26th ABCM International Congress of Mechanical Engineering
November 22-26, 2021. Florianópolis, SC, Brazil

THE USE OF ARTIFICIAL NEURAL NETWORK FOR DETERMINATION OF THE LOAD AND ADJUSTMENT OF THE INTERNAL TEMPERATURE OF A HOUSEHOLD REFRIGERATOR

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Abstract. *The capacity control method most used today in domestic refrigerators is a thermostat that regulates when the compressor will turn on and off, maintaining the internal temperature within the desired values. However, this control method induces significant energy losses due to transients generated during the compressor start and stop. These losses became even more significant when the number of start/stop events increases due a to diverse range of factors. One of them being the adjustment of the internal temperature defined by the user, which has a directed influence on the number of on/off cycles. This parameter is modified many times without a well-defined criterion, increasing, even more, the energetic losses of the refrigerator. This adjustment could be done via an algorithm, considering the product load and the ideal temperature for food perseveration, seeking to minimize the energy consumption, without the risk of harming the user's health. Therefore, this work aims to develop an Artificial Neural Network (ANN) to estimate the product load in the refrigerator and utilize this information to define the adjustment of the internal temperature of operation, contributing to reduce the number of on/off cycles of the equipment. Experimental tests were carried out to characterize the functioning of the refrigerator with different product loads and ambient temperatures. The neural network will use regression techniques and various parameters were autonomously tested using a tuning algorithm, to ensure that the best result can be achieved. As a result, this algorithm was able to estimate the load within the refrigerator with a precision of ±0,88 kg.*

Keywords: *household refrigerator, energy consumption, artificial neural network, product load.*

1. INTRODUCTION

Home refrigerators have great participation in the energetic consumption at a residence, and this equipment is present in most homes. In a work developed by Dupont *et. al*. (2019), it was revealed that about 20% of energy created worldwide is consumed by machines like air conditioners, heaters and refrigerators.
In the United States, it is calculated that during 2016-2026, this sector will increase at a rate of 15%, not just electrical demand, but a prediction concluded that refrigeration could double by 2050. Nevertheless, according to the paper elaborated by Fedrigo *et al.* (2009), in Brazil, home refrigerators can be responsible for up to 45% of the home energy consumed during the summer, this way, it is evident that home refrigerators have a big part within domestic energy consumption; therefore, any kind of improvement in the energy efficiency of these systems would imply great global savings.

Various studies were already made in order to analyze the factors that interfere the most in energetic consumption of home refrigerators. Amaral *et al*. (2013) confirmed that energetic efficiency is directly proportional to the amount of time that the refrigerator is left on in each cycle, and inversely proportional to quantity of turning on and off events. Coulter and Bullard (1997) related the energetic loss principally to a migration of refrigerator fluid during the time that the compressor stayed turned-off. Saidur *et al.* (2002) quantified the effect of the environmental temperature, the opening of doors and how the thermostat remained during the functioning of the system.

Murta *et al. (2015)* examined the position of the thermostat and it´s impact of the thermic weight consumed. Saffar and Maia (2016) introduced a substitution of the thermostat by a microcontroller, for improving the amplitude of the temperature of every cycle. Koporec and Perš (2019) used deep learning to generate a data group of representing figures where the identity of an object, its location, and the level of occupation of the refrigerator are all ready and accessible. Foreseeing this problem, a variety of other authors proposed working with neural networks aiming to find a solution for it. Choi *et al.* (1998), for example used Fuzzy Logic and neural networks to control the refrigerating system, arriving at the results of lower final energy consumption, when compared to the conventional system of turning on and turning off. Saidur *et al.* (2006) changed up the parameters that influenced the final consumption of the house refrigerator, such as the environmental temperature, and utilized the collected data to investigate its energetic performance through neural networks, reaching the conclusion that due to the learning capacity of neural networks, it becomes an alternative to evaluate the refrigerators energetic performance. Erstwhile, Aprea *et al. (*2017) utilized neural networks to optimize the energetic consumption of a RPMMR (Rotary Permanent Magnet Magnetic Refrigerator) and had the conclusion that receiving from the start the internal and external conditions, it can predict the energetic performance of a RPMMR.

One of the factors that impacted the energetic consumption and the preservation of the food in storage is the adjustment configured by the user of the internal temperature of the refrigerator. In a recent study developed by James *et al.* (2017) analyzed the attitudes of many people around the world that owned domestic refrigerators. It was observed that most of them didn´t know the correct temperature at which the equipment should function. In Sweden, for example, 85% of those interviewed knew the correct temperature that the equipment should function but only 60% of the machines analyzed were with temperatures lower than the recommended level.

By consequence, it was clear that most of the thermostats are adjusted at an inadequate form, which compromised the food conservation quality, and also increased the number of cycles of the machine, intensifying the energy consumption of these equipment. The correct adjustment of the thermostat is important not only to keep the correct temperature, but also having an important impact in the energy consumption of the refrigerator. This setup has not been explored as one of the ways to improve energy efficiency of the system.

In this study, we pretend to develop an artificial neural network to identify the load of food contained in a home refrigerator and use this information as a parameter to define the best internal temperature for this machine.

2. METHODOLOGY

The refrigerator used to develop this paper is a household refrigerator of one door, model CRC28EBANA, from the manufacturer Consul, and capacity of 280 liters (Altoé *et al.*, 2021 and Monteiro *et al.*, 2021). The tests presented in this paper had as base ISO 8187 and 7371, which define the tests procedures and conditions for the evaluation of diverse features from domestic refrigerators. The equipment was installed in an environment with controlled temperature measuring from 1.5m per 2m. The temperature was measured by three sensors positioned 1 m from the floor and 50 cm from the sides and the door of the refrigerator, as determined by the ISO 8187.

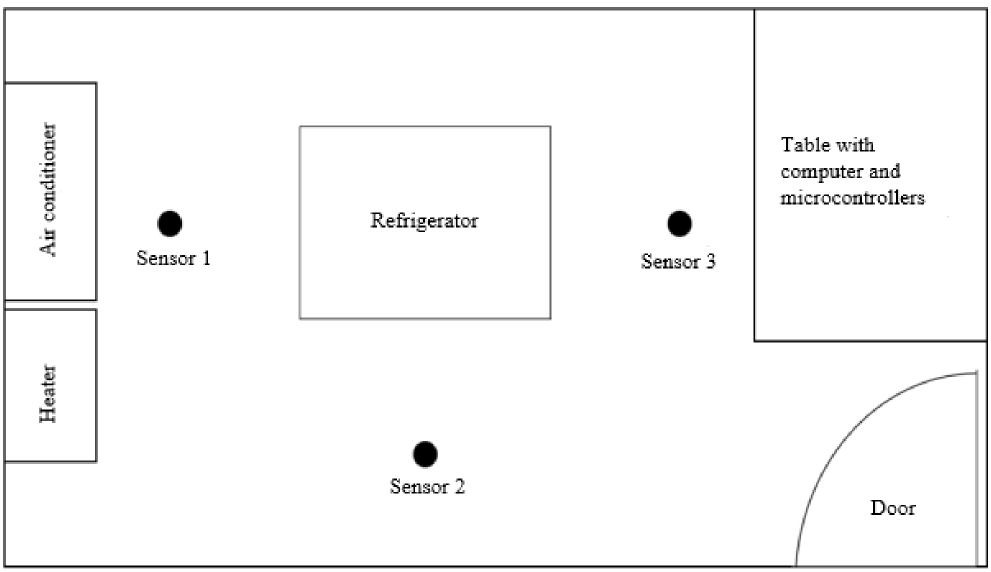

Figure 1. Complete configuration of the controlled room

For a load of products, it was used TetraPak Milk boxes filled with 1000ml of mixture of water and chlorine (2%). The volume of each box was evaluated using a volumetric balloon of 1000±0,4ml. The chorine was added in each recipient to avoid the proliferation of microorganisms.

In order to acquire the database destined to the artificial neural network, the refrigerator thermostat was changed to a Turn on/off controller using a microcontroller ATmega328, which was responsible for triggering a relay that started and stopped the compressor. The microcontroller received the temperature data from an encapsuled sensor DS18B20, positioned in the interior of the freezer compartment. This was necessary due to the temperature limits determined by the thermostat did not remain the same during the tests. (França, 2015). The maximum and minimum temperatures of the operation were kept the same during all the tests, being from -5°C and -16°C respectively, because this range provides an adequate temperature in the other parts of the refrigerator.

The room temperature and the load in the refrigerator were varied, in order to comprehend the system behavior in various operational conditions. As the ISO 8187 establishes, the temperature for consumption tests should be 32±0,5ºC. Other room temperatures adopted were 27ºC, 20ºC and 16,5ºC. For the load of products, the number of boxes was changed from 0, 10, 20 and 30, totalizing 16 tests of data collection, for assuring that the refrigerator was in permanent regime, and each test was at least 48 hours long.

For the database destined to improve the thermostat position, it was kept the refrigerator control through the original thermostat, where the positions Minimum, Medium and Maximum were tested. According to ISO 7371, the room temperature was kept in 32±0,5ºC, for this database the load of 0, 20 and 50 boxes was used. In total, it was measured 12 temperatures inside the refrigerator through type T thermocouples, connected to an acquisition system from National Instruments, model N9211 and NI Cdaq-9178. It is possible to observe some of the data collected and its positions using the Figure 2.

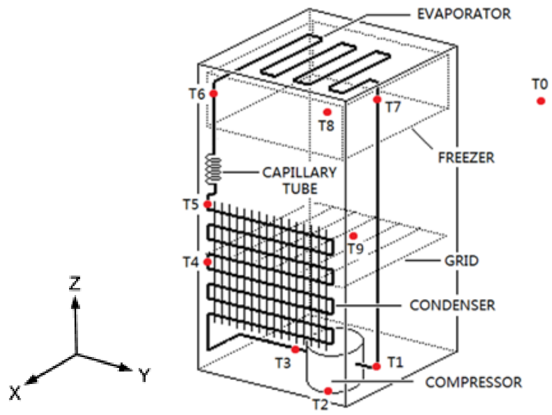

Figure 2. Experimental apparatus showing the position of some thermocouples attached. (Source: Rocha Junior et. al, 2017)

It was chosen five parameters, being the temperatures of the freezer, the condenser, the evaporator, the reason between the time where the compressor was kept on and off and the load contained in the refrigerator. Table 1 shows the amount of data used. The total set of points has approximately 1.28 million vectors, each with 5 values.

Table 1. Example of the database.

T_freezer (ºC)	T_condenser (ºC)	T_evaporator (ºC)	t_rm	Load
-7,72	42,08	-14,54	0,48	30
-13,27	41,98	-19,74	0,39	0
-10,83	37,66	-8,65	0,61	10

The condensing and evaporating temperatures were chosen to figure among the ANN input data because they are quantities that characterize important points in the thermodynamic cycle of the equipment. Besides, the condensing and the evaporating temperatures have a strong relation with the environment and the refrigerator's interior temperature, respectively. França (2015) identified that one of the best parameters in the characterization of the load is the reason between the time the compressor stays on (t_on) and the time the compressor stays off (t_off); therefore, t_rm was chose as a parameter. It was calculated from the average of t_r of each cycle for each test, the values of t_on and t_off were calculated through the measurement of the time interval between the moment where the compressor turns on and off, as illustrated in Figure 3.

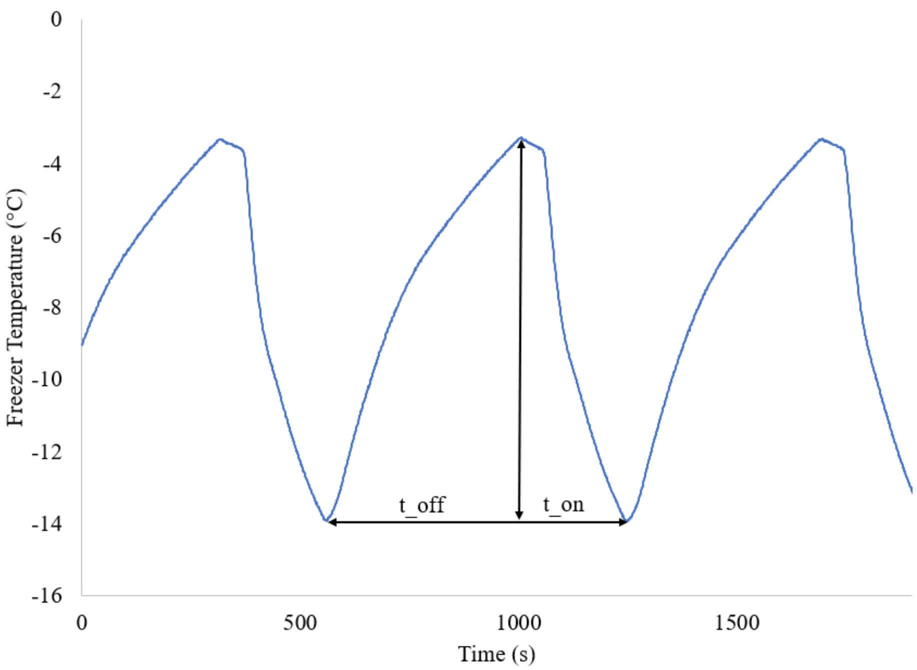

Figure 3. Typical operation of a domestic refrigerator in permanent regime in collected parameters (Source: Altoé et. Al, 2021)

To determine the ideal position of the thermostat, it was measured the temperature T1, T2 and T3, as shown in the Figure 4 and as stablished by ISO 7371. Besides, the active potency was measured through an electric potency measurer from Kron Multi-K Plus, so that a consumption calculus could be done.

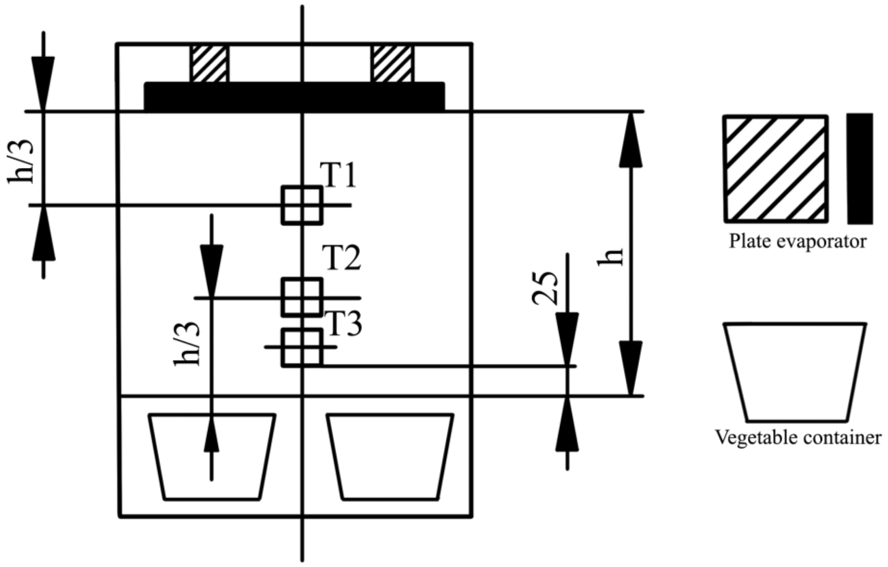

Figure 4. Arrangement of sensors in the refrigerator (Source: ISO 7371)

2.1 Artifical neural network

The ANN is a mathematic model inspired in a biological nervous system, even in its structure than in its functionality. The main features of this model are the learning adaptation, generalization, parallelism, robustness and abstraction (Lújan *et al.*, 2017). This model consists of three main layers, which are input, hidden and output layers. The input layer receives the independent variables that are sent to the ANN, and processed by the hidden layers. The neurons from the input layer ($\mathbf{z_i}$) are connected to the hidden layers ones through weight ($\mathbf{w_{ji}}$). Then, each input from the ANN is multiplied by the weights and these values are summed with the neuron's bias ($\mathbf{b_j}$), forming the following Equation (1):

$$\mathbf{S_j} = \Sigma_{i=1}^{p} (\mathbf{w_{ji}}\, \mathbf{z_i}) + \mathbf{b_j}, \quad (1)$$

where $\boldsymbol{p}$ is the number of elements from the input vector, and the sum $\mathbf{Sj}$ is the input from the hidden layer. One activation function $\mathbf{f(Sj)}$ will generate an output of the neuron. This way, the hidden layer generates inputs of the output layer, which makes the sum of the weighted inputs ($\mathbf{w_{kj}}$) and the bias ($\mathbf{b_k}$) of each neuron pass through an activation function ($\mathbf{Y_k}$), which generates the final output.

$$\mathbf{Y_k} = \Sigma_{i=1}^{q} (\mathbf{w_{kj}}\, \mathbf{f(S_j)}) + \mathbf{b_k}, \quad (2)$$

where $\boldsymbol{q}$ is the number of elements from the hidden vector. Finally, it is important to say that the values from the weights and bias are initially defined randomly, and during a training function of loss will adjust these values. When the training finishes, the ANN will use these weights for decision making. Other important parameters for the training and functioning of the network are: the batch size (number of samples that will be propagate trough the network per iteration), number of epochs (one epoch equals to one cycle of training), optimizer (an algorithm used to change attributes of the ANN, such as weights and learning rate, possibly reducing the training time).

The neural network of this paper was written in Python, using two main libraries, Keras (Chollet *et al.* 2015) and scikit-learn (Pedregosa et al., 2011). The first one is mainly used for the construction and training of the network, whereas the second one was used for a tuning process of the ANN. The chosen type of the network was a regression network, which returns the expected load value; therefore, as an activation function of the output layer was chosen the Rectified Linear Unit (ReLU), which its functioning is possible to be observed in Figure 5, because the number of loads present in the refrigerator will always be higher than zero.

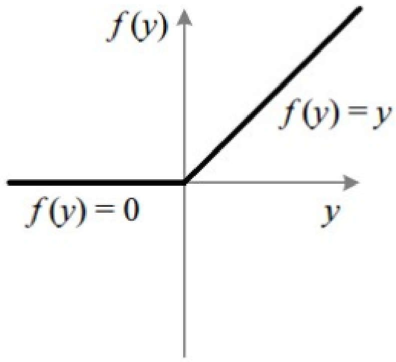

Figure 5. ReLU Function

It is worth mentioning that an ANN can be overtrained, causing a problem known as overfitting, where it will be incapable of producing results for problems that are not present in the training database (Garcia *et. al.*, 2017). Therefore, some measures were taken to avoid this issue, which the first one consisted in dividing the database for the training and for the test, with for a factor of 80% of the original database for the first and 20% for the second one. The second measure taken was utilizing a dropout function, that randomly sets inputs units to 0 with a frequency of 0.2 at each step during training time, which helps prevents overfitting (Chollet *et al.*, 2015). In the tuning process, a total of 30 parameters combinations were tested, as shown on Table 2:

Table 2. Tested parameters

Optimizer	Activation	Number of neurons
Adam	relu	64
Adamax	selu	32
	softmax	8
	sigmoid	
	elu	

For the tuning process, the database was split randomly in five fractions, 4/5 were used for training and 1/5 for the test, the test fraction being rotated five times, in order to test all the possibilities. The parameters that remained unchanged during the process were: the batch size of 35628, resulting in a 29 iteration per epoch, 2000 epochs and the loss function, which was the Mean Squared Error (**MSE**):

$$\mathbf{MSE} = \frac{1}{n} \Sigma_{i=1}^{n} = (\mathbf{y_{exp,i}} - \mathbf{y_{pred,i}})^2, \tag{3}$$

Where $\mathbf{y_{exp,i}}$ is the expected value, $\mathbf{y_{pred,i}}$ is the predicted value, and $\mathbf{n}$ is the number of data points. The number of epochs and the batch size were chosen having in sight the time of duration of the process, because both of them influenced directly the training time. Hence, it was taken the lowest time possible without compromising the precision. The end of test, the best average of precision was chosen, which was measured through the mean absolute error, the chosen combination can be observed on Table 3:

Table 3. Best parameters combination and best average precision

Activation	Batch size	Epochs	loss	neurons	optimizer	Mean Absolute Error
selu	35629	2000	Mean Squared Error	64	adamax	9.718798

The precision was measured by the average of the mean absolute error of all results. Besides, it was tested other two parameters for the network, the functions Early Stop (ES) and Reduce LROnPlateau (RLR), where the first finished the training of the network while the network did not have an improvement of the loss function, even after 500 epochs, and the second one reduced the Learning Rate by a 0.2 factor if the average of the mean absolute error from the training database were stagnated by 100 epochs. After the conduction of the tests, it was determined that with the usage of just a RLR, the best result was obtained. It is worth mentioning that the weights of the network were only saved when the precision of the test database was the smallest; Therefore, avoiding a possible overfitting. Lastly, the final ANN configuration is the one presented in Figure 6:

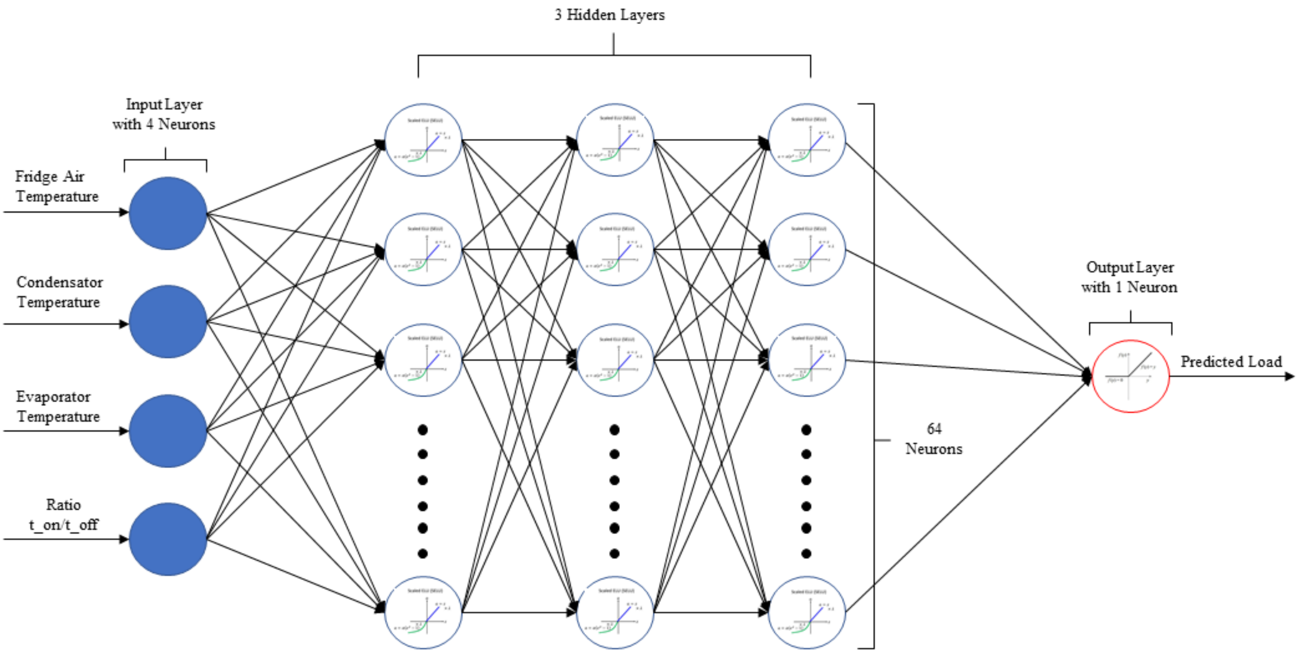

Figure 6. Final ANN configuration

With the activation function in the hidden layers being the Scaled Exponential Linear Unit (SeLU), the optimizer being the Adamax, a batch size of 35629 and a total of 20000 epochs for training, the mean training time was 16 hours, which was done in a Notebook Dell Inspiron 14, equipped with an Intel Core i7 – 8550U CPU, and 16 GB of RAM.

3. RESULTS

The neural network obtained the following results, where **loss** and **mean_absolute_error** values were taken from the training database and **val_loss** and **val_mean_absolute_error** from the test one.

Table 4. ANN Resultes

loss	mean_absolute_error	val_loss	val_mean_absolute_error
8.1606	1.7926	3.0004	0.87809

As we can see, the ANN obtained a **val_mean_absolute_error** lower than 1. In other words, it is failing at an average of ± 0,88 Kg per prediction. In Table 5, it is possible to observe some results from the test database.

Table 5. Fist 8 estimations made by the ANN

T_freezer (°C)	T_condenser (°C)	T_evaporator (°C)	t_rm	Load (kg)	Estimation (kg)
-12.82	27.15	-11.29	0.47	10	10.46
-3.46	36.14	-3.87	0.48	0	0
-12.33	48.79	-16.93	0,48	30	29.39
-9.28	30.18	-7.63	0.47	20	19.74
-5.76	16.70	-5.24	0.33	30	29.76
-4.76	27.11	-3.98	0.47	20	20.37
-10.10	18.81	-7.42	0,37	0	0
-5.09	21.60	-3.41	0.47	10	10.13

Thanks to the ReLU function, the results for 0 Kg load were at the most part very precise. It is possible to notice that the prediction for 30 Kg was also precise, therefore guaranteeing good results for the boundary values prognoses. The major mistakes were when the estimates occurred when t_rm values of near loads approached, for example 10 and 20 boxes, or 20 and 30 boxes, if also the temperature values also approached, the network ended up interpolating an average value. Despite that, these temperatures behaved in a cyclic form, therefore, as these mistakes were not so frequent, thus ensuring the accuracy was achieved. In Figure 7, it is possible to observe a graphic with the dispersion of all the estimates. As it is possible to see, the network has problems in the border value between loads, but had great results in a majority of the estimations.

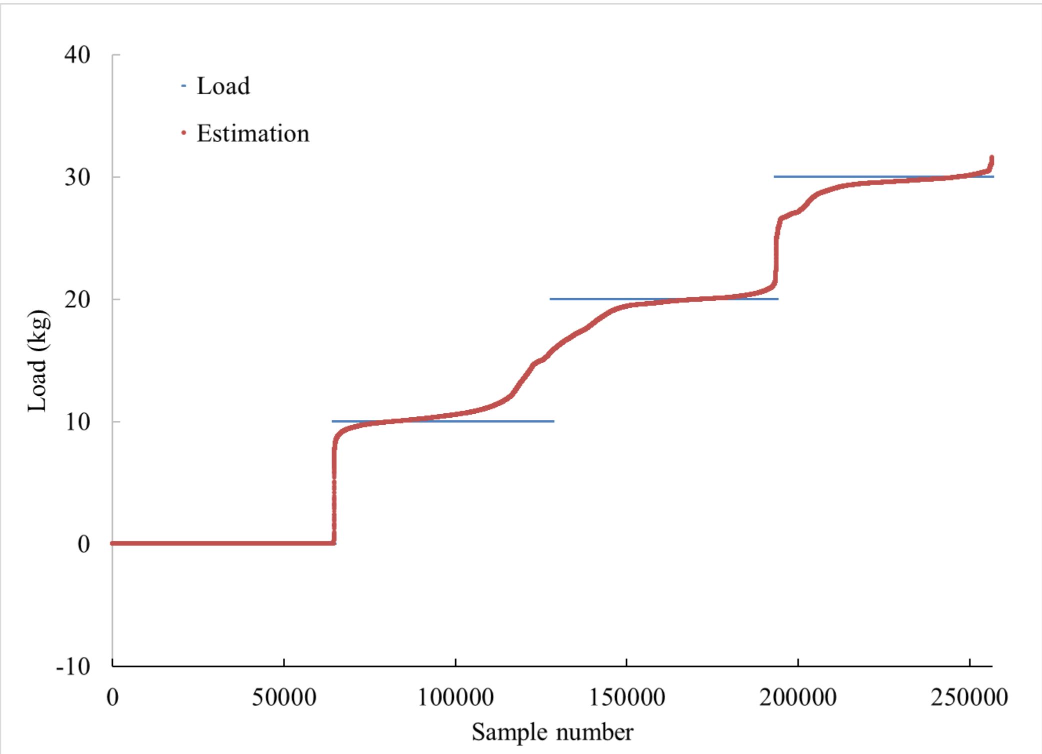

Figure 7. Estimates dispersion

There could be an improvement in the estimation of the border values if the number of epochs was to be increased, however there would be a risk of overfitting the ANN, so it is necessary to highlight that the network did not suffer overfitting because, as it is possible to observe on Figure 8, the Test database accuracy continues to drop along with the training database, and even though there is great fluctuation on the final steps of the training, only the best result was saved in the test database.

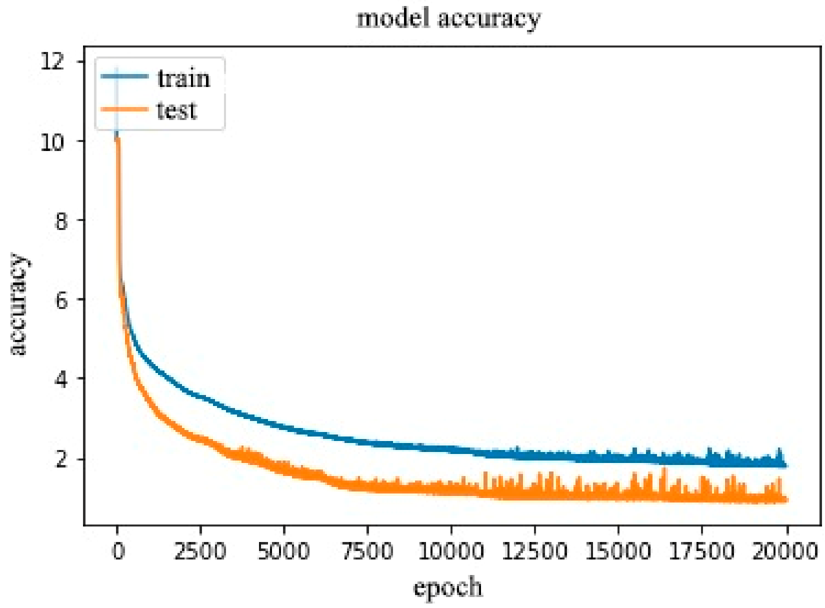

Figure 8. Model Accuracy

On Figure 9, it is exposed the relationship between consume, average temperature and the refrigerators load. It was observed that when the thermostat was at maximum position, the compressor kept constantly on, even though the fridge turned into permanent regime, causing an enormous pick on energy consume. Besides, the average temperatures inside the refrigerator were, at many times, below zero, freezing the water inside the boxes. Now, at a minimum position, the internal temperature kept itself during most part of the test above 5° C, which makes this position inappropriate for food conservation. In conclusion, it is evident that among the three tested positions, the medium position from the thermostat was the best, due to keeping the temperature between 0° and 5° C, as ISO 7371 stablishes, and also for having a similar energy consumption similar to the minimum position, as pointed out in the article from Monteiro et al. (2021).

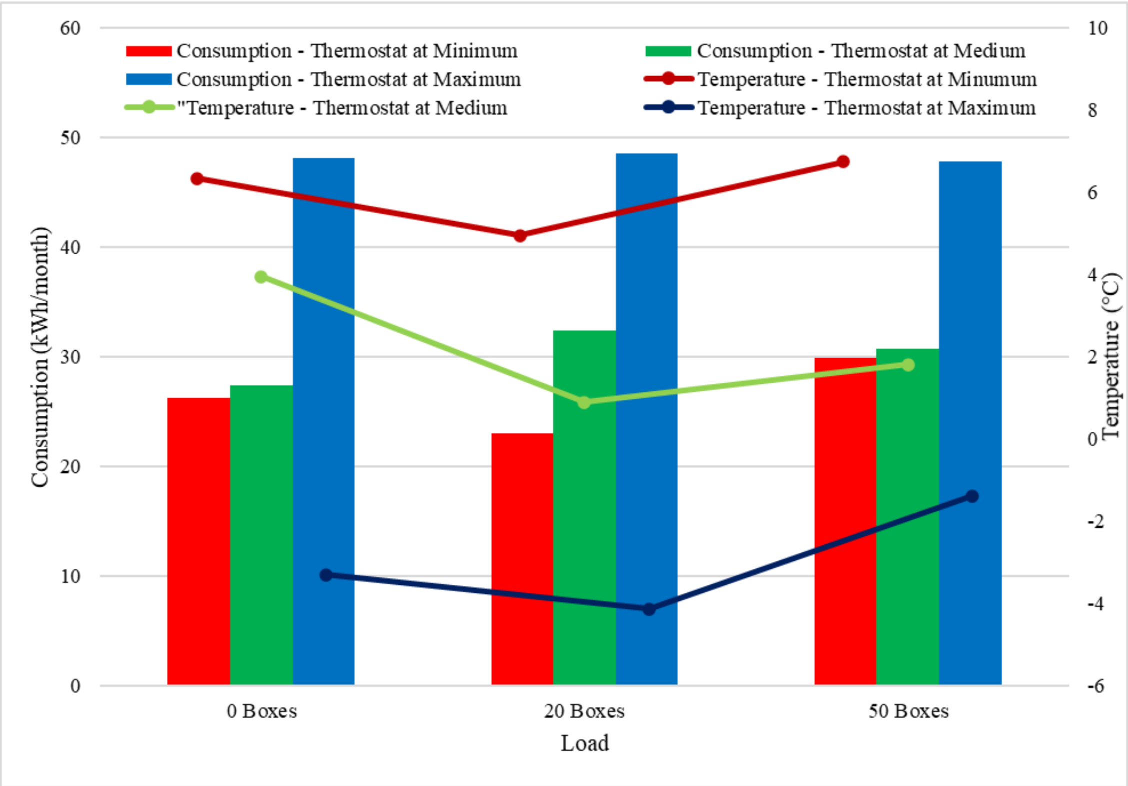

Figure 9. Consumption and Mean Temperature of the fridge vs. Load

It is important to highlight that even though the average temperatures in parts of the tests were within an ideal range, its temperatures varied outside of this range. As it is possible to observe on Table 6, all the maximum temperatures from the thermostat at minimum position were higher than 5° C. Likewise, only one minimum temperature was within this range. For the maximum setup of the thermostat, all its temperatures were below 0º C, which made the water from the boxes to freeze, also making this position inadequate, according to ISO 7371.

Table 6. Maximum and Minimum Temperatures

	Minimum Temperature (ºC)			**Maximum Temperature (ºC)**		
	0	20	50	0	20	50
Therm. Minimum	5,38	4,33	6,21	7,29	5,48	7,27
Therm. Medium	2,76	0,19	1,81	5,06	1,55	2,36
Therm. Maximum	-3,44	-4,19	-1,60	-3,04	-4,07	-1,15

4. CONCLUSION

It was possible to develop an artificial neural network capable of estimating the load contained in the fridge with an error of ± 0,88 kg, however, with the tests varying the load, it was not possible to verify a strategy that could be developed using ANNs as a method of control due to refrigerators behavior in different thermostats positions. Nonetheless, it was observed that in some of the tests, the refrigerator worked at higher or lower temperatures than the necessary stablished in norm. New tests will be developed exploring the ranges allowed by ISO 7371, in order to discover which range would be the most adequate for each load.

5. ACKNOWLEDGEMENTS

The authors thank the Research Support Foundation from the State of Minas Gerais (Fundação Amparo à Pesquisa do Estado de Minas Gerais - FAPEMIG), the Coordination for the Improvement of Higher Education Personnel (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior- CAPES) and the National Council for Scientific and Technological Development Research (Conselho Nacional de Desenvolvimento Científico e Tecnológico Pesquisa - CNPq) for the financial support.

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