Development and Calibration of a Low-Cost Electrical Measurement Instrument

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Abstract: - The most modern technological advances are accompanied by more complex and sophisticated demands of society. Among the main social demands, energy consumption is one of the factors with the highest growth, but technologies related to the theme have not developed at the appropriate pace to the context, especially observing that consumers have little or no information about their consumption data. The wide variety of electronic equipment is evident, therefore, the development of a system that allows the user to monitor the energy consumption of the equipment by only a low-cost sensor and with high precision is an interesting advantage. To this end, it is proposed the implementation of artificial neural networks to increase the accuracy of microcontrolled instrument connected via Wi-Fi, to provide reliable data that can be stored in the cloud and present consumption in real time.

Key-Words: Artificial Neural Networks, Electrical Measurement, Self-adjust.

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1 Introduction

The panorama of the measurement of electricity consumption is on the pending of considerable changes because the measuring equipment has not accompanied the technological advance of the electrical charges being measured. In the production chain and supply of electricity to consumers, this should be the point that needs further upgrades.

Microcontrolled electronic instrumentation systems have solved several issues, in different areas, mainly due to the possibility of intelligent instrumentation, which can attribute the characteristic of self-adjustment to instruments.

The growing attention to this subject can be noticed by works published in recent years, which develop a market analysis of the main trends in the use of smart products, mainly for domestic applications, through an economic perspective of social demand. [1] The work [2] shows how the advancement of home automation has awakened the need for interoperability of the various devices that make up a domestic "ecosystem" and what are the possible paths of this trend.

While [3] had studied how the construction of a domestic digital ecosystem would be able to contribute to an increase in energy efficiency, later studies, such as that of [4] developed a complete system for monitoring and measuring electricity consumption aimed at residential applications.

The creation of the concept of Home Energy Management System (HEMS) is due to [5] and since then it has grown and spread rapidly, giving rise to various technologies, methods and devices, as presented by [6].

The concept of Nonintrusive load monitoring (NILM) was proposed by [7] and was applied by several researchers, such as [8] who made a broad review of NILM methods, mainly targeting residential applications. The work [9] developed an experimental work that delivers a device capable of measuring electrical current data for residential equipment.

The cost of electronic meters that can transmit data online makes the implementation unfeasible, however we seek techniques to improve the performance of power meters without increasing the cost of hardware, using machine learning algorithms to self-adjust sensors and data with accuracy comparable to more expensive equipment.

2 Problem Formulation

Energy is defined as the amount of work that a system Energy can be defined as the amount of work that a system is able to perform. In mathematical terms, energy can be defined as the integral defined in a power time interval. Thus, the energy measurement is dynamic, varies with time.

Digital electronic instruments, such as analog electronic instruments, depend on the use of PT and CT to adjust current and voltage levels for readings. The Figure 1 shows ideal sine waves from PT and CT respectively, to voltage (V) and current (I), as seen in Figure 1.

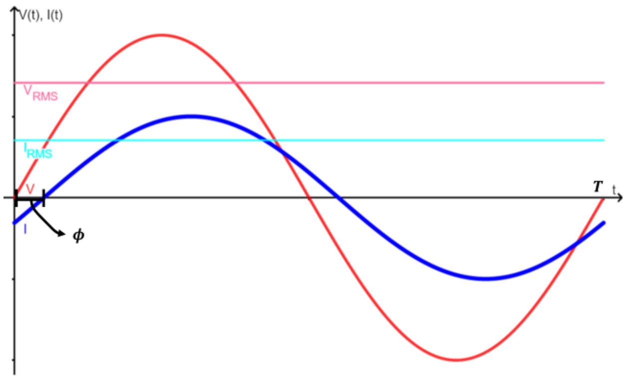

Figure 1 – Period, phase deviation, RMS for voltage and current sines.

In addition to conventional power system transformers, auxiliary transformers are also required, which provide decoupling between circuits, and reduce signals to 5 V and 20 mA, so that such signals are sampled and digitized by digital analog converters (ADC). The voltage and current samples are processed by algorithms to provide the values of electrical quantities of the measurements.

From the samples it is possible to calculate: Phase Difference, Current and Peak Voltage, Frequency, Harmonic Components, Apparent, Active and Reactive Powers and Energy Consumption.

To ensure the necessary accuracy in the measurements, each step must be carefully adjusted and calibrated.

The effective value is calculated by the RMS equation (Root Mean Square), according to equation 1, for both current ($I[n]$) and voltage ($V[n]$) from Figure 1, digitized.

$$V_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} V[n]^2} \quad I_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} I[n]^2} \qquad (1)$$

The interpretation of the effective value of the signals is the load that can be used by the equipment to determine the consumption signature of the loads, as shown in this work.

The electrical frequency is obtained by calculating the voltage period ($f = 1/T$). It can be set to $50Hz$ or $60Hz$ frequency, but some specific loads may change the electrical frequency of the installation. Among the variables, proposed to determine the signature of consumption, it is hypothesized that frequency variations should not effectively contribute to the classification of loads.

The phase deviation (ϕ) between the voltage and current signals is characterized by the time difference of the crossing of each signal at level zero. Therefore, it is possible to calculate this parameter by a zero-crossing detection algorithm, which provides the moments when the voltage and current assume the zero value ($t_{V=0}$ and $t_{I=0}$).

$$\phi = 2\pi f(t_{V=0} - t_{I=0}) \qquad (2)$$

This parameter is variable and depends on the loads connected to the installation, so it allows to distinguish the consumption signatures. It is interpreted as the relationship between the total power supplied to the load system and the active power, actually consumed, so from the phase deviation it is possible to calculate. The apparent power (S) is provided by the equation:

$$S = V_{RMS} I_{RMS} \qquad (3)$$

Therefore, from the phase deviation it is possible to calculate the power factor (PF) of the consumption:

$$PF = cos(\phi) \qquad (4)$$

Active electrical power is an electrical parameter derived from others, important to characterize the input or output of an electrical installation consumption equipment, given by:

$$P = V_{RMS} I_{RMS} \cos(\phi) \qquad (5)$$

Microprocessors as well as other computational components are increasingly easily accessible in terms of availability, variety and cost. This ease makes the implementation of electric energy measurement systems more viable, thus generating greater interest from society, as well as students and the scientific community.

The choice of a low-cost measurement system reflects the instrument's lower accuracy, as several sources deform the measurements performed. Especially the ADC.

3 Problem Solution

A microcontrolled prototype using the ESP32 board was elaborated, with the objective of calculating electrical parameters for different loads, because the DEVELOPMENT PLCA ESP32 is low cost (~$ 3.00), has internal ADCs and integrated Wi-Fi, but depends on the installation of a PT and a CT still.

On the other hand, we considered the PZEM-004T card, which has a slightly higher cost (~$ 20.00),

which has integrated PT and CT, but still depends on another card for Wi-Fi connection.

It was noticed that in the ADC readings of the ESP32 board there were errors. This converter, according to the datasheet, has a nonlinear response considering the entire reading range, being a linear part, but presenting considerable error in relation to the reference instrument. Methods were developed to measure the angle of lag between the sines, in which it is necessary to assume a reference sample of the sine for comparison. The search for the peak of the node was chosen, because there are several algorithms available that propose to this, so when the maximum value sample of each node is found it is possible to infer the time delay between them. Time, in turn, is converted into phase by equation 2. Where the phase deviation given in radians; delay time between peaks; and the period of the senoid, which uses the same peak detection algorithm, but in which it is measured between the peaks of the same $\sin(\phi t_{pp} T)$

Esp32 receives sensor information and processed data must be sent to a database via an ESP32 microcontroller card that has Wi-Fi communication embedded, as represented in the flowchart in Figure 2.

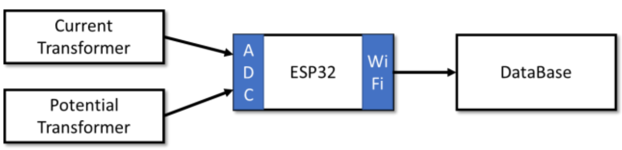

Figure 2 – Instrument system of flowchart.

The PZEM-004T-V3 sensor consists of a current transducer and a voltage transducer, both nonintrusive.
The sensor reading circuit, represented in Figure 3, allows the reading of current, voltage, power factor, active power, apparent power, energy consumed and frequency, such as the instrument proposed using the ESP32 board.

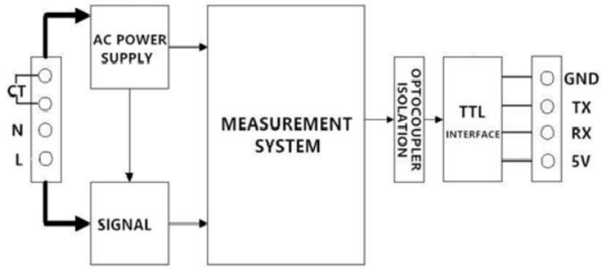

Figure 3 – PZEM circuit diagram.

3.1 Neural Network Improvement to Self-Adjust

Inspired by real neurons and with a massively parallel scope of work, artificial neurons can be employed in both software and hardware. A neuron, itself, has limited capacity, however, by creating a set of these artificial neurons, it is possible to create highly powerful resources. The set of artificial neurons is called an artificial neural network, as illustrated in Figure 4.

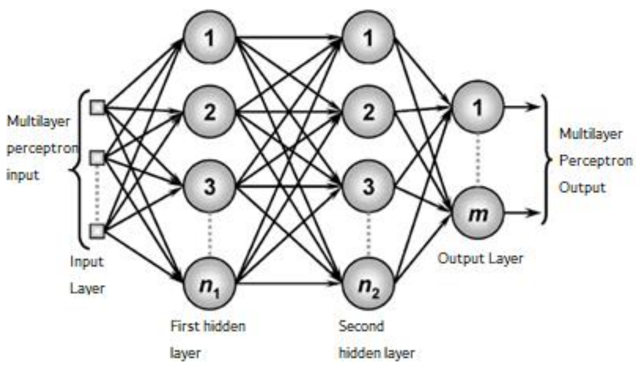

Figure 4 – ANN Multilayer Perceptron.

For training the ANN Multilayer Perceptron, the backpropagation technique is used, which consists of two phases:

- The first phase, called feed-foward, transmits the input signals throughout the network, and at the output the error found is calculated, based on the expected and known target.

- The second phase, called backpropagation, occurs in the opposite direction, updating the weights and connections.

It is in the second (reverse) phase that the weights of each neuron are updated. For this activity, the Levenberg-Marquardt algorithm is used, which was developed to solve non-linear functions, using the least squares method.

This algorithm proposes a compromise solution between the gradient descent algorithm and the Gauss-Newton iterative method, according to equation 5 as a weight update rule.

$$W^{i+1} = W^{i} - (J^{T}J + \mu I)^{-1} \cdot \nabla E(W^{i}) \quad (6)$$

Where W is the matrix of weights, i is the training epoch. The Hessian matrix is approximated by $(J^{T}J + \mu I)^{-1}$, where J is the Jacobian, μ the adjustment factor, and ∇E is the mean squared error gradient for the epoch weight matrix.

3.1.1 Self-Calibration

Self-calibration or self-adjustment consists of enabling the equipment in question, generally applied to sensored systems, to be constantly adjusted during use. This opens up a new horizon, when we talk about reducing machine downtime, for carrying out calibration/gauging procedures, directly reflecting on costs. It is also important to point out that a properly calibrated instrument offers greater reliability and safety for the user.

This type of approach is only possible by concepts of intelligent sensors, which are provided for in IEEE 1451 ("Standard for Transducer Interface for Sensors and Actuators").

It is at this point that, in many cases, ANN becomes quite interesting.

Using the ANN method, described above, it is possible to create an algorithm to carry out the self-adjustment through prior knowledge of the pattern of variation of the signal, that one wants to study, thus making it possible to carry out corrections in real time. Values from uncalibrated sensors are presented to the ANN as a basis for training, and then the expected value for a calibrated sensor is compared. For this, the ANN training must be well planned, before doing it, because if real situations that occur beyond the limits stipulated in the training, may not present the expected effectiveness.

To ensure a constant analysis of the functioning of the sensor in question, the neural network must be connected to the sensor, as shown in the generic diagram in Figure 5.

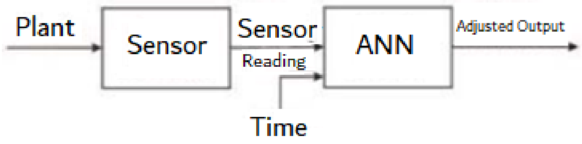

Figure 5 – ANN series adjust.

4 Results

Two stages of application of the artificial neural network were performed in this work, first to correct the ADC of the ESP32 plate and later to reduce the deviation of measurements of different loads by the ESP32 plate.

4.1 ADC correction

After the error in the ADC of the board, a procedure was elaborated to provide a linear ramp ranging from 0 to 3.3V, utilizing the integrated circuit MCP4725 and an external digital converter of 12bits, generated a ramp. This ramp, which is the desired answer, was applied to the ADC converter of the ESP32, and from it the direct response was obtained, as shown in Figure 6.

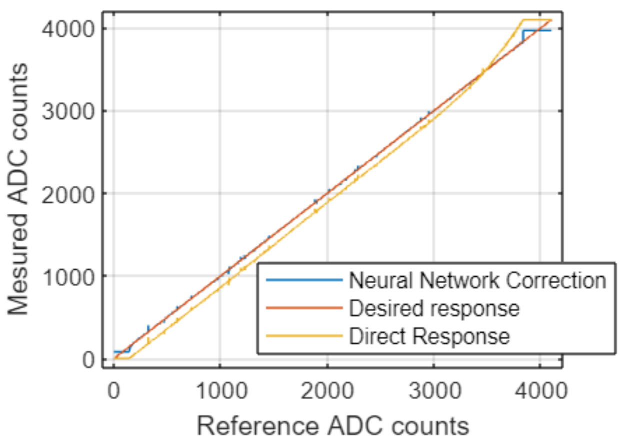

Figure 6 – Response ADC comparation.

The correction provided by the artificial neural network is also presented in Fig.5. It is also perceived with analysis of Fig. 6, that the correction of the network was considerable, from the order of the average of 3% average to 0.5%.

4.2 Instrument Correction

Similarly, the correction performed for the ADC, the correction for the load readings was also performed. For this, 6 different loads were used and their waveforms were measured by the instrument proposed in ESP32. At the same time the data were obtained by the PZEM-004t card, with this the active power and apparent power are taken as a reference for parameterization of the weights of an artificial neural network, which must correct the measured data of the instrument with the ESP32 card.

The neural network must provide the corrected active power and apparent power values, from the RMS Voltage, RMS Current, Power Calculated Active and Calculated Apparent Power. Therefore, it is defined that artificial neural network architecture is 4 inputs and 2 outputs, missing only the definition of the amount of neurons in the hidden layer, in this sense, the exhaustive search was made, testing the performance of the neural network for the amount of 1 to 10 neurons and the result of 5 neurons was reached, according to Figure 7.

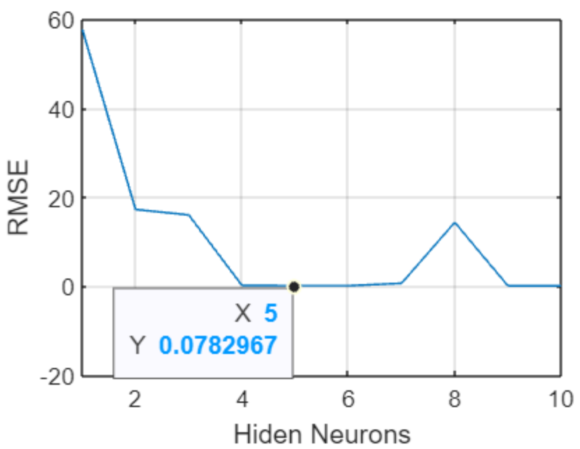

Figure 7 – RMSE to project the architecture of the ANN2.

Figure 8 represents the architecture of the projected artificial neural network. This diagram provides a comprehensive overview of the intricate layers, connections, and flow of information within the network. By examining Figure 8, readers can gain a clearer understanding of how the neural network processes and analyzes the input data.

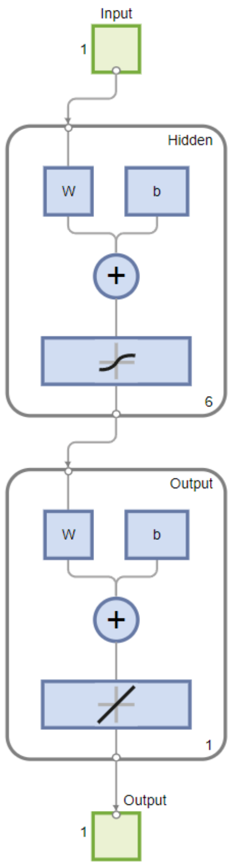

Figure 8 – ANN1 Architecture.

The artificial neural network was used to provide the corrected active power and apparent power values of the 6 different electrical charges (EL), with data not previously presented to the neural network.

Tables 1 and 2 show the results obtained without neural network correction and correction, table 1 shows the apparent power values, while table 2 shows the active power values. It is noticed that in both tables the neural network decreases the standard deviation of the results, which is the advantage expected by the application of this method, by increasing the accuracy, without improving the hardware.

Table 1 – Apparent Power Results

	Uncorrected ESP32 Acquisition	ANN1 Correction	Uncorrected PZEM Acquisition	ANN1+ANN2 Correction
EL1	56.0 ± 1.17	39.3 ± 0.70	36.9 ± 0.98	39.9 ± 0.50
EL2	53.1 ± 0.25	44.3 ± 0.23	44.4 ± 0.24	44.3 ± 0.17
EL3	40.8 ± 0.21	9.2 ± 0.22	9.7 ± 0.20	9.9 ± 0.06
EL4	81.8 ± 3.50	74.9 ± 3.24	74.7 ± 2.92	74.7 ± 2.94
EL5	83.7 ± 1.32	75.6 ± 1.05	66.2 ± 1.73	74.4 ± 0.92
EL6	84.3 ± 0.78	54.5 ± 0.55	57.3 ± 0.61	53.8 ± 0.29

Table 2 – True Power Results

	Uncorrected ESP32 Acquisition	ANN1 Correction	Uncorrected PZEM Acquisition	ANN1+ANN2 Correction
EL1	49.8 ± 1.01	39.3 ± 0.50	36.9 ± 0.97	39.5 ± 0.37
EL2	44.4 ± 0.24	44.3 ± 0.18	44.8 ± 0.20	44.9 ± 0.16
EL3	20.4 ± 0.25	8.7 ± 0.05	9.1 ± 0.19	9.3 ± 0.02
EL4	79.0 ± 2.68	73.5 ± 3.08	73.4 ± 2.66	73.0 ± 2.84
EL5	70.4 ± 1.15	48.4 ± 0.66	53.2 ± 1.04	48.4 ± 0.54
EL6	51.8 ± 0.92	11.1 ± 0.26	11.7 ± 0.20	11.5 ± 0.13

5 Conclusion

It was possible to improve the measurements of a low-cost electricity meter by implementing artificial neural networks, which may facilitate the implementation of low-cost sensors in applications of this type by continuing this study.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Guilherme Cit developed the prototype used to survey the ADC response curve of the Esp32, as well as the code in C embedded in Esp32 responsible for generating the samples in .csv, that compares the power readings between the ADC of Esp32 and the PZEM module.

Jean Monteiro realized a Artificial Neural Network research, focused on perceptron multi-layer type, Self-calibration concept explanation and a description, based on positive and negative results observed.

Jonatas Quirino was responsible to the bibliographical research on the topic's state of the art, methodological adequacy, formatting review and person responsible for the submission, review and publication process.

Tiago Quirino implemented the Artificial Neural Networks to correct the data.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.