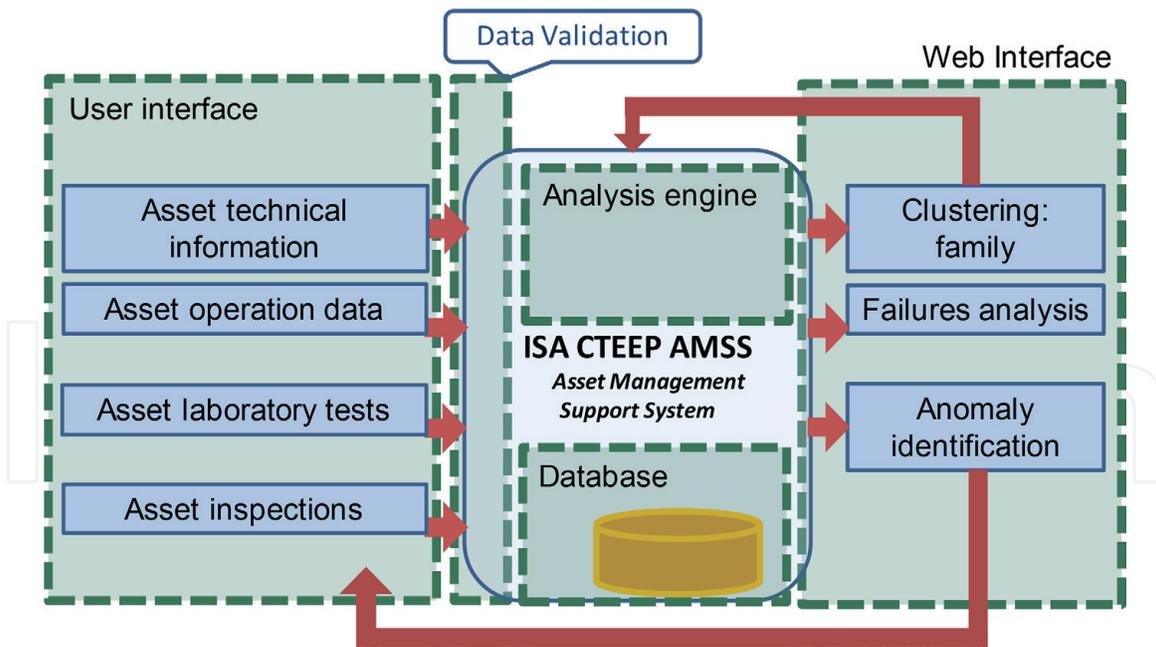


Figure 1.
Structure of the AMSS system.

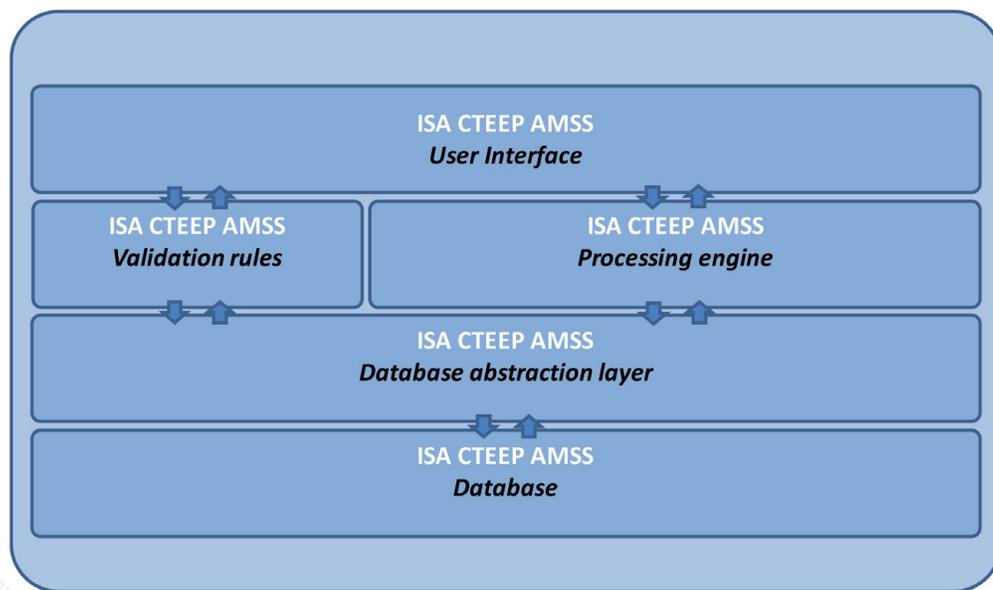


Figure 2.
Layers of the AMSS system.

through a database abstraction (interpreter) layer. These architectural details can be seen in **Figure 1**. **Figure 2** shows, in detail, the functional layers of the software.

The assessment of the health of major interest assets, such as transformers, autotransformers, and reactors, will be made considering three aspects [4]:

- a. History of operation and maintenance
- b. Routine tests:
 - Insulating mineral oil tests:
 - Physicochemical tests
 - Gas chromatography

- Liquid chromatography
- Transformer power factor test

c. Specialized tests:

- Insulation resistance
- Short circuit impedance
- Ohmic resistance
- Transformation ratio
- Inspection of accessories
- Special tests
- Etc.

2. Modeling fault as states

Maintenance procedures are considered inputs to the fault analysis we shall present. In total, there are 5371 maintenance records available in the database from the end of 2008 to the present moment. Maintenance records are mined in order to find relevant information for the analysis. Thus, nonrelevant corrective maintenance records are excluded from the analysis. **Figure 3** shows the relationship between the number of maintenance records as a function of the year of occurrence and the age of the asset [5].

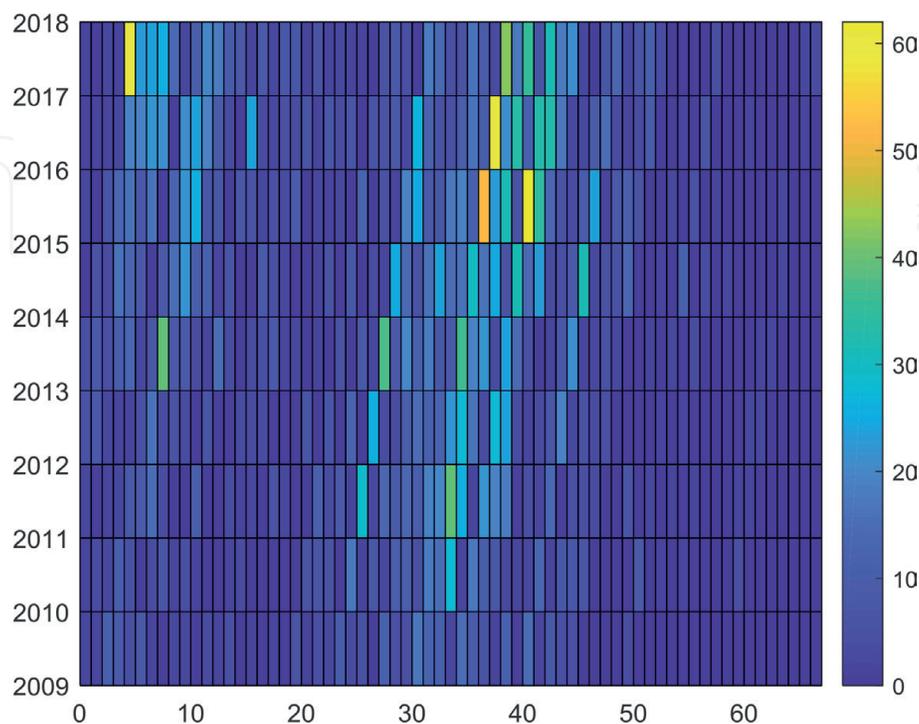


Figure 3.
Summary of the number of records according to the year of occurrence and the age of the asset.

From **Figure 3** it is possible to observe the existence of sparse data, as better highlighted in **Figure 4**. The same sparsity can be perceived in **Figure 5**, where the relationship between the number of equipment and its age is shown.

Assets can be categorized into states. The ideal state in which the equipment must operate is the **NORMAL** state.

Preventive Maintenance processes can ensure that the asset remains in its **NORMAL** state.

However, even with preventive maintenance procedures, there is a transition from the **NORMAL** state to the **DEFECT** state, as shown in **Figure 6**. The state transition occurs given a defect rate.

The transition from the **DEFECT** state (or fault state) to the **NORMAL** state occurs when **Corrective maintenance** actions are made. The transition takes place through a Corrective Maintenance rate, as represented in **Figure 7**.

Still, there is the **FAILURE** state, which is characterized by the complete withdrawal of operation of the asset. The transition takes place through a failure rate, as in **Figure 8**.

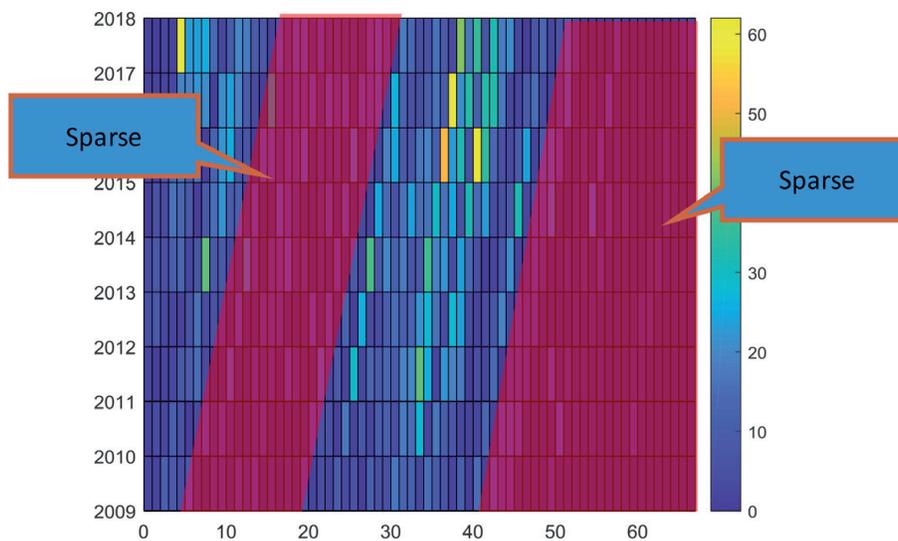


Figure 4. Number of maintenance records with respect to equipment age and year of occurrence. Sparsity highlighted.

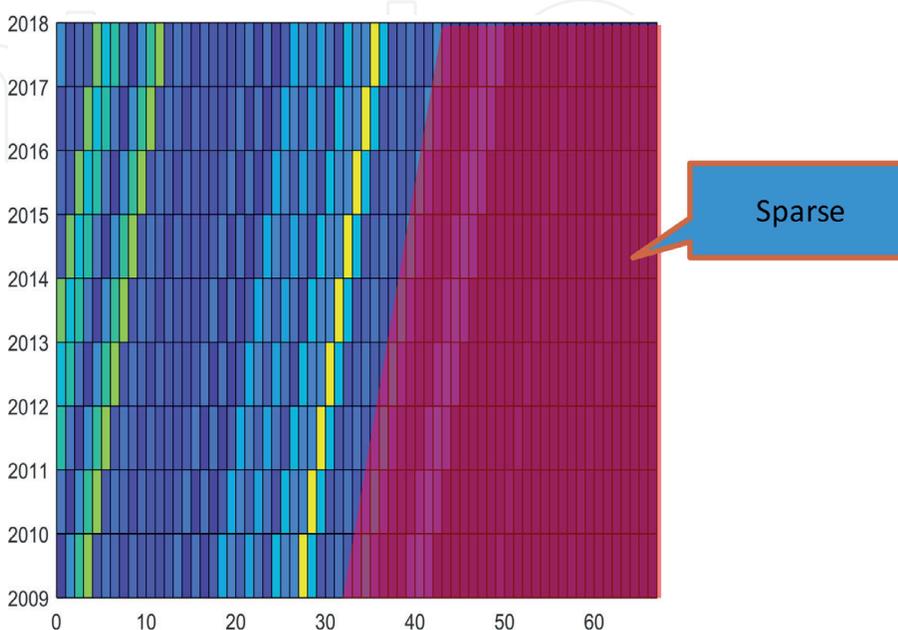


Figure 5. Number of equipment with respect to equipment age. Sparsity highlighted.

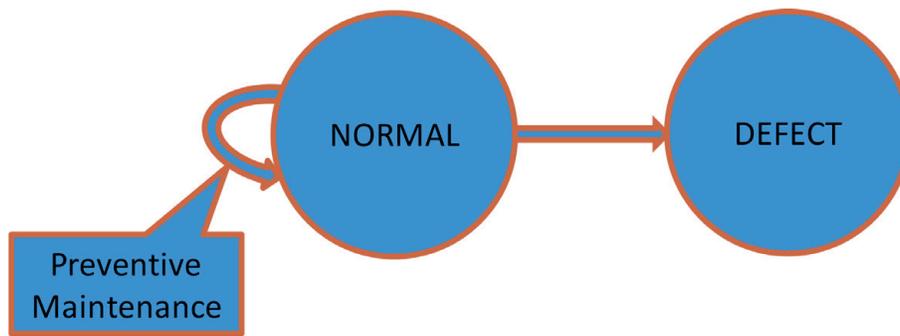


Figure 6.
State transition functions (I).

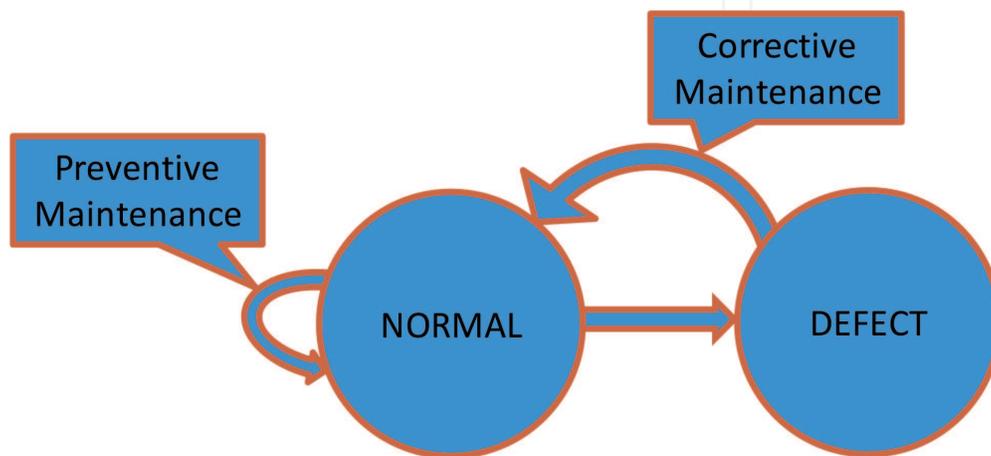


Figure 7.
State transition functions (II).

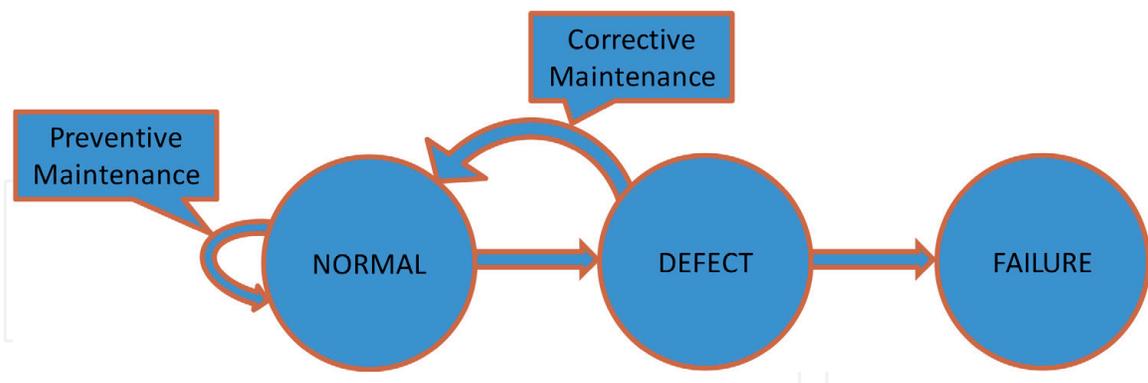


Figure 8.
State transition functions (III).

In the case of transformers, the **FAILURE** state can be divided into two others, i.e., **Internal Failure** and **External failure**, as shown in **Figure 9**.

The approximation of the defect rate function should take into account the quality of the available information. The quality of the information depends on the number of maintenance records available and the number of devices [6]. The relative quality of the data can be seen in **Figure 10**.

A similar approximation can be made for the failure rate, as depicted in **Figure 11**, which is modeled by means of a power type function. **Figure 12** also shows the failures involving peripheral elements and the active parts of transformers.

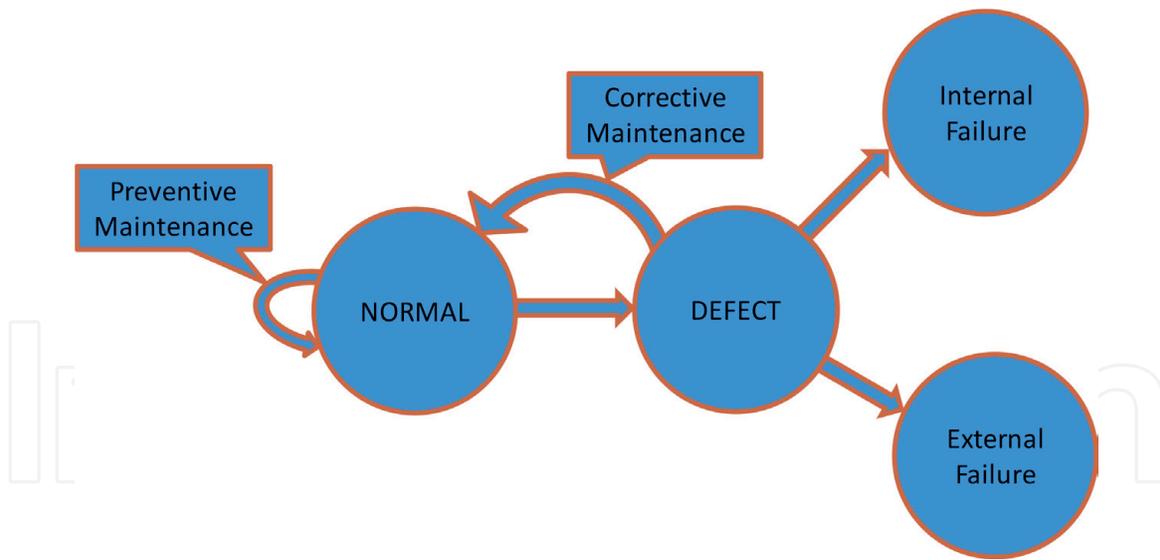


Figure 9.
State transition functions (IV).

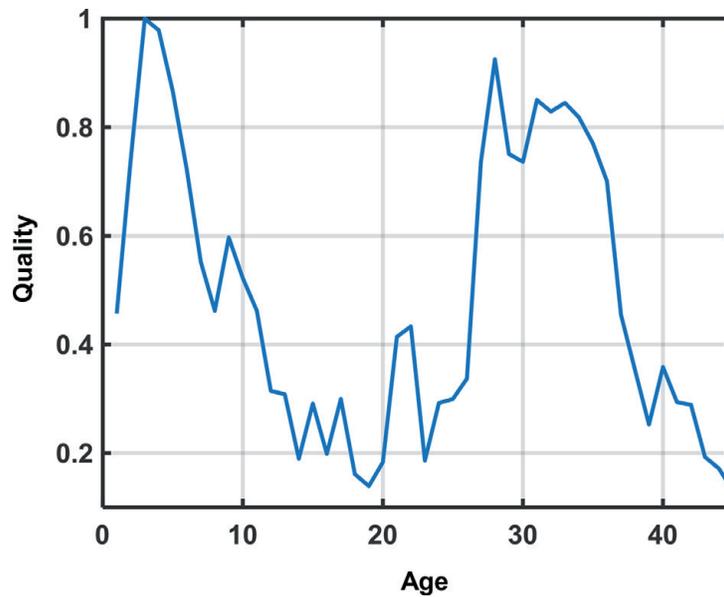


Figure 10.
Relative quality of the available data as a function of the asset age.

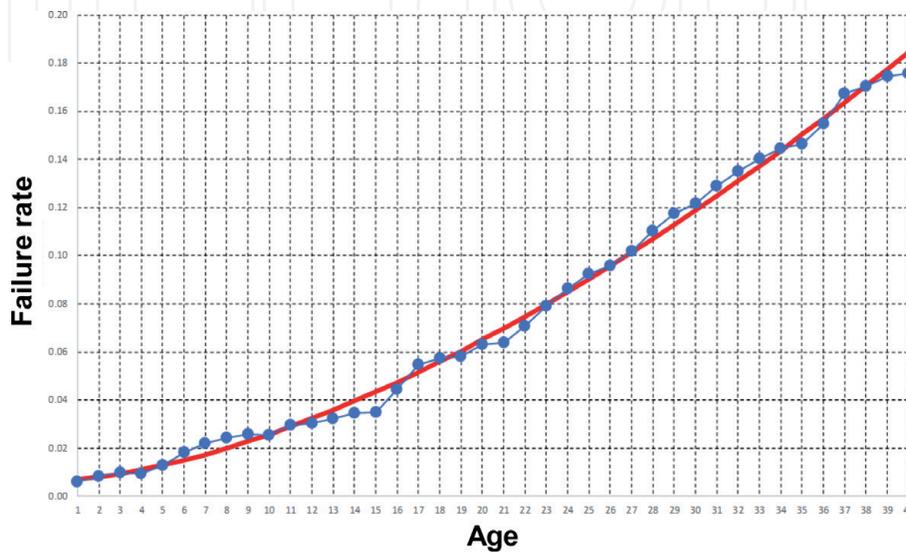


Figure 11.
Approximation of the failure rate.

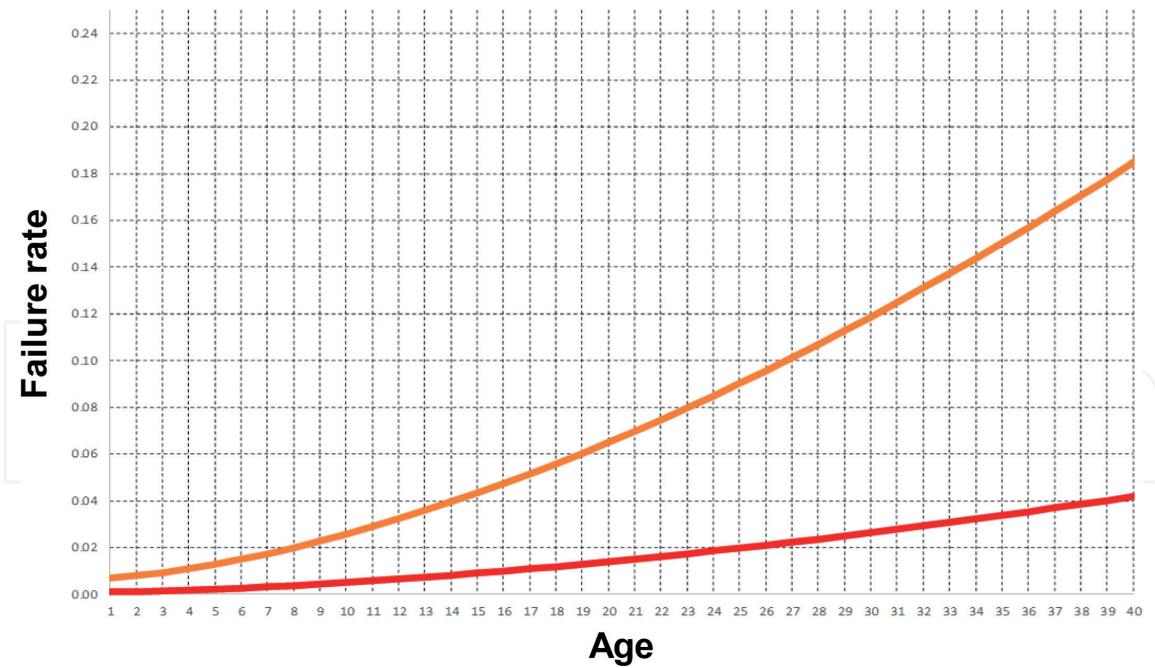


Figure 12. Failures for peripheral (orange) elements and active (red) parts.

3. Business intelligence interface

All intelligence embedded in the AMSS systems was implemented using the concept of Business Intelligence, which uses graphical reports to represent data. The software was divided into nine pages, with several graphical analyses each. The first page can be seen in Figure 13.

In this screen, the user can choose the **Substation**, the **Equipment** type, and also the **Voltage** class, among 729 available equipment in 4843 available corrective maintenance records, as exemplified in Figure 14.



Figure 13. Business intelligence Interface page 1.

Substations	
All	
Equipment	
All	
Voltage	
All	
729 selected equipment	4843 corrective maintenance records

Figure 14.
Selecting substations, equipment, and voltage class detail from page 1.

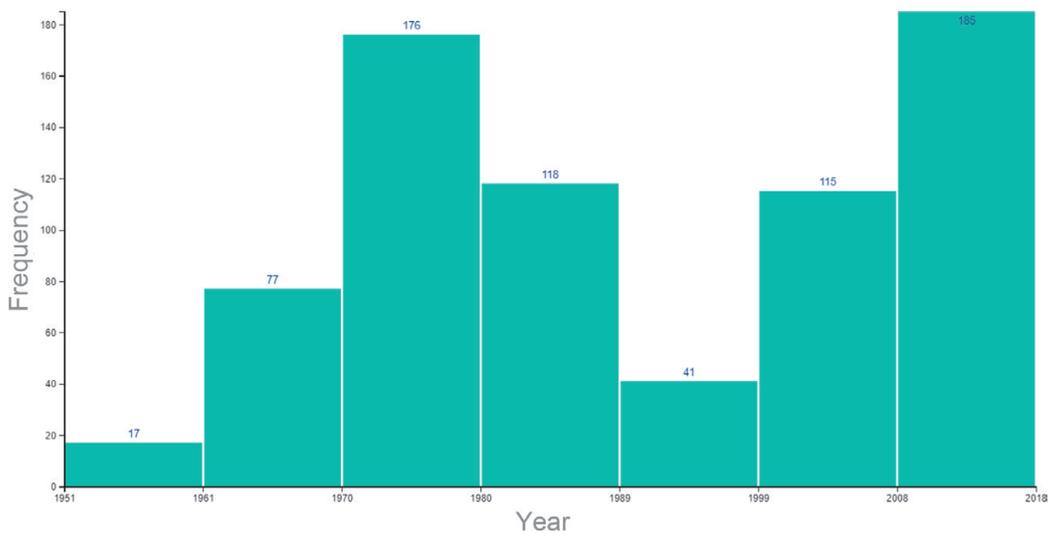


Figure 15.
Equipment fabrication histogram by year (page 1).

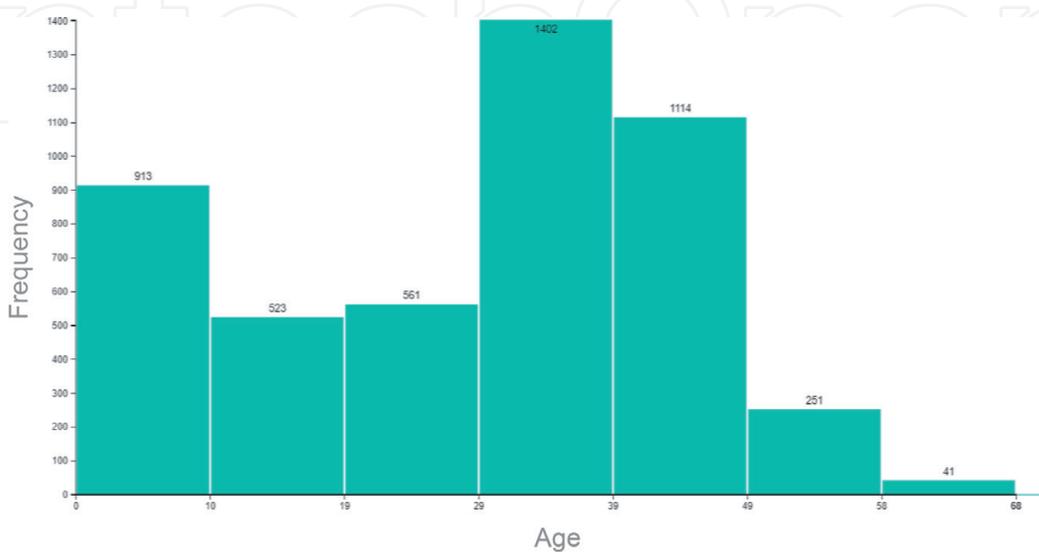


Figure 16.
Corrective maintenance records by age (page 1).

In **Figure 13**, it is still possible to visualize, in detail, the histogram of the manufacturing year of the equipment, as well as the **Corrective maintenance records by age**, detailed in **Figures 15 and 16**, respectively.

The **Maintenance priority** is detailed in **Figure 17**.

Page 2 displays graphical reports involving all corrective maintenance records for all devices, as can be shown in **Figure 18**.

In Page 3 of the AMSS system, **Figure 19**, it is possible to see the correlations of corrective maintenance records with the age of the assets, which are shown in **Figures 20 and 21**.

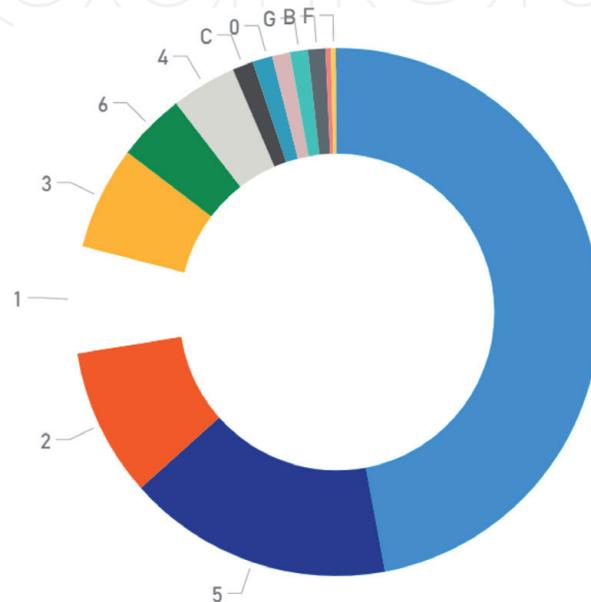


Figure 17.
 Maintenance priority (page 1).

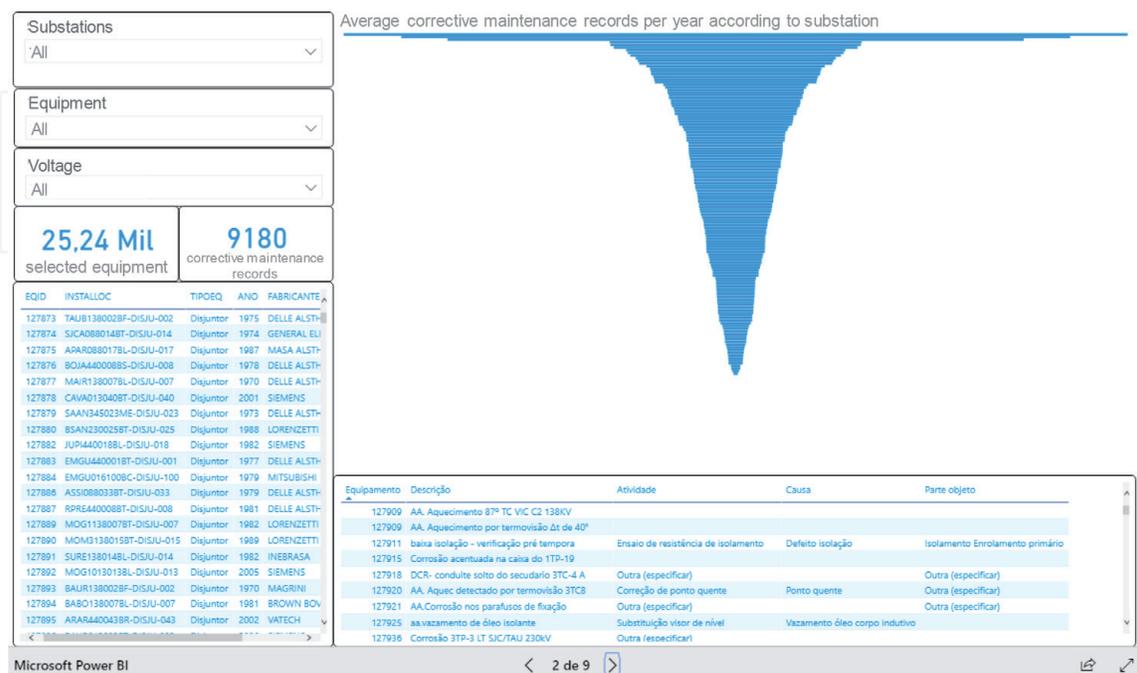


Figure 18.
 Business intelligence Interface page 2.

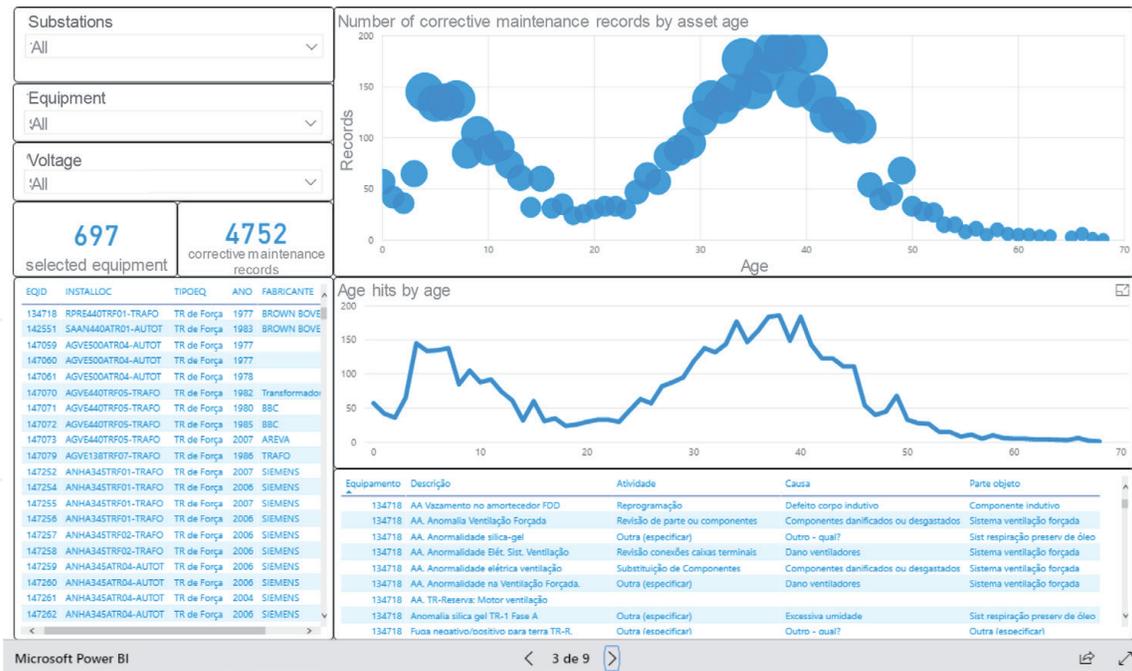


Figure 19. Business intelligence Interface page 3.

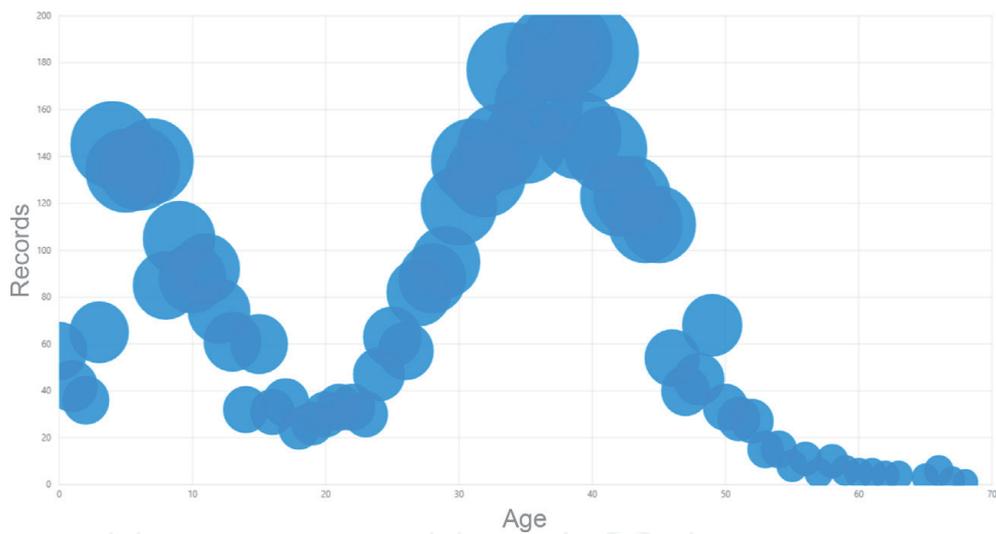


Figure 20. Detailed number of corrective maintenance records by asset age from page 3.

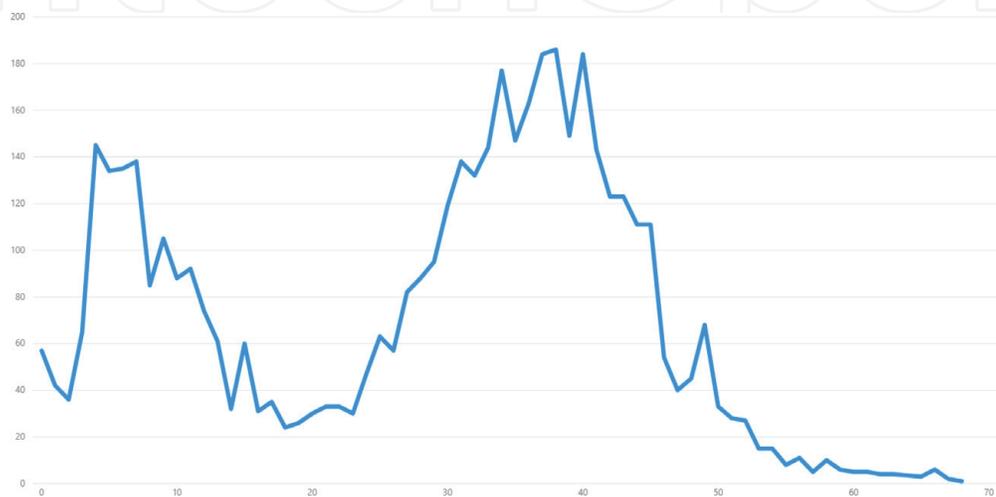


Figure 21. Detailed age count by age from page 3.

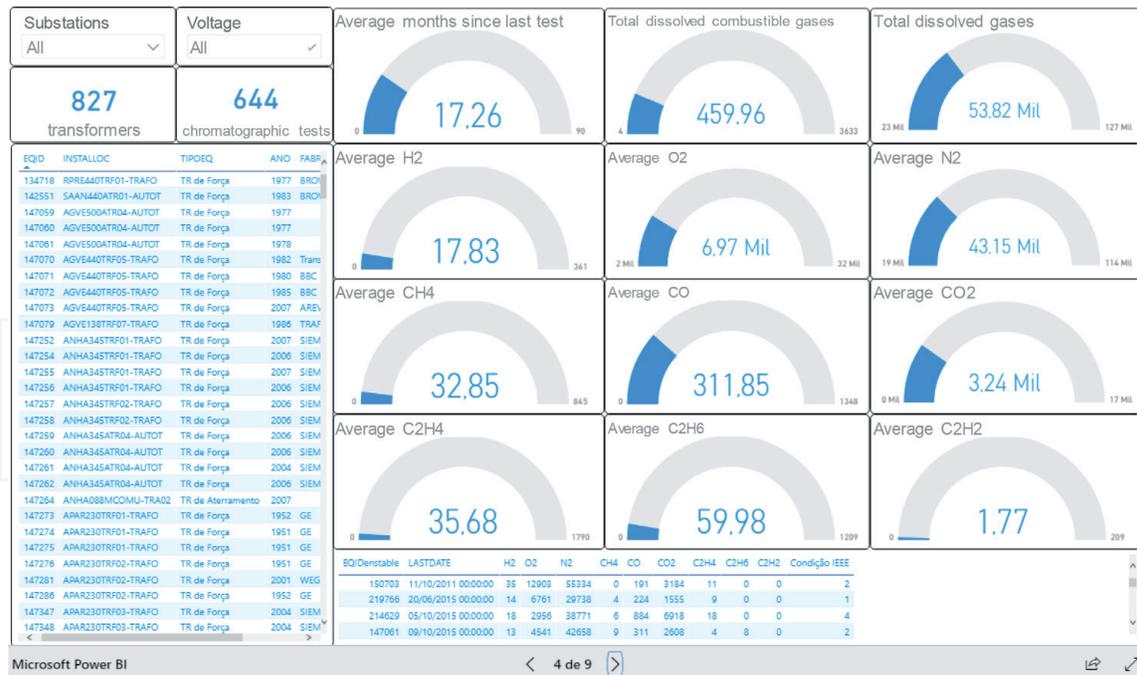


Figure 22. Business intelligence Interface page 4.



Figure 23. Business intelligence Interface page 5.

Page 4 presents the user with information from chromatographic assays for power transformers that can be individually selected, as can be seen in Figure 22.

Pages 5 and 6 still address information from chromatography tests, showing the gas emission evolution over the years, as well as the correlation between the tests and the corrective maintenance history for each asset, as seen in Figures 23 and 24, respectively.

The emission evolution of H₂, CO, CO₂, total dissolved combustible gases, CH₄, C₂H₄, C₂H₆, and C₂H₂ can be seen in details in Figures 25–32.

Page 7 shows the behavior of the dissolved gases as a function of time. The user can select a particular asset or analyze the evolution globally, this is, for all assets.

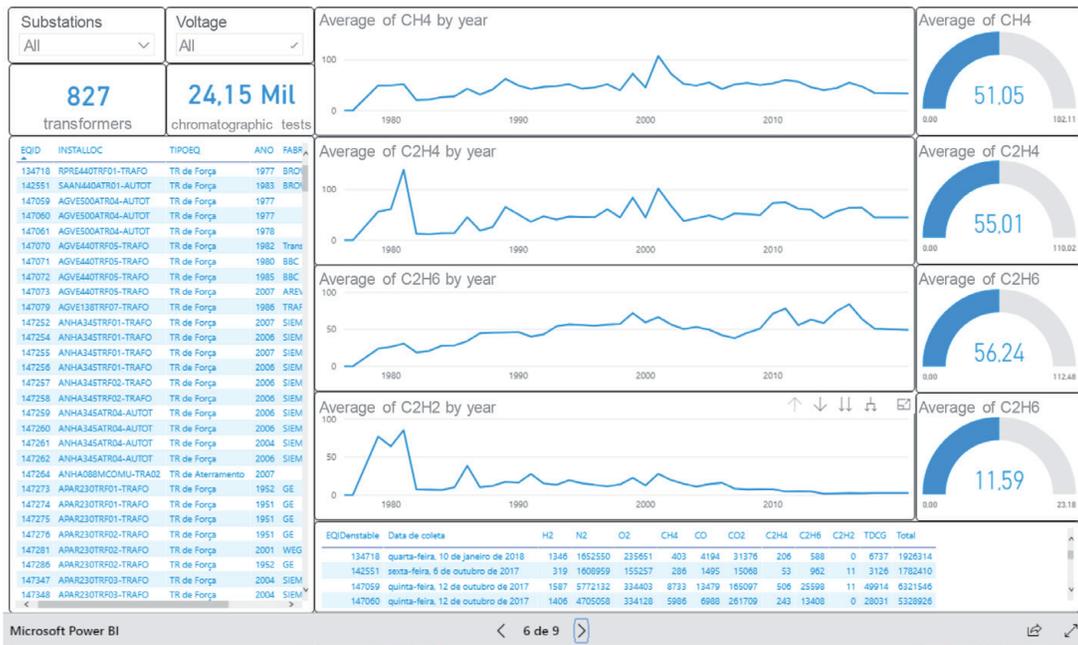


Figure 24. Business intelligence Interface page 6.

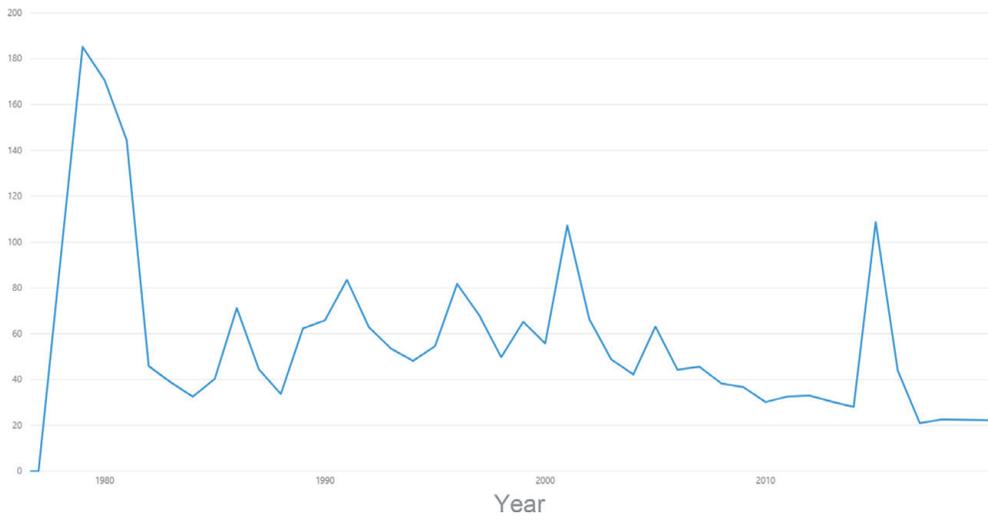


Figure 25. Detailed H₂ emission evolution from page 5.

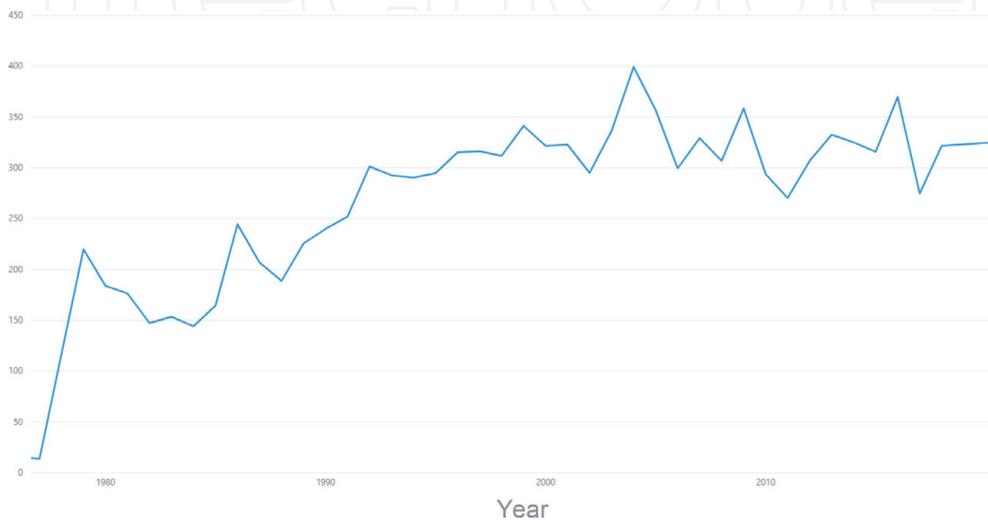


Figure 26. Detailed CO emission evolution from page 5.

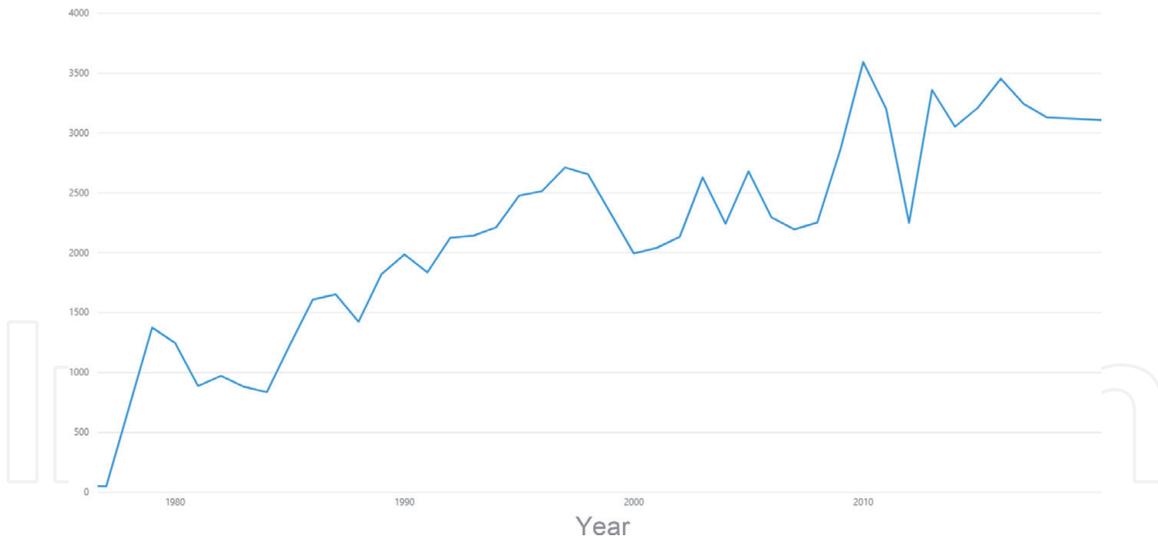


Figure 27.
Detailed CO₂ emission evolution from page 5.

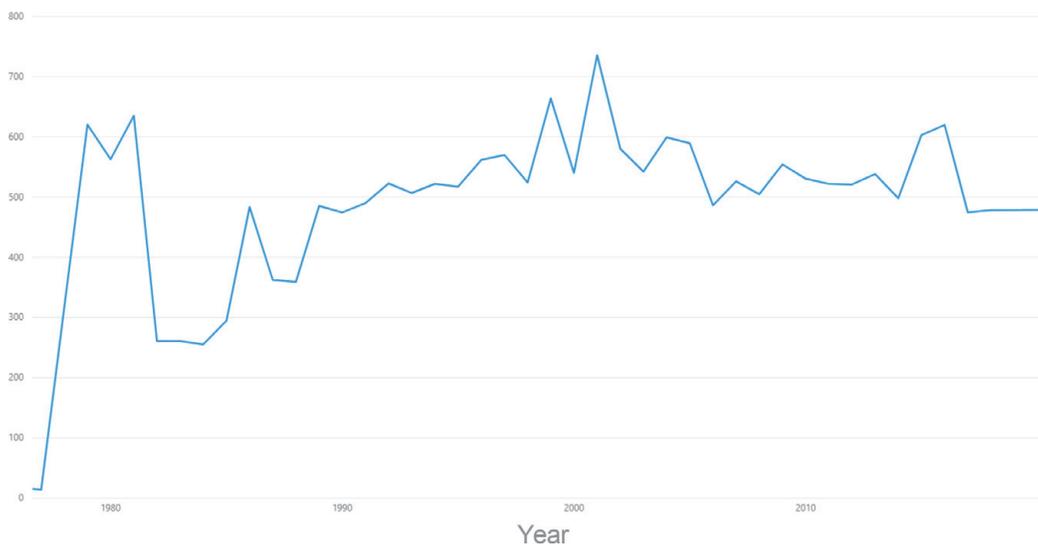


Figure 28.
Detailed TDCG emission evolution from page 5.

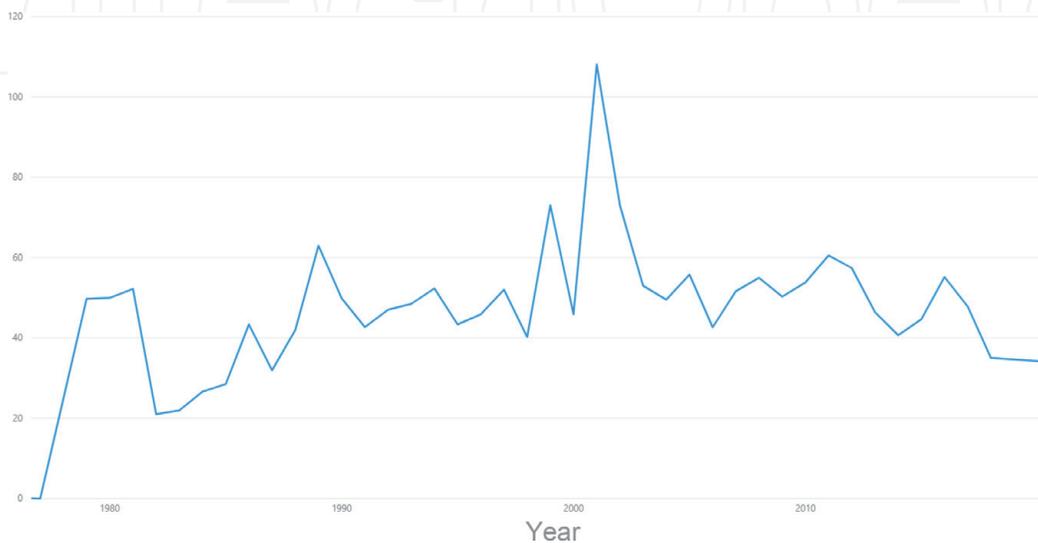


Figure 29.
Detailed CH₄ emission evolution from page 6.

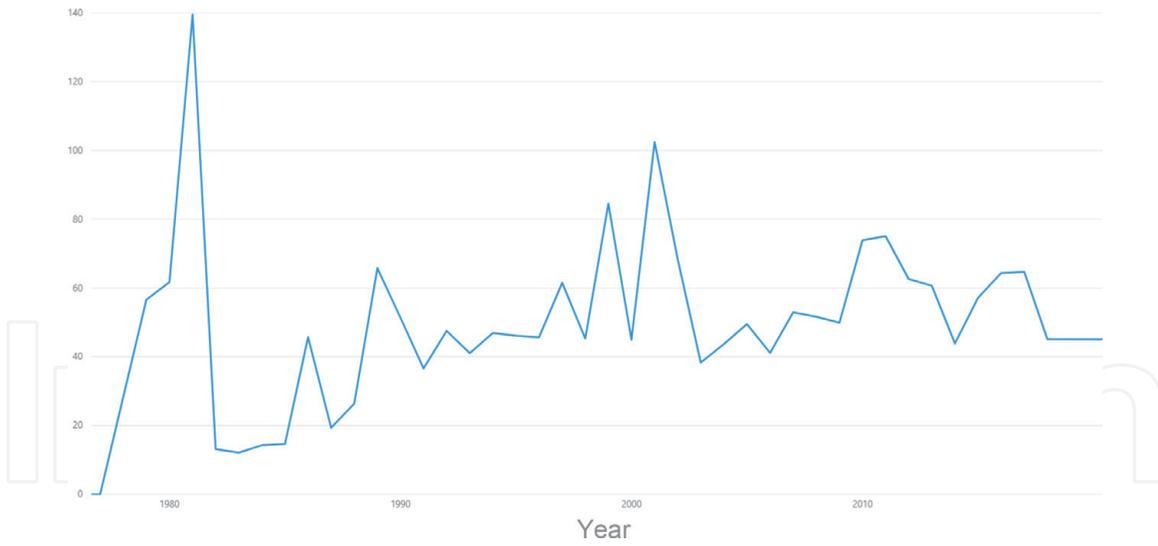


Figure 30.
Detailed C₂H₄ emission evolution from page 6.

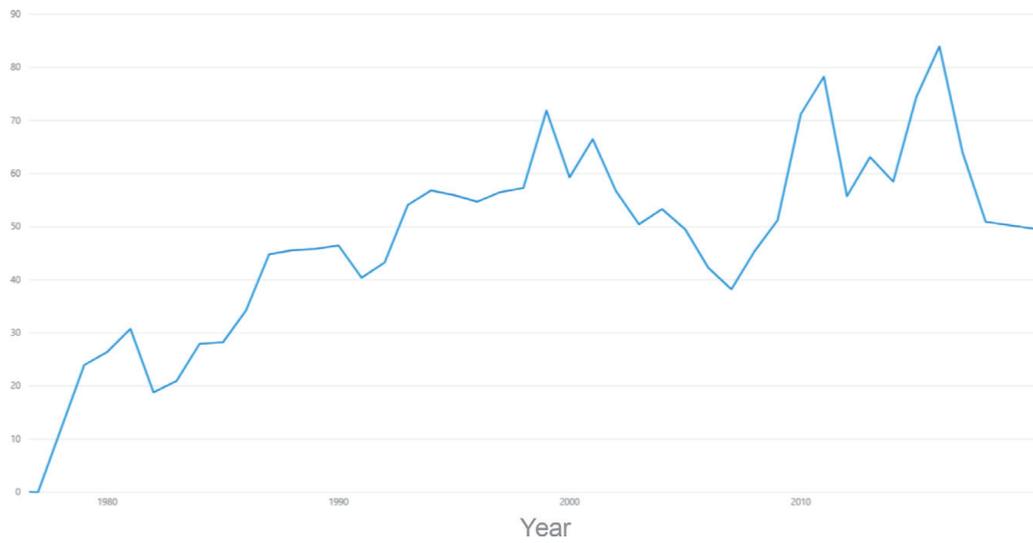


Figure 31.
Detailed C₂H₆ emission evolution from page 6.

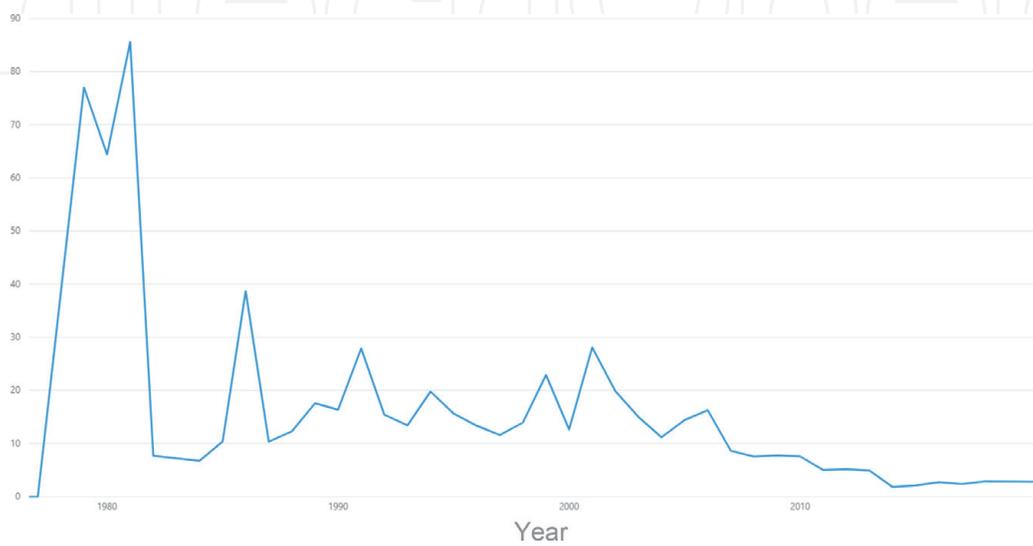


Figure 32.
Detailed C₂H₂ emission evolution from page 6.

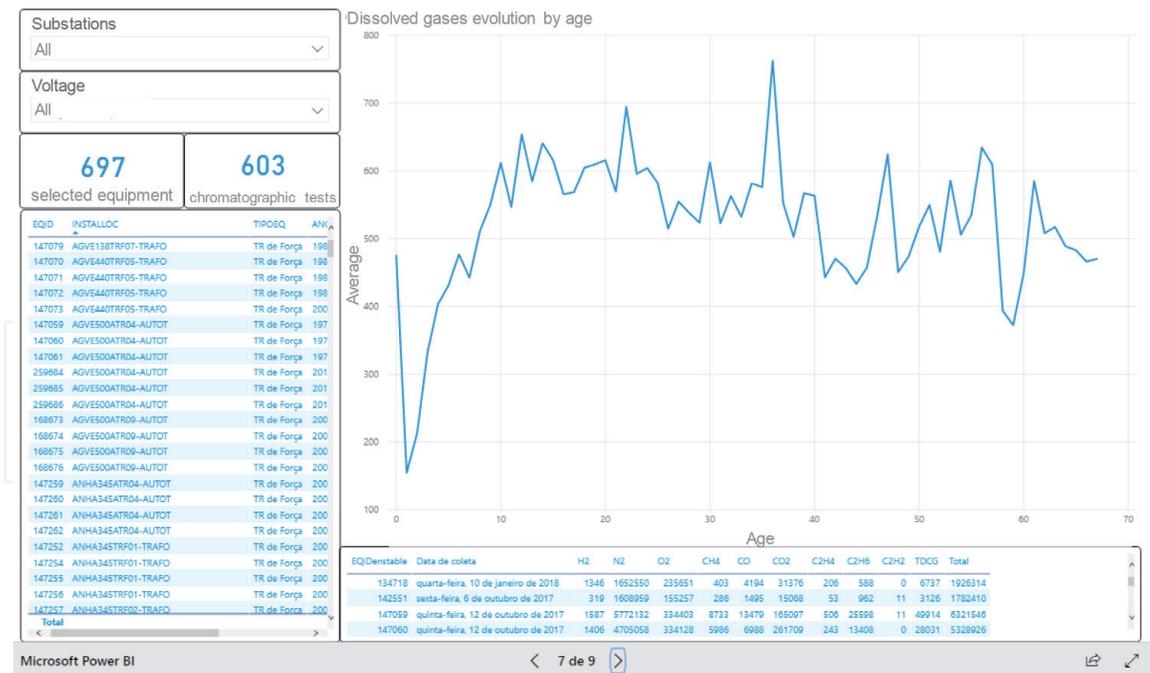


Figure 33.
 Business intelligence Interface page 7.

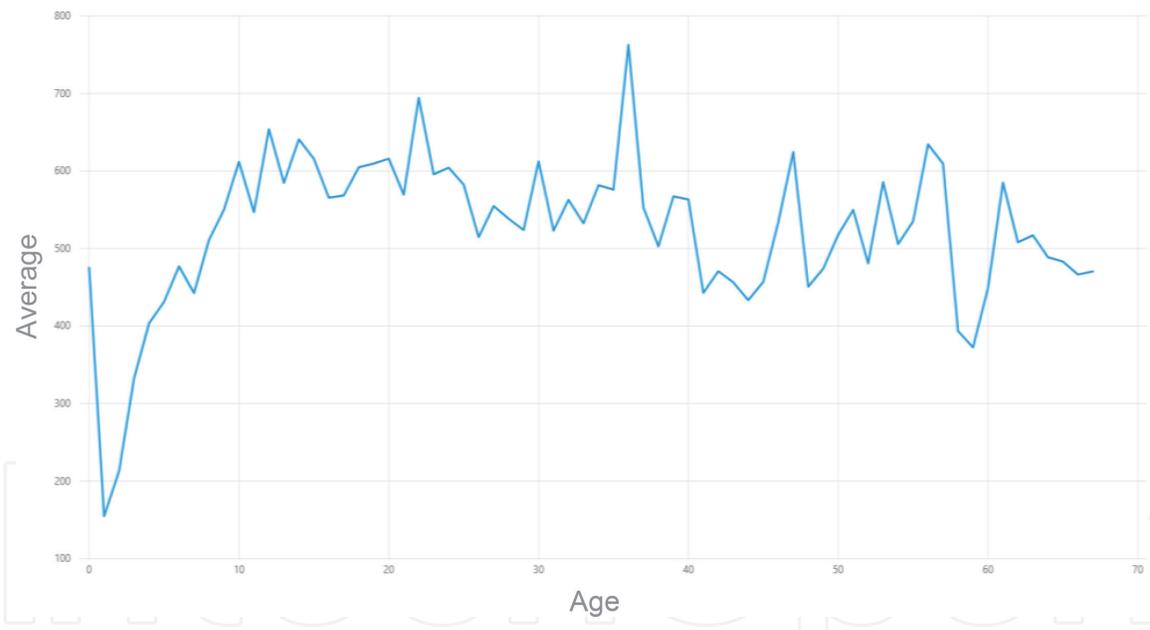


Figure 34.
 Detailed dissolved gases evolution from page 7.

This behavior is shown in **Figure 33**. The detailed evolution of the dissolved gases as a function of the age of the assets can be seen in **Figure 34**.

Page 8 presents the integrated analyses involving the relationship between corrective maintenance records and chromatographic tests, as exemplified in **Figure 35**. **Figure 36** shows the trend line of maintenance records per year as a function of the age of the asset.

Finally, Page 9, which is shown in **Figure 37**, performs an integrated analysis of the health of an asset, along with its maintenance history.

It can be seen from **Figure 37** that the circles represent the transformers, and the diameter of each circle is related to the corrective maintenance rate per year to which this asset is subjected. The ordinate axis represents the current condition that this asset is in.

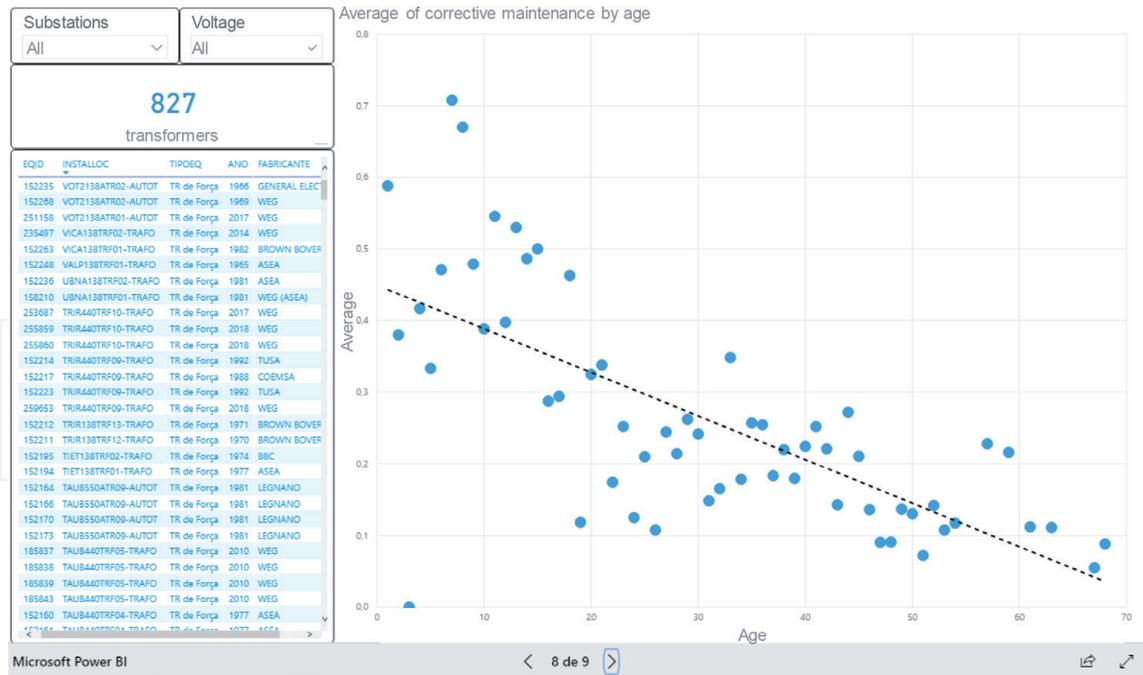


Figure 35. Business intelligence Interface page 8.

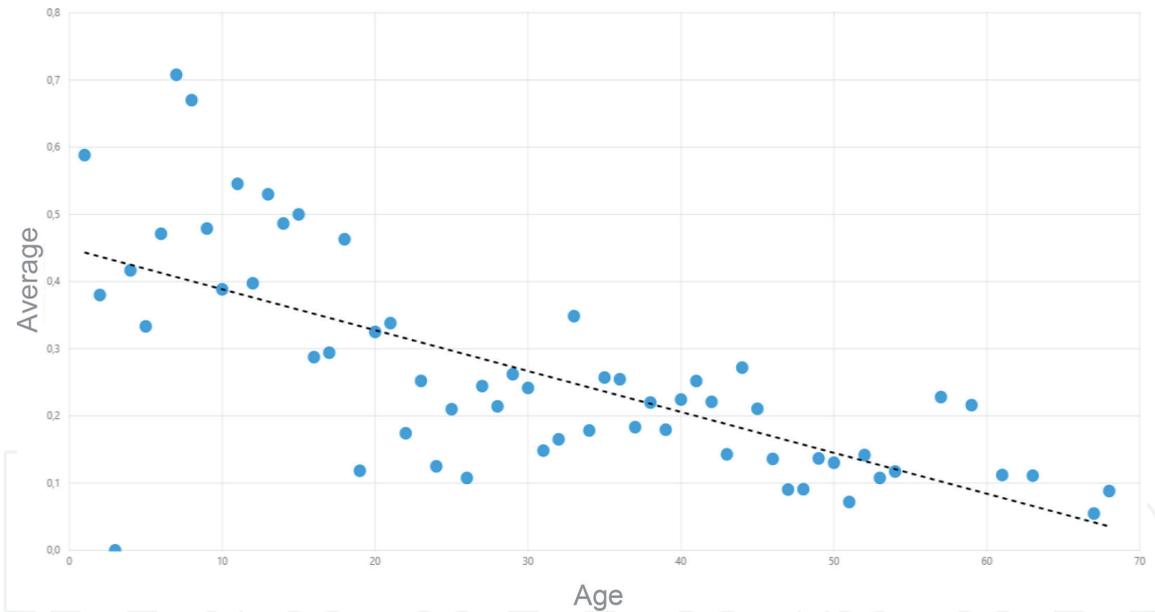


Figure 36. Detailed trend line for corrective maintenance from page 8.

4. Conclusions

Asset management in the power sector, especially in transmission systems, has been driving the development of increasingly efficient feature extraction tools.

This chapter has introduced an integrated method based on business intelligence that analyzes data and failure rates in order to assist decision-making. The computational system takes into account technical information from the assets, data from chromatographic tests, as well as standard information regarding the operative condition of the assets, especially power transformers.

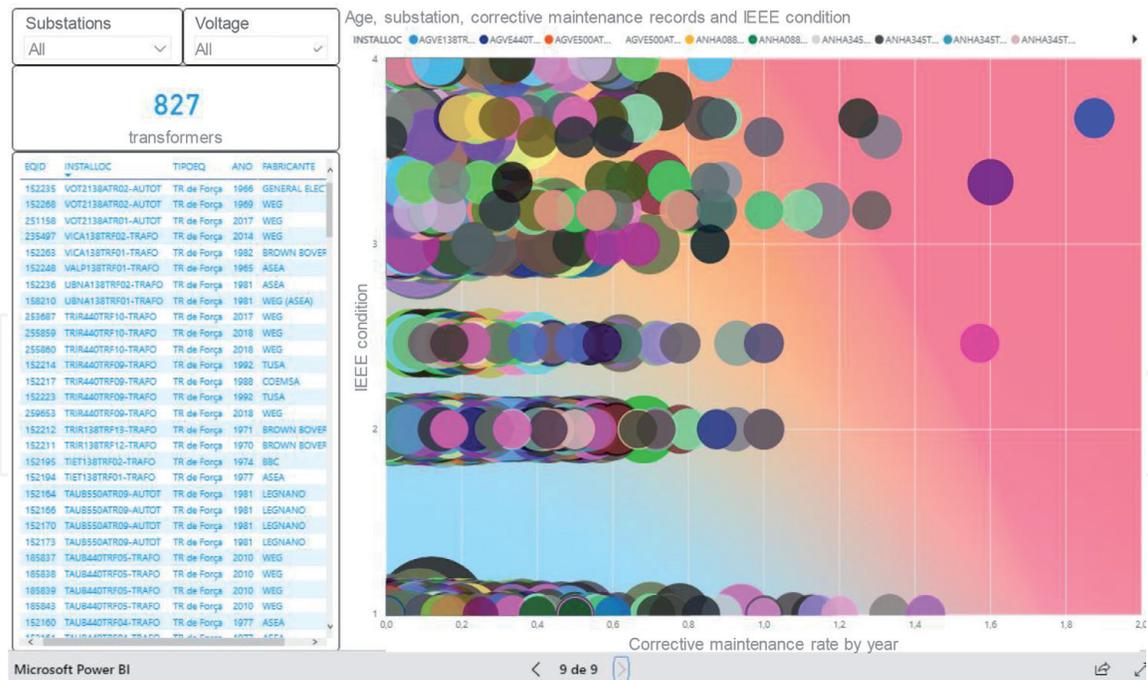


Figure 37. Business intelligence Interface page 9.

Acknowledgements

The authors thank the ANEEL R & D Program contract number PD-0068-0037/2016.

Author details

Danilo Spatti^{1*}, Luisa H.B. Liboni², Marcel Araújo³, Renato Bossolan⁴ and Bruno Vitti⁴

1 University of São Paulo, São Carlos, Brazil

2 Federal Institute of Education, Science, and Technology of São Paulo, Sertãozinho, Brazil

3 Federal Rural University of Pernambuco, Recife, Brazil

4 São Paulo State Electric Power Transmission Company, São Paulo, Brazil

*Address all correspondence to: spatti@icmc.usp.br

IntechOpen

© 2019 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/3.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

[1] Jahromi A, Piercy R, Cress S, Service J, Fan W. An approach to power transformer asset management using health index. *IEEE Electrical Insulation Magazine*. 2009;25(2):20-34

[2] Nemeth B, Benyo T, Jager A, Csepes G, Woynarovich G. Complex diagnostic methods for lifetime extension of power transformers. In: 2008 IEEE ISEI—International Symposium on Electrical Insulation. 2008. pp. 132-135

[3] Zhang X, Gockenbach E. Asset-management of transformers based on condition monitoring and standard diagnosis. *IEEE Electrical Insulation Magazine*. 2008;24(4):26-40

[4] Coble JB. Merging data sources to predict remaining useful life, an automated method to identify prognostic parameters (University of Tennessee PhD dissertation). 2010

[5] Heo JH, Kim MK, Park GP, Yoon YT, Park JK, Lee SS, et al. A reliability-centered approach to an optimal maintenance strategy in transmission systems using a genetic algorithm. *IEEE Transactions on Power Delivery*. 2011;26(4):2171-2179

[6] Sarchiz D, Bica D, Georgescu O. Mathematical model of reliability centered, maintenance (RCM). Power transmission and distribution networks applications. In: 2009 IEEE PowerTech. 2009. 4 p