Artificial neuronal network for monitoring of energy consumption by a home device.

Juan Carlos Ortega Castro
Subdirección de Posgrados
Universidad Católica de Cuenca
Cuenca, Ecuador
jcortegac@ucacue.edu.ec

Luis I. Minchala
Subdirección de Posgrados
Universidad Católica de Cuenca
Cuenca, Ecuador
liminchalaa@ucacue.edu.ec

Ricardo Palacios Rodas
Subdirección de Posgrados
Universidad Católica de Cuenca
Cuenca, Ecuador
ricardopalaciosrodas@gmail.com

***Abstract*—This paper presents the design of a device capable of monitoring the energy consumed by a household device. From this information, a consumption profile is model to detect anomalies of operation, during operation, and to detect electrical faults.**

The prototype of the device is equipped with a current sensor and a communication module, which sends the data to a web application to record energy consumption. The processing of the information, to predict faults, is carried out in an artificial neuronal network with multi-layer architecture implemented in MATLAB.

Keywords— Internet of things, neuronal network, energy, consumption.

I. Introduction

The technological advances that the world is experiencing, are increasingly frequent at home, industry and cities need to have automated processes and tasks which generate confidence and security. An important factor to consider is energy consumption of electronic devices, having control and management over this factor it is possible to contribute with energy efficiency and reduce costs in electricity consumption.

Ecuadorian power distributors demand an important change in their productive matrix, which involves improving production processes, optimizing the use of raw materials, saving and energy efficiency. In this context, it is well known that energy saving implies energy efficiency; therefore the monitoring of electricity consumption data, helps take into account the consumption of different electrical appliances and devices, providing the possibility of obtaining efficient management about them.

Based on the report of a survey carried out by the Electricity Company of the city of Azogues, to know the consumer satisfaction index, it is known that access to electricity consumption information is not provided. In [1] they make proposals to improve the distribution system, including programs to promote the use of energy saving lamps, home automation systems, intelligent measurement systems, and telemeasurement.

The problem lies mainly in the lack of control of the energy consumed in a home, which has become a key point in energy efficiency. Users of energy distributors do not have detailed information on their consumption, so they cannot make energy saving decisions.

The lack of information, knowledge, and control over energy consumption generate conflicts between consumers and the distribution company, in [2] they detail some causes and the consequences this problem has. A reason that they mention is: "There is no a real-time control of the consumption of electricity expressed in dollars, and its consequence is that subscribers waste energy and do not have a saving habit."

The objective of this research was based on: designing and implementing a prototype of an internet of things device, which acquires the information of the consumption profile and generates a monitoring report of the consumed energy of a domestic appliance, in order to predict anomalies in the energy consumption of the same, applying neuronal networks; formulated from the hypothesis that seeks to be proven based on the idea that the limited knowledge and information provided by conventional energy meters to the consumer, is related to a high energy consumption in a home.

II. MATERIALS AND METHODS

A. Initial analysis

The main objective of this work was to develop a prototype of an internet device of things that allows the visualization of energy consumption profiles of household appliances and the prediction of anomalies in energy consumption based on the use of an algorithm, applying the method of ANN (Artificial Neuronal Network).

Obtaining information on energy consumption that allows us to know the behavior of our appliances, will not only allow control over their consumption but will also let the prediction and generation of alerts when certain anomalies occur, applying a neuronal network.

For the development of this research, it was necessary to perform the following tasks:

- Review of literature according to this investigation.
- Establish the theoretical foundation of this research.
- Select the appropriate current sensor for the development of the prototype.
- Select the appropriate voltage sensor for the development of the prototype.
- Perform the conditioning for the sensors.
- Carry out the calibration of the sensor.
- Program an Arduino microcontroller for the acquisition of current, voltage and power data.
- Select the communication module to transmit the acquired data.

- Analysis of options to visualize the data acquired on the web.
- Implementation of algorithm and training of the neuronal network.

It is common to see that every day new devices and applications are created to facilitate and simplify our lives. The energy sector in Ecuador claims an important change in its distribution, the lack of information on energy consumption for consumers is a factor that affects both the distribution company and the consumer, since this information is not available, and efficient consumption management is not carried out.

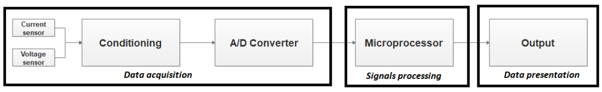
This prototype was implemented in a home located in the city of Azogues, which was equipped with voltage sensors, current sensors, a microprocessor, and a communication module.

This research, besides carrying out the monitoring of energy consumption, also developed the implementation of a neuronal network algorithm with multilayer architecture, which serves to predict possible anomalies in energy consumption.

B. *Proposed model*

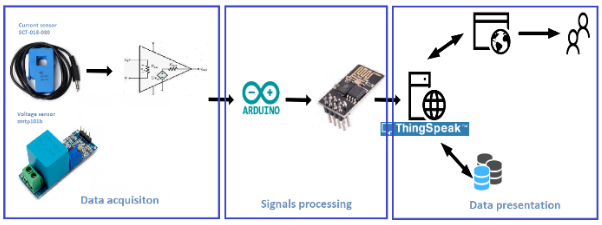
The proposed architecture for the prototype measurement of residential electricity consumption can be seen in figure 1. Three stages are proposed: data acquisition, signal processing, and data presentation.

Figure 1: Prototype architecture.



Based on the described architecture, a model is proposed for the design of the energy consumption measurement prototype, which is shown in Figure 2. It has two sensors, one current, and other voltage. These data are received in the Arduino microcontroller, which processes them through the emonlib library and makes them available remotely through the internet on the thinspeak server.

Figure 2: Prototype design.



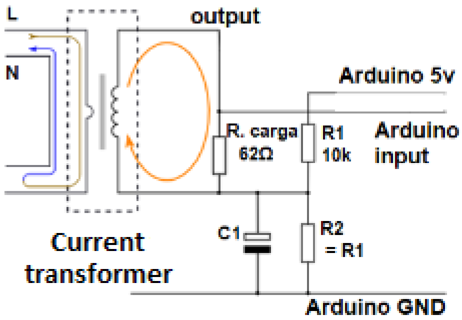
C. *Data acquisition*

For data inquiry is necessary to carry out the assembly process through three stages, the first stage is the current measurement, where the following components were used:

- 1 sensor SCT-013-030
- 2 10kΩ resistors
- 1 capacitor 10uF

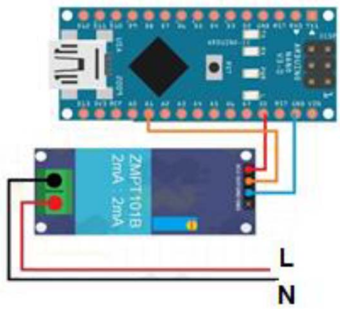
These components were implemented following the scheme of figure 3, allowing the connection of the sensor with the Arduino.

Figure 3: Mounting scheme of the current sensor.



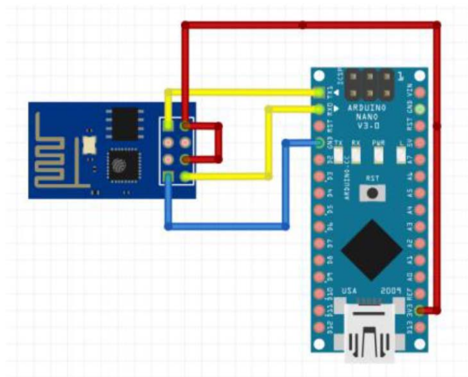
Stage two consists of the assembly of the voltage sensor for voltage measurement of the electrical network, where the zmpt101b module is necessary. In figure 4, shows the connections between the module and the arduino.

Figure 4: Mounting diagram of the voltage sensor.



The third stage consists of the assembly of the wifi communication module esp8266, which is connected to the Arduino according to figure 5. This implementation serves to communicate the Arduino to the server remotely through the Internet.

Figure 5: Assembly diagram of the esp8266 module.

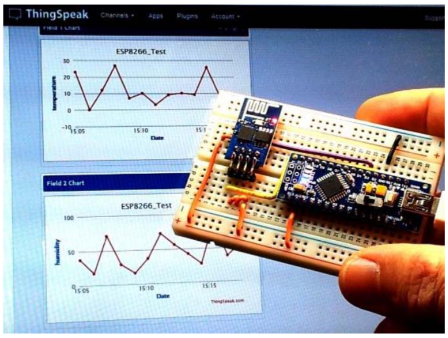


Signal Processing. - For signal processing was necessary becoming familiar with the Arduino development environment. For the processing of acquired signals, it is required to use the calibration commands belonging to the emonlib library, which are emon1.current and emon1.voltage, in which the calibration values found are used.

[3] Says that this library was created by the openenergymonitor project that aims to develop open-source tools to help understanding energy consumption. Using this library the calculation of electricity consumption was simplified, making software development simpler.

Data presentation.- In the presentation of data, the thingspeak server is used. It is necessary to provide a communication module to the Arduino nano, as it is shown in figure 6, to send data to the thingspeak server, it is needed to use an application programming interface (API), create a channel to receive and display the consumption information of the appliance. To do this, a channel was created in the thingspeak server with fields such as Power (W), Consumption (kWh), Voltage (V) and Current (A). This channel generates a write key, which is sent by the Arduino code for the connection to the Thingspeak server where the data is hosted and displayed.

Figure 6: Presentation of data in the thingspeak server.



D. *Programmation*

Implementation of algorithm for neuronal network.- For the implementation of the neuronal network, the mathematical prediction model is considered, based on the reading taken by the prototype, in terms of the physical variables of voltage V and current I and the value of the prediction obtained by the model of the behavior of the domestic appliance, obtaining as a result a residue.

If the absolute value of the waste is higher than the threshold defined experimentally by the consumption profile of the appliance, it is considered a failure, so the equation (1) is:

$$r = x - \tilde{x} \tag{1}$$

$$failure \in \{r \mid abs(r) > lim\}$$

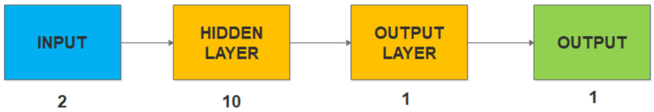
Where r is the residue, x corresponds to the reading of the energy consumption, x corresponds to the estimated consumption calculated by the neuronal network, and lim corresponds to an experimental value that enables the detection of faults.

To implement the algorithm for the neuronal network, the data supplied by the channel created in the Thingspeak server is used, where the prototype data is housed, specifically the active power data of the appliance, which indicate its consumption profile, information that is used to train the neuronal network. Knowing the response of the appliance to different behaviors is important for the training of the neuronal network, for which different events were forged to analyze the behavior of the device.

The algorithm of the neuronal network was implemented in Matlab, importing the data directly from the thinspeak server, and using the nftool tool, which serves to train the neuronal network. The neuronal network used has the following characteristics:

- Multi-layer architecture.
- Use the Levenberg-Marquardt algorithm.
- The configuration of the neuronal network is observed in figure 7.

Figure 7: Presentation of data in the thingspeak server.



To configure the neuronal network it was used the power and the times where the sample is obtained as input data, the number of neurons used in the hidden layer is 10.

III. Results and Discussions

To validate the data collected by the proposed prototype, a comparison was made with the FLUKE 1730 power consumption recorder, for which three scenarios were proposed, which allowed obtaining the voltage and current values for a load with a fluorescent focus, a focus incandescent, and a refrigerator.

The comparative tables (Tables 1-6) are presented below:

Table 1. Load of a fluorescent bulb (voltage)

DATE	FLUKE 1730	PROTOTYPE	ERROR
	V	V	%
5/12/2018 15:40	117,15	117,01	0,12%
5/12/2018 15:50	117,31	117,23	0,07%
5/12/2018 16:00	117,45	117,31	0,12%
5/12/2018 16:10	118,16	117,98	0,15%
5/12/2018 16:20	117,16	117,08	0,07%
5/12/2018 16:30	118,15	117,62	0,45%
5/12/2018 16:40	116,76	116,39	0,32%
Average error			0,18%

Comparison of voltage between FLUKE 1730 and the prototype for the Load of a fluorescent bulb.

Table 2. Load of a fluorescent bulb(current)

DATE	FLUKE 1730	PROTOTYPE	ERROR
	I	I	%
5/12/2018 15:40	0,15	0,14	6,67%
5/12/2018 15:50	0,14	0,14	0,00%
5/12/2018 16:00	0,15	0,15	0,00%
5/12/2018 16:10	0,15	0,14	6,67%
5/12/2018 16:20	0,16	0,15	6,25%

5/12/2018 16:30	0,15	0,15	0,00%
5/12/2018 16:40	0,15	0,15	0,00%
Average error			2,80%

Comparison of current between FLUKE 1730 and the prototype for the Load of a fluorescent bulb.

Table 3. Load of an incandescent bulb (voltage)

DATE	FLUKE 1730	PROTOTYPE	ERROR
	V	V	%
6/12/2018 15:40	110,83	110,78	0,05%
6/12/2018 15:50	112,01	111,78	0,21%
6/12/2018 16:00	111,6	111,24	0,32%
6/12/2018 16:10	110,94	110,87	0,06%
6/12/2018 16:20	110,84	110,76	0,07%
6/12/2018 16:30	113,1	112,83	0,24%
6/12/2018 16:40	112,96	112,83	0,12%
Average error			0,15%

Comparison of voltage between FLUKE 1730 and the prototype for charging an incandescent bulb.

Table 4. Load of an incandescent bulb (current)

DATE	FLUKE 1730	PROTOTYPE	ERROR
	I	I	%
6/12/2018 15:40	0,91	0,94	-3,30%
6/12/2018 15:50	0,91	0,86	5,49%
6/12/2018 16:00	0,89	0,83	6,74%
6/12/2018 16:10	0,89	0,81	8,99%
6/12/2018 16:20	0,89	0,81	8,99%
6/12/2018 16:30	0,87	0,8	8,05%
6/12/2018 16:40	0,91	0,81	10,99%
Average error			6,56%

Comparison of current between FLUKE 1730 and the prototype for charging an incandescent bulb.

Table 5. Charging an Electrolux refrigerator ERDW093MSJW (voltage)

DATE	FLUKE 1730	PROTOTYPE	ERROR
	V	V	%
7/12/2018 12:40	115,795	116,06	-0,23%
7/12/2018 12:50	115,945	115,72	0,19%
7/12/2018 13:00	116,043	116,61	-0,49%
7/12/2018 13:10	116,198	116,63	-0,37%
7/12/2018 13:20	115,668	114,98	0,59%
7/12/2018 13:30	116,654	115,76	0,77%
7/12/2018 13:40	116,689	116,06	0,54%
Average error			0,14%

Comparison of voltage between FLUKE 1730 and the prototype for charging an Electrolux ERDW093MSJW refrigerator.

Table 6. Load of an Electrolux ERDW093MSJW refrigerator (current)

DATE	FLUKE 1730	PROTOTYPE	ERROR
	I	I	%
7/12/2018 12:40	1,13	1,09	3,22%
7/12/2018 12:50	1,5	1,34	10,60%
7/12/2018 13:00	1,14	1,1	3,42%
7/12/2018 13:10	0,85	0,63	25,63%
7/12/2018 13:20	1,05	1,01	3,53%
7/12/2018 13:30	0,84	0,79	6,04%
7/12/2018 13:40	0,77	0,71	8,21%
Average error			8,67%

Comparison of current between FLUKE 1730 and the prototype for the charging of an Electrolux refrigerator ERDW093MSJW.

The registration and presentation of data were done in the Thingspeak server, as can be seen in figures 8, 9, 10 and 11.

Figure 8. Monitoring of the rms voltage.

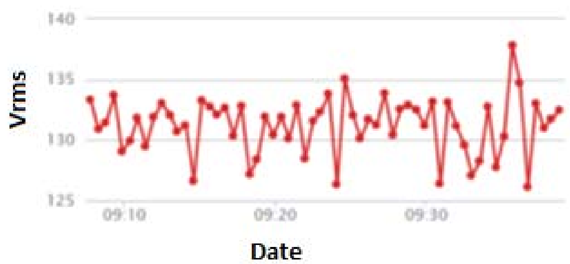


Figure 9. Monitoring of the rms current.

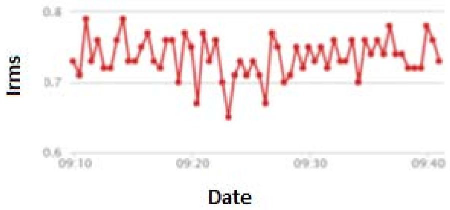


Figure 10. Active power monitoring.

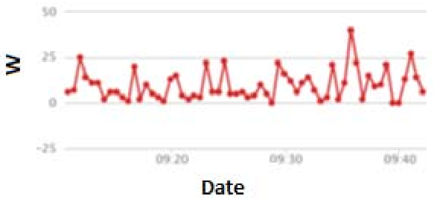


Figure 11. Monitoring of energy consumption.

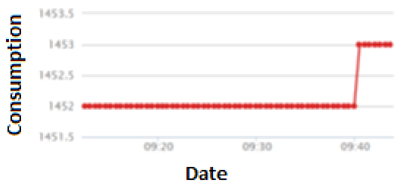


Figure 12 shows the behavior of the neuronal network, reacting to the different events produced by the household appliance.

Figure 12. Behavior of the neuronal network.

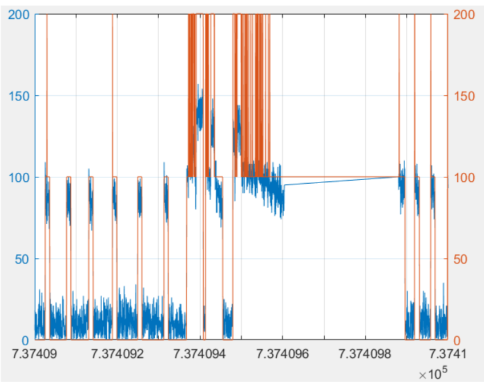


Figure 13 shows the response of the neuronal network, indicating the failure report of the appliance.

Figure 13. Failure report.

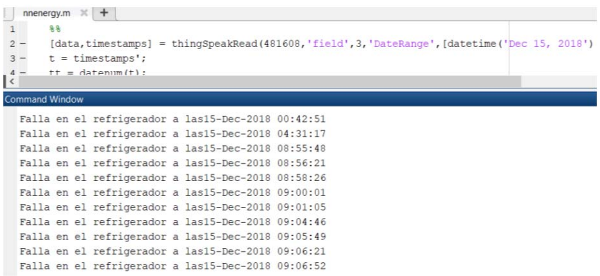
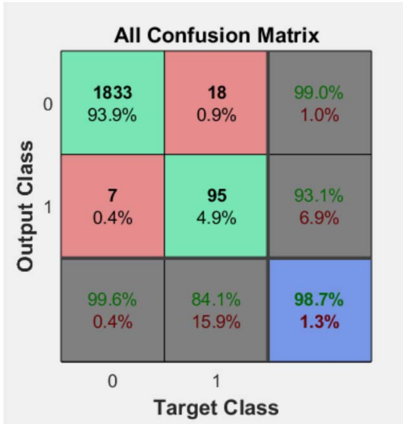


Figure 14 shows the confusion matrix, a tool that allows visualizing the performance of the algorithm used for the training of the neuronal network, where the columns show the number of predictions of the class and the rows show the instances in the real class.

In the same, it is detailed that 98.7% of the samples classified them correctly, and 1.3% confused them, that represent the neuronal network error rate.

Figure 14. Confusion matrix.



IV. Conclusions

Based on the results, the tests carried out indicated that the proposed prototype is capable of taking measurements close to an energy recorder such as the FLUKE 1730, with an error rate of less than 9%, at a much lower cost than the energy mentioned recorder.

Compared to a conventional meter, the prototype facilitates the query of the data to the consumer, either by a mobile device or a desktop computer, because these data are recorded in the cloud. Also, the prototype allows visualizing other parameters such as rms voltage, rms current and instantaneous power, which is not obtained with a conventional meter.

In the context of smart grid, intelligent energy meters play a very important role, generating knowledge of the state of the electricity grid and energy consumption, having the consumer an active role with the distribution company; this allows new business models and ventures.

References

[1] Armijos Abril, J. A., & Pesántez Alvarado, Á. D. (2016). UNIVERSIDAD DE CUENCA FACULTAD DE INGENIERÍA ESCUELA DE ELECTRÓNICA Y TELECOMUNICACIONES DISEÑO DE UN MEDIDOR INTELIGENTE CON FUNCIONES DE RESPUESTA A LA DEMANDA EN INFRAESTRUCTURAS DE MEDICIÓN AVANZADA.

[2] Barera, L., & Pinargote, H. (2018). DISEÑO DE UN SISTEMA DE MONITOREO INALÁMBRICO DE PARÁMETROS ELÉCTRICOS EN CARGAS RESIDENCIALES. Retrieved from http://repositorio.ug.edu.ec/bitstream/redug/27045/1/B-CINT-PTG-N.261 Barrera Gallegos Miguel Leonardo. Pinargote Arteaga Henry Steven.pdf

[3] COELHO SOUSA, I. L. (2017). SISTEMA DE MEDIÇÃO LOCAL E REMOTA DE ENERGIA ELÉTRICA EM CONSUMIDORES DE BAIXA TENSÃO BASEADO EM ARDUINO.

[4] Ashton, K. (2009). That “Internet of Things” Thing. RFiD Journal, 4986. https://doi.org/10.1145/2967977

[5] Carretero Peña, A., & García Sánchez, J. M. (n.d.). Gestión de la eficiencia energética: cálculo del consumo, indicadores y mejora. Retrieved from https://s3.amazonaws.com/academia.edu.documents/40723065/6-

aenor_50001.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1508259451&Signature=p18%2Bh%2B84N80xVRb%2FputGa%2BGTThw%3D&response-content-disposition=inline%3Bfilename%3D6-aenor_50001.pdf

[6] Castro, A. A. (2008). Sensores utilizados en la Automatización Industrial. Retrieved from http://eie.ucr.ac.cr/uploads/file/proybach/pb0813t.pdf

[7] Evans, D. (2011). Internet de las cosas: Cómo la próxima evolución de Internet lo cambia todo. Journal of Food Engineering, 49(Emim), 314–318. https://doi.org/10.2991/emim-15.2015.61

[8] JÁCOME RIERA, O. J., & LEÓN AMORES, G. J. (2014). "Diseño Y Construcción De Un Sistema De Medición Inteligente Para La Gestión De La Energía Eléctrica Y Medición De Agua Potable En Los Hogares". Retrieved from http://repositorio.espe.edu.ec/jspui/bitstream/21000/8293/1/T-ESPEL-ENI-0321.pdf

[9] Lorenzo Ochoa, B. J. (2018). Análisis de consumo monofásico, 63.

[10] Marder, F., Lombardero, A., & G, O. (2003). Sensor lineal de corriente para medición de energía. Comunicaciones Científicas y Tecnológicas.

[11] Muralitharan, K., Sakthivel, R., & Vishnuvarthan, R. (2017). Neural network based optimization approach for energy demand prediction in smart grid. Neurocomputing, 273, 199–208. https://doi.org/10.1016/j.neucom.2017.08.017

[12] Pallas, R. (2005). Sensores Y Acondicionadores De Señal. Marcombo (4ta Edició).

[13] Pocero, L., Amaxilatis, D., Mylonas, G., & Chatzigiannakis, I. (2017). Open source IoT meter devices for smart and energy-efficient school buildings. HardwareX, 1, 54–67. https://doi.org/10.1016/j.ohx.2017.02.002

[14] Sundmaeker, H., Guillemin, P., Friess, P., & Woelfflé, S. (2010). Vision and challenges for realizing the internet of things. Proceedings of the 3rd STI Roadmapping Workshop (Vol. 1). https://doi.org/10.2759/26127

[15] Taki, M., Rohani, A., Soheili-Fard, F., & Abdeshahi, A. (2017). Assessment of energy consumption and modeling of output energy for wheat production by neural network (MLP and RBF) and Gaussian process regression (GPR) models. Journal of Cleaner Production, 172, 3028–3041. https://doi.org/10.1016/j.jclepro.2017.11.107