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Article

Analysis of Asset Management Models for a Transformer Fleet in the National Laboratory of Smart Grids (LAB+i)

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Abstract: The study of the degradation of power transformers in the electrical network has become a subject of relevant analysis by network operators and companies, associated with the probability of failures and operation quality. For this reason this paper firstly presents the classification of a set of 12 Asset Management models related to power transformers monitoring and, then, the application of three of them in three substations of the National Laboratory of Smart Grids (LAB+i) located at Bogotá Campus of the Universidad Nacional de Colombia. As a result, the main challenges were identified concerning the Asset Management application in transformer fleets related to data availability and precision. Finally, it was identified that the development of an Asset Management model that uses non-invasive real-time measurements is needed for continuous monitoring of power systems and diagnosis.

1. Introduction

In power systems, transformers play a key role in the processes associated with the transmission and distribution of electricity worldwide [1]. Therefore, life cycle monitoring has become an important subject of study in the Asset Management framework due to the use of those systems to diagnose the performance of network reliability and safety [2].

As a result, several types of research on Asset Management in power systems have been developed, covering from ISO 55000 Standards [1] to the incorporation of real-time measurements and diagnosis of Power System Assets. In addition, transformers life cycle modeling is improving as there is more data availability and recognition of its economic impacts. [3] At the same time, thanks to the progress made in Artificial Intelligence, Neural Networks and probabilistic models, systems with a high degree of reliability, besides limited data availability, have been developed [4].

The present article is divided into three sections. First, in Section II, the model classification method is defined by four main decision-making components and by the summary of the 12 analyzed models. Then,

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the main categorization results are shown, providing an initial insight into possible research fields and their application in the National Laboratory of Smart Grids (LAB+i). In Section III, three models from the classification methodology were implemented, considering the data availability of three substations connected to the LAB+i. Finally in Section IV, the main conclusions and future research opportunities from both sections are presented.

2. Transformer Asset Management classification

For the Asset Management classification, 12 models were taken as reference. The type of modeling used for the power transformer, life cycle, final indicator calculation and required data were analyzed.

2.1. Power Transformer Modeling

- **Thermal model:** The transformer is modeled through its insulation material and critical components by thermal phenomena. The International Electrotechnical Commission (IEC) established a guide of the transformer thermal conditions IEC 60354, which is mostly used by IEEE calculations and IEC 60905 [5].
- **Dissolved Gas Model:** It is developed from the measurement of chemical components in insulation and their classification based on reference data. The Dissolved Gas Analysis modeling is based on standards such as IEC 60559, IEEE C57.104-1991, CIGRE TF 15.01.01, and GB 725287 [6].
- **Frequency Response model:** The objective of this model is to relate the Transformer condition with the detection of coil movement faults due to the loss of clamping pressure or short circuit forces. The referenced standards are DL/T 911-2004, CIGRE WGA2.26-2006, and IEEE PC57.149 [6].
- **Partial Discharge model:** Partial discharges occur when a local electric field exceeds a threshold value, resulting in the creation of a small discharge, as identified in IEC 60270. This type of phenomenon causes degradation of the transformer insulation [6].
- **Hybrid models**: A system that considers two or more transformer models for the development of status indicators related to research at different levels [7].

2.2. Life cycle approach

- **Consequence Factor:** It is defined as an economic analysis, in which it is assumed that all assets will fail in the future. In this case, it is translated as a representation of operating costs and associated risks [8].
- **Failure probability:** Given the evaluation of the asset technical condition from diagnostic tests, health index, etc., it is bounded by the transformer modeling and its various subsystems, which are fully divided by the IEEE C57.140 standard [8].
- **Economic Lifetime:** This is based on the analysis of the economic evaluation of device components, represented by the value of the assets, which is reduced over many years of use. However, some of these parts may still be physically used [6].

2.3. Output Indicator Calculation

- **Machine Learning:** Given the use of autonomous learning resources, the calculation of the final value is made to serve as a decision-making indicator by the interested parties of an intermediate process. Examples are Neural Networks and some probabilistic methods [9].
- **The weighting of direct and indirect measurements:** These methodologies assign a weight value to each of the data components from field measurements. This number represents the relative importance of each factor in the final indicator calculation [7].

- **Fuzzy logic:** A form of decision-making that seeks to include human language or categories in the mathematical and technical development of Asset Management [10].
- **Mathematical or Normative Formulation:** The application of formulas of international standards or mathematical models developed independently [7].

2.4. Measurement and output data frequency

- **Calculation Time:** Given the information census frequency within the Asset Management system, it is considered a real-time measurement with smart metering as a key component [9].
- **Output data format:** The analysis is divided into two categories. The first one corresponding to a numerical value, which is used as a key parameter for decision-making. The second one is a logical value, which is usually used to implement a specific action.[9].

From this classification, 3 models were considered for their implementation in the LAB+i, with a description of the current state of research associated with this type of diagnostics.

2.5. Key points of Reference Models

First, in the model in [3], there is an analysis of the probability of failure and consequence factor of the power transformer based on system operating data and Dissolved Gases Analysis (DGA). Similarly, the DGA in [9] is complemented with predictive systems such as Neural Networks to improve overall performance, including oil quality and furan analysis in [11]. In [12], the same machine learning tools are used to identify the most significant parameters in power transformer assessment.

On the other hand, [13] presents an analysis of the power transformer insulation degradation process, considering its thermal properties and the insulation degree of polymerization. The study in [4] postulates a monitoring system of the thermal and chemical parameters of a transformer fleet, which aims to diagnose its state in real-time. A similar trend can be observed in [14], where a Key Performance Indicator (KPI) shows the likelihood of this asset failing. Meanwhile, in [10], this advancement was supplemented with a Fuzzy Logic-based transformer status classification system.

In [7] and [15], a general approach to transformers Asset Management is presented, considering measurements associated with DGA, thermography, insulation resistance, among others. Based on a similar method, [16] evaluates the quality of the power transformer, in consideration of Dissolved Gases measurements and age coefficients. Finally, in [17] influence diagrams and Bayesian learning tools are used to schedule preventive maintenance of the Transformer Fleet.

2.6. Classification Results

2.6.1. Power Transformer Modeling

In the model classification, as presented in the bar chart of Figure 1, the following categories were identified:

- **2 or more models:** The articles performed the lifetime calculation from the measurement based on weighting methods or fuzzy logic approaches, categories that need data from various models [8, 14, 7].
- **Dissolved Gases Analysis:** The methodologies inputs correspond to dissolved gases concentrations in complement with information coming from power systems operation [3].
- **Thermal model:** In this last category, the methodologies use the hot spot temperature of the transformers as reference point for the development of diagnosis.

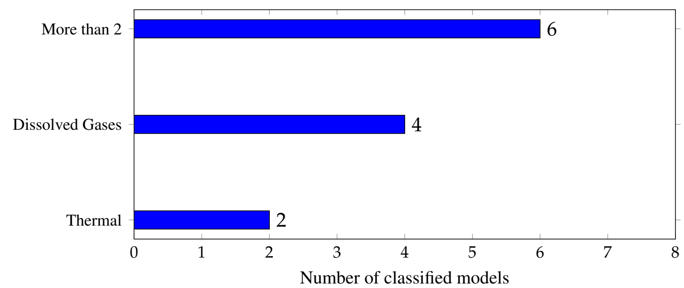

Figure 1. Power Transformer modeling classification

2.6.2. Life cycle components

As shown in the bar chart in Figure 2, the **Failure Probability** in nine models is taken into account as the performance cornerstone, mainly due to the calculation of factors associated with the physical remaining time of the transformer critical components. However, in three of them, the **Consequence Factor** was also calculated, since other power system conditions were taken into consideration [17, 14, 3].

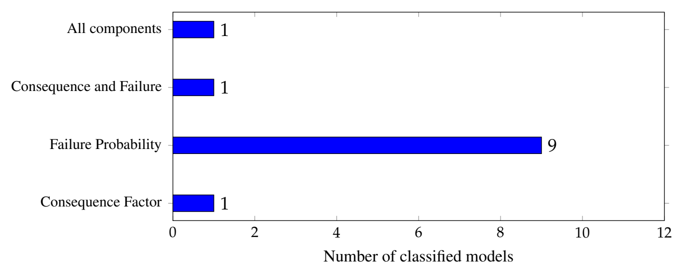

Figure 2. Classification of life cycle components

2.6.3. Indicator calculation models

As presented in Figure 3, the most used method is the **weighting of the quality measurements** of the variables associated with the power transformer degradation. It assigns a weight of importance to each of their factors. However, **Machine Learning methods** were used for optimizing the calculation of their factors based on the limited availability of information, alongside **Fuzzy Logic implementations** and the **Formulation application** given international standards.

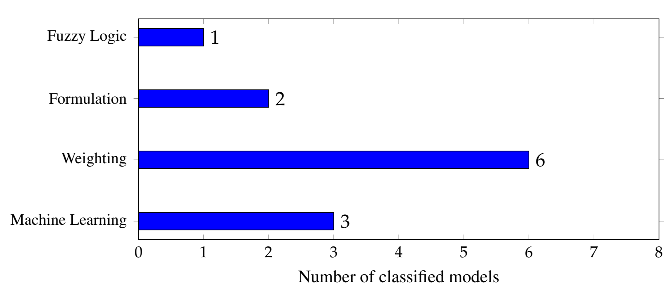

Figure 3. Classification of indicator calculation models

2.6.4. Measurement and output data frequency

Finally, in Figure 4 it was identified that eight of the Asset Management models present no update of the status of the devices in **real-time** and require an invasive measurement process, such as a temporary shutdown, while this measurement is performed.

In contrast, four models use real-time measurement, mainly due to their coupling to a smart metering system and computational intelligence [4]. Then, in the case of the type of output data, it was identified that in seven of the models, a **numerical value** is presented as output data rather than a **logical value**.

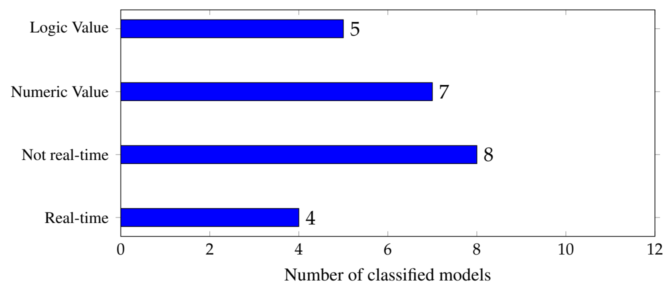

Figure 4. Measurement and output data frequency classification

3. Asset Management Implementation

In the classification of the 12 reference models, it was identified that, for the evaluation of Asset Management implementation in a real case, investigations are developed with two or more models of the transformer, as evidenced in Figure 1.

At the same time, the probability of failure identified in Figure 2 must be considered together with the quantification of the relationship between variables for the construction of a diagnosis, taking into account the results of Figure 3. Finally, the implementation of transformer management models was considered. The final diagnosis of these models was based on a numerical value as shown in Figure 4, although it was decided to take into account the real-time analysis of the information associated with the LAB+i characteristics.

The LAB+i is built on six layers, as shown in Figure 5. Specifically, a system of smart meters was installed throughout the University Campus in its main substations, corresponding to the Physical Layer. This equipment is composed of sensors that allow registering the main parameters of the quality of electricity distribution (interface layer) [18].

Consequently, these sensors are connected to an internet network that allows the transmission of data in real-time (communication layer) to the platform designed based on the PI System software, where the laboratory administration process is carried out (management layer). Finally, some network models have been developed that can be used for studies on the quality of the electrical network within the framework of smart grids (model layer) and the display of results from end-user-friendly applications (analytics layer) [18].

Currently, there are real-time available measurement data for 33 substations of the Bogota Campus, from an AMI system, where parameters associated with the operation and power quality of the electrical system are recorded. [18]. The oil temperature measurements are available in three of these substations, as shown in the daily plot of Figure 6.

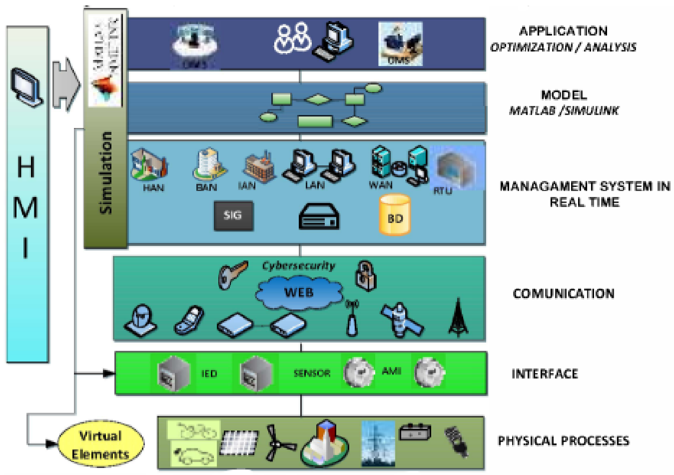

Figure 5. LAB+i Laboratory Scheme [18]

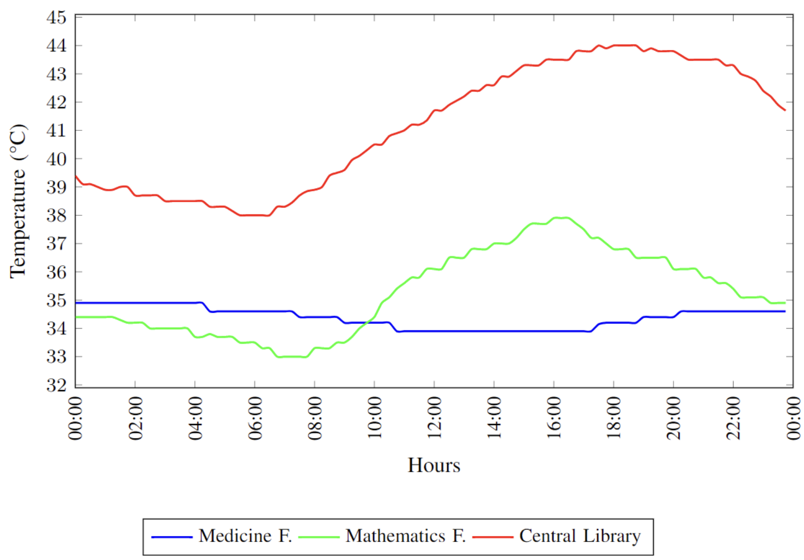

Figure 6. Initial temperature measurements of oil insulation of 3 substations

With these values and the total operating time (Transformer Age), three models of the presented methodology were chosen to demonstrate the effects of the Asset Management modeling with real data.

3.1. Thermal Model

For the development of this first model, the guidelines of IEEE Standard C57.91 were considered. [5]. In the LAB+i, only the transformer demand curve data and the oil temperature value are available, both in real-time. As a result, the GTC 50 guide is used to approximate the device hot spot temperature [19].

The hot spot temperature was calculated from a *python* code, in which the reference parameters for physical properties were established in addition to the real-time measurements. This resulted in the years of remaining service predicted throughout a day as presented in the daily curve of Figure 7.

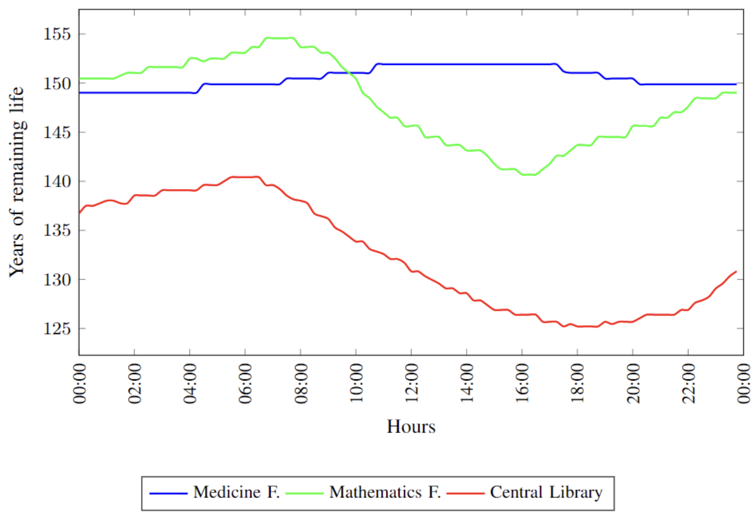

Figure 7. Thermal model results of the 3 analyzed substations

However, the final values between 120 and 150 remaining years in Figure 7 show that the transformers have a theoretical remnant life of more than 100 years. This is related to a low power consumption ratio and missing values that could change the overall diagnosis.

3.2. Fuzzy Logic Model

For the fuzzy logic method presented in [10], the following 3 variables were measured:

- **Transformer age:** It considers the historical installation of the electrical substation.
- **Insulating oil temperature:** Data used to monitor the overall condition of the power transformer insulation.
- **Hot spot temperature:** It is used to indicate the degradation degree of insulation.

This model was constructed based on expert opinion related to the performance of medium and high voltage systems in conjunction with the availability of on-site measurements and according to international standards [10].

An implementation of the reduced fuzzy logic system was developed in *Matlab* and divided into two subsystems, according to the parameters taken into account.

First, the output function corresponding to the analysis of the thermal model is presented in Figure 8. It is determined by the main transformer insulator and hot spot value, which are classified by the analysis of the IEEE Standard C57.140 between 0 and 10 [20].

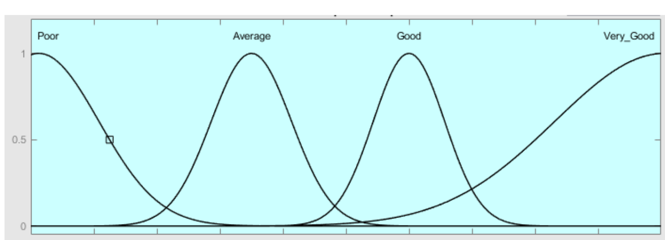

Figure 8. Membership Output function for Temperature [10]

At the same time, in Table 1 the main fuzzy rules are shown.

If **insulating temperature** is catastrophic and **hot spot temperature** is catastrophic then **health** is poor
If **insulating temperature** is high and **hot spot temperature** is high then **health** is average
If **insulating temperature** is normal and **hot spot temperature** is normal then **health** is very good
If **insulating temperature** is high and **hot spot temperature** is normal then **health** is good
If **insulating temperature** is high and **hot spot temperature** is catastrophic then **health** is poor

Table 1. Fuzzy rules for temperature component

The second one, shown in Figure 9, corresponds to the transformer condition estimation from the total operating time measured in years, which is classified as Bad, Medium or Good. This output function estimates that a transformer has a life cycle between 0 and 60 years and it assigns a value from 0 to 3. However, in this case and as in [10] the input function share the same categories as the output.

Finally, the overall indicator is calculated as the sum of both outputs , to incorporate the two original models.

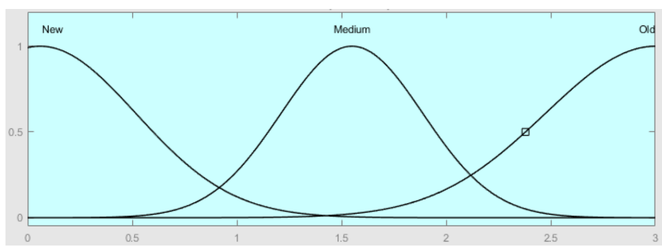

Figure 9. Membership Output function for transformer age[10]

3.3. Weighting Model

This method represents a simplified application of the thermal and fuzzy logic models since each variable is assigned a weight that quantifies its relative importance. The model presented in [7] identified the available data that was stored in the University Campus server or that could be calculated considering these reference values. These data correspond to:

- **Transformer age:** It is given by the furan quantity test. However, an alternative is presented in which this parameter is directly associated with the transformer operation years in the categories cited in [7].
- **Transformer load:**It is calculated by obtaining the number of power peaks N_i registered by month and their magnitude. Specifically, there were established categories from N_0 to N_4, associated with the relation between the registered value and the nominal power, as shown in (1),

$$LF = \frac{\sum_{i=0}^{4}(4-i)N_i}{\sum_{i=0}^{4} N_i}. \tag{1}$$

3.4. Performance Comparison

The indicator values in the daily plot of Figure 10 show that the weighting model results correspond to values between 0.81 and 0.86 for each of the substations, while for the Fuzzy Logic Model these values are from 0.71 to 0.78.

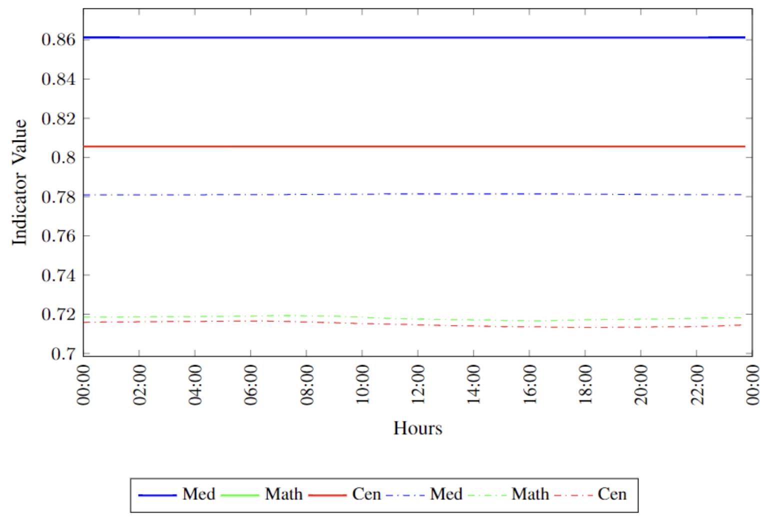

Figure 10. Normalized fuzzy logic and weighting model results of the 3 analyzed substations

Considering the demand similarities of the three substations, as presented in the temperature plot of Figure 6, and the number of operation years, the weighting indicator show no significant difference between substations as shown in Figure 10. The results obtained in the modeling based on fuzzy logic have the same behavior, where the transformer of the School of Medicine (Blue line) has a better overall condition than the other ones with an age difference of 10 years.

However, as illustrated in the Fuzzy Logic results in Figure 10, due to the implemented scales and the weight of total age, there is an effect on the final value of the Mathematics building and the Central Library, where there is a change in the indicator throughout the day.

As a result, after three model calculations, the categorization of the results was made. The case of the thermal model was related to the guidelines of standard C57.140 while the fuzzy logic system and weighting model the same categories as [7] and [10], considering the same output fuzzy function. The results are summarized in Table 2.

Table 2. Transformers Categorization

Substation	**Thermal Model**	**Weighting Model**	**Fuzzy Logic Model**
Medicine F.	Very Good	Very Good	Good
Mathematics F.	Very Good	Good	Good
Central Library	Very Good	Good	Good

In contrast, an indicator of hourly changes was calculated in Table 3, considering the standard deviation of each of the final values obtained for each model. In the case of the thermal model, it corresponds to the remaining life, while in the fuzzy logic model it is the final defuzzification value. Ultimately, the value of the weighting corresponds to the final numeric value. In this way, it could be evidenced that the thermal model has a higher standard deviation than the other models, which remains relatively constant.

Table 3. Indicator Standard deviation

Substation	Thermal Model	Weighting Model	Fuzzy Logic Model
Medicine F.	1.06380452	1.78568E-15	0.002605641
Mathematics F.	4.22224748	1.96425E-14	0.01056496
Central Library	5.5627336	1.96425E-14	0.015725283

As shown in Table 2, Figure 7 and Figure 10, the transformer conditions are good according to the metrics of each item, although the thermal model shows a high standard deviation. On the one hand, a relationship was discovered between the thermal model and the fuzzy logic model, as both are dependent on the hot spot temperature. On the other hand, there was a relationship in the transformer age between the fuzzy logic and weighting models, shown by a higher indicator value in the building of the School of Medicine.

4. Conclusions and Development Opportunities

In the definition of the considered elements related to the analysis of Asset Management systems on Power Transformers, the challenge of establishing a general model to diagnose the status of a fleet of transformers was identified, as evidenced by the variety of model properties.

Likewise, it was identified that the Asset Management Modeling development in Power Transformers depends on the available resources, which means that currently no model can be universally applied. This is related to their usage in the LAB+i where the bar plots shows a lack of real-time modeling of Asset Management systems.

Consequently, in the development and analysis it was also identified that:

- The **thermal model** presents an important level of daily standard deviation according to the temperature changes throughout the operation time.
- The **fuzzy logic model** had the best results in stability and confidence based on real-time measurement information, with opportunities for improvement associated with the usage of new membership functions and fuzzy rules improvement limited by the conditions of the LAB+I.
- The weight assigned to each factor in the **weighting model** causes a significant change in the final value, thus making it difficult to compare the Asset Management methodologies results with other methods without normalizing the values.

Finally, in the analysis of Section I and Section II of the report, it was identified that:

- There is a need to develop an Asset Management model that can use non-invasive real-time measurements for the continuous monitoring of power systems and diagnosis without sacrificing reliability and taking full advantage of new computational tools.
- In the model performance comparison, the three models cataloged the power transformers of the LAB+i in the highest categories although there is no direct relationship among them.
- The categorization of the 12 models together with the application of three of them to a realistic situation show that the variety of Asset Management approaches of a transformer fleet limits their application in actual cases. Therefore, it is necessary to identify a common field of development to facilitate the application of these models by different stakeholders and researchers.

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