



Expert System for an Optimized Asset Management in Electric Power Transmission Systems

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Abstract

Poor asset-management practices can be considered one of the primary sources of high financial costs of electric power companies. Mostly defined as an optimization problem, asset management programs aim to guide the use of the physical assets of a company, mainly by optimizing their life cycle. Operation and maintenance policies are established for each equipment, from its acquisition, until the most appropriate time for its replacement. Therefore, it becomes strategic to use decision-making processes to reduce the global costs of an active asset and to extend its life time maximally. Based on these assumptions, we propose a method, which is instantiated by computer software, to assist asset-management decision making in the electric power companies.

Keywords Asset management · Fault identification · Fault location · Automation · Distribution systems · Neural networks · Expert systems

1 Introduction

Power systems have recently undergone changes that result in a significant impact in the energy sector, not only regarding technical aspects but also regarding management features, this is, organizational, economic, environmental, and technological aspects. A much more modern infrastructure with newly developed technologies and the inevitable trend that electric utility companies face within the new paradigms of the industry 4.0 are examples of some of these changes (Liboni et al. 2018). Since electric utilities are industries that have a significant impact on the environment and are strategic, modernization is crucial and can be achieved by a properly designed management system.

As other basic mass utility industries, companies have to respect regulation policies regarding technical solutions on the generation and distribution of electricity, economic aspects, such as commercial rates, and policies in the life cycle of assets. Another critical aspect in this sector is the

strict environmental policies ranging from generation to distribution. Recently, economic and environmental restrictions have made it difficult for utilities to implement new generation plants, construct transmission and distribution lines, and substations. This fact implies that equipment will have to be used for a longer time, close to their limits of operation and near to the end of their lifetime. Consequently, the electric sector companies will have to necessarily use sophisticated control and management systems for the equipment and elements of the electrical system.

In a modern electric company utility, information management, asset maintenance, and remote diagnostics should allow security and better services for the customers. All these aspects result in the well-known smart grid concept (Spatti and Liboni 2016). As pointed out in Liboni et al. (2018), the industry 4.0 paradigm for the electric utilities means having interconnectivity of equipment and sensors and information to monitor, optimize, and control the electric system. Industries should be able to assess and communicate information about the health of equipment to other systems. Thus, these new practices involve having a significant volume of information regarding health indices of equipment and other relevant information. Moreover, the continuous technological evolution in the field of computing and information technology is resulting in computational systems with higher capacities of processing, storage,

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communication, and data transmission, especially those dedicated to smart grid technologies (Pesente et al. 2018).

With this much modern framework, more and more crucial data should be generated in large databases, and critical analysis should be made in order to learn from data. For example, through machine learning and other mathematical tools, systems could influence decision making in the substitution or exchange of assets taking into account the current regulatory context. Intelligent systems can help decision making based on historical data and current scenarios and also help to establish better practices through a possible change in the regulation policies. Therefore, a modern and structured asset management system can estimate the value assets created by estimating risks and maintenance schedules based on historical data from assets.

Several studies, as in Nemeth et al. (2008), Lapworth and Wilson (2008), Zhang and Gockenbach (2008), Jahromi et al. (2009), and Carneiro et al. (2012), among others, show that the reliability of electrical systems can be analyzed statistically. Thus, a database with information on the age of the equipment, the history of defects and failures and also of the preventive and corrective interventions carried out, allows the elaboration of optimized maintenance policies. As a direct result, we have the optimization of equipment maintenance and control by the use of reliable and low-cost tools and a better knowledge of the operational condition of the existing assets and consequently a better use of the equipment. This new information can be used in a feedback process to regulators in order to define planning, maintenance, and operation tasks with dynamism.

However, it can be verified that few works can quantitatively relate the benefits of asset management; the current business model used by the electric utility and regulation scenarios to the reliability indices in power systems (Mahdavi et al. 2018). Some companies carry out audits to ensure that maintenance inspections are taking place in the planned manner and at the predetermined intervals. The risk assessment is done annually, and the results directly influence the investment decisions of the company (Khuntia et al. 2015). Still, many important variables and information that lie within historical data can be ignored, and the evaluation of equipment lifecycle should consider that not all the equipment presents characteristics fault rates similar to bathtub curves (Nowlan and Heap 1978). This fact underlines the operational challenges posed by the aging of the electric systems, especially the transmission systems (Rudd et al. 2011).

Traditionally, significant evolutionary efforts in power system have focused on the development of algorithms and the refinement of technical computational models. However, from all the discussed above and according to Zhang and Gockenbach (2008), an infinity of information on the assets of the electric system is currently available, being, therefore,

Table 1 Some of the attributes from the database

Equipment ID	Category
Manufacturer	Year of construction
Time in operation	Feeder phase
Did achieve its lifetime according to regulation policies?	Power
Location	Voltage
Level of priority of the maintenances	Preventive maintenance dates
Technical maintenance team	Corrective maintenance dates
Age of the transformer when corrective maintenance was performed	

a new challenge to extract the characteristics of more significant interest.

Based on this discussion, we present a method for the estimation of the fault rates of assets based on historical data and recorded events in power transmission systems.

2 Asset-Aging Statistical Analysis

Failure rates in electrical systems are obtained when, eventually, a particular device connected to the system fails. Among all the equipment connected to the system and in active mode, some of them have an increased failure rate and, consequently, are considered relevant to the system reliability (Setreus et al. 2012). One can understand the failure rate of an electric system as represented by the indices that measure the quality of the service provided by the electric utility. This is due to the difficulty in obtaining historical data that represent the individual faults of the equipment that compose the analyzed system. However, as a theoretical basis, it should be emphasized that if there is the possibility of using the historical data of individual faults, they would add greater precision to the reliability estimation of the electric system (Chowdhury et al. 2008).

Some management questions can arise from such analysis regarding the substitution or new acquisition of assets or manufacturers with increased fault rates. The main goal of our proposed method is to assist such important decision making.

In this study, we analyze a database composed of information regarding power transformers of a large Brazilian utility company. The information was extracted from the databases, and then the variables were conditioned and processed, making statistical analyses possible. Some new attributes were created from initial attributes, such as “Did the transformer achieve its lifetime according to regulation policies?” and “Age of the transformer when corrective maintenance was performed.”

The database consists of information such as those given in Table 1.

The proposed method consists, initially, of a preprocessing step. Statistical summaries of all attributes were made. For numerical attributes, maximum, minimum, and mean values were calculated, as shown, for example in Table 2. For categorical attributes and dates, count distributions were made, as shown, for example, in Table 2.

Simple statistics are very helpful, and the majority of businesses do not implement them. Either because it is difficult to gather all the information or because they lack specialized force work to analyze the data, this initial analysis, in a feedback loop, could help on continuously improving the entry of data into the database by the technical staff as well as point out flaws in the database system.

In order for such information to result in more useful data, the repositories underwent a preprocessing stage, which consists of database packaging, inconsistent data correction, and the treatment of missing values. Information with different formatting was standardized for analysis, as well as different databases were cross-referenced and united. Missing and poor quality information was assessed and corrected.

Then, analysis through relational graphs and probability distributions was taken into account considering the age of the assets.

Figure 1 shows a histogram regarding the manufacturing year of the transformers in the database. Such relational graphs allow us to characterize age wise the registered assets.

In Fig. 2, it is possible to verify the relative counts (in percentage) of the power transforms with respect to the equipment age. It is clear that this distribution has a bimodal characteristic with peaks around 20 years and 45 years.

Table 2 Example of statistical summaries before preprocessing

Time in operation		Did achieve the lifespan according to regulation policies?	
Min	2	No	327
Median	34	Yes	301
Max	67		
Missing	22		
Preventive maintenance DATES		Feeder phase	
Min	04-01-2009	Blue	106
Median	31-08-2013	White	103
Max	31-12-2017	Red	104
		Three phase	99
		Spare	41
		Missing	175

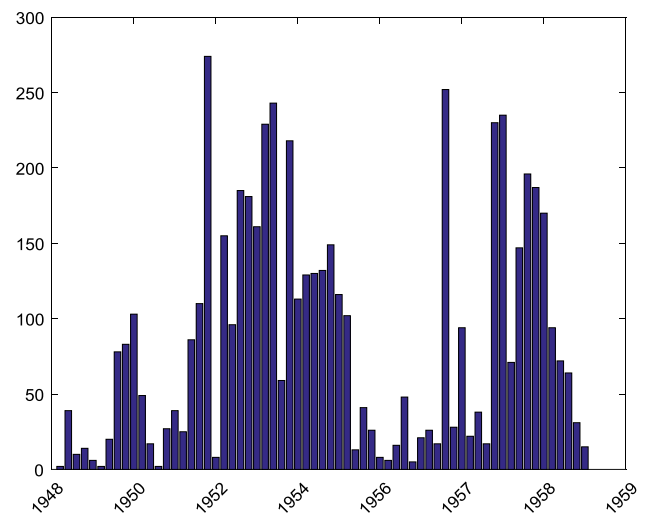


Fig. 1 Histogram (count percentage) of the transformers with respect to their manufacturing date

In Fig. 3, we show the relative counts of the transformers with respect to preventive and corrective maintenance taking into account if their lifetime was achieved (1) or not (0).

In Fig. 4, we show the rate in which corrective maintenance was performed for each manufacturer (in a total of 24); this is the number of corrective maintenances divided by the total of equipment of a given manufacturer.

One should observe that such analysis should help managers evaluate the substitution or new acquisition of assets or manufacturers.

After these initial analyses, in order to obtain the equipment fault rates, which is our primary goal, analyses based on classical statistical theories were used.

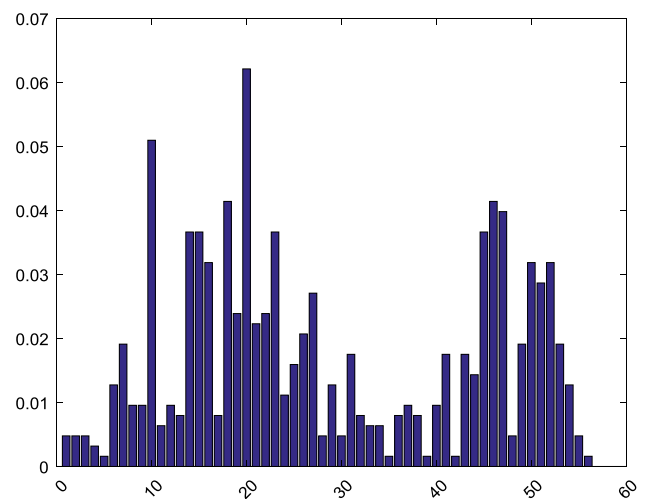


Fig. 2 Histogram (count percentage) of the transformers with respect to their age

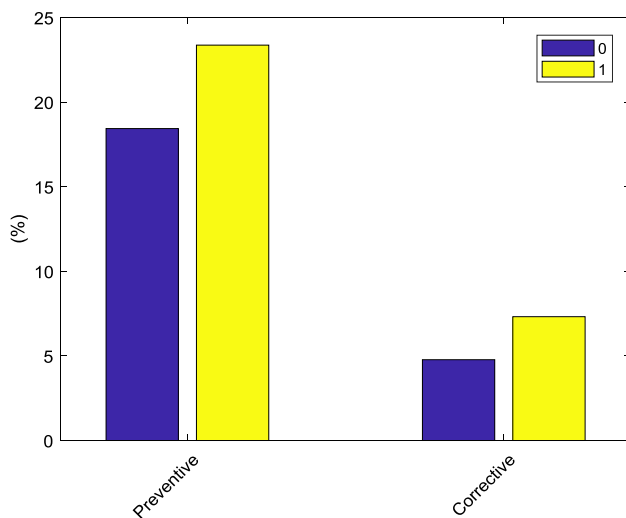


Fig. 3 Histogram (count percentage) of the transformers with respect to preventive and corrective maintenance taking into account if the lifetime was achieved (1) or not (0)

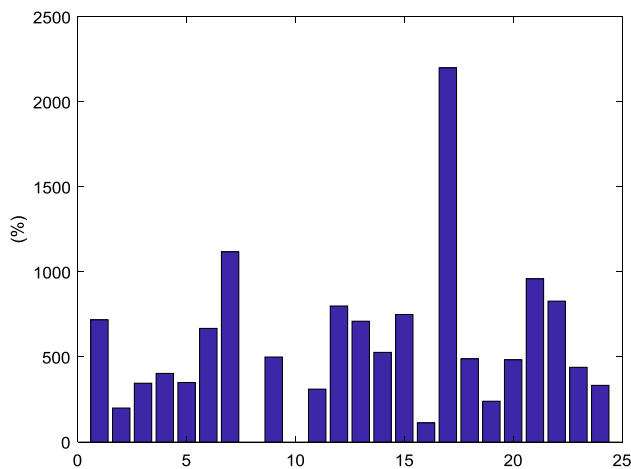


Fig. 4 The rate in which corrective maintenance was performed for each manufacturer (in a total of 24)

The following figures of the preventive and corrective maintenance rate with respect to the age of the asset were also compiled, as illustrated in Figs. 5 and 6.

By definition, corrective maintenance requires that the equipment has failed or is beginning to degrade in such a way that an amplified risk of failure is eminent in the future.

To better understand how the corrective maintenance rate is related to fault rates, we shall make some definitions regarding fault, error, and failure (Parhami 1997). A fault is a physical defect that occurs and after a latency period incurs in a deviation (error) from the expected correct operation of the system. Not all faults result in failures. On the other hand, failure is the nonperformance of some action that is expected. Therefore, a failure is a malfunction where the

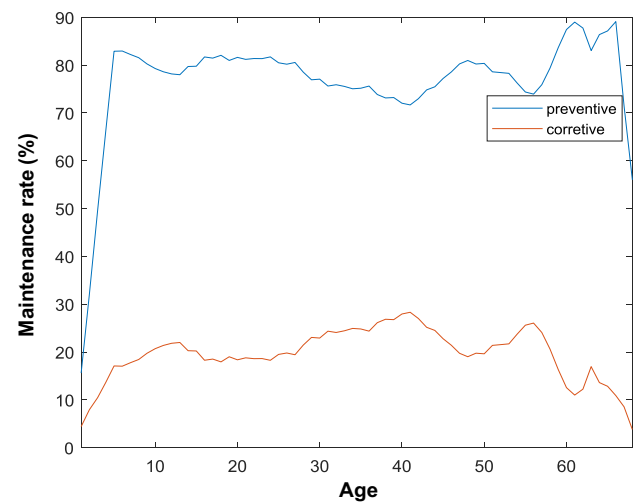


Fig. 5 Maintenance rate with respect to the age of the assets

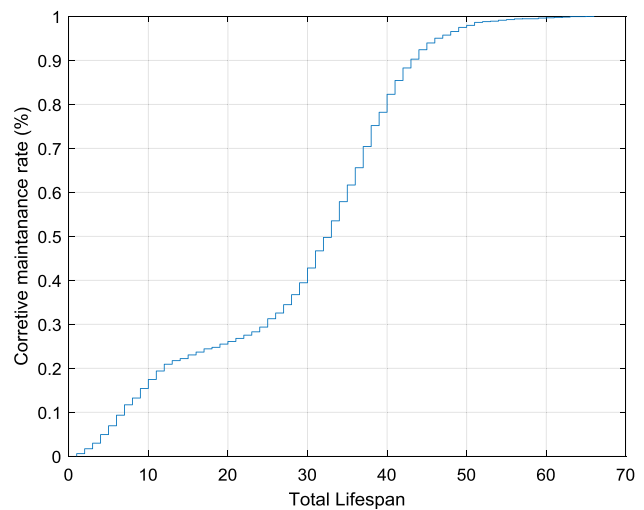


Fig. 6 Cumulative probability density function for corrective maintenance

user of the system ultimately sees the effects. In power systems, a failure incurs in a breakdown of the system. Given the role of power transformers, risky degradation will force the system to a maintenance shutdown, and therefore, usually, corrective maintenance is also related to a failure rate since the system is forced to stop. In this sense, and in the case of power systems, one can observe that corrective maintenance rates are excellent representatives of equipment and systems failure rates.

One can observe that preventive maintenance in equipment such as power transformers is made in a more uniform way throughout its operating lifespan. This result corroborates with the fact that this kind of equipment is crucial and should be robust and should not fail.

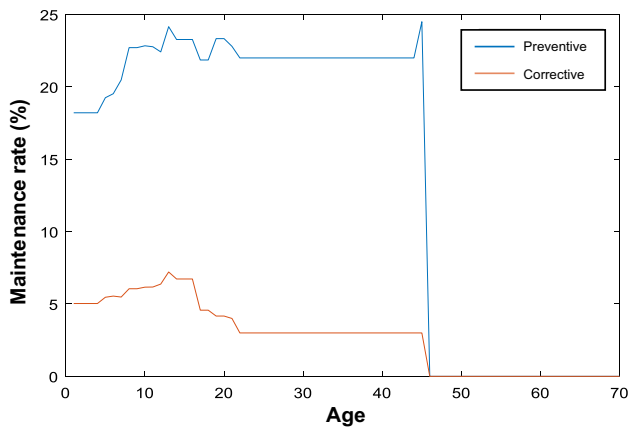


Fig. 7 Maintenance rate with respect to the age of the assets for manufacturer 1

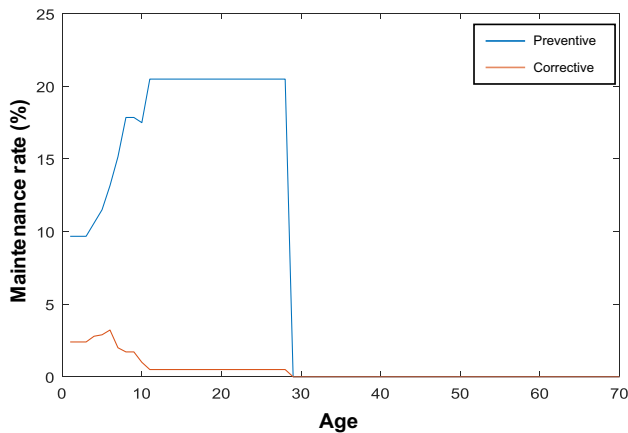


Fig. 8 Maintenance rate with respect to age of the assets for manufacturer 2

Finally, Fig. 6 shows the cumulative probability density function of the corrective maintenance rate, where it is easy to see that for those transformers that fail, 50% have age inferior to 32 years.

3 Preventive Maintenance and Fault Correlation

A usual question that arises in asset management is whether preventive maintenance can prevent faults. To answer this question, several analyses were made, using fault history for different transformers manufacturers, as registered in Figs. 7 and 8. In these graphs, the transformer age is accumulated; this means that failure rates are analyzed with respect to transformers with ages bigger than a determined age. For example, for manufacturer 1, corrective maintenance rate for transformers older than 5 years is near 5%.

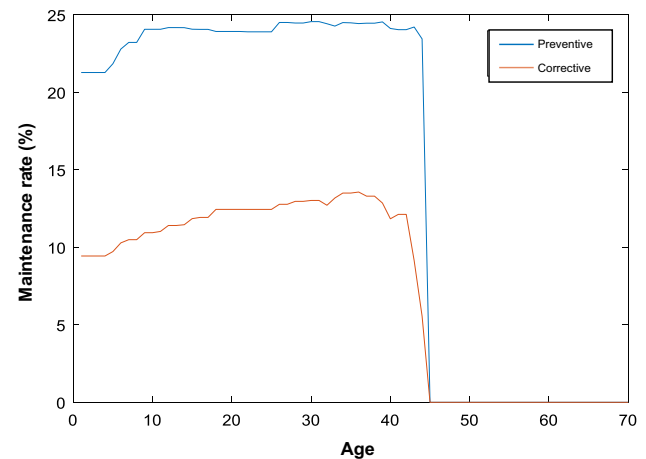


Fig. 9 Maintenance rate with respect to the age of 345 kV transformers

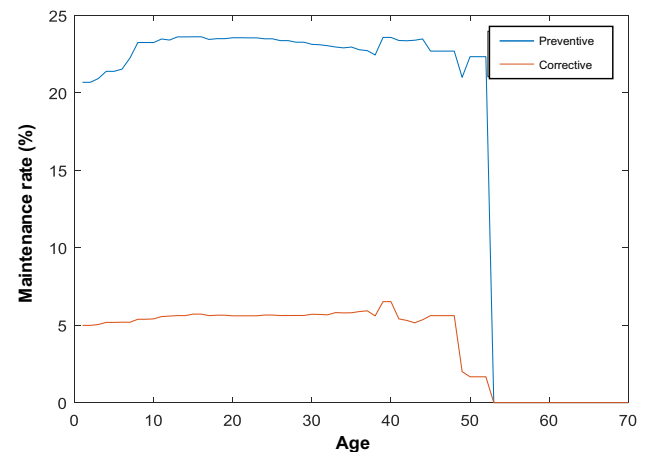


Fig. 10 Maintenance rate with respect to the age of 440 kV transformers

For transformers older than 20 years, then rates decrease to near 3%.

From these graphs, one can see that when increasing preventive maintenance, the corrective maintenance can decrease since the curves are slightly displaced.

Statistical studies on asset health were conducted within the domain of decades. In order to improve the accuracy of the rates, a polynomial interpolation was performed. This approximation technique consists of dividing the interval of interest into several subintervals and approaching, as gently as possible, these subintervals with small (cubic) degree polynomials. This type of interpolation reduces numerical instabilities that cause undesirable oscillations when several points are joined in a curve.

Graphs were also made that relate the maintenance rates to the voltage class of the equipment, as in Figs. 9 and 10. Similar graphs with respect to the technical maintenance

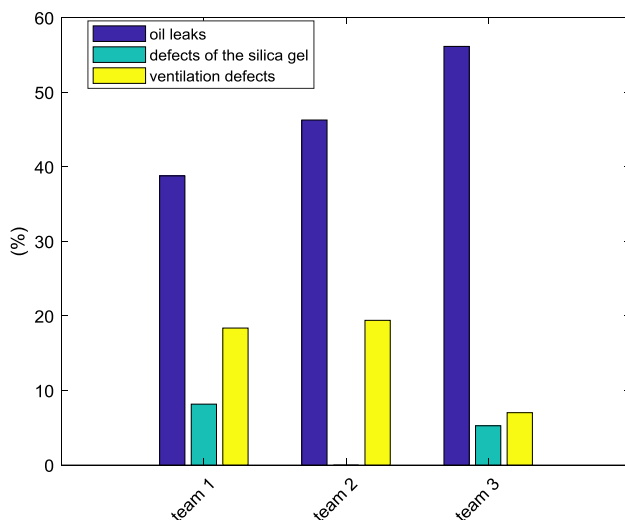


Fig. 11 Corrective maintenance rates of the most frequent faults registered within 4 months after preventive maintenance was made

teams that perform the maintenance operations and other graphs were also plotted.

Finally, we have performed analysis such as calculating the maintenance rates of the most frequent faults registered within 4 months after preventive maintenances. In Fig. 11, one can see that, for different maintenance team, faults have different rates of occurrences. For example, for team 1, for all faults that have happened within 4 months after preventive maintenances, approximately 40% are oil leaks. In general, such faults should not be present considering that preventive maintenances were made earlier with the maximum period of 4 months. Such graphs can help managers investigate such phenomena.

Indeed, with a correctly prepared database, various analyses are possible, and the managers and staff from the asset management program can outline such studies as needed.

4 Conclusions

Asset management programs in electric power systems have been playing an essential role in the strategic scenario of modern electric utilities. Critical assets present in transmission and distribution industries need special care and attention, mainly regarding the aging of the equipment since their lifespan impacts profits as well as the reliability and safety of the electric system.

As the lifespan of these devices become longer, it is justifiable to develop methods to identify their health condition, taking into account not only historical data but also all available asset-management tools that companies currently own.

In this work, we have presented the partial developments of a method, based on database processing and statistical

studies, which can help decision making on asset management. Analysis through relational graphs and probability distributions was taken into account considering the age of the assets and preventive maintenance practices. Our results are from case studies of real databases of an electric utility company.

As the vast majority of companies still struggle to learn from the abundant data acquired, such a method should have significant implications in helping managers evaluate and question in-company policies regarding manufacturers and preventive maintenance practices.

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