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Article

Smart Building: Use of the ANN Approach for Indoor Temperature Forecasting

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Abstract: Smart buildings concept aims at the use of the smart technology to reduce energy consumption as well as improvement of the comfort conditions and users' satisfaction. It is based on the use of smart sensors to follow both outdoor and indoor conditions as well as software for the control of comfort and security devices. The optimal control of the energy devices requires software for indoor temperature forecasting. This paper presents an ANN – based model for the indoor temperature forecasting. The model is developed using data recoded in an old building of the engineering school Polytech'Lille. Data covered both indoor and outdoor conditions. Analysis of the relevance of the input parameters allowed to develop a simplified forecasting model of the indoor temperature that uses only the outdoor temperature as well as the history of the façade temperature as input parameters. The paper presents successively, data collection, the ANN concept used in the temperature forecasting, and finally the ANN model developed for the façade and indoor forecasting. It shows that an ANN-based model using outdoor and façade temperature sensors provides a good forecasting of the indoor temperature. This model could be used for the optimal control of buildings energy devices.

Keywords: smart building; artificial neural network (ANN); indoor; temperature; façade; outdoor; forecasting; relevance; sensors; recorded data

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1. Introduction

Smart buildings concept aims at the use of the smart technology to reduce energy consumption as well as improvement of the comfort conditions and users' satisfaction. Indoor temperature has an important role on both users' comfort and energy consumption [1,2]. The forecasting of this temperature is necessary for the regulation of energy devices to ensure occupants comfort as well as to optimize energy use. The indoor temperature forecasting constitutes a complex task, because it is governed by complex physical and behavioral phenomena. It is affected by a multitude of parameters, which can be classified into three groups: outdoor conditions, building characteristics and occupants' behavior [3-5]. In addition, investigations showed that the indoor temperature doesn't have uniform distribution [6].

The determination of the indoor temperature could be carried out using physical or data-driven approaches [7]. The physical approach is based on the use of numerical modelling [8,9], which requires detailed information about the buildings characteristics, appliances and occupant behavior.

The data-driven approach is based on the use of collected data for developing relationships (models) between "input" parameters and "output" parameters. These relationships could be established by learning from collected data. The Artificial Neural Networks (ANN) approach is widely used to building data-driven models [10-12]. Investigations were carried out by Soleimani-Mohseni et al. [13] to estimate the operative temperature in building using indoor air temperature, electrical power, outdoor temperature, time, wall's temperature and ventilation flow rate. Lu and Viljanen [14] used ANN to predict room air temperature and relative humidity. Recently, Zabada and Shahrour [15] used the ANN approach for the analysis of the heating expenses in social housing. This paper presents a simplified ANN forecasting model of the indoor temperature that uses only the outdoor temperature and history of the façade temperature as input parameters. This model could be easily used for the optimal control of buildings energy devices.

2. Data Collection

Data were collected using a smart monitoring of an old building of Polytech'Lille Engineering School in the North of France. Monitoring concerned indoor and outdoor temperature and humidity as well solar radiation [16,17]. Parameters were recorded at 5-minutes interval and then sent to a Raspberry Pi. Figure 1 illustrates an example of recorded data in a summer day. Data concern the outdoor temperature as well as the indoor temperature at three locations in the office: façade, center of the lateral wall and office center. The external temperature varied between 17.5°C and 34°C, while the façade indoor temperature varied between 21°C and 25.5°C. The temperatures at the center of the office and the center of the lateral wall varied between 22 and 24.2 °C.

Data were collected for 2 summer months (June and July) in different offices of the building.

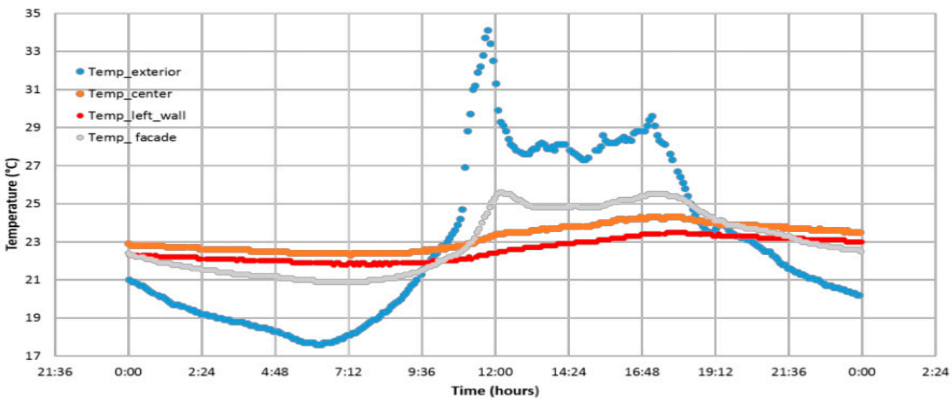

Figure 1. Temperature variation in a summer day

3. ANN Approach

The ANN approach is inspired from the ability of the human brain to predict patterns based on learning and recalling processes. It allows the construction of relationships between input parameters and output parameters using artificial neurons, which are arranged in an input layer, an output layer and one or more hidden layers [18]. Analyses were conducted using the multilayer back-propagation neural network. We used a three-layer ANN with n, m, and p as the number of input, hidden and output nodes, respectively, based on the following equation:

$$Y_k = S\left(\sum_{j=1}^{m} W_{jk} \times S\left(\sum_{i=1}^{n} W_{ij} X_i\right)\right), \quad (1)$$

where Y_k stands for the output values and X_i denotes the input values; W_{ij} gives the weights of connection between the input layer and the hidden layer.

The ANN performances could be evaluated using the mean square error (MSE) and the coefficient of correlation (R):

$$MSE = \sum_{i=1}^{n} \left(\frac{e_i^2}{N}\right), \tag{2}$$

$$R = \pm \sqrt{\frac{\sum_{i=1}^{N} (Y_i - \bar{X})^2}{\sum_{i=1}^{N} (X_i - \bar{X})^2}} = \sqrt{1 - \frac{\sum_{i=1}^{N} (e_i)^2}{\sum_{i=1}^{N} (X_i - \bar{X})^2}} \tag{3}$$

where e_i is the error between the ANN output (Y_i) and the experimental input (X_i), $\bar{X}$ represents the mean of the input target.

Different ANN architectures exist. The multilayer perception (MLP) structure is the most popular [19-24]. Its use with a single hidden layer and a sufficient number of neurons provided good accuracy for the approximated function [25, 26]. This architecture is used in this work.

The use of ANN for temperature forecasting aims at the prediction of the building indoor temperature for the optimal regulation of the energy devices as well as for ensuring occupants' comfort. The input parameters concern the outdoor conditions, the indoor conditions as well as the occupants' behavior. The forecasting time depends on the building thermal inertia and the energy regulation system. Each building is characterized by its time lag and the time of heat transmission delay [27-30]. Furthermore, the HVAC system constitutes an important factor in determining the prediction time. It depends on the operation schedule of the HVAC that may varies from building to another [27].

Two ANN models were developed for forecasting the indoor temperature. They allow to forecast the façade indoor temperature and the temperature in the office center, respectively.

Analyses were conducted using MATLAB for ANN modelling and IBM SPSS Statistics for input parameters ranking.

4. Façade indoor temperature forecasting

4.1 Analysis of the input parameters relevance

The input parameters used in the global analysis are summarized in table 1. They concern the outdoor conditions (temperature, humidity and solar radiation), outdoor temperature history (input matrix for the last 3h values having 30min lag between its different columns: if the actual outdoor temperature was recorded at time t, the history matrix corresponds to t-0.5h, t-1h, t-1.5h, t-2h, t-2.5h and t-3h, the indoor facade temperature history (similar matrix history as the outdoor temperature) and time (cumulative minutes of the day).

Table 1. Input parameters for the façade temperature forecasting

Input Parameters
Outdoor temperature
Outdoor Humidity
Solar radiation
Outdoor temperature history
Time
Façade temperature history

The ANN optimal architecture is presented in figure 2. It includes 1 hidden layer with 4 neurons. Table 2 provides the weight of neurons' connections. We can observe that the weight could be negative or positive providing excitatory or inhibitory influence on each input. It varies for different parameters and neurons revealing complex connections and relations.

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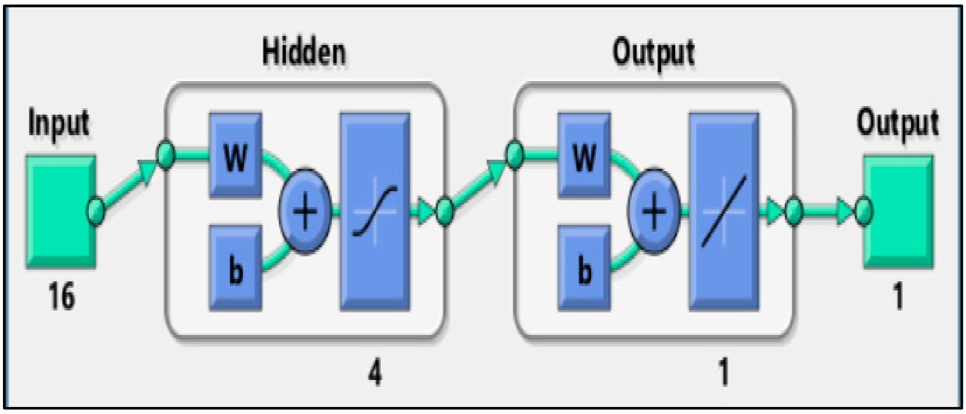

Figure 2. ANN optimal architecture.

Table 2. Weight of neurons' connections.

Input parameters	Neuron 1	Neuron 2	Neuron 3	Neuron 4
Time	2.59	0.02	1.46	-0.02
Outdoor temperature	1.13	-1.25	-0.05	1.32
History of outdoor temperature	2.55	1.65	-0.93	-1.60
	1.79	-1.05	-1.66	0.93
	2.67	0.62	-2.02	-0.64
	-1.11	-0.95	0.17	0.92
	-1.21	0.21	-0.54	-0.27
History of façade temperature	0.86	-0.02	0.23	0.06
	-2.65	-0.72	-2.76	1.43
	-3.00	0.90	-1.58	-1.12
	-1.04	0.50	-1.20	-0.38
	-0.26	0.61	-1.18	-0.57
	0.50	-0.31	-0.13	0.33
	-0.34	0.07	-1.10	-0.12
Solar radiation	1.27	0.23	3.52	-0.22
Outdoor humidity	0.01	-0.10	-0.43	0.09

Figure 3 shows a comparison of "predicted" and "recorded" façade temperatures. We observe a good agreement between these values with R=0.9967 and MSE=0.0277. This result shows that the ANN model predicts well the façade indoor temperature. The determination of input parameters requires 2 temperature sensors (outdoor and indoor), an external humidity sensor and a solar radiation sensor.

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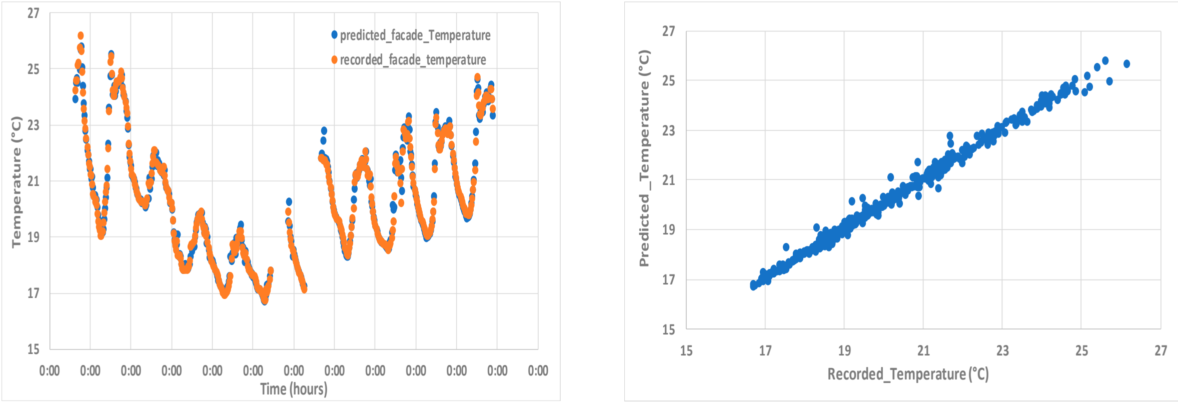

(a) (b)

Figure 3. Predicted and recorded façade temperatures: (**a**) Variation of both temperatures in time domain; (**b**) Predicted façade temperature with the recorded façade temperature.

In order to determine the most relevant input parameters in the ANN model, IBM SPSS Statistics software was used to analyze the "importance" of these parameters. Table 3 summarizes the obtained results. It shows that the solar radiation, time and humidity have a very low role in the model, with an importance factor lower than 5.1%. The outdoor temperature has the highest importance (Importance Factor = 42%), followed by the historical façade temperature (Importance Factor = 31.9%). The historical outdoor temperature has an intermediate influence with an Importance Factor = 12.8%.

Table 3. Analysis of the relevance of input parameters

Parameter	Importance Factor (%)
Solar radiation	3.7
Time	4.5
Humidity	5.1
Historic Outdoor Temperature	12.8
Historic Façade Temperature	31.9
Outdoor Temperature	42.0

Since the role of some input parameters in the ANN model is very weak, analyses were conducted in neglecting these parameters. Table 4 summarizes the results of these analyses. It shows clearly that the neglect of solar radiation, humidity and historical outdoor temperature does not deteriorate significantly the quality of the ANN model: The mean square error (MSE) increases from 0.0277 to 0.0365, while the coefficient of correlation (R) decreases from 0.9967 to 0.9959. The additional neglect of the historical data of the façade temperature has a higher influence. MSE increases from 0.0277 to 0.4922, while R decreases from 0.9967 to 0.946. This result shows that the façade temperature could be predicted with a high precision in considering only the outdoor temperature and the historical data of the facade indoor temperature. Figure 4 illustrates the results of models 1,5 and 6.

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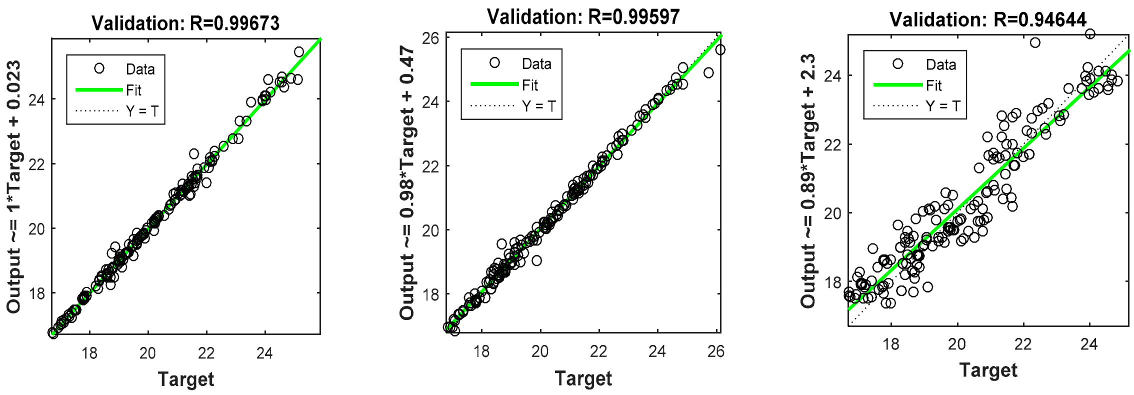
Table 4. Degraded models results

Model	Input parameter	R	MSE
1	Outdoor Temperature, Historic, Outdoor Humidity, time, Facade Historic	0.9967	0.0277
2	Outdoor Temperature, Historic, Outdoor Humidity, Facade Historic	0.99687	0.0300
3	Outdoor Temperature, Historic, Facade Historic	0.9969	0.0269
4	Outdoor Temperature, Facade Historic	0.9975	0.0199
5	Outdoor Temperature,	0.9959	0.0365
6	Outdoor Temperature, Historic, Outdoor Humidity, Sun radiation, time, Facade Historic	0.946	0.4922



(a) (b) (c)

Figure 4. R results for different models: (**a**) Model 1; (**b**) Model 5; (**c**) Model 6.

4.2 Façade temperature forecasting model

4.2.1 Use of the outdoor temperature as input parameter

Considering the results of the previous section, the outdoor temperature is first used as input parameter for forecasting the façade indoor temperature. The forecasting model provides the temperature at 0.5, 1, 2 and 4 hours.

Figures 5 and 6 show the forecasting results at 0.5 and 1.0 hour. We observe that the ANN model reproduces well the recorded temperature. For 0.5-hour forecasting, R is equal to 0.956 and MSE is equal to 0.4369; while for 1-hour forecasting, R = 0.928 and MSE = 0.48454. Figure 7 shows the

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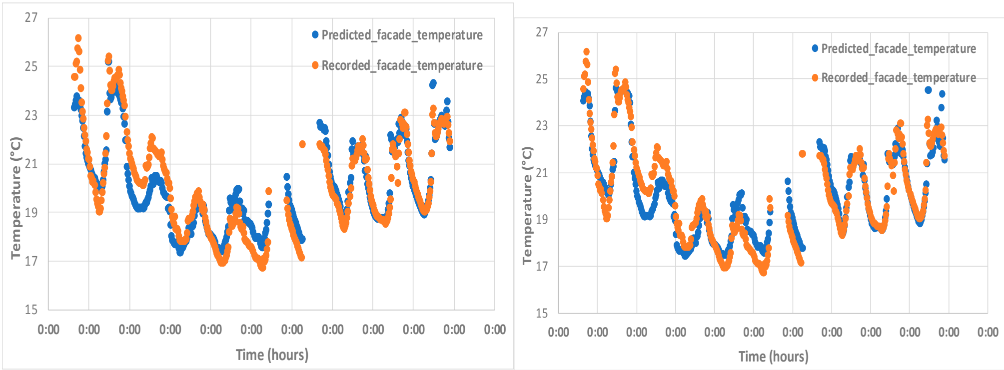
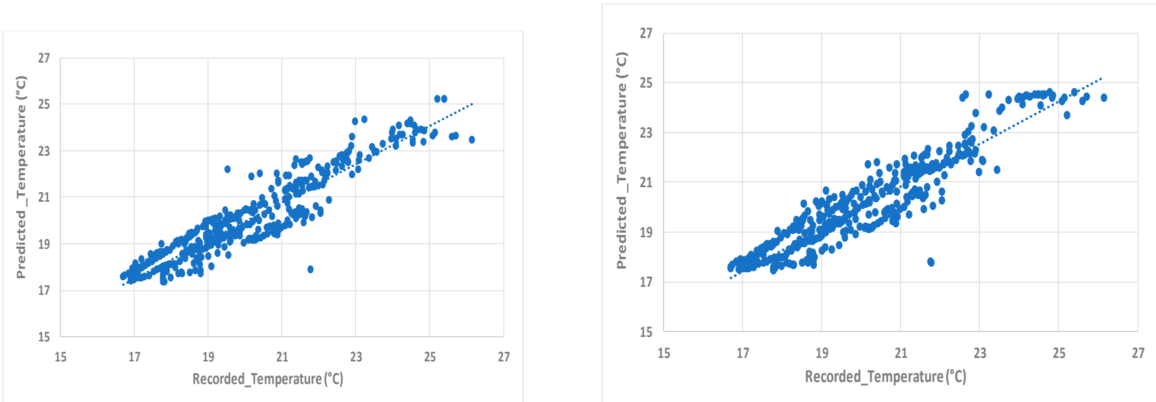
forecasting error distribution for 0.5 and 1 hour. It shows that about 90% of the forecasting error are less than 1° C.



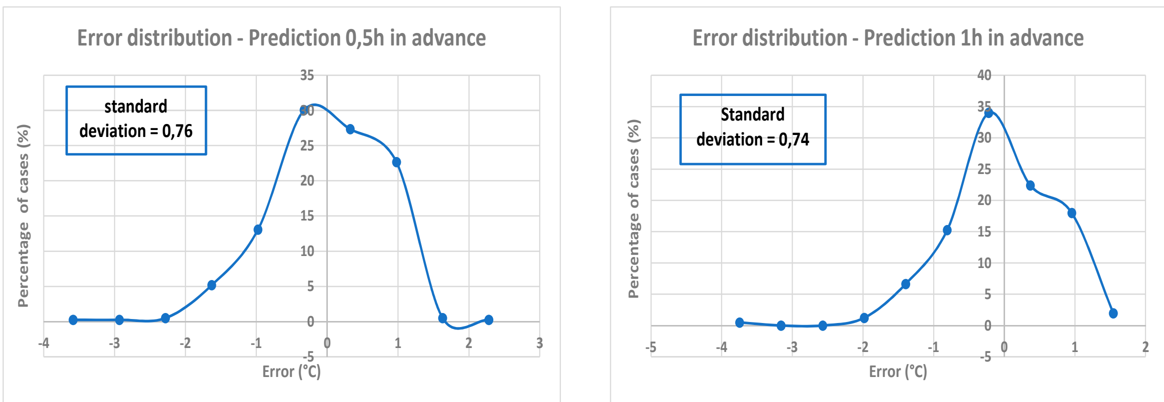
(a) (b)

Figures 5. Recorded and predicted façade temperature variation in the time domain: (**a**) prediction for 0.5h; (**b**) prediction for 1h.



(a) (b)

Figures 6. Predicted façade temperature with the recorded façade temperature (Input parameter = Outdoor temperature): (**a**) prediction for 0.5h; (**b**) prediction for 1h.



(a) (b)

Figures 7. Distribution of the error forecasting (Input parameter = Outdoor temperature): (**a**) prediction for 0.5h; (**b**) prediction for 1h.

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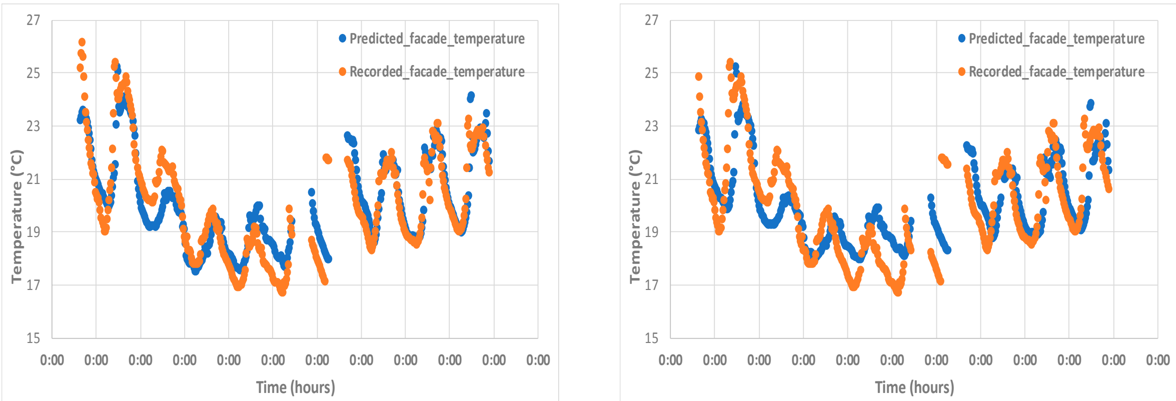
Figures 8 and 9 shows the forecasting results at 2 and 4 hours. We observe a deterioration in the quality of forecasting regarding to those obtained at 0.5 and 1 hour. For 2 h forecasting, R = 0.9109 and MSE = 0.89078, while for 4-hours forecasting, R = 0.8370 and MSE =1.23783. Figure 10 shows the forecasting error distribution for 2 and 4 hours. It shows that for the former, about 70% of the forecasting error are less than 1° C, while for the latter about 64 % of the forecasting error are less than 1° C. Table 5 summarizes the forecasting results.

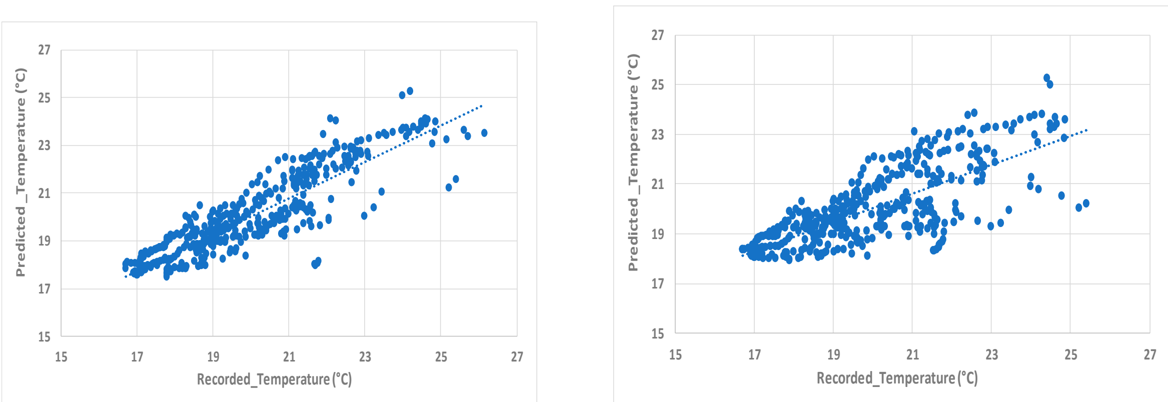
Table 5. Performances of the forecasting models (Input parameter = Outdoor temperature)

Model	Time	R	MSE
1	+ 0.5 hour	0.9560	0.436900
2	+ 1 hour	0.9528	0.484594
3	+ 2 hours	0.9109	0.89078
4	+ 4 hours	0.8370	1.23783



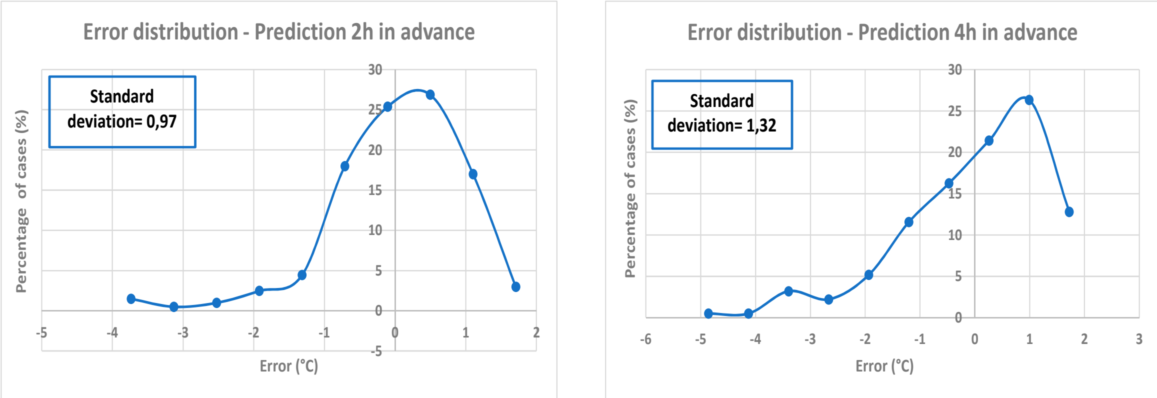
(a) (b)

Figures 8. Recorded and predicted façade temperature variation in the time domain: (**a**) prediction for 2h; (**b**) prediction for 4h.



(a) (b)

Figures 9. Predicted façade temperature with the recorded façade temperature (Input parameter = Outdoor temperature): (**a**) prediction for 2h; (**b**) prediction for 4h.



(a) (b)

Figures 10. Distribution of error forecasting (Input parameter = Outdoor temperature): (**a**) prediction for 2h; (**b**) prediction for 4h.

4.2.2 Use of the outdoor temperature and the history of the façade temperature as input parameters

In this section, both outdoor temperature and 3 hours façade temperature history are used as input parameters in the forecasting model. The forecasting model provides the temperature at 0.5, 1, 2 and 4 hours. Table 6 summarizes the obtained results. The temperature forecasting is improved regarding the forecasting model using the outdoor temperature as input. This result is particularly interesting for the temperature foresting at 2 hours: R = 0.957 and MSE = 0.3299 to be compared with R = 0.9109 and MSE = 0.89078 obtained with the outdoor temperature as input parameter. Figure 11 shows the forecasting error distribution for 2 hours. It shows that about 88% of the forecasting errorare less than 1° C to be compared with 70% obtained with the previous model.

The 4-hours foresting at is still weak with R = 0.852; MSE = 1.0533. About 68% of the forecasting error are less than 1°C (Figure 11).

Table 6. Performances of the forecasting models (Input parameters = Outdoor temperature and 3 hours façade temperature)

Model	Time	R	MSE
1	+ 0.5 hour	0.992	0.0701
2	+ 1 hour	0.982	0.1515
3	+ 2 hours	0.957	0.3299
4	+ 4 hours	0.852	1.0533

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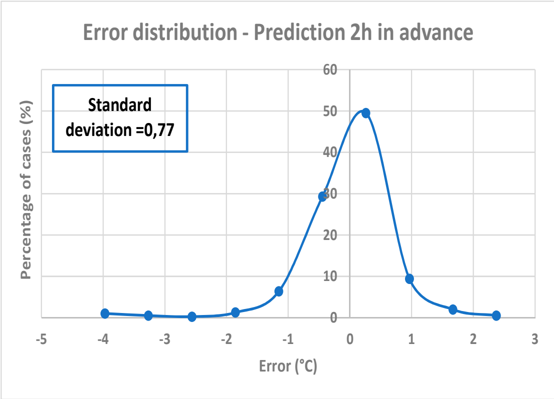
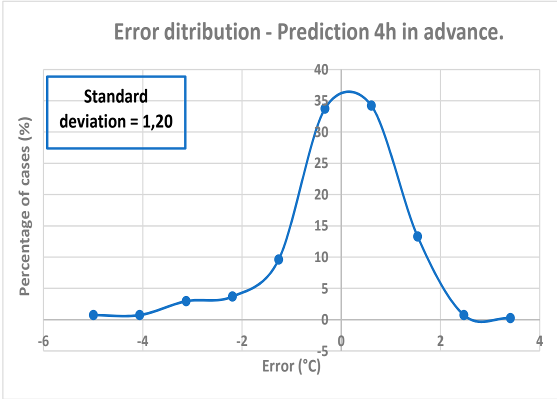


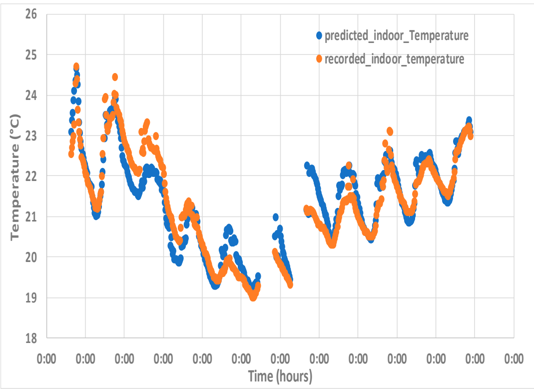


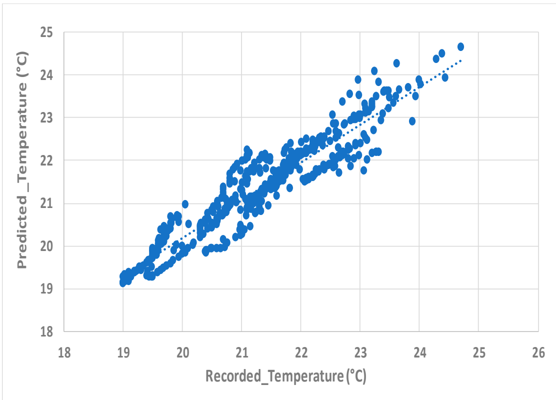
(a) (b)

Figures 11. Distribution of error forecasting (Input parameter = Outdoor temperature and 3h façade temperature): (**a**) prediction for 2h; (**b**) prediction for 4h.

4.3 Indoor temperature forecasting (room center)

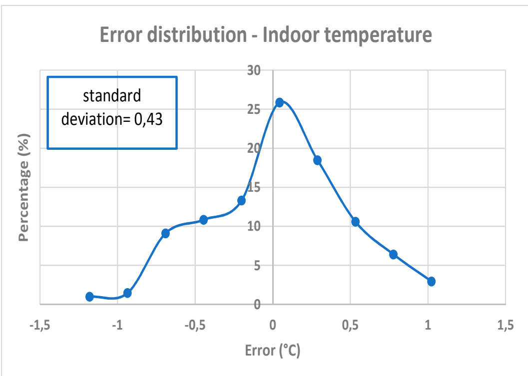
The ANN approach is used for forecasting the temperature at the room center considering only the façade temperature as input parameter. Figure 12 shows a comparison of "predicted" and "recorded" indoor temperatures. A good agreement is observed between recorded temperature and ANN prediction: R =0.951; MSE=0.1679. Only 1% of data have a mean absolute error greater than 1° C (Figure 13).





(a) (b)

Figure 12. Predicted and recorded indoor temperatures: (**a**) Variation of both temperatures in time domain; (**b**) Predicted indoor temperature with the recorded indoor temperature.



Figures 13. Distribution of error forecasting for indoor temperature (input parameters = façade temperature).

5. Conclusion

The purpose of this article is to forecast the indoor temperature through a simplified ANN-based model to optimize the control of energy building devices. Two ANN models were developed for forecasting the façade indoor temperature and the temperature in the office center, respectively. Analysis of the relevance of input parameters shows that some input parameters can be neglected in the forecasting model (solar radiation, humidity and historical outdoor temperature) and that the façade temperature could be predicted with a good precision in considering only the outdoor temperature and the historical data of the façade indoor temperature. Forecasting the façade temperature, using the outdoor temperature as inputs has good performances for 0.5h and 1h predictions, but lower performances for 2h and 4h forecasting. The façade temperature forecasting is improved when adding 3 hours façade temperature history as input. Analysis shows that the ANN approach can effectively forecast the temperature at the room center considering only the façade temperature as input parameter.

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