

MODELING FOR THE MEASUREMENT OF ELECTRICITY CONSUMPTION BASED ON READING ELECTRICAL CURRENT: A CASE STUDY.

Gregor Gama de Carvalho

Instituto Federal de Alagoas, Campus Maceió – Rua Mizael Domingues, nº 75 – Centro – Maceió/AL
e-mail: gregor_gama@hotmail.com

Marcus Vinicius Americano da Costa

Universidade Federal da Bahia, Escola Politécnica. Rua Aristides Novis, nº 2, 6º Andar – Federação – Salvador/BA.
e-mail: marcus.americano@ufba.br

Robson da Silva Magalhães

Universidade Federal do Sul da Bahia, Campus Jorge Amado. Rod. Ilhéus-Vitória da Conquista, km 39, BR 415, Ferradas, Itabuna/BA.
e-mail: robsonmagalhaes@ufsb.edu.br

Abstract - In the process of opening a new Shopping Mall, not all operational sectors have been adjusted and are ready to function. In this case, the management often prioritizes the main services to be completed for the establishment's basic functioning during its early days. The electric section is essential and includes the lights, elevator and escalator functioning. However, items such as automatic loading and other specific needs can be finalized during the following months if not initially included. Measuring the energy consumption of each store falls under the responsibility of the Shopping Mall. The Shopping Mall buys the electric energy from the energy company and distributes it internally through its electric substation to its in-house customers. Therefore, it is necessary to calculate each store's individual consumption by reading the properties of the electrical current. In order to obtain the properties of the electric current certain techniques are used like the use of a clamp meter. The measurement of the properties of the electric current must be conducted during a store's normal hours of operation so that enough data to generate an invoice for each store in the absence of or problems with the energy meter. In the following paper, the consumption data of a variety of stores in the Arapiraca Garden Shopping, in the city of Arapiraca – Alagoas (Brazil) were analyzed. The data processed allowed for a comparative analysis of the results obtained with the use of formulas that calculated the electric monthly consumption, as well as those obtained through the use of a model based on an Artificial Neural Network (ANN), and the results of actual energy consumption measurements done with a meter.

Keywords: Energy measurement, Mathematical Modelling, Artificial Neural Networks, Electric Consumption Calculation.

1. INTRODUCTION

Nowadays, the several of electric energy generation forms are the main energy sources. Electric energy is used to generate the driving force, to light and feed various types of electric charges. According to Caldeirão (2005), in order to meet the growing demand for electric energy, investments in all of its phases (generation, transmission, and distribution) are needed. Tolmasquim (2012) states that energy demands in Brazil should grow 5,3% a year for the next ten years. Energetic planning has the objective of promoting the rational consumption of various energetic forms and optimizing their supply within the present economic, social, and environmental politics in the country (Bajay, 1989).

In order to control the electric energy consumption it is necessary to measure its consumption. To do so, a specific equipment that can measure it must exist. This equipment is the electric energy meter. For Paulino (2006), the values obtained through this equipment must be the most exact possible, as the economic interests of energy generators and distributors as well as consumers are involved and must be respected. With the goal of keeping meters within established parameters they must be calibrated according to the specific norm for Energy Meters (NBR 14519). To be calibrated the meter must be adjusted to measure electric energy consumption within the admissible margin of error. This norm specifies that the margin of error of an electronic meter cannot exceed 2,5% compared to the actual amount consumed.

Melo (2006) states that the electric energy measurement used, in practical terms, in order to allow the distributing entity the appropriate revenues for electric energy consumption of each consumer according to the previously established fare.

In recent decades a significant increase in new types of technologies being applied to electric energy meters in industrial, commercial and domestic units has been observed. The current energy measurement technology guarantees

better precision while offering detailed consumption information. Similarly, the energy distribution system can be better dimensioned and the energy consumer can therefore have an increased quality of energy output with less variation and supply interruption. Paula (2013) has shown that amongst the main advantages of an electronic meter are the automation of the acquisition process, data processing for billing purposes and accuracy gains. During the measurement process eventual failures can occur in a meter's serial communication door or computer locks. These occurrences prevent the electronic meter from reading leading to data loss and other important influences like decreased measurement reliability.

Accordingly, this paper aims to develop a model, based in neural networks, to estimate the reading of energy electronic meters, minimizing the effect of meter failure during the operations of the Arapiraca Garden Shopping energy system. This mall is located in the city of Arapiraca – Alagoas and consists of 194 stores. The development of a model, besides enabling data processing, control, automation and optimization of the project, will guarantee an alternative way of charging consumers. In Section 2, the current data measurement method is explained along with the technology utilized. Section 3, the results the phenomenological formulations are compared to an Artificial neural Network (ANN) model developed. A database that included the consumption record of 51 stores was used to train the ANN. Section 4 concludes by demonstrating the relevance of the paper in regards to energy measurement in commercial establishments.

2. MATERIALS OR METHODS

Data collection was held in each store for the first five months of operation of the mall. The collection followed a basic procedure that included the following steps: the energy meter for each store was located, the access to the meter was guaranteed in order to measure the current, the current was measured through the use of a clamp meter.



Figure 1. Electrical current measurement using the Clamp meter.

The technical procedure for the measurement of the properties of the electric current consisted of visiting the selected store, ensuring that all the existing electric charges are operating such as, air conditioning, window display lighting, television and sound equipment, in other words, all the equipment usually used throughout a regular day of operations. Consequently, it can be guaranteed that the nominal electric current properties that feed the store were measured. A clamp meter was used to measure the current. This device is turned on and adjusted to the appropriate scale. The clamp meter is placed on the cable of one of the electric phases that feeds the store and the measurement of the instantaneous properties of the electric current cursing through this cable is completed.

Most stores are fed through a three-phase network. Therefore it is necessary to complete the measurement of the properties of the current in all three phases. In order to calculate the consumption, it is necessary to verify the amount of days and hours that each store was open during each month observed. The mall functions Monday through Saturday, 12 hours a day. On Sunday most store are open for 6 hours with the exception of a few larger stores and restaurants. Consequently, the average daily hours of operation for a small scale store is approximately 11 hours with that being the value used for consumption calculations. According to Creder (2007), it is possible to calculate the electric energy consumption for each store by applying Equation 1.

$$\text{Calculated} = \frac{v * i_m * fp * \sqrt{3} * d * h}{1000} \quad (1)$$

where,

$$i_m = \frac{i_1 + i_2 + i_3}{3} \quad (2)$$

Where v is the three-phase electric tension measured in Volts, and i_m is the arithmetic average of the three currents measured (i_1 , i_2 e i_3) in Amperes, as shown in Equation 2. The mall has a capacitor bank installed that maintains a default power (f_p) of 0,92. d is the amount of day the store used energy in the given month, and h is the average amount of hours the store operates a day.

By applying the data in Equation 1, the consumption in kWh is obtained for each store of the defined sample. The calculated value (Equation 1) can then be compared to the value obtained by the meter. Two cases are exemplified in table 1 (Store – 109 and Store – 110), where there is a large discrepancy between the average consumption calculated and the amount calculated using Equation 1. Store – 119, however represents a typical case where the two amounts are very similar.

Table 1 – Energy Measurement Comparison Shopping 03 stores for the month February 2014.

STORE	Energy Consumption					kWh (Meter)		
	I_1	I_2	I_3	Days	kWh(currents)	Previous	Present	Measured
Store - 109	2,9	1,7	2,1	29	431	2235	2853	618
Store - 110	4,9	5,1	4,3	29	920	139	142	3
Store - 119	4	5,1	5,1	29	913	4193	5142	949

This table shows how the energy distribution spreadsheet should be completed by the mall's store owners. The measurement of the properties of the electric currents is conferred every month. The column referring to the amount of day is also updated, as it is not always possible to maintain constant measurement intervals. When comparing the measurements for all three stores on Table 1 an error in measurement interval can be found in the measurements for Store – 110's meter. The calculated consumption (Equation 1) for the month estimates a value of 920 kW, which coupled with the regular hours of operation for the months would make the consumption of 3 kWh measured by the energy meter impossible. Consequently, the mall's sector of operations investigates the consumption of each store and generates the monthly energy invoice.

The discrepancy (Dp) has been defined as the relative difference between the calculated value and the amount measured by the meter. Equation 3 calculates, in percentage value, the relative discrepancy between the two ways of charging the store, where (*Calculated*) is the energy amount (kWh) obtained by the calculation of the consumption per current (Equation 1) and (*Measured*) is the measurement obtained by the meter.

$$Dp = \frac{(Measured - Calculated) * 100}{Measured} \quad (3)$$

The discrepancy is used to make the decision about which amount better represents a store's energy consumption every month. The sector of operations adopted a perceptual discrepancy value of 10%, as the limit for the acceptance of the amount received by the meter. When the discrepancy is smaller than 10% it is recommended that the amount calculated per current be discarded (Equation 1) and the consumption measurement received by the meter (*Measured*) be accepted. However, when Dp is higher than 10%, the recommendation is for the use of the energy consumption amount calculated by the current (Equation 1) to generate the client's billing. In this case it is also recommended that a new electrical current measurement is conducted to confirm the previous reading. The new measurement of the properties of the electric current may indicate a meter defect, a change in electric consumption charge inside the store, or another factor that has not been identified by the inspection and operation sectors of the mall.

The objective of this paper, according to the presenting problem, is to add another way to estimate the consumption of store owners. The proposal is the development of a model based on an Artificial neural network (ANN) that represents the energy consumption. The ANN will have the electric currents measure at each feeding phase of a given store as its entries. The network output will be the estimated monthly consumption of the store. The amount will be registered in a new column of the distribution spreadsheet (Table 1), and will contribute to the choice of the best option for consumer billing generation.

3. MODELLING AND ANALYSIS

The software Matlab® was utilized to process the data. The artificial neural network is one of the tools offered by the software. It was chosen to build the model that represents the energy consumption. The consumption model was

developed from the data set where the input was established as the three-phase electrical currents that feed any given mall store. The data was applied to the model, considering the measurements of the five months studied (November 2013 to March 2014), one input for each month. The model output is the estimated monthly consumption for the store, in kWh.

The Artificial Neural Networks are trained in relation to the data set until they learn the patterns presented (Ata, 2015). Once the network has been trained new data can be included in the input for the output estimation. The neural network is a great alternative for the complex phenomenological problems representing real situations. According to Ganesan et al. (2015) the artificial neural network models are more precise and efficient to deal a non-linear data relationship.

The data was organized according to 51 stores from a total of 194 mall stores. The choice of stores included in the sample was made due to data availability. The mall opened in September 2013 and in the first operational months few stores were open. After the data was organized 225 patterns (patterns of inputs and outputs) were obtained, as five measurement data sets were made available for each of the 51 stores. Table 2 shows how the data was organized. Each column represents a pattern, composed of three entries and one output. From the data set organized according to table 2, two matrices were extracted for network training. Matrix P (input) is comprised of the current data, and matrix T (output) is comprised of the consumption data.

To build the output data matrix T, the energy consumption amount was established according to the following algorithm:

- 1) For a Discrepancy (Equation 3) lower than 10%: the meter (Measured) amount is adopted;
- 2) For a Discrepancy (Equation 3) higher than 10%: the energy consumption amount calculated by the current (Equation 1) is adopted.

Table 2 – Part of the matrices P and T, with the data of 51 stores power measurements.

		STORE - 01					STORE - 02				
		nov/ 13	dez/13	jan/14	feb/14	mar/14	nov/13	dez/13	jan/14	feb/14	mar/14
Input 1	i1 (Amperes)	4,3	4,2	4,4	4,8	4,3	4,1	3,9	4,1	4,3	4,2
Input 2	i2 (Amperes)	3,3	3,5	3,4	3,1	3,4	5,7	5,6	5,6	5,8	5,6
Input 3	i3 (Amperes)	3,6	3,8	3,7	3,2	3,2	4,4	4,3	4,5	4,6	4,7
Output	Consumption (kWh)	769	812	769	781	689	1142	957	1056	1202	1018

The developed model is an empirical MISO (Multiple Input, Single Output) model. During the training of the model the 255 patterns corresponding to the months between November 2013 and March 2014 were applied. The Matlab® software was utilized to develop the model. The network topology definition is a result of the application of the Dynamic Division Method (DDM) proposed by Mendes, et. al., (2015). The model obtained through the artificial neural networks feedforward is composed by two layers with 17 neurons in its hidden layer. Figure 2 shows the choice of the number of neurons.

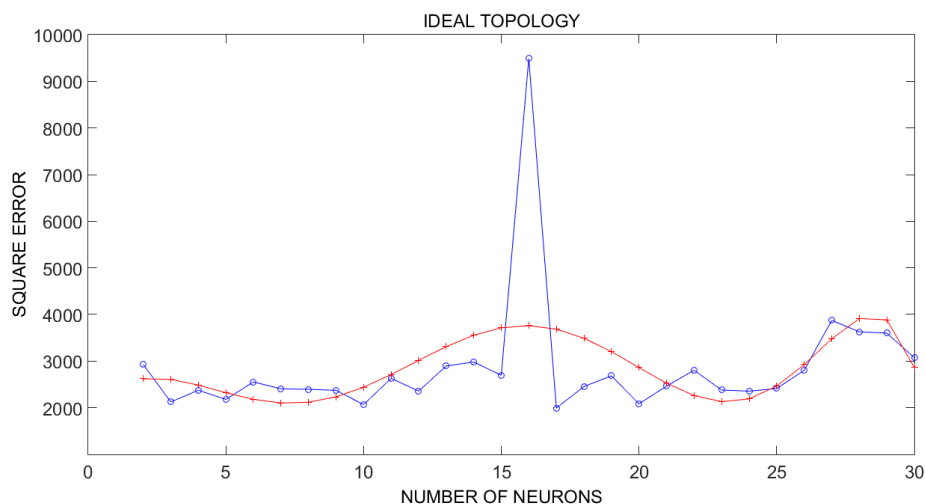


Figure 2 – graph that defines the choice of the number of neurons.

The input data was normalized seeking to optimize the learning process of the neural network. According to Mendes, et. al., (2015) the main reason to normalize is the discrepancy between the input values. The function of the activation chosen for the hidden layer training was its log sigmoid function. The application of the elevated input values to the neural network training can saturate the activation function and harm the neural network's convergence. The algorithm convergence can be difficult without the data optimization completion.

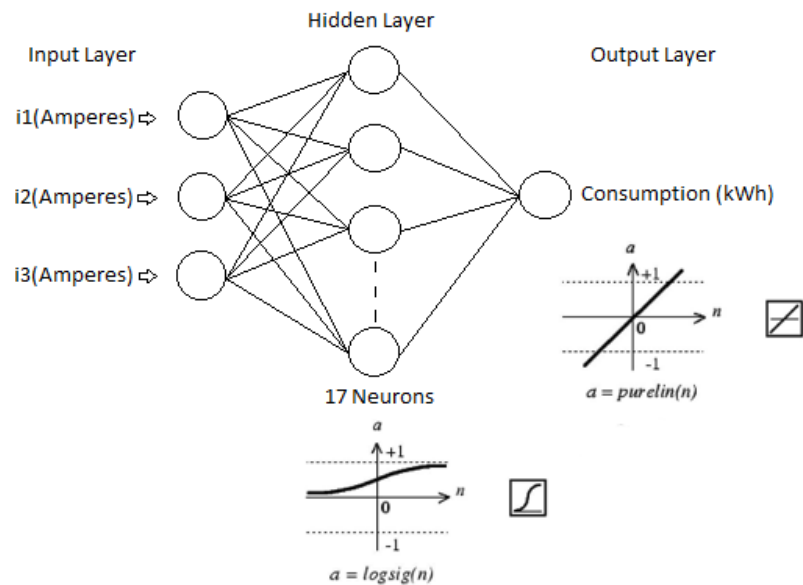


Figure 3 –Backpropagation network architecture.

The learning method used was backpropagation. For the output layer, a linear function was applied to the training. According to Felipe Rodriguez, et. al., (2014) the backpropagation learning algorithm is usually applied to multiple network neural layers, with a descending gradient method. The output layer is then analyzed for the contribution of each neural, in order to minimize errors between the desired output and the output provided by the artificial neural network. This way the neurons and their weight can be readjusted during the network training to minimize errors in the following iteration. The proposed architecture is shown schematically in Fig. 3.

After the neural network training, knowing the inputs, the current amounts of a given store fed by a three-phase network, the model is applied to simulate the output amount, giving the estimated monthly energy consumption (kWh) for the store. Figure 4 shows the developed model corresponded to the expectations, with output amounts very close to the real measurements given by the meter.

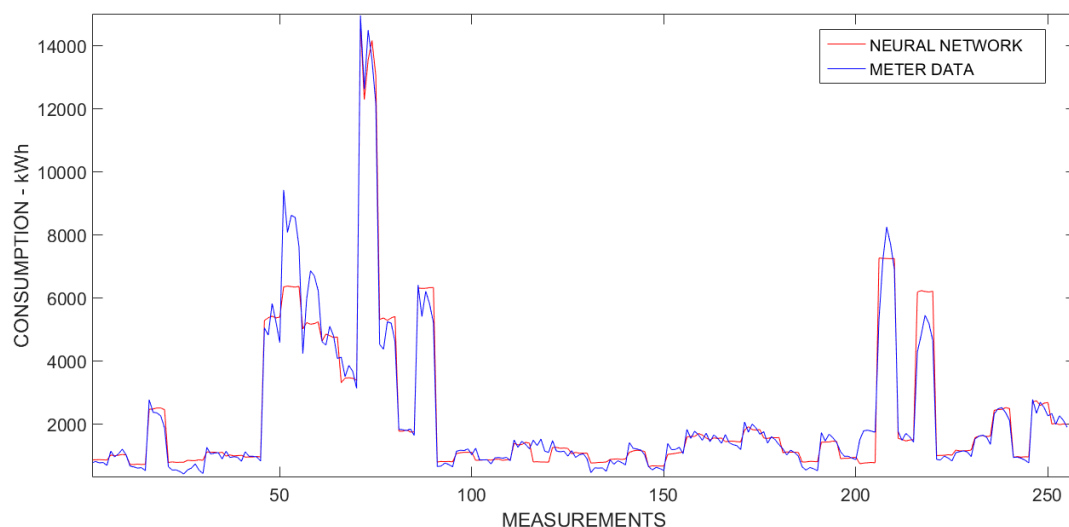


Figure 4 – Plots of energy consumption measured by the meter compared to the output obtained by the neural network model relating to a sample 51 stores.

The next step after obtaining the model is the validation, by applying the data from other stores that did not participate in the initial neural network training.

4. RESULTS AND DISCUSSION

After applying the input data to the model (ANN), it is verified that all the initial 51 sample stores reached the D_p values (Equation 3) inferior to 10%. The performance of the proposed model can be considered great, since it provides a solution to the cases where the veracity of the consumption amount obtained by the energy meter (*Measured*) was contested.

Table 3 shows the relative discrepancy percentage values (Equation 3). The model was validated with a new data set (Table 3) comprised of 20 stores that were not a part of the initial sample provided for the network training. The validation test shows that 55% of store benefited from the chosen form of monthly energy consumption billing. These stores paid less for energy this month. After the application of the ANN, the discrepancy amount (Equation 3) was inferior to 10% allowing for the adoption of the electronic energy meter measurement.

Table 3 represents the amounts that were not billed to some stores. By adding them it has concluded that the mall failed to bill 4.945 kWh for this sample of 20 stores for the month of February.

Table 3 – Analysis of discrepancy value for choosing the adopted column

Number of Store	MONTH: FEBRUARY / 2014							
	Consumption Calculation	Consumption Model	Consumption Monthly	Discrepancy Equation 3	Discrepancy ANN	ADOPTED COLUMN	ANN	Difference
	Equation 1	ANN	METER	Meter	Meter	Charging	Indication	ANN - Charging
Store - 122	1.073	1.089	1.091	2%	0%	1.091	1.091	-
Store - 132	915	998	949	4%	-5%	949	949	-
Store - 133	840	972	957	12%	-2%	840	957	117
Store - 135	4.386	5.365	5.243	16%	-2%	4.386	5.243	857
Store - 139	3.666	4.745	4.797	24%	1%	3.666	4.797	1.131
Store - 141	3.087	3.450	3.669	16%	6%	3.087	3.669	582
Store - 145	4.052	5.366	5.200	22%	-3%	4.052	5.200	1.148
Store - 151	1.743	1.746	1.845	6%	5%	1.845	1.845	-
Store - 190	1.055	1.103	1.214	13%	9%	1.055	1.214	159
Store - 197	605	867	866	30%	0%	605	866	261
Store - 198	772	864	944	18%	8%	772	944	172
Store - 216	1.254	1.239	1.140	-10%	-9%	1.140	1.140	-
Store - 221	933	1.075	1.058	12%	-2%	933	1.058	125
Store - 236	926	1.156	1.173	21%	1%	926	1.173	247
Store - 243	1.653	1.699	1.659	0%	-2%	1.659	1.659	-
Store - 245	1.543	1.542	1.549	0%	0%	1.549	1.549	-
Store - 266	1.093	1.106	1.097	0%	-1%	1.097	1.097	-
Store - 005	772	932	918	16%	-2%	772	918	146
Store - 129	1.042	1.155	1.117	7%	-3%	1.117	1.117	-
Store - 162	1.556	1.603	1.588	2%	-1%	1.588	1.588	-
TOTAL						33.129	38.074	4.945

5. CONCLUSION

In the current paper, the data set from 51 consumers, store owners, and one shopping mall in Alagoas was utilized to analyze the monthly consumption of electric energy. The data set allowed for a detailed analysis with precision and representation.

After the mathematical manipulation of the data collected two forms of monthly energy consumption for a store were presented. The first is the phenomenological mathematical model, which calculates consumption through the measurement of the three-phase electric currents that feed the store, using the average consumption time, in hours, of the determined establishment. The second is the application of a developed model of a artificial neural network.

Consequently, the proposed model of a neural network obtained an improvement for the measurement system in comparison to the consumption calculation method in Equation 1.

This measure aimed at reducing the margin of error on the consumption calculation in case of meter failure. The electric energy provider, in this case the mall, has great interest in the perfect and correct performance of the equipment as one of the company's economical bases lie on it.

Keeping in mind that an increased efficiency in reading process automation and data control was obtained, and motivated by the new model presented, the evaluation and study of the new concept's applicability became very important, as well as the verification of the difficulties that could be encountered in creation and implementation. Consequently, there was a reduction in litigation between consumers and providers, given that the margin of error was inferior to 10%, a margin assumed by the company. This determined the success of the model proposed by this paper.

6. ACKNOWLEDGEMENTS

To all the teaching body at PEI-UFBA, for all the new knowledge and teaching in the field.

7. REFERENCES

- Ata, R. 2015. "Artificial neural applications in wind energy systems: a review." *Renewable and Sustainable Energy Reviews*. Vol. 49, p. 534-562.
- Bajay, S.V., 1989. "Planejamento Energético: Necessidade, objetivo e metodologia." *Revista Brasileira de Energia*, Vol. 1, p. 1-6.
- Caldeirão, L.C., 2005. "Avaliação Experimental de Medidores Watt-Hora Operando em Condições Não Senoidais". São Paulo, Brasil.
- Creder, H., 2007. "Instalações Elétricas". Editora LTC, 15ª Edição. Rio de Janeiro, Brasil.
- Ganesan, P., Rajakarunakaran, S., Thirugnanasambandam, M. and Devaraj, D. 2015. "Artificial neural network model to predict the diesel generator performance and exhaust emissions." *Energy*, Vol. 83, p. 115-124.
- Melo, W.G., 2006. *Estudo e Aplicação da Norma IEEE 1459-2000 para Medidores Digitais de Energia*. Dissertação de Mestrado, Pontifícia Universidade Católica do Rio Grande do Sul, Rio Grande do Sul, Brasil.
- Mendes, C.; Magalhães, R. S.; Esquerre, K. and Queiroz, L. M., 2015. "Artificial Neural Network Modeling for Predicting Organic Matter in a Full-Scale Up-Flow Anaerobic Sludge Blanket (UASB) Reactor". *Environmental Modeling & Assessment*, p.1-11.
- NBR 14519, 2011. "Medidores Eletrônicos de Energia Elétrica (estáticos) – Especificação". 22 Mai. 2015 <<http://pt.scribd.com>>
- Paula, G.J., 2013. *Medidor de Demanda de Energia Elétrica Residencial com Acesso Remoto*. Trabalho de Conclusão de Curso, Centro Universitário de Brasília, Distrito Federal, Brasil.
- Paulino, C.A., 2006. *Estudo de Tecnologias Aplicáveis a Automação da Medição de Energia Elétrica Residencial visando a Minimização de Perdas*. Dissertação de Mestrado, Universidade de São Paulo, Escola Politécnica, São Paulo, Brasil.
- Rodrigues, F., Carreira, C. and Calado, J.M.F., 2014. "The Daily and Hourly Energy Consumption and Load Forecasting Using Artificial Neural Network Method: A Case Study a Set of 93 Households in Portugal." *Energy Procedia*, Vol. 62, p. 220-229.
- Tolmasquim, M.T., 2012. "Perspectivas e planejamento do setor energético no Brasil" *Estudos Avançados*, Vol. 26, p. 249-260.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.