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Consumption Prediction and Evaluation of Harmonic Distortion in a Hospital using Neural Networks

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Abstract – This article aims to present a proposal for a methodology to analyze the energy efficiency of a hospital according to the current consumption obtained through field measurements. In addition, it aims to present the prediction of the increase in consumption over the years and correlate it with the possible increase in the harmonic distortion of stress. This analysis is essential for the studies of the connection impacts, allowing the estimation and evaluation of the energy quality through the harmonic voltage distortions over the years. The study is validated by comparing the consumption prediction curve obtained by Neural Network training with the data extracted from measurements and analysis of energy bills. The results show that the model generates the best prediction performance.

Key words – Artificial Neural Networks, Prediction of consumption, power quality, voltage harmonic distortion.

1. Introduction

It is clear how dependence on electricity and its demand has increased in recent decades. Therefore, the electric energy issue, in its different segments of generation, transmission, distribution and use, has stimulated discussions involving researchers, energy concessionaires and regulatory agents from the electric sector to society in general.

This is because, although electricity is of paramount importance for economic development, the assessment of the social and environmental impacts of countries' energy policies on the population and the environment has become as valuable as the broad and secure supply of energy.

In this way, it becomes clear the necessity of the search for energy efficiency, that is, for the maximum use of the available energy resources, through the sustainable exploitation of these goods, the optimization of the conversion and distribution processes, besides their rational use [1].

Thus, it can be said that energy efficiency covers the set of rationalization actions, which lead to the reduction of energy consumption, without loss in the quantity or quality of the goods and services produced, or in the comfort provided by the energy systems used [2].

Therefore, the measures adopted for energy efficiency in an electrical system are also related to other areas of interest, such as power quality (PQ).

For a long time, the definition of PQ was limited to the amount of shutdowns that the electrical system was subjected to, that is, the fewer these occurrences, the better the PQ delivered to the consumer.

Currently, the PQ concept can be defined as the relative absence of variations in voltage levels caused by the utility system, including the absence of shutdowns, voltage fluctuation, transients and harmonics measured at the point of energy delivery [3], capable of causing failures of defects in any consumer equipment.

In general, the analysis of consumption reduction present in energy efficiency programs, which include the use of electronic equipment, consider the reduction for the final consumer, however, they do not account for the additional energy and economic losses arising from disturbances in the electrical system [4].

Among these disturbances, the harmonic distortions of current and voltage have great relevance, due to their interferences in the behavior and operation of devices. In addition, it is known that connecting non-linear loads to the electrical grid can impact the voltage of the bus, directly influencing the PQ of the consumers connected there [5].

Therefore, the PQ cannot be seen as a one-sided issue, where the only one responsible is the energy concessionaire, since many problems related to the PQ stem from the profile of the current drained by the load, ergo the consumer, who thus also becomes an agent responsible for the PQ [6].

Hospital buildings stand out as major consumers of energy, so effective consumption management is required for the implementation of energy efficiency measures [7]. Moreover, as it is a continuous operating environment, it requires the guarantee of reliability and continuity of electrical power supply to provide comfort to hospitalized patients and ensure the regularity of care. Therefore, although the concept of continuity of energy supply does not encompass the entire universe of phenomena associated with the PQ, both complement each other to guarantee the adequate supply to the consumer, that is, electrical energy with lower levels of degradation and unavailability.

These needs foster interest in the development and use of methods that analyze and relate energy efficiency to PQ indicators in order to ensure adequate supply for the installation.

Among the methodologies used for electric energy management are the indicators associated with PQ such as THDi and THDt, which can be obtained through measurements, as well as the management of invoices and the monitoring of consumption, which result in a history of the installation and substantiate the decisions of those responsible in relation to, for example, the contracted demand and the most appropriate tariff modality [8].

As for systematic data prediction, the use of computational solutions has become an important ally, enabling energy efficiency plans for energy generation and public security policies from data analysis tools. In this environment, the use of classical regression models and neural nets in highlighted due to the greater ease of analysis of databases and tests for training [9].

Despite the numerous studies of consumption prediction analyzed [10],[11], encountered some difficulty in finding works that actually present the prognosis of future data, since the vast majority of researchers analyzed trained their algorithms on top of existing data, without performing the expected prediction and therefore only validated the methodology, not presenting values of future data.

In view of the previous facts, this work presents a methodology for predicting the increase in energy consumption and its correlation with the increase in THD, based on the analysis of mass memory data provided by CEMIG and on measurements, in loco, of consumption and THD of the transformers present in the studied substation.

To this end, this article is organized as follows: Section II highlights the site studied. Section III presents the methodology used. The correlation of THD with consumption, previously presented, is performed in section IC, where the results obtained in this study are also reported. Finally, the conclusions of this study are presented in section V.

2. Place of study

The UFTM School Hospital is a university hospital, where, in addition to care, teaching and research activities are performed. Its service covers 27 municipalities that make up the southern triangle macro-region of the state of Minas Gerais. It accounts for 73% of all medium and high complexity in the macro-region and 100% of high complexity in the same area, with the exception of cancer treatment.

Regarding the structure, it has more than 302 active beds in an area of 26.000 m², distributed among hospitalization environments, outpatient clinics, emergency room and diagnostic services and specialized treatments [12].

The simplified diagram shown in Figure 1 shows the 6 transformers present in the substation (SS) studied, as well as the main parameters that characterize the elements that make up the system.

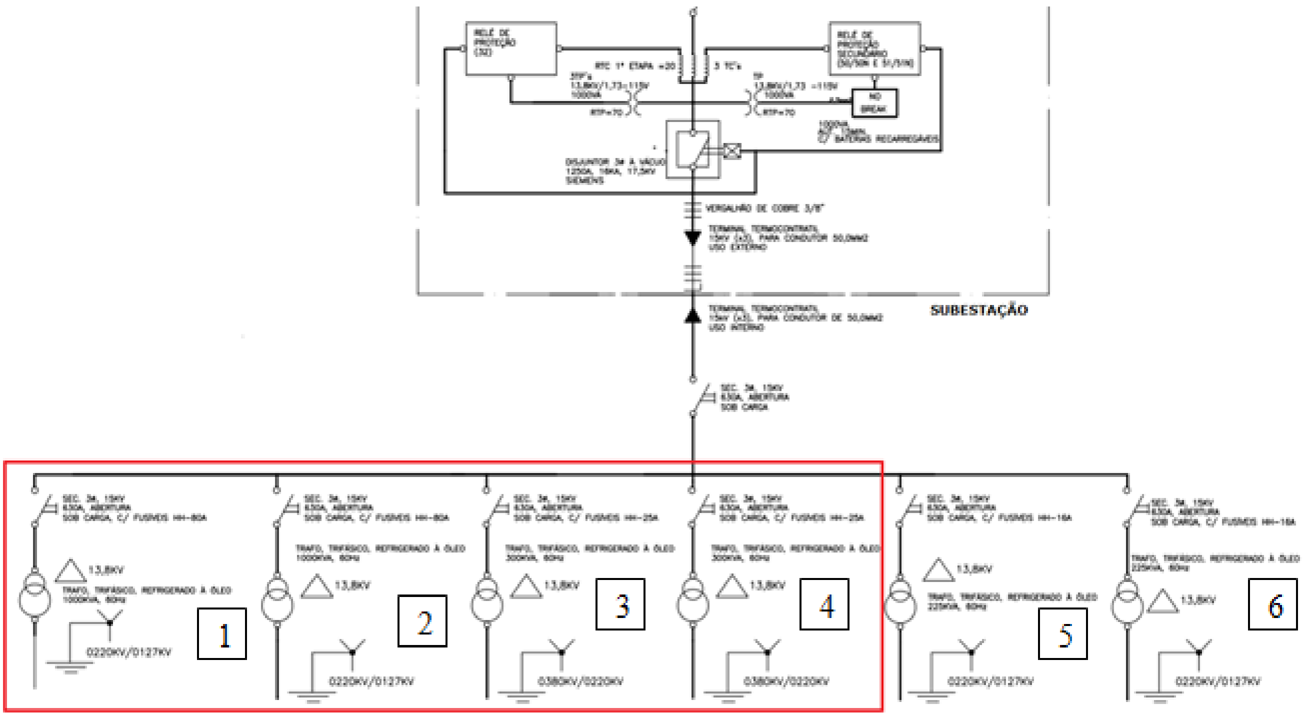

Fig.1. Simplified HU single-line diagram from UFTM.

For the recording of the electrical data, a measurement plan was drawn up in which strategic points of the network were chosen, a time interval for aggregating the data, as well as the appropriate equipment for the analysis.

The ideal monitoring of the electrical network would be the simultaneous collection of data at the points of interest, so that diagnosis would be more accurate. However, due to the difficulty of access for measurement on the medium voltage bus, consumer's delivery point, this was not possible. In addition, transformers 5 and 6 were not analyzed, due to their little influence on the results, since they have a low consumption.

In addition, due to the limitation of the quantity of measuring equipment, the monitoring was done with a fixed meter at the output of transformers 1, 2, 3 and 4.

3. Methodology Application

A. Diagnosis of energy efficiency

1) THD and THDi

The degree of harmonic distortion present in the voltage and/or current can be expressed mathematically based on the study of non-periodic waves by means of the Fourier series.

Fourie's Theorem guarantees that every periodic non-sine function can be represented by a sum of expressions composed by a sine expression in fundamental frequency and by sine expressions whose frequencies are multiple integers of fundamental, that is, harmonics [13].

Equation 1 presents, in a mathematical form, a sign f non-periodic sinusoidal tension.

$$(t) = V_o + V_{max1} sin(1\omega t + \varphi_1) + V_{max2} sin(2\omega t + \varphi_2) + \cdots + V_{maxh} sin(h\omega t + \varphi_h) \qquad (1)$$

Thus, knowing the values of harmonic voltages or currents present in the system, we tried to analyze the influence of the harmonic content for this study. This analysis was performed using the method of Total Harmonic Distortion (THD) and Individual Harmonic Distortion (THDi), which can be calculated according to equation 2.

$$THD = \sqrt{\frac{\sum_{h>1}^{hmax} {V^2}_h}{{V^2}_1}} \qquad (2)$$

According to module 8 of Prodist, in addition to THD, some specific cases must be calculated:

- h = all even harmonic orders, not multiple of 3;
- h = all odd harmonic orders, not multiple of 3;
- h = all multiple harmonic orders of 3.

2) On-site measurements

Measurements were performed on the buses of transformers 1, 2, 3 and 4. Given the limitations of equipment, each transformer was measured for 24 hours in two consecutive weeks in October, since it is one of the hottest months of the year and consequently of higher consumption. To enable these records, the Fluke 1735 portable PQ recorder with 4 MB Flash memory, sampling rate of 10.24 kHz, 50 Hz/60 Hz, precision class S and manufactured according to the DIN ISO 9D01 standard was used [14]. At this stage of measurement, during the first week, the consumption data in kWh and the THD of each transformer were obtained, with measurements performed every 15 minutes. Figure 2 displays the meter installed on the SS during measurements.

Fig. 2. Meter Fluke 1735.

In order to analyze the THDi of the system, transformers 1, 2 and 3 were measured during the same period of time in the consecutive week. Transformer 4 has not been measured, as it has charging characteristics very similar to transformer 3.

The first two transformers, 1 and 2, are 1000 kVA and are in parallel, feed various types of loads, such as strength and lighting circuits. The 3rd is 300 kVA and feeds only nonlinear loads such as: MRI, X-ray and CT.

3) Consumption x Temperature

Although it does not have a discrimination of the percentage of each type of load installed, due to its great diversity, it is remarkable that, over the years, in addition to the large amount of nonlinear loads and lighting, there is a constant growth of requests for installation of air conditioning.Therefore, the purpose of this section was to verify that there is a correlation between the measured consumption and temperature of the city of Uberaba. For this, the months in which the highest consumption stake and the months with the lowest consumption were recorded.

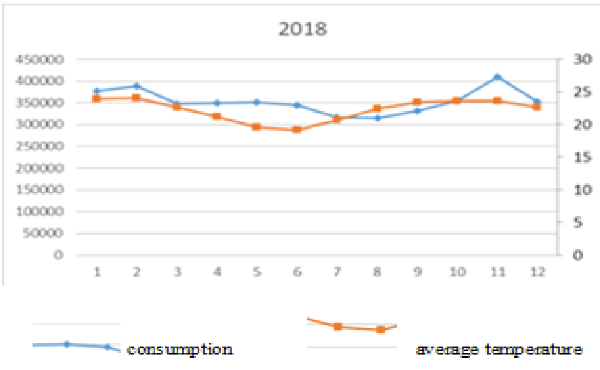

Fig. 3. Correlation between consumption and temperature in 2018.

When comparing the two curves of Figure 3, it can be said that the change in consumption throughout the year is also related to temperature, since the profile of the consumption curve seems to accompany the temperature curve. In fact, the correlation coefficient for these two quantities was calculated, which indicates the strength and direction of the linear relationship between two variables, and the result obtained from 0.492 indicated a moderate correlation.

B. Artificial Neural Networks (ANN)

1) Architecture

ANNs are computational algorithms that present a mathematical model, which allows simplified insertion of the functioning of the human brain into computers. In this way, like the human brain, ANN is able to learn and make decisions based on its own learning. That is, it corresponds to a processing scheme capable of storing learning-based knowledge and making this knowledge available to the application to which it is intended [15].

Defining the architecture of an ANN is the first step to solving the problem, since your arrangement depends on the problem to be handled by the network. In addition, the network architecture is closely related to the learning algorithm used in training [16].

For this study, 4 Networks of the Type Perceptron Multilayers, which present one-way information flow (Feedfoward), but unlike single-layer networks, there is the presence of hidden layers. Due to the extra set of synaptic connections and the richness of neural iterations, hidden layers are able to extract complex characteristics from the environment in which they operate [17].

2) Learning and training

The set of well-defined procedures to adapt the parameters of an ANN, making it learn a certain function, is named as a learning algorithm.

What differentiates the various existing algorithms is the way in which weights are adjusted. In summary, applying a learning algorithm to an ANN is to present it with information patterns in an iterative process where synaptic weights will be adjusted, causing it to identify the environment in which it will operate [16].

For multi-layered network training, the back propagation algorithm (Backpropagation) is used, which is based on the learning rule by error correction [15].

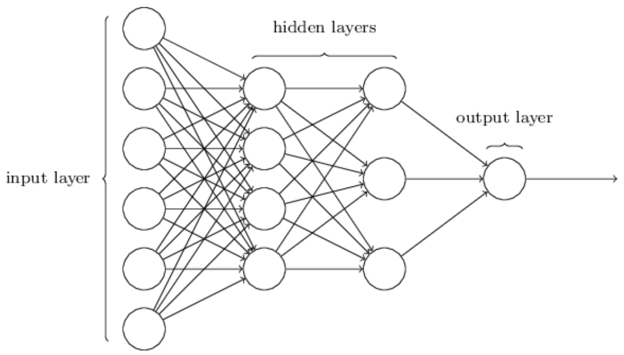

Fig.4. Network with two hidden layers.

Most techniques were obtained to improve the performance of the algorithm empirically, such as the choice of activation function and the number of layers and neurons used, since there are no clear rules for defining these data.

The activation function is a very important part when it comes to multilayer networks, this is due to the fact that the choice of an activation function most often includes a nonlinear and differentiable function in order to solve problems linearly non-separable and that the gradient can be calculated, directing the adjustment of weights [18].

Therefore, ANN was used to predict, through data from mass memory, the typical H.S. consumption curve in the coming years. The analysis of the load curve allows us to know the behavior of consumption over a period of time [19], to know the months of higher and lower consumption and correlate the variation in consumption with another magnitude, such as THD.

However, each type of consumer has a standard consumption curve type, that is, the shape of these curves depends on the consumption habits of the population [19].

To model the typical monthly consumption curve of the facility, its revenue mass memory of the second half of 2016, 1st semester of 2017 and the full year of 2018, provided by the local concessionaire, in which the active power of all this is recorded period with aggregation times of 15 minutes.

Thus, the first ANN received the concatenated consumption data (kWh) from the billing mass memory. With this, it was possible to determine the typical consumption profile of H.E, which is presented in Figure 5.

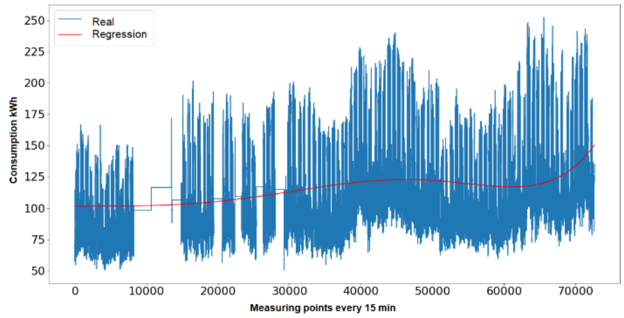

Fig. 5. Energy consumption (kWh).

The first network consists of the input layer, 3 intermediate layers, and the output layer. The input layer, as well as the 3 intermediate layers, consists of 100 neurons each and use the hyperbolic tangent as an activation function. The output layer is composed of 1 neuron and uses the linear function.

The hyperbolic tangent function is smooth and continuously differentiable, that is, it is a nonlinear function, is characteristic is its greatest advantage and makes it widely used in more complex problems, such as classifying values for a class specific.

When analyzing H.S's accounts for the period 2017 to September 2019, recurrent patterns were found in consumption. Thus, to enable the learning and training of the network, ensuring that it identified them, weights were attributed to these parameters.

In the analysis, it was noticed that the months of November, December, January and February, presented the highest consumption, while the months of May, June and July, the lowest. In this context, the months for the one-year period were divided into three distinct categories: summer, winter and other. The latter category covers the other months, which present nearby consumption values and with small variations.

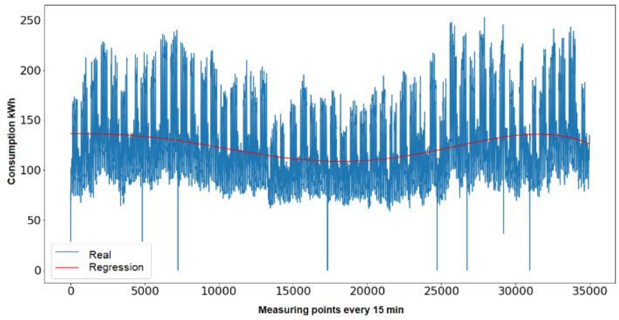

Fig. 6. Graph for consumption 2018.

At this stage, the relu function was used due to the ease of network optimization with this function.

To exemplify, phase A analysis is assumed. In this case, the network works with data entry-out pairs during the training period, where the input refers to the consumption related to phase A and output, THD of this same phase.

After the training phase, the ANNs receive, as input, the consumption data provided by the first ANN implemented. So, from the forecast of consumption and what the network assimilated during training, the profile of increase in THD is expected.

4. Presentation of Results

C. THD e THDi

According to the limits established by Prodist Module 8, the total and individual harmonic distortions of maximum voltage recorded in a system with rated voltage of 220V/380V must be equal to or less than 10% [20].

However, the statistical values of total harmonic distortion of tension were lower than the reference value of 10% indicated by Prodist, more specifically, were below 2.5%.

In addition, it was noticed that the behavior of total harmonic distortion of tension during the measurement periods varied in a narrow range of values and presented a certain similarity between the three phases.

Based on the knowledge of the loads served by se, which are largely nonlinear, it became necessary to verify which harmonic orders stand out most at the points of measurements.

Figures 7 present a synthesis of the values of individual harmonic distortions of the three phases at the measured point, in the form of frequency spectrum. By analyzing these spectra, the most significant harmonic stress is of order 5, followed by order 7 and 3.

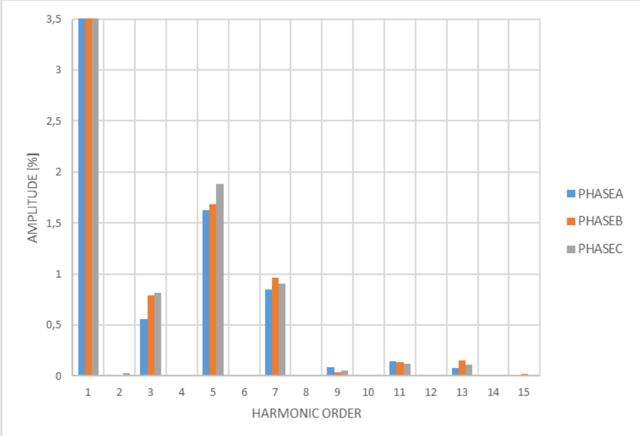

Fig. 7. THDi 1,000 kVA transformer.

The harmonic stress of order 5, which is more significant in all periods and measuring points, should be lower 7.5%, according to the reference values determined by Prodist for nominal voltages less than 1,000 V. Therefore, it can be affirmed that the measured values were lower than the reference value, more precisely, were below 2%.

For order distortions 7 and 3, the value stipulated by Prodist is 6.5% and has also not been exceeded in any of the charts. All voltage distortion values in this order were below 1%.

D. Correlation of THD and consumption

As stated earlier, maintaining the PQ is paramount in hospital environments due to the continuous characteristic of operation. In addition, logistics is needed focused on effective consumption, since hospitals are large consumers of energy.

Given this and, knowing that reliable and continuous energy supply is also related to the concept of energy efficiency, an algorithm was created capable of presenting a prediction of H.S consumption and thus a prognosis of behavior and possible increased harmonic voltage distortions.

From Figure 8, it is possible to notice that, although they are different data, the way consumption and THD scans of each phase are similar. In this image, aiming at a greater detail of the chart, only 96 points were plotted, which are equivalent to the period of one month.

With this, it can be affirmed that consumption is directly related to THD.

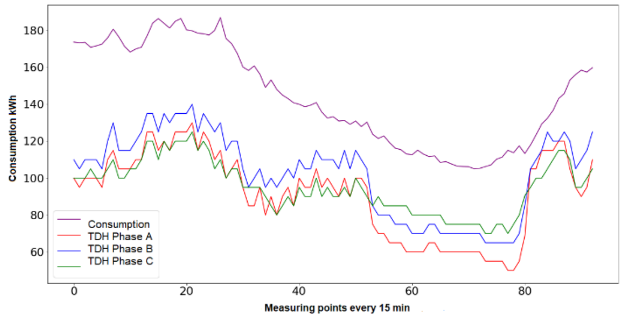

Fig 8. Consumption and THD curve profile of each phase.

The first part of the algorithm, which corresponds to one of the four ANNs used, was able to understand the profile of the load curve presented to neurons of its first layer, perceiving the months of higher and lower consumption, besides identifying the increase that occurred to each year.

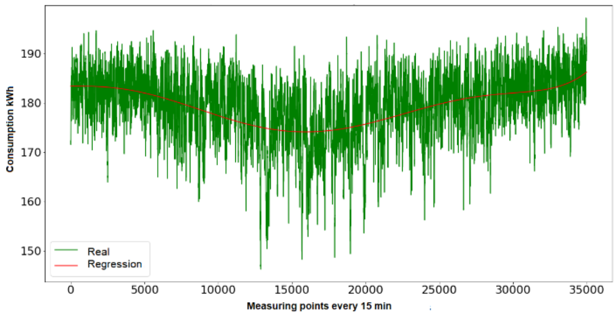

Fig. 9. Predicting consumption for the year 2019.

The maximum peak of prediction was 196.16 kWh and polynomial regression peak, 185.52 kWh. These values are acceptable, since the consumption estimate was made according to the average consumption provided by mass memory. As in Figure 9, the maximum predictive and regression values are acceptable, they are, respectively, 196.69 kWh and 190.13 kWh.

5. Conclusion

This paper presented an alternative for predicting consumption and THD based on measurements made by the concessionaire and field measurements. For this, the methodology used was presented, where four ANNs were implemented. Thus, through the consumption profile extracted from S.H. mass memory, the proposal was applied.

Finally, the computational models were validated through the analysis of the plotted profiles and the average quadratic error obtained at the end of the net training. The analyses show that the method is very effective, despite the limitations, both in the on-site measurements and in the machines used for the prediction, since they are consistent between the results presented by the implemented ANN model and the actual values used.

Thus, this proposal proves to be an important tool for hospitals and large energy consumers, allowing a deeper analysis of consumption and preventive decisions regarding the insertion of disturbing loads in the installations and, consequently, the possible exceeding of the limits determines by Prodist.

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