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Asset Management Support Tool for Energy Systems using AHP and Monte Carlo Methods applied to Power Transformers

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ABSTRACT

The assets of electric power transmission systems are characterized by their high cost and complexity, leading utilities to seek ways to improve the efficiency and economic-financial performance of these assets. Thus, this article proposes a tool to support asset management for electricity transmission systems. This tool considers the useful life of the equipment, its importance to the system, financial aspects, and the forecast of electricity demand. An evaluation of the criteria that impact decision-making on the replacement of assets with specialists was carried out. Thus, the tool uses the Analytic Hierarchy Process method to classify the most critical equipment in the system. For analysis of future scenarios, the Monte Carlo Method was incorporated into the tool to simulate the behavior of equipment during a defined time horizon. As a result, the tool presents a ranking of the most critical equipment in the system under analysis within the simulated time horizon. The tool was applied in a case study with real data in the power transformer of a Brazilian utility. The tool helps in decision-making indicating changes that may be made in the period under review, their likely impact on equipment loading, and the list of critical transformers in the system.

Keywords: Electric Power System, Asset Management, AHP, Monte Carlo Method, Power Transformers Management
JEL Classifications: Q400, L940, L970, L640

1. INTRODUCTION

The aging of assets that make up electrical power systems has become a constant concern, both in technical and economic terms (Campelo et al., 2016). High-voltage power transformers are important equipment in the electrical sector due to their importance for system reliability and continuity (Demirci et al., 2023). Besides, these transformers are constantly subjected to electrical, mechanical, thermal, and chemical stresses that can degrade their elements (Soni and Mehta, 2023). In the United States, the average age of power transformers installed was between 38 and 40 years (ENERGY, 2014). In European countries, such as the Netherlands, most equipment were also installed until the 1980s, making the need for short-term replacement imminent (Van Schijndel et al., 2012). The situation in Brazil is no different, as a large part of the electrical system was implemented in the mid-1980s, requiring the development of planning to manage these assets. In this sense, the management of this equipment is considered a critical element of the electrical system due to the high costs involved, the difficult determination of the best period for replacing the equipment, and the current stage of aging of the equipment (Abu-Elanien et al., 2011).

Energy transmission utilities are companies with a large presence of physical assets due to the nature of their services. For this reason, they must seek to keep their assets operational, in good condition use, and generating value for the company. Therefore, the management of their assets is extremely important so that they can meet the requirements of reliability and quality of service provision, with the lowest possible rates for consumers, generating a financial return for their investors (Wenzler, 2005), and seeking a reliable operation of all its assets with minimum cost throughout their useful life (Abu-Elanien et al., 2012; Peimankar et al., 2017).

Planning and decision-making for asset management involve a large amount of information, in addition to several players who are responsible for decision-making. On several occasions, this decision-making involves conflicting objectives, having to consider which ones have the greatest and least impact on the final objective of the choice (Grabisch et al., 2019). In this environment, the Multicriteria Decision Support Methods-MCDA appear, which, despite not leading to a precise and absolute decision, serve as a support tool for managers in their choices. MCDA methods are tools that help in the assessment of complex situations, being able to synthesize the knowledge of specialists (Carayannis et al., 2018). In the context of this research, multicriteria methods based on multiobjective optimization simultaneously minimize maintenance costs and the expected cost of failures, which can help in resource allocation and the definition of replacement priorities (Campelo et al., 2016).

In addition to deep data analysis, it is important to determine the behavior that the systems may present in a certain future. However, this future behavior has uncertainties. Analysis in the form of possible scenarios helps manage these uncertainties. The forecast scenarios allow the analysis of the possible behavior results of the equipment when subjected to different degrees of freedom for the evaluated criteria. The elaboration of scenarios is carried out through a calculation method, generating a series of results to be analyzed. For this, it is necessary to carry out modeling, that is, to create a representation of a real situation to be able to analyze it in a simulated environment. The created model can be used to examine the situation, its results, and its implications (Munier, 2014).

Several approaches have been applied in the management of power transformers. Studies involving maintenance strategies based on reliability-centered maintenance show promising results in terms of equipment replacement costs. Maintenance can increase the life of the transformer and help reduce equivalent annual expenses (Aldhubaib and Salama, 2014). Takahashi and Okamoto (2016) present two programs developed in Japan to assess the life cycle cost of power transformers. One of the programs optimizes maintenance strategies by considering the time and cost of repairs, while the other considers the cost and probability of replacing components. Both programs were tested with real data from a Japanese dealership. An approach to optimizing the maintenance interval, minimizing maintenance costs, and loss due to failure, repair, replacement, and displacements, is presented by Zhong et al. (2017). The method is applied to two-region transformers and uses a fault model for optimization. Da Silva et al. (2020) present a methodology for ranking power transformers with the aid of the multicriteria Analytic Hierarchy Process method. For this, the authors perform the analysis of the structural importance of each transformer through composite reliability indices.

Strategies for replacing transformers in distribution systems have been improved. The studies use parameters such as energy savings, energy reserve, and average equipment availability to define equipment replacement priority. In addition, data such as load factor, operating time, and location are used to define priority groups of equipment to be replaced (Chelaru and Grigoras, 2020b, 2020a). Still, on distribution network transformers, Hu et al. (2021) present a study using characteristics of the transformer failure rate in its life cycle to perform an opportunity cost analysis considering the maintenance and replacement of equipment. Yang et al. (2023) present a 10kV distribution transformer replacement investment prediction model based on Lasso and GBDT algorithms. The model is used to forecast investments in replacing transformers in distribution networks in China. Hasan et al. (2020) use a probabilistic model with simulations through the Monte Carlo Method to define a strategy for replacing transformers in a transmission system. To develop the strategy, the authors use equipment failure data, repair, and replacement costs, simulating a long period to analyze the behavior of the number of replaced transformers and the frequency of loss of load. The simulation employed transformer failures modeled as a function of transformer age and condition.

The evolution of studies in this area shows great concern with strategies for replacing assets in the electrical system, with a focus on power transformers, due to their high cost and impact on the system. As presented, several studies have been carried out seeking to optimize the maintenance and replacement of equipment. Most published works analyze the failure rate of equipment and its cost of maintenance and replacement. Based on these data, a strategy for transformer replacement is elaborated. A limitation among the works already published is the financial analysis that is limited to the cost of maintenance and replacement, in addition to the limitation in the evaluation of regulatory costs generated by the non-supply of energy in the system. In short, most of the published works present a historical analysis of the equipment, elaborating a replacement strategy focused on the current moment of the equipment.

Therefore, the objective of this article is to present a tool for evaluating assets that encompass multiple criteria, such as useful life, system reliability, and costs, both maintenance and replacement, as well as regulatory costs of unavailability. The criteria will be used to rank the criticality of the equipment, using the Hierarchical Process Analysis method as a multicriteria method. These data will be submitted to a probabilistic analysis through the Monte Carlo method and, based on this, a tool will be presented that allows analysis with a greater number of criteria and that allows simulating future scenarios to assist in the management of equipment in a defined horizon.

The main contribution of this work is the development of a methodology to support asset management, involving both technical and economic aspects. The tool allows the prediction of configurable future scenarios, being able to provide a broad view of the planning horizon, based on real equipment data.

2. RESEARCH DEVELOPMENT

To achieve the proposed objective, the research was divided into three steps: Prioritization of critical equipment; Scenario simulation, and Analysis of changes in the system.

2.1. Step 1

The first stage aims to identify the most critical equipment in the system based on criteria that impact the decision. At this step, the criteria that impact the management of assets of a power system will be presented, both from the point of view of the useful life of the equipment, as well as impacts on the system and financial impact. These criteria were submitted to an analysis using the AHP method, resulting in a ranking of the most critical equipment.

2.2. Step 2

In the second step, a scenario simulation was carried out using the Monte Carlo Method. For this, a period of 10 years was considered and the possible changes that the criteria may suffer in the period of analysis. The tasks for carrying out the simulation involve surveying equipment loading history data, as well as other criteria of impact on the system, useful life and financial impact, the mathematical modeling of the simulation, and the generation of probabilistic results. The application was carried out through a case study in a Brazilian utility, using real data from its transformer park.

2.3. Step 3

In the third step, some changes to the system were proposed based on the simulated scenario, such as expanding capacities or replacing equipment according to need and financial availability. Such changes were again simulated to analyze the impact of the changes on the results found. The tool allows for easy changes in scenarios, with the possibility of simulating various operating and system evolution conditions, as well as changing the input data to evaluate possible changes to be implemented in the electrical power system.

In the next sections, these three steps are detailed.

3. PRIORITIZATION OF CRITICAL EQUIPMENT

The definition of priority corresponds to one of the main steps for planning the replacement of equipment in power systems. For this definition, the Analytic Hierarchy Processes (AHP) methodology (Saaty, 1977), was chosen, as it is a widely used methodology to aid in decision-making in problems related to energy management and also due to the suitability of the method to the proposed problem (Kaya et al., 2018; Wang et al., 2009). The AHP method consists of defining the criteria that have an impact on decision-making, followed by a pairwise comparison of the criteria carried out by specialists with technical knowledge in the area (Schaefer et al., 2023). Through the data, the calculations of the weights of each criterion are performed, as well as the consistency of the answers.

When defining the priority for replacing or maintaining equipment in power systems, all aspects that affect decision-making must be taken into account. For this, all available technical and financial indicators that can be used for decision-making must be analyzed. Considering electrical power systems, this article proposes that 4 criteria are considered in decision-making: Charging, the useful life of equipment, system reliability, and the financial impact involved. Each of these criteria was broken down into sub-criteria for a better weighting of the amounts. Figure 1 shows the criteria and sub-criteria used in this decision support tool.

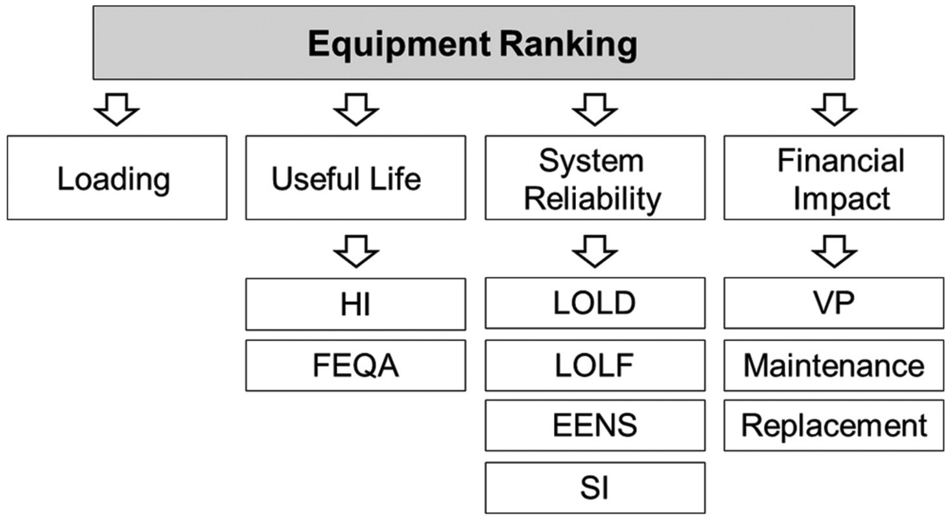
The first criterion considered, transformer loading plays a fundamental role, as it impacts the useful life of the equipment, and the substations maneuverability, in addition to being a limiting factor for the expansion of the system load. As it is a direct criterion, sub-criteria within the loading was not considered.

As for the equipment useful life criterion, two sub-criteria we used, the Health Index and the Equivalent Aging Factor presented by Feil (2019). The author presents the HI for 104 transforming units in the CEEE-GT concession area, using the methodology adapted by Carraro (2017) for the reality of Brazilian utilities, using 06 factors that are weighted, resulting in a general index of the operating condition of the transformer (HI). The Health Index is an objective and quantitative factor, capable of providing the general operating condition of power transformers defined from a method that quantifies the results obtained from chemical and electrical tests, field inspections, operational observations, and charging history, into a single index of equipment operating conditions (Abu-Elanien et al., 2012; Jahromi et al., 2009; Wattakapaiboon and Pattanadech, 2016; Zeinoddini-Meymand and Vahidi, 2016). To calculate the EQAF, the thermal model included in Annex G of IEEE Std C57.91-2011 IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators (IEEE Standars Association, 2012) was adopted, calculating the Hot Spot temperature and, subsequently, the equivalent aging factor of the transformer in operation according to its operating conditions. The EQAF of a transformer is the degree of deterioration to which the insulation is being submitted as a function of time and operating temperature, and it follows an adaptation of the Arrhenius theory, based on the temperature of the hottest point in the transformer winding, known as the Hot Spot temperature (IEEE Standars Association, 2012).

The third criterion, system reliability can be defined as its ability to perform the required functions, during a certain period and under certain operating conditions (Ebeling, 2001). In this sense, the reliability evaluation of generation-transmission systems, or just composite reliability (NH2), is carried out through the evaluation of the effects of faults in the generation, transmission, and composition of both (Andrade, 2007; Billinton and Allan, 1992). As a sub-criteria to be evaluated, Feil (2019) proposes Loss of Load Frequency (LOLF), Loss of Load Duration (LOLD), Expected Energy Not Supplied (EENS), and Severity Index (SI). The LOLD is the expected average time, calculated in hours, that the equipment stops supplying electrical energy to the system. The LOLF is the expected average frequency of pressure loss. The EENS factor represents the expected value of energy not supplied to the system during a period of time, generally considered a period of 1 year. While the SI is the equivalent duration (in minutes) in the total load loss of the system operating under peak load conditions.

The financial impact sub-criteria were defined in discussions between researchers and utility managers due to the difficulty in obtaining such information in the literature. In this way, it was

Figure 1: Decision support tool criteria and sub-criteria



defined that the sub-criteria would be: Variable Portion (PV) that deals with the fines deducted from the utility's remuneration due to the outage of operation of a piece of equipment; maintenance cost, encompassing both preventive, corrective and emergency maintenance, including parts and labor costs for carrying out the service; and the cost of replacing the equipment, using the ANEEL price bank as a reference (ANEEL, 2016).

In a survey with specialists, criteria, and sub-criteria were weighed, and the consistency of answers was calculated. In the AHP method, the criteria weighting is carried out from a square matrix designed to pairwise evaluate the criteria and sub-criteria through the Saaty scale that goes from 01 for equally important to 09 for extremely more important. For this work, 21 specialists were consulted, a number above the minimum indicated by Powell (2003) and below the maximum indicated by Marques (2018). These specialists were selected because they had graduated in the area, including master's and doctors, as well as a professional career in the area.

The geometric mean of responses was calculated to maintain the characteristics of weights and reciprocal values (Aczél and Saaty, 1983). These responses were synthesized in square comparison matrices, where the main diagonals contain a unit value, the response values were allocated above the main diagonal, and the inverse values were allocated at the bottom. Table 1 presents the geometric mean of the responses for the importance of the criteria among themselves.

From this comparison matrix, the data are submitted to the AHP method, resulting in a relative weight of each criterion, which is multiplied by the weight of the criterion to which it is linked, resulting in the absolute weight of the sub-criteria. Once the calculation of the weights has been completed, the analysis of the consistency ratio for each factor is carried out, which must be <10% for the result to be considered consistent.

Using the AHP method, a weight of 18.1% is obtained for Useful Life, 9.9% for Loading, 51.1% for Impact on the System, and 20.9% for Financial Impact. The consistency ratio is 4.8%, demonstrating that the answers are consistent for the addressed criteria.

Table 1: Geometric mean of the responses for the criteria importance

	Criteria importance			
	Useful life	Loading	System reliability	Financial impact
Useful life	1.00	1.99	0.37	0.76
Loading	0.50	1.00	0.29	0.34
System reliability	2.67	3.46	1.00	3.88
Financial impact	1.32	2.93	0.26	1.00

The Loading criterion does not have a sub-criteria, so there is no matrix for it. Table 2 brings the geometric mean of the sub-criteria of the Useful Life criterion.

Within the useful life criterion, a relative weight of 77.9% is obtained for the HI and 22.1% for the FEQA, and it is not necessary to calculate the consistency ratio, since it is a direct comparison between two factors.

Table 3 shows the geometric mean of the sub-criteria of the System Reliability criterion.

Regarding the impact on the system, the relative weight of 23.3% for LOLD, 14.8% for LOLF, 27.6% for EENS, and 34.2% for SI is obtained, with a consistency ratio of 1.9%.

Table 4 brings the geometric mean of the sub-criteria of the Financial Impact criterion.

As for the financial impact, it reaches a weight of 46.5% for the variable portion, 17.9% for maintenance costs, and 35.6% for replacement costs, with a consistency ratio of 0.6%.

After performing the geometric mean of the responses, all the weightings carried out showed a consistency ratio below 10%, giving reliability to the application of the method. In this way, the decision tree can be elaborated with the weights of the criteria and subcriteria, as shown in Figure 2.

The results show the greater relevance of factors linked to the impact generated in the system, representing more than 50% of the total weight. Having already analyzed the absolute weights of the addressed sub-criteria, the importance of loading, health index, and variable portion costs, corresponding to 9.9%, 14.1%, and 9.7% of the total weight, respectively, are highlighted.

The final step of prioritization consists of ranking the most critical assets in the system. For this, it is necessary to gather data for each of the sub-criteria used for prioritization. After collecting the data, as they have different scales and must be compared, the data must be normalized, which is performed through Equation 1:

$$x' = (x - x_{mín})/(x_{máx} - x_{mín}) \quad (1)$$

Where:
x' - Normalized value of the indicator;
x_{max} - Maximum value found;

Table 2: Geometric mean of useful life subcriteria

	Useful life	
	HI	FEQA
HI	1.00	3.53
FEQA	0.28	1.00

Table 3: Geometric mean of system reliability Subcriteria

	System reliability			
	LOLD	LOLF	EENS	SI
LOLD	1.00	1.81	0.86	0.58
LOLF	0.55	1.00	0.70	0.39
EENS	1.16	1.44	1.00	1.07
SI	1.73	2.58	0.94	1.00

Table 4: Geometric mean of financial impact Subcriteria

	Financial impact		
Subcriteria	VP	Maintenance	Replacement
VP	1.00	2.39	1.42
Maintenance	0.42	1.00	0.46
Replacement	0.70	2.16	1.00

x_{min} - Minimum value found;
x - Indicator value.

With the data values of the indicators of each subcriteria already normalized and their weight, the final ranking is prepared, whose value that defines its position is given by Equation 2:

$$R = \sum_{i=1}^{n} \left(x_i' * P_i \right) \quad (2)$$

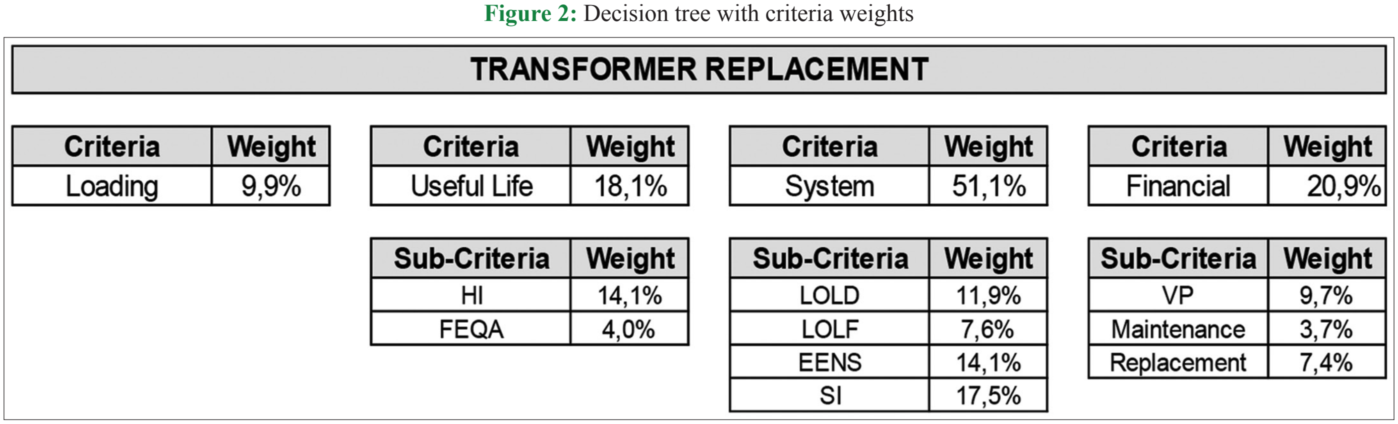
Where:
R - Final value of equipment;
x_i' - Normalized value found for subcriterion i;
P_i - Calculated weight for subcriterion i.

After calculating the value of R for all the assets to be appraised, they are ordered in descending order of value, thus having the ordering of the most critical assets. The study was applied in the area of operation of a concessionaire in the south of Brazil. Has 56 substations, which add up to its own installed capacity of 10,500 MVA, and operates another 18 units. The company is also responsible for the operation and maintenance of 6,000 km of transmission lines, of which 5,900 km are owned, supplying energy to all distributors operating in the state and also to potential free consumers (CEEE - Companhia Estadual de Energia Elétrica, 2022). To prepare the ranking, shown in Table 5, data from the transformer park from 2017 to 2022 were used, with a total of 104 transformers being analyzed. The table shows the 30 most critical pieces of equipment according to the analyzed parameters.

3.1. Sensitivity Analysis

The Sensitivity Analysis is carried out through the individual alteration of the calculated parameters, observing the behavior of the model as each of the alterations is performed. The use of this technique favors the identification of the most critical variables to the model, which are the ones that provide a greater relative variation of the analyzed results. In the model developed for ranking the equipment, a sensitivity analysis was carried out on the weights of the four criteria involved, loading, useful life, impact on the system, and financial impact. In the analysis, the ranking of critical equipment was simulated by changing each of the criteria individually by 1% in each simulation. The reduction or increase in the weight of one of the criteria was

Figure 2: Decision tree with criteria weights



proportionally compensated for the other criteria, simulating an individual error in the analysis of each specific criterion. After performing all the simulations, the equipment rankings generated in the simulations were compared with the base ranking, verifying the correlation of the results. For the System and Financial Impact indicators (Figure 3c and d), the results showed small variations, with differences smaller than 2%, even when subjected to 10% weight variations for the criteria. Therefore, the ranking of equipment is not very sensitive to the weight of these indicators. The Useful Life presented an intermediate result in the analysis, as shown in Figure 3b, with the result generating a change in the ranking close to 6% when the weight of the criterion is reduced by 10%. In the loading analysis, Figure 3a, the sensitivity analysis showed a high impact caused by the variation in the weight of the criterion, with variation in the results exceeding 10%.

The sensitivity analysis shows that the ranking results are more sensitive to a variation in the load weight in the system, and such results must be taken into account for the verification of critical equipment since any mistake in the weight of the indicators can lead to a distortion in the elaborated ranking.

Table 5: Equipment ranking

Position	Equipment	R	Position	Equipment	R
1	VAI-TR2	65.945	16	URU5-TR2	20.484
2	SAG2-TR1	45.549	17	PAL4-TR3	19.976
3	SAG2-TR2	44.666	18	BAG2-TR2	19.782
4	SMT-AT1	36.698	19	CAX5-TR1	19.646
5	SMT-AT2	35.856	20	CIN-TR1	19.157
6	GAR1-TR2	31.593	21	PAL4-TR1	18.562
7	URU5-TR1	28.701	22	CIN-TR2	18.478
8	GAR1-TR1	26.879	23	GRA2-TR2	18.391
9	QUI-TR5	26.874	24	VAI-TR1	18.252
10	NPR2-TR1	26.274	25	LIV2-TR4	18.208
11	GRA2-TR3	22.635	26	PAL4-TR6	17.668
12	CAM-TR1	22.492	27	PAL13-TR2	17.641
13	SRO1-TR1	22.439	28	SBO2-TR1	17.341
14	PAL4-TR2	22.232	29	ELD-TR1	17.249
15	BAG2-TR1	22.020	30	CNA1-TR1	17.224

4. MONTE CARLO METHOD APPLICATION

The Monte Carlo method is used in stochastic programming to analyze complex systems and make decisions under uncertainty, as it provides a realistic view and enables the use of sensitivity analysis (Samani and Hosseini-Motlagh, 2023). This method is used for analysis of stochastic processes, where a large number of sample points are selected from the uncertain input space and, by means of performing several deterministic calculations, the output variables of the load flow problem are determined to each of the input sample points (Salehi and Rezaei, 2023). Thus, in the proposed tool, the application of the Monte Carlo method depends on programming to be carried out in a system capable of performing some functions, such as storing an input database, generating random numbers within a predetermined range and distribution in the model, generating repetitions until it reaches the stop objective of the proposed model and stores the results of such simulations. This tool was developed with the help of Microsoft Excel software, which meets the needs of generating random values, performing repetitions, and recording data by recording macros to automate the work and easy replication of the method. Figure 4 shows a schematic flowchart of the Monte Carlo method configured to carry out the simulations of this tool.

The method starts by counting repetitions, setting the initial number of simulations equal to zero (n = 0) to start the simulation. Afterward, the data of the Historical Indicators is read.

The next step is the Generation of Pseudo-random Factors. The pseudo-random nomenclature is because any number generated in a computer program follows some generation rule, not being completely random. Interfering with the generation of results. This stage can be considered the most important of the Monte Carlo Simulation, as these parameters will dictate the behavior of the indicators in the simulations. These parameters are defined based on the behavior of the indicators. They will give the maximum

Figure 3: (a-d) Criteria sensitivity analysis

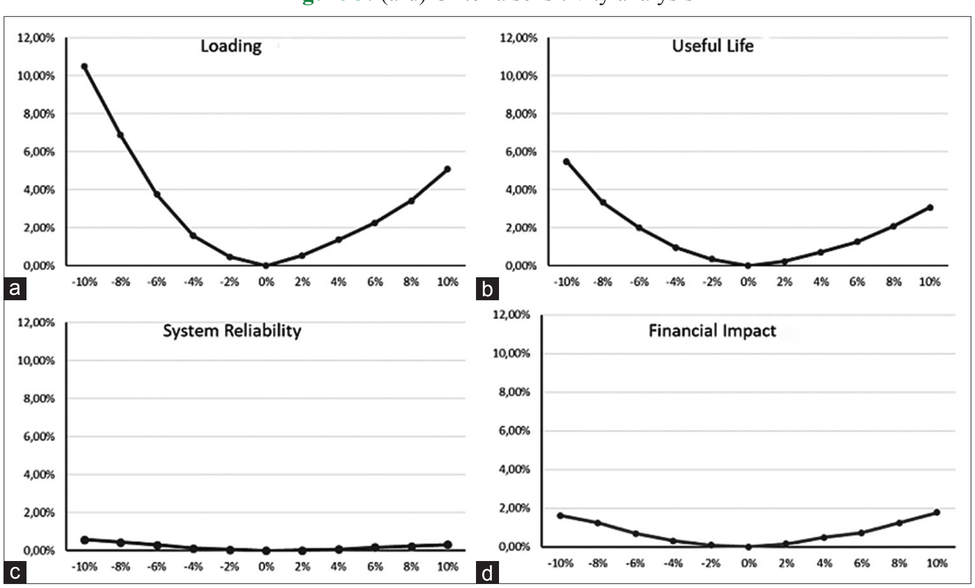
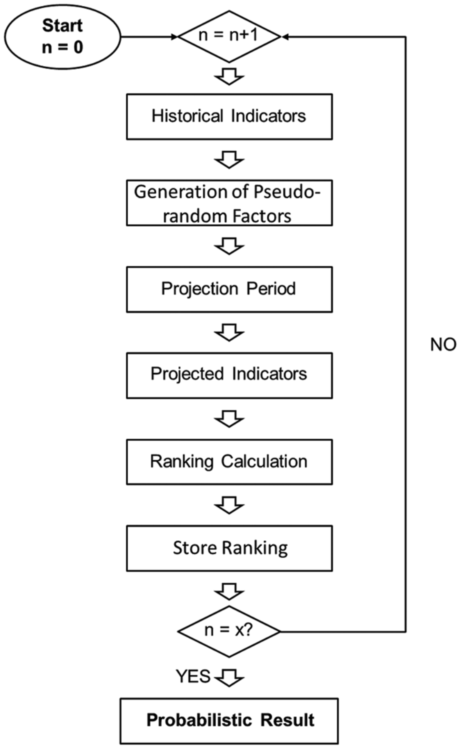


Figure 4: Flowchart of the Monte Carlo method application



limits in which the indicator can vary and also the distribution of this variation between the simulations and between the equipment. They will also be responsible for generating a simulation with a more or less conservative scenario.

The projection period is the last simulation input data, it refers to the number of years that will be simulated ahead. The longer the period used in the simulation, the greater the variations between the results found, since the data variation occurs annually, multiplying the initial data by the random factors generated.

With all the input data present, the projected indicators are generated, and calculated through the correction of the historical indicator by the random factor raised to the number of years adopted in the simulation. This calculation generates a new table of indicators for the proposed period, generating a possible scenario for the condition of the equipment in the simulation period.

Subsequently, the projected indicators are used for the ranking calculation through the AHP method, generating a ranking of the most critical equipment for the presented condition. In addition to the ranking, the maximum loads of the transformers for the simulated period are saved, to analyze the possibility of the equipment exceeding the maximum power, requiring replacement of the equipment or expansion of the system to balance the load.

Once the ranking and the projected loading have been generated, in the store ranking step, the data are saved for each transformer and the first repetition of the Monte Carlo method can be considered completed. With this, the number of repetitions "n" is compared with the stipulated number of repetitions, if it has not been reached, the process returns to the beginning, adding one more iteration to the simulation and repeating all the steps. After performing the defined number of simulations, the stored data are used to calculate the result of the proposed scenario, showing the probability of each transformer exceeding its nominal capacity in the period and the probability of the equipment is among the most critical of the system, after the window of time analyzed in the scenario.

The model presented is in line with what Costa (1998), says, showing that Monte Carlo methods vary, but tend to follow a specific pattern: define a domain of possible entries, randomly generate entries from a probability distribution in the domain, perform a deterministic calculation on the inputs and aggregate the results obtained.

4.1. Simulated Scenario

The preparation of the scenario took as base parameters the variation found in the indicators according to the historical data presented and data from the Decennial Energy Expansion Plan - DEEP 2031. The DEEP 2031 considers a scenario of estimated economic growth of 2.9%/year in the Product Gross Domestic Product (GDP), with an investment of approximately R$ 530 billion in the generation and transmission of electricity in Brazil for the next 10 years. In the reference scenario, the energy load in the National Interconnected System (NIS) is expected to grow at an average rate of 3.4% p.a. between 2021 and 2031. However, considering the great uncertainty for the 10 years, two alternative scenarios for the generation requirements were elaborated. The lower scenario considers growth at an average annual rate of 2.8%. In the superior scenario, with a better business environment and greater competitiveness, the dynamism of the economy is greater and the energy load grows by 4.0%/year.

For the scenario simulation, an environment of continuity of the indicators was considered, with few alterations in the behavior of the data, being used the historical data as the base for the simulation. Therefore, for the configuration of the simulation, we started with the current historical data of each of the equipment, considering that the behavior will remain similar to the historical values collected during the study. From the current values found, a variation corresponding to a standard deviation for more or less in the indicators of HI, FEQA, variable portion, and maintenance costs was allowed, establishing a continuity behavior of the current behavior. For the system impact indicators (LOLD, LOLF, EENS, and SI), random variations were not considered, since they follow the configuration of the existing transmission system. Replacement cost values were also considered constant, since, as they are normalized values, the increase in prices must be linear between equipment, not changing the impact on the model.

The simulation carried out considers 10 years, the same as that used in the decennial energy expansion plan, however, the proposed model allows changing the period to carry out new simulations. As for the number of iterations, 10,000 were performed to achieve accurate data convergence, making it possible to reduce this value to 1,000 to speed up the process, reaching an average error below 1% for the results and making the simulation more agile.

5. RESULTS AND DISCUSSION

The results obtained through the simulations are divided into two parts: The simulated results for the current system and the results of the proposed changes. These results show the possible behavior of the system for the continuity of current conditions and in a scenario in which system changes are proposed based on the results found.

5.1. Continuity Scenarios Simulation

The simulation carried out for the loading starts from the current maximum loading of each piece of equipment, projecting, from the Monte Carlo Method, the maximum loading probabilities for 10 years. Most of the load projections carried out use other methodologies to ensure the maximum proximity of the acquired forecast values, however, as it is a long-term horizon, the variables are often difficult to predict, and this method is used for an analysis probabilistic rather than an accurate prediction of future loading.

The analysis of the simulated loading scenario (Figure 5) shows that 26 pieces of equipment must reach the maximum loading of 100% of the nominal capacity during the 10 years, considering a regular growth between 2.8% and 4.0%. That is, even if all equipment has a load increase in line with the more conservative scenario of DEEP 2031, 26 pieces of equipment will exceed the rated power of the transformer in the period.

Of this equipment, 21 are located in regions of high population concentration. The other equipment is located in LAJ2 and SMT substations. Analyzing the charging histories, the transformers at substation LAJ2 already showed a significant reduction in the load between the end of 2020 and the beginning of 2021, with loads of the three transformers far from the maximums after this period. This fact is in line with the results found and eliminates the substation from the point of attention concerning loading. The SMT substation transformers show increasing loading, with an average growth above 3% for all equipment. However, the 2 transformers with the highest power in the substation, TR3, and TR11, load <50% of their rated power, and the possible redistribution of load between equipment in the same substation can be analyzed.

As for equipment in regions with higher population concentration, an analysis of the possible installation of new substations or expansion of existing ones with reconfiguration of loads is necessary, to equalize the load on equipment for the coming years. This load expansion and redistribution planning is not part of the scope of this work, it is limited to presenting a support tool in the identification of possible critical equipment present in the system.

For the analysis of the results, the probability of the equipment being among the 10 most critical equipment according to the methodology was considered. Differences between positions within this range were not considered, as the entire range is considered critical for the equipment. The positioning of the equipment among the critics entails the need for attention, to monitor the aspects that contribute to the equipment being in this situation. Critical equipment can be subjected to interventions to extend its useful life of the equipment, reduce costs, or even anticipate the replacement of equipment that is generating costs or operational risks for the utility.

The simulation of critical equipment, highlighted in Figure 6, shows the probability of the equipment being among the critical equipment for an environment with continuity conditions for current indicators, allowing for small variations. In this scenario, a variation in loading between 2.8% and 4% and one standard deviation was configured about the current indicators for HI, FEQA, Variable Portion, and Maintenance costs.

In the simulated scenario, the 6 transformers that have a 100% chance of remaining among the critical ones stand out, VAI-TR2, SMT-AT1 and AT2, SAG2-TR1 and TR2, and GAR1-TR2. In addition, the scenario shows that 34 of the 104 pieces of equipment have a chance of being among the most critical, 9 of which are above a 50% chance. When these pieces of equipment are analyzed individually, it is possible to observe the causes of their

Figure 5: Simulated loading in the continuity scenario

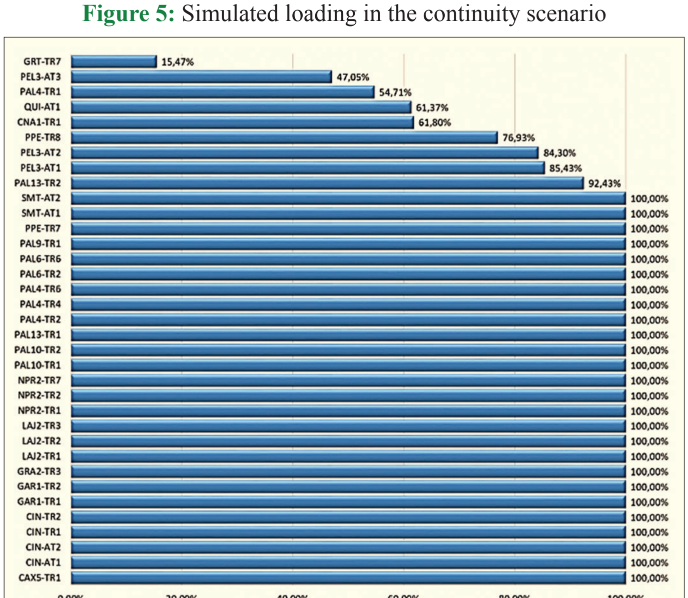
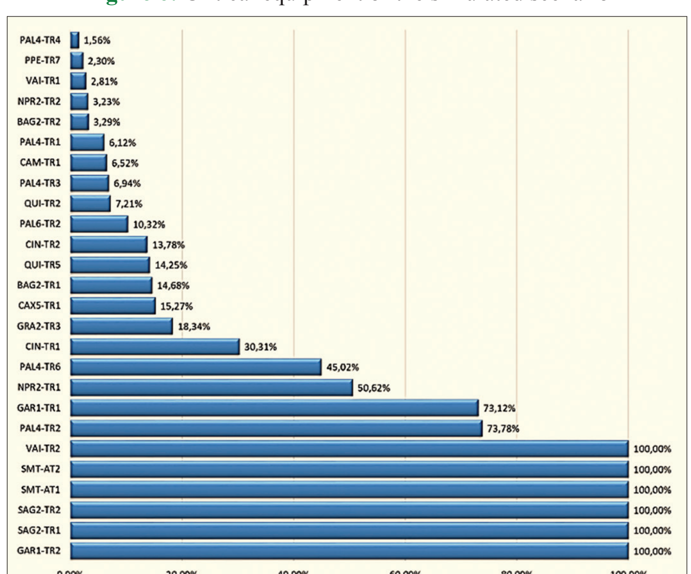


Figure 6: Critical equipment of the simulated scenario



being highlighted. The VAI-TR2, SMT-AT1, and AT2 equipment have been in operation for over 40 years and have HI and FEQA values that are significantly above average. In addition, the VAI-TR2 equipment presents all systemic reliability indicators close to the maximum calculated values, while the SMT-AT1 and AT2 equipment present the highest maintenance costs combined with a low replacement cost. These factors make these 3 pieces of equipment strong candidates to be replaced in the short to medium term. As for the GAR1-TR2, SAG-TR1, and TR2 equipment, despite not having a high operating time, they have all high indicators, with values close to or above average. The GAR1-TR2 transformer stands out, which has the highest load among all the equipment analyzed. In this way, it can be considered that the tool can help in the identification of equipment to be monitored with greater attention, also allowing the simulation of already modified environments, considering specific changes and corrections of possible strategies to be adopted by the management.

5.2. System Modifications Simulations

The presented tool can be used not only for the current system with a projection of the future scenario but also, always in parallel with other management and planning tools of the utility, to analyze the impact that possible changes can generate over time in the system in the condition of the criticality of the equipment. To illustrate this application, an altered scenario is presented, considering some modifications that are proposed based on the analysis of the simulation performed. In this simulation, punctual variations are used for the indicators of some equipment, attributed linearly to demonstrate the application of the tool. Therefore, the following changes were made:

- Reduction of 0.20 pu in loading transformers CIN-AT1, AT2, TR1, and TR2, PAL4-TR2, TR4, and TR6, PAL6-TR2 and TR6, PAL9-TR1, PAL10-TR1, and TR2, PAL13-TR1 and TR2, PPE-TR7 and TR8, and GRA2-TR3, simulating possible load adjustments with the installation of a new substation or reinforcement of existing ones in the metropolitan region of Porto Alegre;
- Reduction of 0.20 pu in the loading of transformers CAX5-TR1, GAR1-TR1, and TR2, NPR2-TR1, TR2, and TR7, simulating possible load adjustments with the installation of a new substation or reinforcement of existing ones in the mountain region;
- Reduction of approximately 0.23 pu for transformers LAJ2-TR1, TR2, and TR3. Such a reduction was observed in the last year's loading history of the 3 pieces of equipment;
- Replacement of SMT-AT1 and AT2 equipment with higher power equipment (83 kVA) and rebalancing of the substation transformer load;
- Replacement of the VAI-TR2 transformer and adjustments in the substation to bring the reliability and FEQA indicators to values close to the average of the other equipment;
- Implementation of improvements or reinforcements in the SAG substation to improve the systemic reliability indicators of the two pieces of equipment.

All proposed changes were simulated by changing the input data, based on the initial configuration of the simulated base scenario. The results obtained are shown in Figures 7 and 8.

Figure 7: Loading results for the scenario with modifications

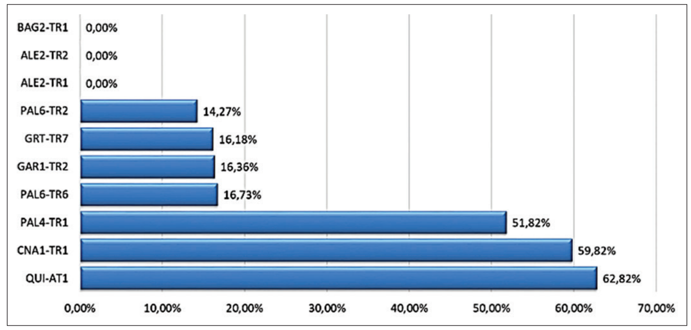
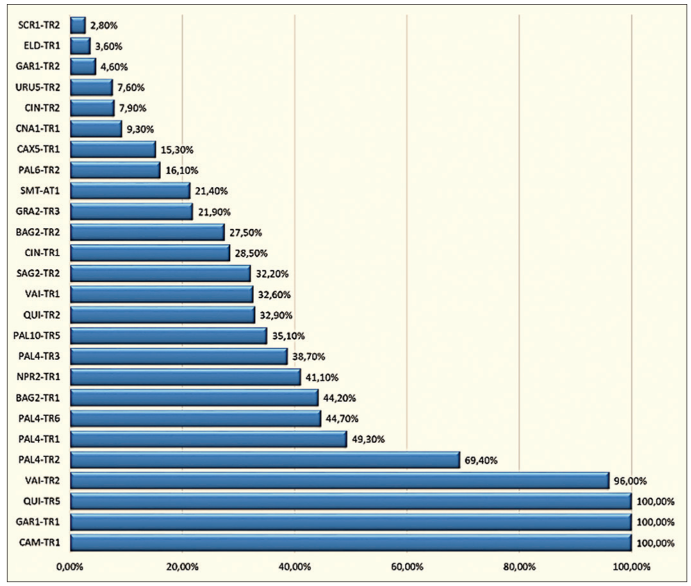


Figure 8: Critical equipment for the scenario with modifications



After changing the load as described, none of the devices had a 100% chance of reaching the maximum load in the period, while only 7 devices had such a possibility. Thus, the changes should be sufficient to meet the demands of the next 10 years, considering the proposed growth scenario. As for the critical equipment, there was a greater balance in the results, and of the 6 equipment that had a 100% chance of being among the most critical in the system, none presented such a possibility after the changes, being the VAI-TR2 transformer, with 96% of probability. After such changes, the equipment to be monitored more carefully would be QUI-TR5, GAR-TR1, and CAM-TR1.

6. CONCLUSION

This work presented a new tool to assist in the management of electrical power system equipment, as well as its application in a case study of power transformers in the transmission system of CEEE Transmissão, encompassing the substations present in southern Brazil. A ranking of transformers was carried out, with the AHP method, regarding their criticality for the system. The main indicators that affect the performance of the equipment and that contribute to its replacement by the concessionaires were raised. The indicators were submitted to a group of specialists with different activities, both in supplier companies, concessionaires, and academia, for paired comparison of the importance of each attribute. Through the assigned weights, a ranking of the most critical equipment for the systems was reached. The indicators were also submitted to a correlation and sensitivity analysis for validation.

Afterward, the behaviors of all the indicators and their distribution among the equipment were analyzed, in addition to the historical evolution of the loading data per equipment. Based on these data, a scenario simulation was carried out using the Monte Carlo Method. The simulations were carried out for 10 years, analyzing, in a probabilistic way, the behavior of the transformers in terms of their loading and criticality. Based on the results of the simulations, changes were proposed to adapt the system to the projected horizon, reducing the critical equipment of the system and equalizing the load in order not to leave any equipment in a condition to exceed the capacity in a situation of maximum load.

The results obtained show an easy-to-operate and very useful tool for forecasting scenarios and aiding in the planning of the electrical system. Different equipment operating conditions can be simulated, with practicality and speed, with variation both in the input data for the indicators and in the degree of freedom for their variation over time. The tool should be used in parallel with other tools and data for planning transmission systems, serving as support in the elaboration of strategies and decision-making.

As limitations, the presented tool was applied in only one utility. In addition, the tool was not applied in conjunction with electricity dispatch simulation tools, which can bring more reliability to the proposed modified scenarios. For the future studies, the use of the tool should be considered in conjunction with the analysis of the load dispatch for the system and the application of the tool in other types of equipment in the electric power system

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