THE EVOLUTION OF MAINTENANCE IN DIGITAL AGE: BETTING ON IOT AND EXPERT SYSTEMS

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Abstract - The digital world is fast transforming with the emergence of new tools and frameworks. In this landscape, predictive maintenance is leading its own revolution: transitioning from a reliance on general alarms, triggered when limits are reached, to an approach where trends and foresights, grounded in online monitoring, play a dominant role. The goal is to reduce costs by minimizing both planned and unplanned interventions, thereby enhancing asset availability through the Internet of Things (IoT) and expert systems. By connecting seemingly decoupled information, unexplored operational paths are found, supported by the IoT ecosystem and AI tools such as neural networks. The article highlights how a digital twin, based on real-time monitoring of an electrical machine, can anticipate operations and detect trends, thereby enhancing predictive maintenance. Leveraging AI and IoT does not guarantee perfect outcomes but prepares industries for the most probable scenarios, ensuring smooth operations and prolonging asset life. With this strategy, industries equipped with such systems are undoubtedly placing the right bets for the future.

Index Terms — IIoT, PdM, Neural Networks, Predictive Maintenance, Medium-Voltage Induction Motors, Medium-Voltage Synchronous Motors and Generators.

I. INTRODUCTION

The **I**nternet of **T**hings applied to the **I**ndustry (IIoT) refers to the technology that connects machines to sensors and devices, generating data that, processed at the edge and/or in the cloud by statistical analysis software or artificial intelligence, seeks to improve the efficiency and productivity of the monitored assets and the system as a whole. The application of the Internet of Things (IoT) to the industrial environment has the mission of reducing costs by optimizing maintenance, with a special focus on predictive maintenance.

Predictive Maintenance (PdM) is an effective and important tool for preventing failures and saving money which has been long applied to the industry. It is also a widely and generic term used to describe very different maturity stages of analytics applied to asset reliability and its progress since specific employment of analytic equations up to latest Artificial Intelligence (AI) techniques [1].

The synergistic development of PdM and IIoT in the past years has promised a game-changing industry savings. This promising outlook has been shared by both academic studies and analyses. However, the expectation of a high return on investment is not always equally achieved by all who apply it. According to Cortes, et al. (2022) and observed in some proofs of concept performed by authors, when focused on predictive maintenance using currently AI, part of the gains is consumed by false positives and the advantages diluted in unnecessary shutdowns.

In order to mitigate that, there are two aspects to be considered as proposals. The first one is more technical, and it is focus on developing more powerful models to represent the assets, scaling from analytical equations to AI and Neural Networks (NN). The second one, and more strategic, proposed in [1], is to broaden the perspective of how the IIoT infrastructure can be used, combining Advanced Troubleshooting (ATS) and Condition-Based Maintenance (CBM) with more PdM advanced techniques, instead of just replacing the past practices.

It is important to emphasize that although it is possible to extend the debate to other piece of equipment in industry, the assets considered in this paper are large, medium-voltage induction and synchronous electrical motors and generators. In addition, for this discussion development, a significant characteristic it is necessary to be taken in account is that as the size of electrical machines increase and shifting from low to medium voltage, more components, and thus more complexity are added to the system.

As components such as hydrodynamic bearings, cooling systems, and excitation systems in synchronous machines, for instance are introduced, it becomes necessary to have their performances monitored and analyzed in conjunction with the main machine. In this new scenario, models employing specific NN are more than necessary, they are required. Additionally, as the larger and more dedicated for their applications are the machines, less data are available to train the neural network. In other words, as more extraordinary the defects and failures are prone to happen, less data was available for the model to be trained.

This paper will focus firstly on the technical features, using as example a development of specific neural network for a complex application in large, medium-voltage electrical machine and the training strategy for mitigate the lack of data to be used to construct the model. Afterwards the paper evolves it to a more holistic discussion, to explore how both approaches discussed in some paragraphs above are connected to each other in order to ensure the success of IIoT and PdM in the returning of investment.

For better understanding, it is briefly explained the differences between the layers of IIoT: assets, hardware (gateway and sensors), connectivity, platform, software and visualization. Afterwards the text proceeds by highlighting the differences between the monitoring and expert layers and their interdependence. Finally, the authors will discuss how more advanced data analysis models improve performance, increasing the value of IIoT and how to overcome the challenge of obtaining data for machines that are unique in their specialties.

II. IIOT LAYERS

To demystify the topic, this paper will break down the IIoT solution into four key layers:

1. Firstly, the layer relating to the assets being monitored;
2. Secondly, the array of dedicated sensors and the device tasked with acquiring, treating, and transmitting sensor data to the cloud platform;
3. Thirdly, the cloud platform where data is stored and processed by software for asset management and expert systems applications;
4. Finally, the dashboards showing the asset information and its operating conditions and diagnoses.

A. Assets: Medium Voltage Motors and Generators

There are many market solutions for IIoT for small low-voltage induction motors. Such solutions have already proven their efficiency by using data for monitoring and identifying defects, at an acceptable cost. Motors that normally are not sensorized, become part of an asset monitoring system, with data analyzed in the cloud, through non-invasive sensors, with easy installation and simple commissioning.

However, unlike small low-voltage motors, large medium-voltage rotating electrical machines (motors and generators) are regularly engineered, often intended for specific processes with high added value, and have several components, as showed at Fig.1. All these features translate into their complexity: with many peripheral systems, such as the cooling and excitation, or sets of sliding bearings for example, the possibilities of failures are increased.

Fig. 1 – Medium-voltage synchronous and induction machines with different heat exchangers and sleeve bearings

As central equipment in several critical processes, these medium-voltage machines have sensors installed and are monitored. The differential will not lie in data collected, in these cases, the value exists due to processed information and by associating it to the predictive maintenance, combined with condition-based maintenance (CBM) and advanced troubleshooting (ATS). Consequently, in order to guarantee the quality and quantity of the information, the data samples must meet specific acquisition characteristics for use in advanced diagnostics through data.

B. Data Acquiring Central Device and Sensors

One of the several challenges of a proper IIoT system is found in how the dedicated hardware and the collected data perform together. Data needs to meet certain specifications for bringing valuable information from the application. Due to that, the acquisition of different electrical and mechanical magnitudes requires different intervals and sampling frequencies, in order to allow the data being proper to be used in the analytical models, artificial intelligence, and neural networks.

The hardware specification, consequently, depends on the functionalities and intelligence each manufacturer will imprint to their system. For the Data Acquiring Central Device of this manufacturer, it is showed the façade of the system for how it is recognized. For medium-voltage machines, the equipment is installed and prepared at manufacturer shop floor, according fig. 2.

Fig. 2 – Data Acquiring Central Device aspect

The entire system still includes, besides the Data Acquiring Central Device, several sensors, such vibration, temperature, speed sensors, voltage and current transformers and flowmeters, among others, as showed at fig. 3.

Fig. 3 – Sensors and Data Acquiring Central Device

It is possible as well having sensors especially designed for the application able to connect to the acquiring device, as synchronous rotor current and voltage telemetry, according fig. 4, since there is an engineered functionality that requires these parameters.

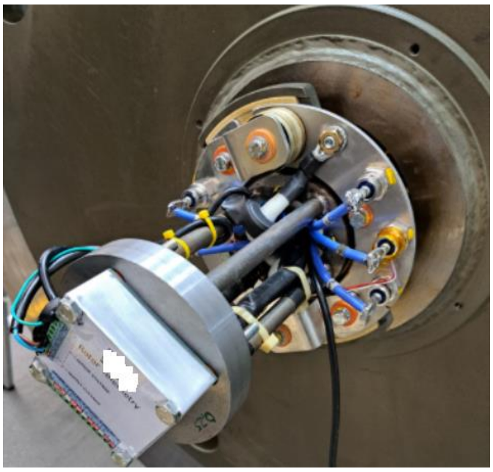

Fig. 4 – Engineered device for synchronous rotor telemetry

The data from all sensors are sent to the central device that translates different protocols, at specific sampling rate, and operating as a gateway as well, it sends the sets of data to the cloud, where the processing will be settled.

C. Cloud Platform, Condition and Diagnoses Dashboards

On the cloud platform, at least two primary layers must exist: management and expert systems. These layers are interconnected as they utilize the same datasets for their construction. Nonetheless, the similarity ceases there.

Straightforward algorithms, offering immediate information such as vibration levels, temperature, voltage, and current at specific moments, for instance, are the base of the Management layer. At platform, the information displayed must be on user-friendly dashboards, available just not at computer but in smartphone of each one of maintenance personnel, as shown at Fig. 5.

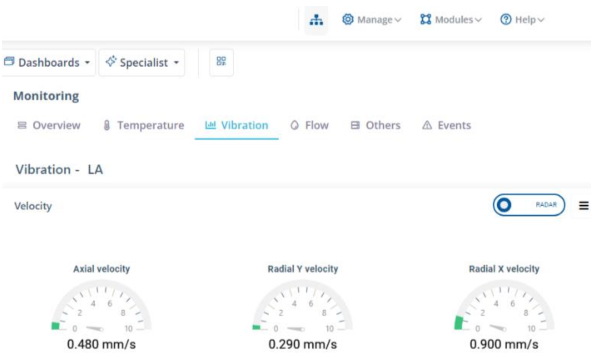

Figure 5 – Velocity vibration levels displayed at cloud platform

As introduced before, it is common for large and medium-voltage electrical machines play a leading role in their applications, being the central piece in some critical processes. This is the reason why the machines are generally fully sensorized. Therefore, initially, the management layer alone seems that would not provide more value. However, although the answer of the management system is simple and direct, such as the value of the current at a given moment, the data sample is scaled from the perspective of who will use the data and for what reason they will use it.

Since the proposal is to have an expert layer, the current, for instance, is not measured second by second, but at a much higher sampling rate, in kHz samples, for being possible to extract information from its waveform. This way, management system inheres from expert system a dataset ready, for example, to be used to identify properly the root causes in case of a failure in a transient mode among other routines.

However, it is in the expert system that lies the innovation of IIoT. To exemplify what was mentioned before, the same sensors and data from management are used at next example, in this case to feed an analytical model. This model was designed to providing a diagnose of unbalance and misalignment, depicted at Fig. 6, based on vibration signature.

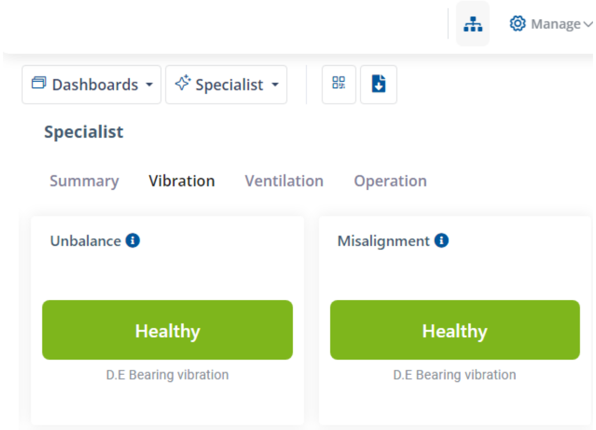

Fig. 6 – Expert system for diagnosing of mechanical misalignment and unbalance using vibration data.

Comparing the dashboards presented at fig. 5 and fig. 6, it is observed the improvement of information. The data and the user-friendly environment are the same, but while the velocity vibration levels describe organized data, misalignment and unbalance diagnoses represent rather more than that, they are data empowered by knowledge.

Pushing the boundaries further, beyond the analytical models, as the previous example, there are the heuristic models, like neural networks, tailored for applications of electrical machines, shaped on the expertise of the electrical machine human specialist. This will be discussed as example at the next chapter along with its challenges.

III. Functionalities in Expert Systems

The functionalities of an online expert system for medium-voltage rotating electrical machines should be able to identify, monitor, and diagnose defects, failures, and deterioration processes that may occur in these pieces of equipment. Different types of models can be used for this purpose, depending on the interaction between variables and system parameters.

As examples of expert systems are the diagnosis of misalignment and unbalance, bearing failures, rotor broken bars in induction motors, failures in the cooling system, detection of stator winding failures, detection of failures in synchronous machine rotors, and detection of partial discharges.

IV. Expert Systems using Neural Networks and AI

According to Gupta & Nagpal (2020), an expert system is a computer program that simulates the ability of a human who has knowledge and experience in a particular field. Expert systems are designed to solve complex problems by reasoning about knowledge, as an expert human would do it.

A characteristic of a good expert system is the use of heuristics. This allows for the construction of a flexible and adapted system, prepared for exceptional situations where a conventional algorithm cannot provide information from the presented data in an appropriate time. In other words, a conventional system, based on algorithms, follows a clear and deterministic sequence of actions, issuing a unique and correct result as long as it has sufficient data and time to be processed. An expert system, alternatively, operates in an area of uncertainty, using data, general principles, and previous learnings in an emulation of human analysis, and does so in an acceptable time.

Time is an important parameter when building a system to respond online and in real time. The value for the customer lies in anticipating a possible defect, which may be hidden in the way many parameters interact and not just present in trends of an isolated parameter. Following this path, using a procedural model that will go through each of the values, of each of the parameters in a complex problem, makes the analysis impractical.

A. *Constructing Heuristic Models for Large Machines*

The first challenge, that requires ingenuity from a human specialist, is to understand how to construct and to test an AI model and ensure that it is accurate.

Unlike small low-voltage motors, large medium-voltage motors and generators, along with their application, are often unique examples, as is the dynamics of their failures. Even if it were financially possible to build several machines, of different frames and cooling systems, and induce various defects, to obtain data, it would still require dedicated laboratory, and eventually time. Although not impossible, it would be very unlikely to have resources available for this purpose [2].

Validation, proposed by [2], comes through tests in virtual scenario, employing a digital twin. The process is validated with available real machine data, where the specialist in the cooling system of rotating electrical machines is an essential piece: the quality of analysis and virtual tests will depend on their knowledge.

B. *Expert System's Functionality using Neural Network for diagnosis and prognosis*

In practical terms, displaying a specific functionality, the authors will exemplify the value of the expert system to illustrate the discussion. This case considers the problem of the efficiency loss of the cooling system of an induction motor driven by a frequency inverter and load variation. It will be considered one of the cooling topologies applied to medium-voltage rotating machines, an air-air system.

Over time, exposed to the weather and industrial environment, the cooling system slowly loses its factory efficiency. Depending on the installation location, this occurs from slow to a high-rate range. As ventilation load's losses gradually increase, and considering the motor has variable speed and power, it is difficult to notice the process unveiling, just monitoring the temperature. The aspect of the one phase winding temperature of a motor over three years is shown at fig. 7.

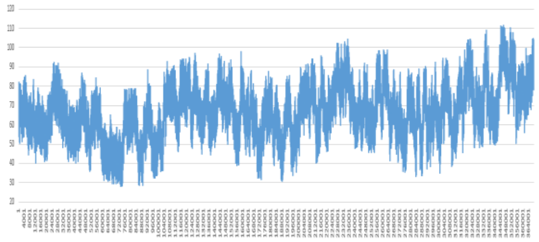

Fig. 7 - Temperature over three years with simulation of loss of ventilation efficiency

It is possible for a human specialist to gather information. He or she would need to raise, process, and check periodically temperature, output power and load, continuously crossing information about these parameters. Therefore, in a real situation, only when the temperature triggers some protection limit does the maintenance team realize the failure, which can be something relatively simple to solve like a clogging of the radiator channels or an unexpected and new problem.

The monitoring system by itself cannot perceive the evolution of the problem because the machine works at various load points and speeds. Besides, without context, the temperature can appear to be within allowed parameters in operation since no alarm is triggered. The loss of efficiency goes unnoticed and the available time for the maintenance team to act, or schedule a correction, is consumed.

Once there is no analytical model that integrates so many, for various failure situations, the interaction between the parameters power, rotation and airflow, predicting the temperature and providing a real-time diagnosis by comparing the calculated and measured temperatures. The neural network becomes, in this situation, a viable option. Considering that nowadays there are many topologies and tools available for any data scientist to assemble a neural network and train it with data, it might seem that the expert in rotating electrical machines could easily be replaced by a data scientist.

This is not the practical experience observed by the authors. General-purpose neural network models will hardly meet specific tasks. The adaptation and optimization of the neural network require expert knowledge to adjust the model to the peculiarities of the dataset and the physics governing their interaction. The neural network topology suitable for machines with frequency inverters in this case is customized, with strong inference from the human specialist thinking about the physics of the problem and the non-linearities involved.

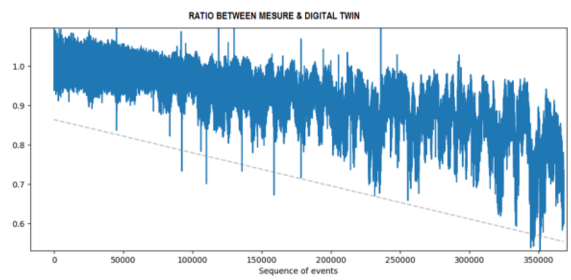

Fig. 8 – NN designed to identify and foresee deterioration Ratio between motor and its digital twin

In Figure 8, the ratio between the measured value and the estimate provided by the digital model is presented. Under normal operating conditions, this ratio should always be close to unity, meaning that, for normal operation, the temperatures should be equal. When the ratio of these temperatures deviates from unity, a potential problem in the cooling system can be identified, such as a sudden blockage or accumulation of debris over time. This conclusion is drawn from, in addition to the measured temperature, the use of neural networks and operational information, such as power, rotational speed, and ambient temperature.

As previously shown for vibration, the diagnosis for ventilation is also presented in a user-friendly manner to assist in the asset's maintenance management, as shown in fig. 9.

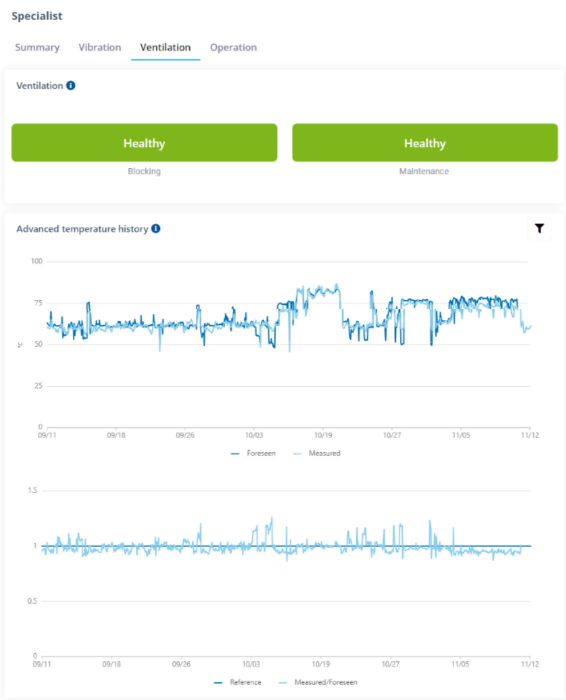

Fig. 9 – Expert system for diagnosing cooling issues using operational data.

C. *Case of Fault Diagnostics by Expert System*

To illustrate how the expert system, discussed in the previous chapter, reacts to an event, it is proposed to analyze the "Warning" condition of the "Blocking" functionality, as shown in fig. 10.

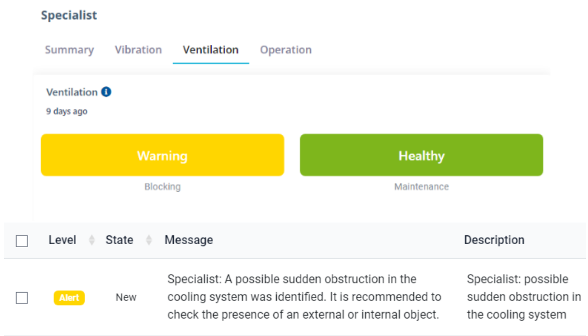

Fig. 10 - Event recorded by the expert ventilation system, with the *Blocking* functionality in *Warning*

There are two functionalities in the expert system in question: Blocking and Maintenance. In the "Blocking" functionality, the obstruction process occurs quickly. The advantage proposed by this expert system is the detection of the fault regardless of the load condition and ambient temperature. Without the system, the fault could be hidden in a low load situation and could cause, when at rated load, an emergency stop, for example. The temperature profile graph compared to that of its digital twin, shown in fig. 11, refers to this event. It exposes a critical condition in evolution, hidden within a situation where the temperature class is preserved.

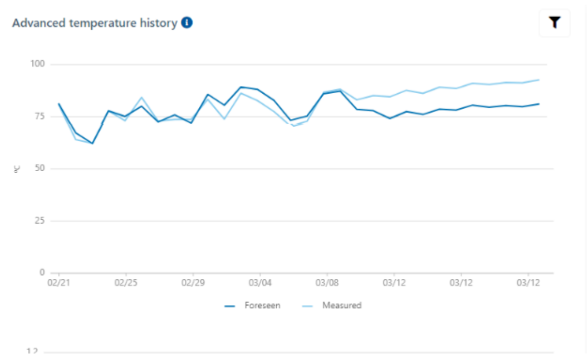

Fig. 11 - Measured temperature that deviates from the profile predicted by the digital twin.

Visually, it is possible to identify and track the condition and decide, in the case of stabilization, to postpone maintenance to a more opportune moment, with the least impact on the production process, for example. Or it is possible to deliberate, if feasible, on mitigating the problem with the machine in operation.

For the situation where the failure continues to evolve, emergency maintenance scheduling is used to control the damages, with the available reaction time as an advantage. The graph shown in fig. 12 helps track the failure by highlighting how the actual measured parameters diverge from their expected values.

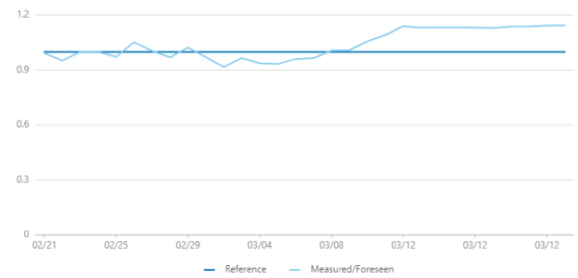

Fig. 12 - Comparison of the machine measured online with its digital twin.

The second event, shown in Fig. 10 as "Maintenance" occurs more slowly, over the life of the machine, as scaling accumulates in the heat exchanger, reducing its efficiency. Here, the indication is subtle and hardly noticed by human analysis. The proposed and developing advantage for this functionality is to provide the probability of failure in operation windows, both to allow for scheduled maintenance planning in advance and to avoid scheduled but unnecessary verification shutdowns.

D. Expanding Expert System's Functionalities

As previously mentioned, some medium-voltage electrical machines are key players in their applications. One implication of this status is that there are similar failures across different applications and industries, but there are also unique ones. This affects the construction of the asset management system and expert system. To generate value, the whole system needs to be modular and capable of incorporating new functionalities to cater to specific applications and the unique histories of the plants where they will be installed. The system then needs to be flexible and modular to adapt to the application and evolve in the face of specific challenges.

As an example of this evolution, the authors will illustrate in this paper is a functionality that is being built and will be integrated into the system we are discussing here. It is the Operating Deflection Shapes (ODS): vibration signal analysis technique in conjunction with low-cost wireless condition monitoring IIoT sensors [4].

ODS is a diagnostic tool that assesses not only the vibration amplitudes but also how these amplitudes behave in the form of deflection in the evaluated body. This functionality integrated to an online system requires the use of specific IIoT condition monitoring sensors: hardware designed for the function and embedded software to assess vibration patterns. It offers favorable results compared to traditional ODS analysis at a much lower investment.

By paralleling vibration signatures under different load conditions, information can be assessed as depicted in the fig. 13 at one of the tests with the bench set, in the condition with or without load.

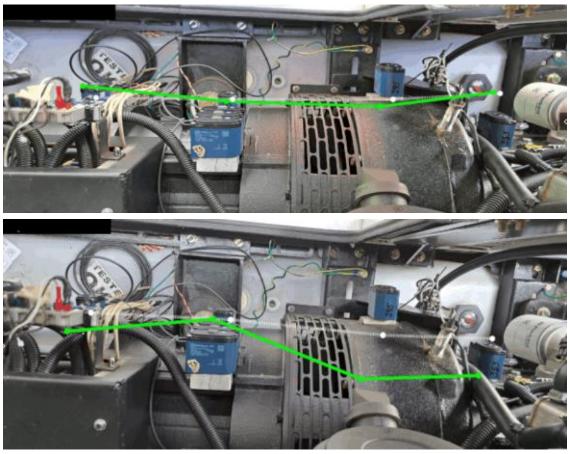

Fig. 13 – ODS analysis with and without load at test bench.

V. Preventive and Predictive Maintenance

The cost of a medium voltage electric machine encompasses much more than its acquisition cost. According to the Total Cost of Ownership (TCO) model [5], the costs of the asset throughout its lifecycle are considered, such as energy costs during operation and maintenance costs. This model helps us better understand the impact of efficiency, diagnosis, and prognosis on the total cost.

Equation (1) shows the structure of TCO, including the salvage value, which is the value returned from the asset at the end of its useful life in the form of metal and dismantled parts, for example.

$$TCO = AC + OC + MC - SV \qquad (1)$$

Where:

TCO	Total Cost of Ownership – Cost over asset's life span;
AC	Acquisition Cost;
OC	Operational Costs;
MC	Maintenance Costs;
SV	Salvage Value.

However, data availability to evaluate this cost distribution for each type of equipment is not always present. It is well-founded assumption that cost distribution varies according to the electric machine's prominence, application, and consumption. Once, the more critical the application and the more central the role of the motor or generator, the less the acquisition cost matters to the total cost, and the more useful a management system is for data collection and quantification of this equation and planning.

Even if the data does not exist and the cost proportions are not clear, it is still possible to optimize the asset's operation to reduce its impact on the plant, using the expert system. The loss of efficiency over the operation time of the electric machine, for example, discussed in the previous chapter, can be anticipated using a neural network constructed by a human expert. With this functionality, not only can energy be saved throughout the process, but also maintenance can be managed, anticipated, or, depending on the health of the asset, postponed. The time between the point at the first failure signs appear and the point they are detected, as depicted in the fig. 14, provides additional response time which can empower the decision-making with data and define the best course of action.

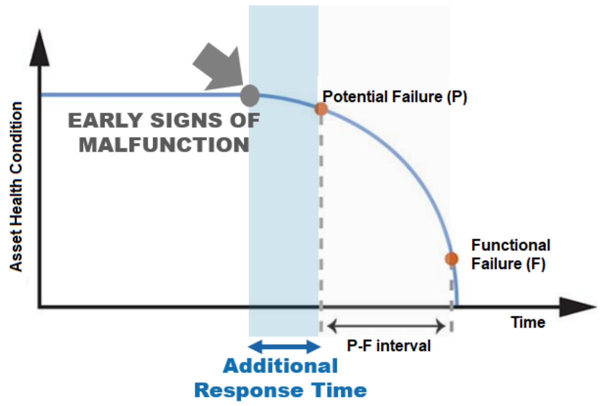

Fig. 14 – Intervals between first signs of failure and detection and between detection and failure

VI. Conclusions

Digital transformation, through the Internet of Things (IoT) and expert systems, is in a rapid expansion, delivering value across a broad spectrum of business sectors—from healthcare and agricultural production to entertainment. This emerging trend foresee a reality where no industry, be it manufacturing or extraction, remains untouched. The adoption of online monitoring and predictive analytics promises to dramatically enhance operational efficiency, costs, and extend the lifespan of assets, revolutionizing, this way, the maintenance practices. Furthermore, deploying neural networks and other artificial intelligence technologies, to go through data gathered from sensors on medium-voltage machinery, marks a significant leap forward in forecasting and mitigating failures, as well as optimizing industrial asset maintenance.

Through the authors' experience in developing proof of concepts in transformational industrial environments for the specialized monitoring and diagnostic system for medium-voltage rotating machines, we have built a strong conviction. It became evident that, given the critical nature of these machines in their respective applications, the approach of generalist solutions is not suitable. It is indispensable to adopt customized solutions that recognize and respect the uniqueness of each type of industry and plant. This insight leads us to advocate for systems designed not only to meet specific needs from the outset but also capable of dynamically adapting and adjusting throughout the operation. Such flexibility and modularity, combined with an arsenal of sensors and heuristic tools developed by teams specialized in rotating electrical machines, are fundamental to driving value creation. This proposal represents an 'haute couture' approach, in direct contrast to the 'prêt-à-porter' solutions commonly applied to low-voltage machines, thereby promoting a new era in maintenance guided by data and grounded in information.

However, the adoption of these technologies is not without challenges. A critical issue to be addressed is information security. Some industries, for instance, are especially sensitive to information leak and having their data at cloud services is not a choice. This issue represents a challenge instead of a barrier, calling for cooperative resolution between consumer and supplier. And based on our experience there is a solution: an island platform settled at customer own servers can be developed.

Summarizing, we still have a path to tread, but the future holds promising profitable results. The key to success lies in effective collaboration among all parties involved, the use of suitable tools to ensure the system's flexibility and modularity, and the undeniable expertise of human specialists in electrical machines.

VII. ACKNOWLEDGEMENTS

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IX. VITA

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