

Use of Arduino for Monitoring the Air Quality of Indoor Environments

Uso do Arduino para Monitoramento da Qualidade do Ar em Ambientes Fechados

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Resumo

Neste trabalho, um protótipo foi desenvolvido para avaliar a qualidade do ar em ambientes internos usando um sistema Arduino. O sistema é baseado na medição do nível de luz, concentração de fumaça, temperatura e umidade do ar. Foi proposto um índice de conforto térmico (ICT), onde foi desenvolvida uma escala de 0 a 1 com base na média ponderada dos índices individuais. Outra abordagem, baseada em redes neurais artificiais, foi formulada na qual os parâmetros foram utilizados como argumentos de entrada da rede e o ICT foi usado como variável de saída. A resposta dos dois modelos foi comparada, onde foi possível observar que os valores de ICT calculados pela rede neural foram consideravelmente próximos dos valores obtidos pelo modelo determinístico, com erro médio quadrático de $1,73 \cdot 10^{-5}$.

Palavras-chave: Arduino. Aprendizado de Máquina. Controle de Processos.

Abstract

In this work, a prototype was developed to assess indoor air quality using an Arduino system. The system is based on the measurement of the light level, smoke concentration, temperature and air humidity. A thermal comfort index (TCI) was proposed, where a scale from 0 to 1 based on the weighted average of the individual indices was developed. Another approach, based on artificial neural networks, was formulated in which the parameters were used as input arguments of the network and the TCI was used as a target parameter. The response of the two models was compared, where it was possible to observe that the TCI values calculated by the network were considerably close to the values obtained by the deterministic model, with MSE of $1.73 \cdot 10^{-5}$.

Keywords: Arduino. Machine Learning. Process Control.

1. Introduction

It is known that hands-on use of actuators and sensors in chemical engineering curricula is typically reserved for students in process control projects. Such a postponement in inclusion of real-time data is due to the difficulties found in giving students access to microcontrollers and sensors. Arduino is broadly used by all kinds of makers worldwide. The main advantages are a large number of sensors and libraries available to implement an extensive amount of engineering applications (Barbon et al., 2016).

The use of Arduino for engineering education has increased in the last years. For example, (Omar, 2018) applied a strategy for teaching systems dynamics and control for engineering students based on Arduino usage. The approach allowed improving the learning of the main components and concepts of automatic control. Besides, it gave the students the ability to develop small control projects in serving the local community through the implementations of useful real-life systems. Yang et al. (2019) developed a portable device to measure the methane concentration of biogas samples. The MQ-4 sensor and humidity, temperature and pressure sensors were connected with an Arduino microcontroller for collecting measured data. According to the authors, the device produced an average error of 0.69 in relation to gas chromatograph measurements. C ezar et al. (2020) implemented a flow control system with Arduino for a saline recirculation system in absorption chillers. The proposed strategy allowed controlling flow and keeping optimal operating conditions. Karami; Mcmorrow; Wang (2018) built a portable measurement device for indoor environmental quality monitoring. The prototype was based on a set of sensors, e.g., humidity, CO₂, luminosity and temperature, which were connected into the Arduino controller. In the work of Sobota (2013) an Arduino board was used for interaction with the physical world via its inputs and outputs and the REX Control System (Balda; Schlegel, 2012) was used for the algorithms monitoring. Huba; Bist ak and Huba (2016) developed an Arduino based thermos-opto-mechanical laboratory plant to study different control tuning strategies using filter approaches. Docekal and Golembiovsky (2018) designed a low-cost laboratory plant for control system education based on an Arduino platform. Kal uz et al. (2014) also proposed remote laboratory for education in area of process control with the use of Arduino and Raspberry Pi.

One of the main strategies to stimulate the creativity and innovative capacity of undergraduate students is to encourage them to put into practice the theoretical knowledge learned in the classroom. In this regard, Arduino appears to be an appropriate tool to facilitate the design of prototypes applied to the dissemination of engineering education.

The Arduino is a microcontroller board consisting of digital input/output pins, analog inputs, USB connection, power input, and a reset button. The board is easy to handle and has an average price of \$ 20.00. It contains all the necessary components to support the microcontroller, directly connecting to a computer via the USB port or with a battery. One of the advantages of using these devices is that it has its programming language (based on C++ language), where it is possible to configure programming logic for monitoring and control computational routines. Besides, there are several sensors already developed for use with Arduino systems, so it is possible to collect information from external variables as input data to the computer, such as temperature, humidity, pressure, flow rate, level, luminosity, vibration, etc. (Arduino, 2020).

Some authors have developed Arduino prototypes for measuring the air quality. Angelvik (2016) developed a portable air quality Arduino Uno with sensor components that can register time and GPS coordinates, measure dust density, temperature and humidity, and store the recordings on an on-board memory card. Sung; Hsiao and Shih (2019) developed an indoor thermal comfort monitoring system through the Internet of Things (IoT) architecture. Some indoor environmental parameters, such as, temperature, humidity, indoor wind speed were analyzed and simulated on MATLAB® to obtain the impact on the thermal comfort indicators. Zhuo (2017) developed an Arduino device for monitoring the level of O₂, PM_{2.5}, CO₂, rain, temperature and humidity for measure the air quality.

The dissemination of the use of Arduino in the chemical engineering course at the Fluminense Federal University is still preliminary. However, as previously reviewed, the implementation of this type of technology facilitates the transfer of theoretical knowledge to laboratory practice. The objective of this work is to design a simple device to measure some properties of indoor environments, covering the phases of design, assembly, modeling and simulation with the use of Arduino microcontroller.

2. Methodology

2.1 Prototype description

One of the main causes of respiratory diseases caused recently is the quality of the air in closed environments. It is known that in closed refrigerated environments, evaporation of the water present is necessary. Consequently, there is a decrease in moisture content, which causes lesions in the nasal mucous membranes. This project aims to contribute to the monitoring and control of indoor air quality through the development of an automated system using Arduino to measure the following properties: (i) temperature, (ii) humidity, (iii) smoke and (iv) luminosity, as represented in Fig. 1:

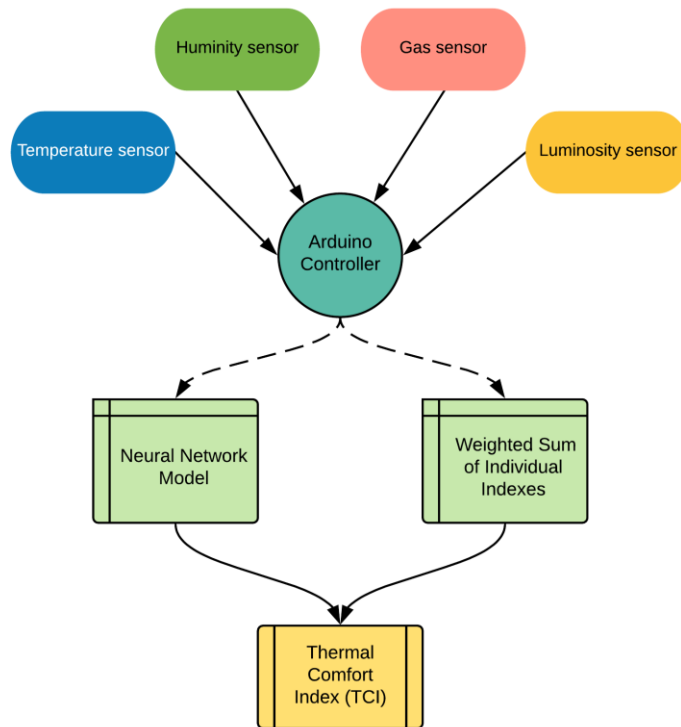


Figure 1 - Scheme of the Thermal Comfort Sensor)

According to Figure 1, the input parameters are measured by specific sensors and the data is sent to the Arduino device, where the Thermal Comfort Index (TCI) is calculated by two different models: (i) Neural Network Model and (ii) Weighted Sum Model. The list of instruments used for this project is summarized in Table 1.

Table 1 – List of instruments used for Project 1

Instrument	Quantity	Characteristics
Humidity sensor	1	Model: DHT22
Gas sensor	1	Model: MQ-2
Temperature sensor	1	Model: DHT22
Luminosity sensor	1	Model: LDR
Arduino UNO	1	
Protoboard	1	
Resistors	2	
Jumpers and wires		

The gas sensor, MQ2, is a Metal Oxide Semiconductor (MOS) type Gas Sensor in which the detection is based on the change of resistance of the sensing material when the gas comes in contact with the metal. Concentrations of gas can be detected with a voltage divider system. It can detect LPG, Smoke, Alcohol, Propane, Hydrogen, Methane and Carbon Monoxide concentrations from 200 to 10000ppm (Arduino, 2020).

The luminosity sensor is measured by the Light Dependent Resistor (LDR) device. It is an electronic component whose resistance varies depending on the luminosity that affects it. This component is sensitive to light and its purpose is to limit the flow of current in a circuit. The Arduino converts the analog voltage (from 0-5V) into a digital value in the range of (0-1023) (Arduino, 2020).

The DHT22 sensor measures the temperature from $-40\text{ }^{\circ}\text{C}$ to $80\text{ }^{\circ}\text{C}$ and the air humidity in the 0 to 100% range. The precision of the sensor for temperature measurement is approximately 0.5° Celsius and for humidity it is 2%. This sensor is made by a semiconductive material such as ceramics or polymers in order to provide larger changes in the resistance with just small changes in temperature. A thermistor is a variable resistor that changes its resistance with change of the temperature. The humidity component has two electrodes with moisture holding substrate between them. As the humidity changes, the resistance between these electrodes changes. This change in resistance is measured and processed by the internal circuit which makes it ready to be read by a microcontroller (Arduino, 2020). Fig. 2 illustrates the Arduino circuit of prototype.

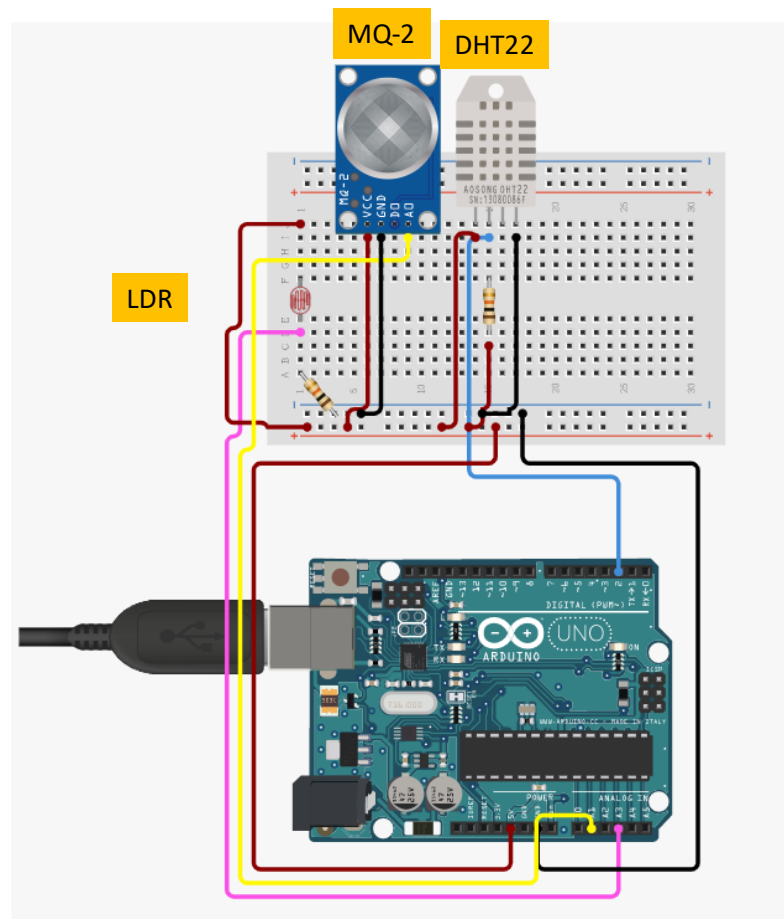


Figure 2 - Arduino circuit.

2.2 TCI model: weighted sum model

The following rules were adopted to normalize the scores for each individual index:

- (i) For luminosity and gas concentration, a linear relationship between the minimum and maximum values was considered.
- (ii) For humidity and temperature, a non-linear algebraic model was considered, in which the maximum index is reached when optimal values are obtained. The optimal values were 50% and 25 °C for humidity and temperature, respectively. The Fig. 3 illustrates the graphical interpretation of the measured indexes.

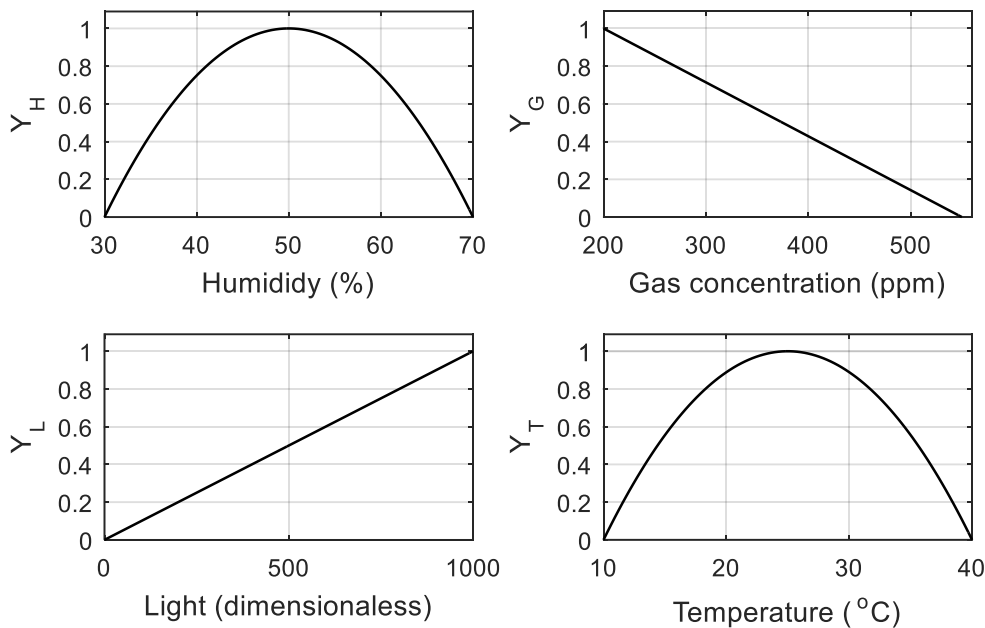


Figure 3 - Graphical interpretation of the measured indexes

Notice in Fig. 3 that the humidity and temperature present a parabolic profile while the luminosity and gas concentration present a linear rule. Table 2 describes the resulting model of the four indexes.

Table 2 – Expressions used to quantify the individual indexes¹

Property	Minimum	Maximum	Expression
Humidity	40	60	$Y_H = -0.025x^2 + 0.25x - 5.25$
Gas	200	550	$Y_G = -0.003x + 1.667$
Temperature	10 °C	40 °C	$Y_T = -0.0044x^2 + 0.222x - 1.778$
Luminosity	0	1000	$Y_L = -0.003x + 1.667$

¹ The subscripts H, G, T, L refer to humidity, gas, temperature and light, respectively.

The thermal comfort index (TCI) can be written as:

$$TCI = \omega_H y_H + \omega_G y_G + \omega_T y_T + \omega_L y_L \quad (1)$$

in which $\omega_i, i = H, G, T, L$ are the weighting factors associated with the properties: humidity, gas concentration, temperature and light, respectively. In order to normalize the TCI , the weighting factors follow the rule:

$$\sum \omega_i = 1, \text{ with } 0 \leq \omega_i \leq 1, i = H, G, T, L \quad (2)$$

To evaluate the TCI, several experiments were carried out in which the values of independent variables were changed.

To modify the gas concentration, a smoke source was used with the use of a cigarette inside the compartment. The humidity level was changed with the use of an air conditioning installed in

the room. The temperature was changed using the air conditioner and the luminosity by changing the intensity of light inside the environment through the partial blocks of light from the external environment.

2.3 TCI model: weighted sum model

A neural network is a computational model of how the neurons in our brain work. Basically, a neuron receives weighted inputs from other neuron and are added, resulting in the output z that is sent to an activation function g . The output y is then sent to other neurons. Fig. 4 illustrates an artificial neuron.

In Fig. 4 x represents the input variables, W the weights, a the intermediate results, g the activation function and y the output variable. A neural network can have one or multiple layers. Fig. 5 shows a typical neural network with three layers: (1) the input layer, in which the system receives the information; (2) the middle layer, where the characteristics are extracted from the object; and (3) the output layer, which calculates the final result. The greater the number of layers, the better the learning capacity of the network. The inputs can be connected to many neurons, thus resulting in a series of outputs, where each neuron represents an output. The different possibilities of connections between the layers of neurons can generate different structures.

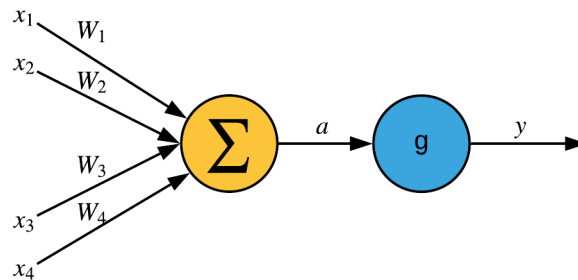


Figure 4 - Representation of an artificial neuron.

The network training can be divided into two phases: one of learning and the other of validation. In the first phase, a known set of input and output data is presented to the network. Then, the weights between the neurons are adjusted by an optimization algorithm to minimize the error between the output and reference variables.

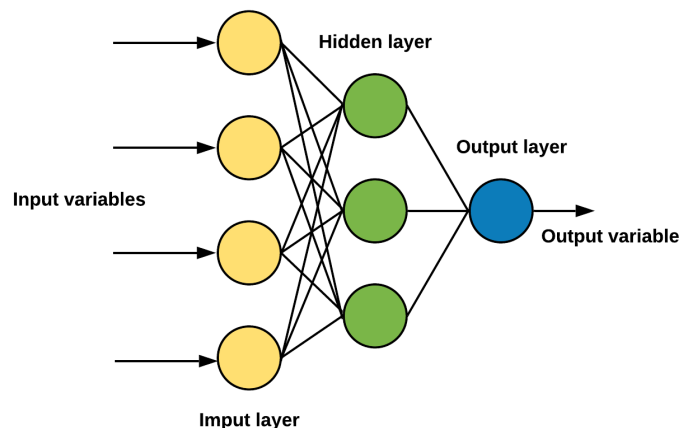


Figure 5 - Neural Network structure (illustration of one input layer, one hidden layer and one output layer).

The Neural Network configuration is detailed in Table 3. In order to evaluate the results of TIC computed by the NN model the Mean Square Error (MSE) in relation to the theoretical TCI was calculated.

Table 3 – Neural Network configuration

Data	Description
Software	Scilab®
Algorithm	Backpropagation (Marchi and Mitchell, 2019)
Input variables	Humidity, Gas Concentration, Temperature, Luminosity
Output variable	TCI
Number of hidden layers	3
Activation function	Log-sigmoidal

3. Results and Discussion

The tests were performed during the period of 500 seconds in which the independent variables were changed simultaneously. The results of individual indices are depicted in Fig. 6 and the corresponding normalized indexes plotted in Fig. 7

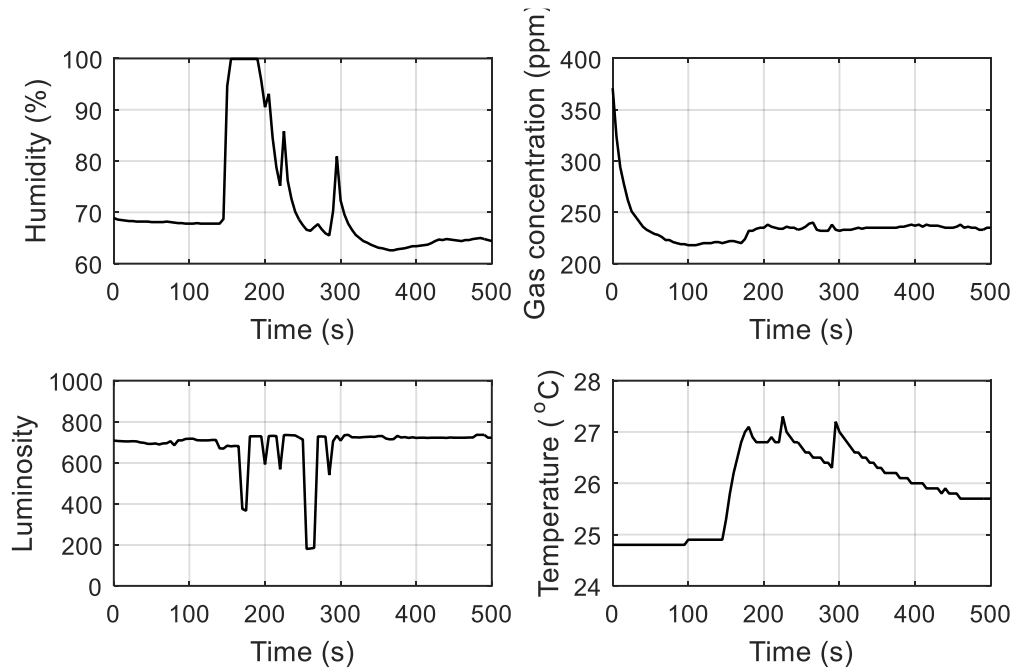


Figure 6. Profiles of humidity, gas concentration, luminosity and temperature along time.

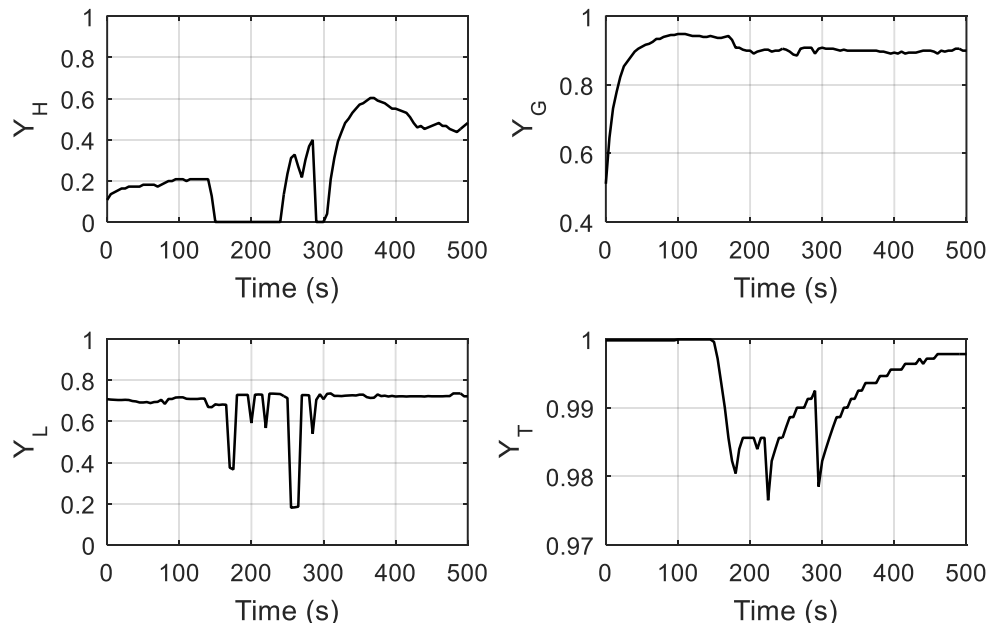


Figure 7. Profiles of dimensionless humidity, gas concentration, luminosity and temperature along time.

By observing the collected data, it is possible to see that a high variation of humidity (minimum of 0 and maximum of 0.6) and gas concentration (minimum of 0.03 and maximum of 0.92) indices was provoked during the experiment. It is also possible to observe that the luminosity index (Y_L) presented localized fast variations but presented an average value close to 0.7. Finally, the temperature remained close to the maximum index, with a very small variation.

The TCI profiles were evaluated for different weighting factors. The results can be viewed in Fig. 8. It evidences that the weighting factors are relevant to calibrate the degree of importance of each individual index. In the case of equal importance, the maximum TCI achieved the value of 0.8 between 300 and 350 seconds. By checking the results of Fig 5 it is possible to see that in this period the humidity and temperature increased to 0.6 and 0.995, respectively, contributing for the TCI rise. On the other hand, in the beginning of the experiment (before 100 seconds), lower values of TCI were observed, principally caused by the values of Y_G .

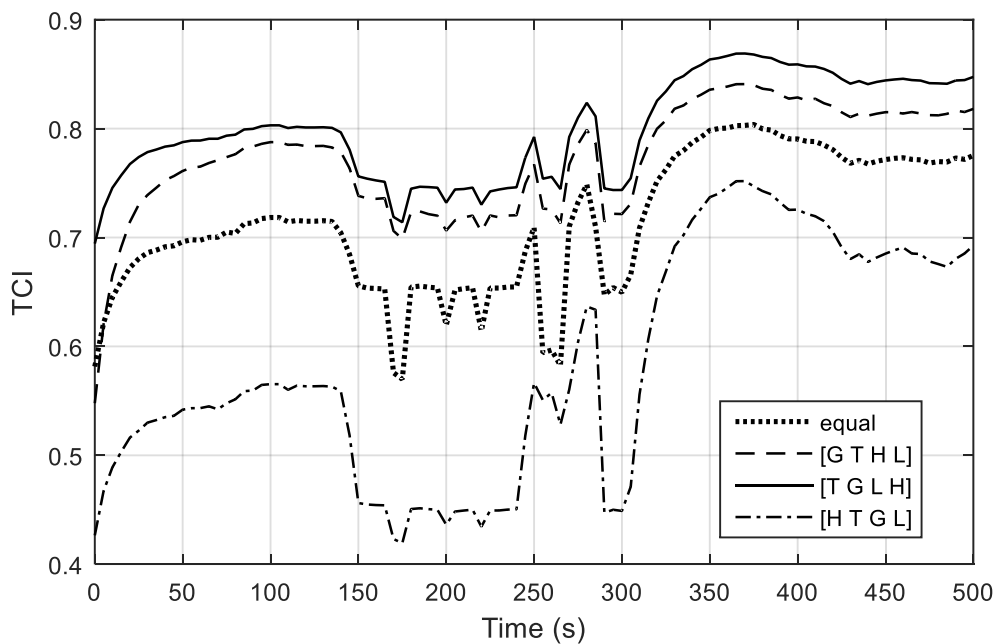


Figure 8. TCI for different weighing factors (equal - $\omega_H = 0.25, \omega_G = 0.25, \omega_T = 0.25, \omega_L = 0.25$; [G T H L] - $\omega_H = 0.2, \omega_G = 0.5, \omega_T = 0.2, \omega_L = 0.1$); [T G L H] - $\omega_H = 0.2, \omega_G = 0.2, \omega_T = 0.5, \omega_L = 0.1$; [H T L H] - $\omega_H = 0.5, \omega_G = 0.2, \omega_T = 0.2, \omega_L = 0.1$).

The results of the neural network model can be seen in Fig. 9. It is noted that 50% of the data were used for training the Neural Network while 50% was used for validation. The results clearly show that in the training stage it was possible to obtain an adjustment very close to the data estimated by the TCI, with MSE equals to $2.34 \cdot 10^{-6}$. The results also reveal that in the prediction (second) stage, the TCI predicted by the neural network was considerably close to the TCI obtained by the deterministic model, with a MSE equals to $7.81 \cdot 10^{-6}$.

Another data set was generated to compare the results of the deterministic a Neural Network models. Fig. 10 illustrates the normalized profiles of the four independent variables, according to the rule described in Table 3. It is noted that the profiles have very different shapes compared with the profiles of the last topic (Fig. 7).

The TCI was calculated for different weighing factors, as plotted in Fig. 11. The results evidence that weights can considerably affect the TCI values. Notice that in some situations there is a change in the direction of variation of the TCI over time (observe the curve [G T H L]).

Finally, the results in Fig. 12 compare the data of the Neural Network with the deterministic model. In this case, the entire data set was considered for the simulation. It can be observed that the

curves have very close results, indicating that the Neural Network algorithm was able to predict the TCI from the measured data satisfactorily, presenting a MSE of $1.73 \cdot 10^{-5}$.

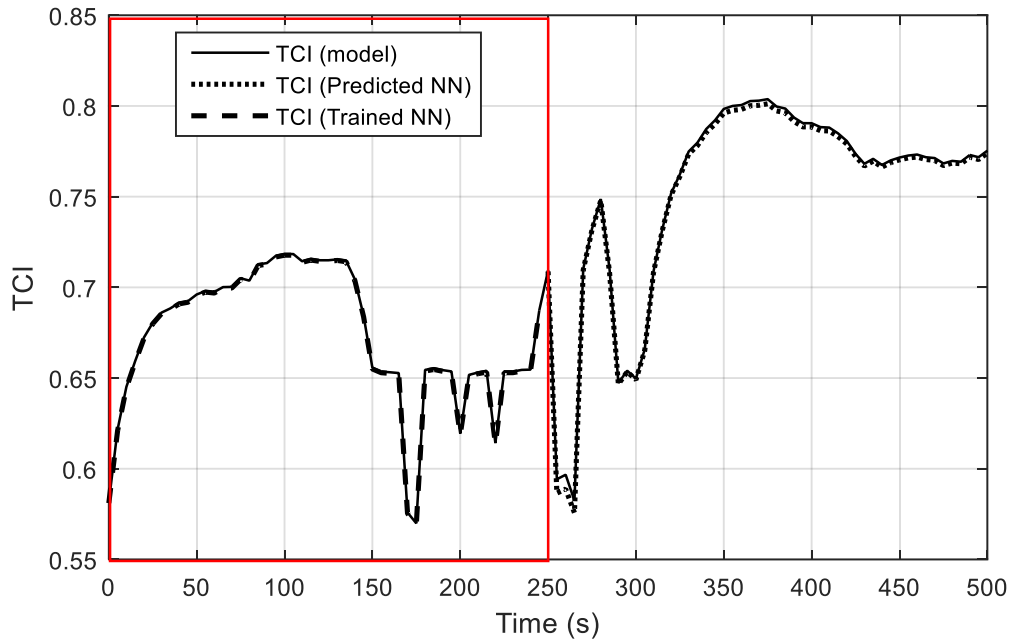


Figure 9 - Comparison of Neural Network and theoretical TCI responses (experiment 1).

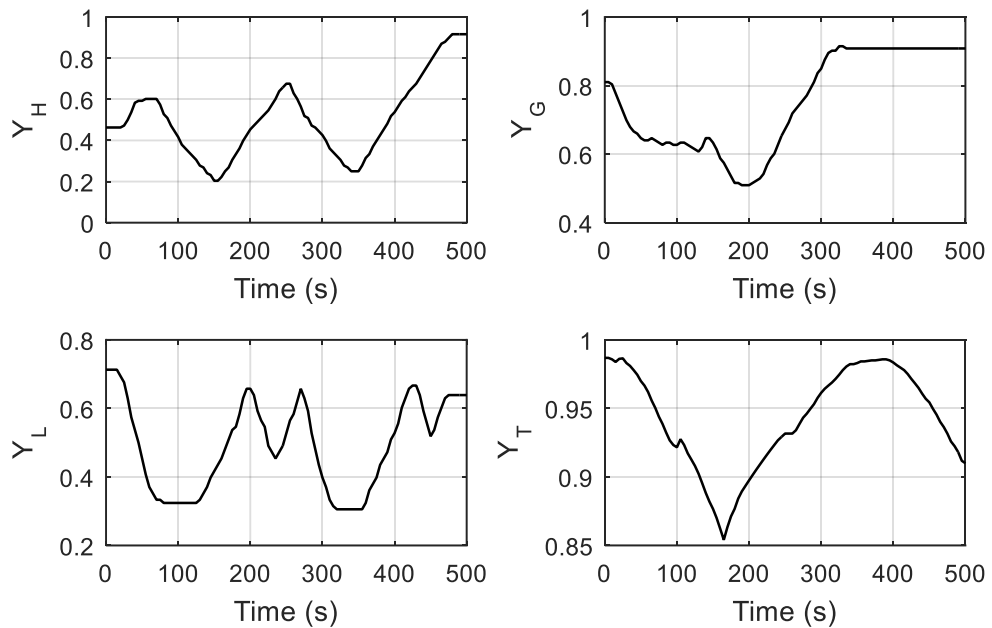


Figure 10 - Profiles of dimensionless humidity, gas concentration, luminosity and temperature along time.

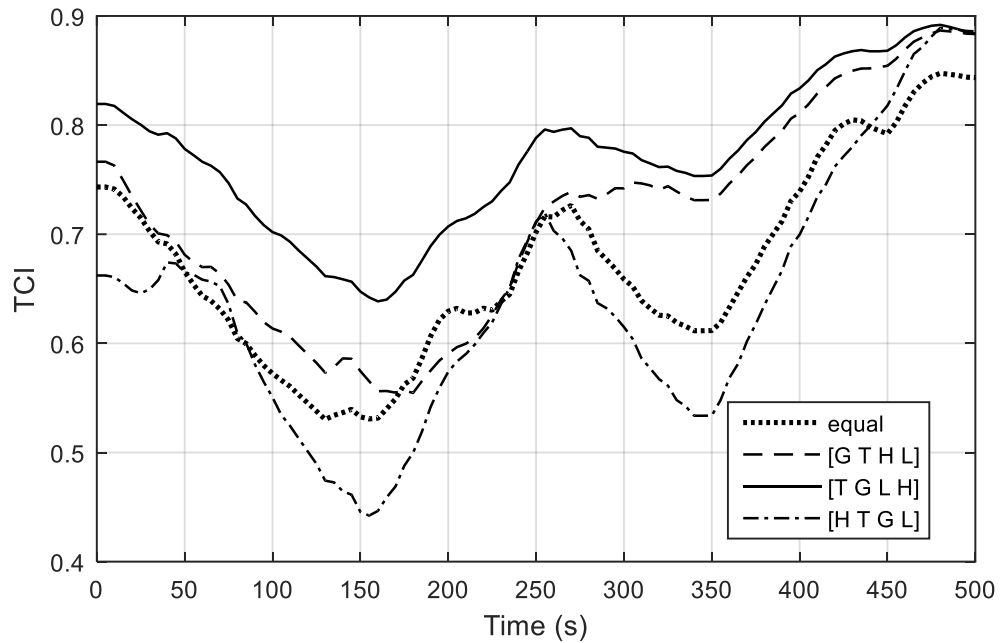


Figure 11 – TCI for different weighing factors (equal - $\omega_H = 0.25, \omega_G = 0.25, \omega_T = 0.25, \omega_L = 0.25$; [G T H L] - $\omega_H = 0.2, \omega_G = 0.5, \omega_T = 0.2, \omega_L = 0.1$); [T G L H] - $\omega_H = 0.2, \omega_G = 0.2, \omega_T = 0.5, \omega_L = 0.1$; [H T L H] - $\omega_H = 0.5, \omega_G = 0.2, \omega_T = 0.2, \omega_L = 0.1$).

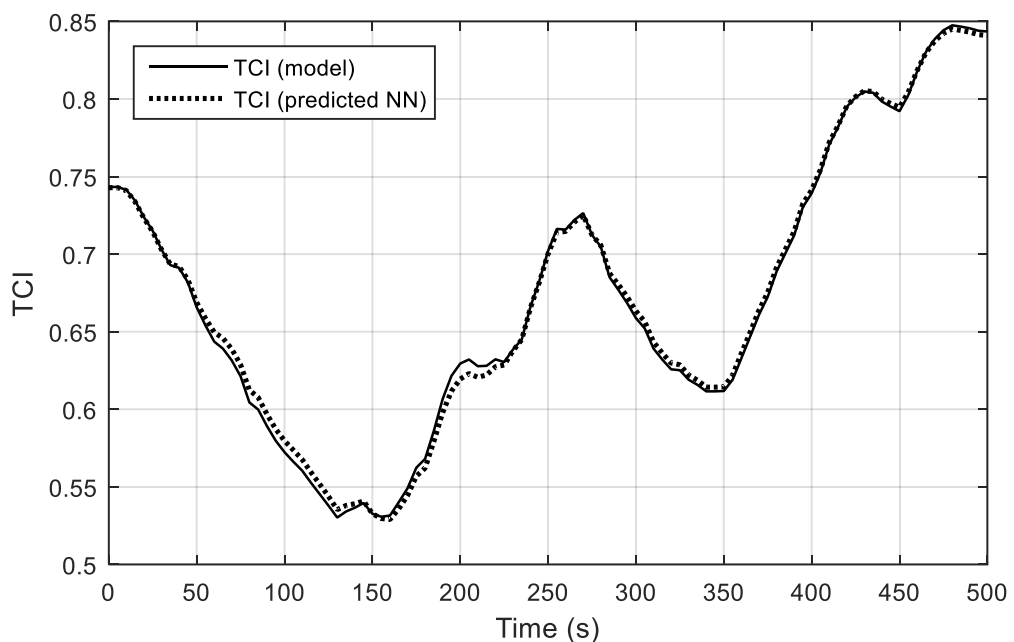


Figure 12. - Comparison of Neural Network and theoretical TCI responses (experiment-1).

4. Conclusions

In this work an Arduino system for monitoring indoor air quality was developed. The Arduino was used as a microcontroller to acquire data from light, temperature, humidity and gas concentration (smoke) sensors. Two experiments were carried out, where the data were obtained in a time horizon of 500 sec. A global index was proposed, where the weighted sum of the individual values was aggregated, generating the thermal comfort index (TCI). Additionally, a model based on artificial neural networks was proposed, where part of the experiments was used for training the network.

The results showed that the TCI varied from 0.4 to 0.9 in the analyzed range. It was noted that the weight values influence, as expected, the sensitivity of the TCI to the individual indices.

The results of the neural network allowed to simulate the TCI from the experimental data. Part of the first experiment data (50%) was used to train the network while the other part of the dataset was used to validate the results. It was possible to observe that the network had performance very close to the TCI, with MSE of $1.72 \cdot 10^{-5}$.

Finally, this work shows that it is possible, from simple experiments, to develop systems for teaching engineering that involves the stages of experimental design, mathematical modeling and application of machine learning.

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