Modeling the effect of roof coatings materials on the building thermal temperature variations based on an artificial intelligence

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Abstract: This paper presents the benefits of applying the artificial neural networks technique to model the building indoor temperature variations caused by implementing roof coatings. Four of the most common roof coating used in Mexican constructions were considered. The study evaluated test cells at outdoors and instrumented them to measure the indoor temperature variation. The environmental parameters solar radiation, wind speed, ambient temperature, and relative humidity were also monitored. The results showed the viability of modeling the thermal behavior generated by the roof coatings with an accuracy greater than 90%. It implies the ability to predict internal temperatures based on the physical properties of the material and environmental variables, being a feasible tool in the search for thermal comfort for buildings in the region. In addition, the results of the sensitivity analysis identified to what extent to improve the optical properties of the material impact on the heat transferred to the interior.

1. Introduction
Nowadays, there is a constant search for the identification of passive energy efficiency strategies that allow reducing the internal temperature in rooms. The roof is the element with the highest thermal gain in buildings. Various alternatives have been studied to minimize the indoor temperature produced by this effect, being the coating roof one of the most striking [1]. This technology is economical, does not require modifications to the building structure, and is easy to implement; this translates into economic and energy benefits for building occupants by reducing consumption in artificial air conditioning and the inherent cost that this entails. On the other hand, artificial intelligence (AI) has proven to be a viable option for modeling complex thermal behaviors in buildings [2]. Specifically, Artificial Neural Networks (ANN) have become one of the most attractive alternatives for multivariate modeling of complex thermal phenomena occurring in buildings. This technique has been successfully used to synthesize the thermal processes inside buildings that use green roofs [3], for hygrothermal modeling in green walls [4], as well as to estimate the humidity and temperature inside buildings [5].
Thus, the work presents the application of ANN as an alternative to model the effect of coatings material on the internal temperature of enclosures, the foregoing as a function of the present climatic conditions and thermal parameters of the materials under test. The results show that this approach represents a feasible tool in the search for thermal satisfaction in certain rooms.

2. Experiment description
In order to identify the effects of roof coatings' optical properties (reflectance and transmittance) on the building internal temperature, four of the roof coatings with the greatest distribution in Mexico were evaluated under the climatic conditions of Cuernavaca, Morelos. To obtain a representative margin, coatings of various shades were selected: 2 white from different manufacturers, 1 terracotta color and 1 black color. Additionally, the study considered the optical properties of the uncoated slab (gray color). The evaluation was carried out using test cells with dimensions of 1 m x 1 m x 1 m. The cells are built with insulating materials to prevent heat flow at all points except where the roof coating is located, this in order to exclusively evaluate the thermal input of the material in one direction. To guarantee a unique heat flow, the walls of the test cells are in contact with a cooling system, which allows them to maintain their constant temperature.

The test cell was instrumented with temperature sensors (thermocouples) at the ends of the slab and the interior space to measure the temperature changes by using each of the selective coatings. On the other hand, given that the environmental variables play an important role in the daily temperature generated inside the buildings, a meteorological station was placed in the study area. The intention of the station was to record the behavior of solar radiation, wind speed, relative humidity and ambient temperature that interact with the roof. Figure 1 presents the schematic diagram of the test cell used during the experimental phase.

![Figure 1. Schematic diagram of the experimental system for roof coatings evaluation.](image)

3. Artificial intelligence technique
An ANN is a set of mathematical subfunctions called neurons, which are distributed in layers and interconnected with each other through weights. The conventional architecture of an ANN consists of an input layer, a single hidden layer, and an output layer [6]. The number of neurons in the input and output
layers are defined by the experimental variables, while the hidden layer is made up of sigmoid neurons whose number is difficult to specify and requires an iterative process for their identification. For the neurons of the hidden layer, the sigmoid function used corresponds to the Tangent-Sigmoid (Eq. 1), while for the output neuron(s) the purline linear activation function (Eq. 2) is used:

$$Tansig(a) = \frac{2}{1 + \exp^{-2a}} - 1$$  \hspace{1cm} (1)$$

$$Purline(a) = a$$  \hspace{1cm} (2)$$

where $a$ represents the weighted sum of the signals coming from the neurons of the previous layer:

$$a = \sum_{i} w_i x_i + b$$  \hspace{1cm} (3)$$

where $w_i$ are the weight between layers, $b$ is a bias factor, $x_i$ is the incoming signal, and the $n$ represents the total number of neurons in the previous layer. In order for an ANN model to be able to interpret the phenomenon that it wishes to simulate, a process called training is carried out. The training process is carried out through specific algorithms, where the most effective is the known as back-propagation [7].

4. Computational modeling framework
A computational methodology consisting of four stages was used to model the indoor temperature variations caused by implementing roof coating materials (Figure 2):

![Figure 2. Computational framework for modeling the indoor temperature by roof coating application.](image-url)
In the first instance, by varying the roof coating the temperature inside the cell, solar radiation, ambient temperature, wind speed, and relative humidity were monitored. Measurements were compiled in a spreadsheet, together with the optical properties (reflectance and emissivity) of the coating materials applied to the roof. The product of this process was forming a database composed of 6,686 samples for the training of the ANN model (Table 1).

Table 1. Experimental data considered for the ANN modeling process.

| Variables (6,865 samples) | Min. | Max |
|---------------------------|------|-----|
| **Indoor parameters**     |      |     |
| Solar radiation (W/m²²)   | 0    | 1200|
| Wind speed (m/s)          | 0    | 4   |
| Ambient temperature (°C)  | 17   | 37  |
| Relative humidity (%)     | 15   | 83  |
| Emissivity (%)            | 87   | 90  |
| Reflectance (%)           | 5    | 85  |
| **Output parameter**      |      |     |
| Indoor temperature (°C)   | 18   | 48  |

In order to estimate the temperature inside the test cell, based on environmental variables, the working database (table 1) was normalized in the range 0-1 [8]:

\[
y_n = \frac{y - y_{min}}{y_{max} - y_{min}}
\]  

(4)

where \( y_n \) and \( y \) represent the normalized and original variable, respectively; while \( y_{min} \) and \( y_{max} \) are the maximum and minimum value of the input/output variable to normalize. The purpose of normalization is to avoid that the disproportion in the magnitude of the various input variables affects the modeling process.

With the normalized database formed, the mathematical model was trained, randomly segmenting it into three groups: 70% for the creation of the model, 15% for validation and 15% for the testing. Using a supervised learning process based on trial and error, the number of neurons in the hidden layer (S) is gradually incremented to reduce the difference between the data estimated by the ANN and the targets. The learning algorithm used in this study for the backpropagation process was the Levenberg-Marquardt (LM). The last stage consists of the statistical validation of the model using the tools root mean square error (RMSE) and correlation coefficient (R). Various models were compared at this stage to identify the one that best emulates the behavior of the internal temperature. The objective of this stage is to identify the ANN architecture with the least number of S neurons, which ensures the best possible statistical estimation.

5. ANN modeling results

In order to find the best ANN model, several architectures were trained and statically compared. The architectures were built by varying the number of hidden neurons from 4 to 12, in step of two; performing all numerical calculations in the MATLAB programming environment using its ANN toolbox plugin. Table 2 shows the statistical results for the training, validation and testing data sets. In summary, it is observed that by applying 10 neurons in the hidden layer, the best statistical indicators are obtained,
mainly for the training set, which is the most important indicator since it is data that is not part of the creation of the model. Thus, the best ANN architecture that estimates the temperature inside the cell is given by 6-10-1.

Table 2. Statistical comparison of various ANN architecture created to estimate the indoor temperature after the application of the roof coatings.

| Hidden neuron (s) | Training | Validation | Testing |
|------------------|----------|------------|---------|
|                  | R (%)    | RMSE (°C)  | R (%)   | RMSE (°C)  | R (%)   | RMSE (°C)  |
| 4                | 97.87    | 0.0341     | 98.50   | 0.0332     | 97.51   | 0.0358     |
| 6                | 98.18    | 0.0313     | 98.30   | 0.0312     | 98.18   | 0.0324     |
| 8                | 98.74    | 0.0262     | 98.49   | 0.0290     | 98.62   | 0.0286     |
| 10               | 98.67    | 0.0263     | 98.72   | 0.0277     | 98.70   | 0.0277     |
| 12               | 98.95    | 0.0239     | 98.73   | 0.0269     | 98.86   | 0.0255     |

The mathematical expression of the ANN that describes the behavior of the internal temperature for the different optical properties of coating is presented in Eq. 5. The parameter $w_l$ represents the weights between the input and hidden layer, and $w_l$ are the weights between the hidden and output layer. $b1$ and $b2$ are the bias of the neurons in the hidden and output layers respectively. Finally, the suffix $k$ represents the number of neurons in the input layer ($K = 6k$), while $s$ is the number of neurons in the hidden layer ($S = 10$). The optimal values of bias and weights associated with each of the neurons that make up the ANN architecture and that make said equation effective are presented in table 3.

$$T_{in,ANN} = \sum_{s=1}^{S} \left[ \frac{1}{1 + \exp\left(-\sum_{k=1}^{K} (w_{i(s,k)x(k)} + b1)\right)} \right] + b2_t$$

(5)

Table 3. ANN model prediction optimum weights and bias.

| Hidden neurons (s) | $G$   | $w_s$ | $T_a$ | RH | $\epsilon$ | $\rho$ | $w_l$ | $b1$ | $b2$ |
|-------------------|-------|-------|-------|----|------------|--------|-------|------|------|
| 1                 | -1.621| 2.688 | 1.926 | -1.460 | -0.246 | -2.570 | 0.555 | 3.957 | -1.096 |
| 2                 | 0.701 | -0.938 | -1.519 | 0.570 | -0.469 | -0.535 | -2.050 | -1.646 |
| 3                 | 1.567 | 0.169 | -0.769 | 0.266 | -1.499 | -0.691 | 1.194 | 2.777 |
| 4                 | 0.346 | 2.391 | -1.220 | 0.740 | 2.291 | 1.858 | 0.584 | -0.425 |
| 5                 | -0.949 | -0.631 | -1.198 | 0.566 | 0.162 | -1.712 | 1.278 | -0.936 |
| 6                 | 0.197 | -2.314 | 1.656 | 0.668 | 0.193 | -0.124 | -4.207 | 1.335 |
| 7                 | -0.082 | -2.056 | 1.842 | -0.639 | -2.844 | -1.033 | 0.819 | 1.588 |
| 8                 | 0.334 | 0.607 | -1.393 | -2.414 | -0.975 | 0.770 | 0.446 | -2.137 |
| 9                 | -0.329 | 1.777 | -0.909 | -0.717 | -0.329 | 0.191 | -5.647 | -0.691 |
| 10                | 1.655 | -1.100 | -0.519 | 1.407 | -0.232 | -1.664 | 0.528 | 0.962 |
5.1. Sensitivity analysis

Once the complex thermal energy transfer process through the coating roof had been synthesized into a mathematical expression, a sensitivity analysis was performed using the Garson equation [9]. This analysis allows to determine the relative impact of the environmental variables considered in this study on temperature inside the enclosure (test cell). For this purpose, the Garson equation takes advantage of the values of the weights and bias (presented in Table 3), estimating the relative importance of each variable from the following mathematical expression:

\[ R_{ij} = \frac{\sum_{s=1}^{S} \left( \frac{|w_{i,s}|}{\sum_{m=1}^{M} |w_{m,s}|} x |w_{s,k}| \right)}{\sum_{m=1}^{M} \left( \sum_{s=1}^{S} \left( \frac{|w_{i,s}|}{\sum_{m=1}^{M} |w_{m,s}|} x |w_{s,k}| \right) \right)} \times 100 \]  

(6)

where RI represents the relative importance of the j-th input. According to table 4 all the parameters have a significant impact for the indoor temperature. The emissivity and reflectance of roof coatings are the parameters with the greatest impact on temperature. The foregoing implies that the choice of coating actually plays an important role in the temperature inside the building, which impacts more than 40% of this parameter. In addition, the importance of these lies in the fact that of the parameters considered in the model they are the only ones in which we can have control through the development of new materials focused on reducing the interior temperature. Finally, the results obtained, both from the model and from the sensitivity analysis, are promising. These open the door to the search for materials based on their physical properties aimed at extending thermal comfort inside buildings.

| Independent variables     | Sensitivity percentage (%) |
|---------------------------|----------------------------|
| Solar radiation (W/m²)    | 14.03                      |
| Wind speed (m/s)          | 12.03                      |
| Ambient temperature (°C)  | 11.79                      |
| Relative humidity (%)     | 11.39                      |
| Emissivity (%)            | 32.21                      |
| Reflectance (%)           | 18.55                      |

6. Conclusions

The work presented the implementation of artificial neural networks to estimate the temperature changes caused inside rooms after the application of selective coatings on the roof. From a numerical point of view, it was shown that neural networks are an adequate alternative to synthesize the complex thermal processes involved in calculating the interior temperature, reaching a model precision of more than 95%. In addition, the feasibility of creating a model that can estimate said temperature from the knowledge of the environmental variables and optical characteristics of the coating was demonstrated. On the other hand, the results of the sensitivity analysis showed that in order to reach temperatures of thermal comfort, the variable that must be paid more attention is the emissivity, as it impacts the temperature inside the room by more than 30%. On the other hand, it is essential to emphasize that the main limitation of this computational approach concerning conventional strategies is that they are trained with data from a specific problem. However, they are very useful in sensitivity analysis and as an easy-to-compute objective function to search for optimal comfort conditions for particular locations. Finally, the results obtained are
promising, since they allow us to visualize ways of establishing strategies aimed at identifying coating properties that guarantee the highest possible thermal comfort through the development of materials engineering.

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