future internet

Article

Use of Machine Learning Methods for Indoor Temperature Forecasting

Lara Ramadan [1,2], Isam Shahrour [1,*], Hussein Mroueh [1] and Fadi Hage Chehade [2]

[1] Laboratoire Génie Civil et Géo-Environnement, University Lille, IMT Lille Douai, JUNIA Hauts de France, ULR 4515–LGCgE, F-59000 Lille, France; lara.ramadan@univ-lille.fr (L.R.); hussein.mroueh@univ-lille.fr (H.M.)
[2] Modeling Center, Doctoral school of Science and Technology and Faculty of Technology, Lebanese University, Hadath 99000, Lebanon; fchehade@ul.edu.lb
* Correspondence: isam.shahrour@univ-lille.fr

Abstract: Improving the energy efficiency of the building sector has become an increasing concern in the world, given the alarming reports of greenhouse gas emissions. The management of building energy systems is considered an essential means for achieving this goal. Predicting indoor temperature constitutes a critical task for the management strategies of these systems. Several approaches have been developed for predicting indoor temperature. Determining the most effective has thus become a necessity. This paper contributes to this objective by comparing the ability of seven machine learning algorithms (ML) and the thermal gray box model to predict the indoor temperature of a closed room. The comparison was conducted on a set of data recorded in a room of the Laboratory of Civil Engineering and geo-Environment (LGCgE) at Lille University. The results showed that the best prediction was obtained with the artificial neural network (ANN) and extra trees regressor (ET) methods, which outperformed the thermal gray box model.

Keywords: energy efficiency; prediction; indoor temperature; machine learning; gray box model

Citation: Ramadan, L.; Shahrour, I.; Mroueh, H; Chehade, F.H. Use of Machine Learning Methods for Indoor Temperature Forecasting. *Future Internet* **2021**, *13*, 242. https://doi.org/10.3390/fi13100242

Academic Editor: Efstathios Stamatatos

Received: 29 August 2021
Accepted: 17 September 2021
Published: 23 September 2021

1. Introduction

Improving buildings' energy efficiency is a priority area for progress. The design and the implementation of efficient energy management strategies to balance energy consumption and occupant comfort have a particular interest in this domain. The indoor temperature is a major key to such a strategy, being one of the most critical parameters affecting energy consumption and personal comfort. In this context, predicting the indoor temperature is an essential task.

Temperature forecasting has been considered an interesting subject, widely studied in the literature [1–4]. Moreover, it has also been integrated into predictive control models, developed to optimize energy devices [5,6].

The estimation of indoor temperature has been tackled with different approaches, classified according to their foundations in two main categories: the physical approach and the data-driven approach [7]. Physical modeling uses detailed equations based on physical engineering principles [8]. This approach requires thorough knowledge of the overall structure of the building, its components, and energy systems and has a reasonably high computational cost [8–10]. The data-driven approach allows the dynamic system to be written in purely mathematical relations expressing the output data as a function of the input data. The adopted mathematical functions can have a physical meaning; it is then a gray box model, or they may not carry any physical sense, and the model will then be known as a black box.

The black box model forgoes the need for detailed input data of the simulated building and focuses on learning from the available historical data [11]. This approach has been used in a wide variety of building energy performance applications. It has proven its applicability in the modeling of building thermal behavior [12] as well as the forecast of the energy consumption [13–15] and the energy demand of buildings [16,17].

Machine learning methods, a branch of artificial intelligence (AI), are considered an effective tool for black-box modeling. In the past decade, these algorithms have experienced remarkable progress [18]. They have offered a promising pathway for the development of prediction models [19]. Scholars have reported their application in the energy prediction of buildings due to their ability to overcome the limits encountered by existing models [20–23].

Several AI-based techniques have been used to improve buildings' energy performance. The study conducted in [24] tested the capacity of various AI-based algorithms (ANN, fuzzy logic ((FL)), and adaptive neuro-fuzzy inference systems (ANFIS)) to control the thermal conditions and optimize heating loads in double-skin buildings. The study results showed that the selection of the optimal algorithm depends on the objective of the control strategy. ANN was the most suitable energy-saving strategy, while the others were more adapted to thermal comfort strategies. Cotrufo et al. [23] proposed a methodology for the development of an AI-based model for the thermal control of institutional buildings. The results showed that the Gaussian process regression (GPR) outperformed the ANN, support vector machine (SVM), decision tree (DT), and random forest (RF) models.

Sholuhadin and Han [25] used two ANN models to predict hourly heating loads using fewer meteorological parameters. Li et al. [26,27] applied an SVM-based model to predict the hourly cooling load of an office building. The developed model outperformed the back propagation neural network (BPNN) and the radial basis function neural network (RBFNN) techniques. Chammas et al. [22] developed a system based on a multi-layer perception neural network (MLP) to predict energy consumption using data collected from wireless sensors in a two-story building. Compared to four algorithms (linear regression, SVM, RF, and gradient boosting (GB)), the model had improved performance. This model, enhanced with deep learning capabilities, has also outperformed SVM, LR, regression trees (RT), ensemble boosting, and GPR in predicting buildings' aggregated energy demand [28]. In [29] a DT algorithm showed its ability to predict the energy demand of a residential building accurately. Wang et al. [30] demonstrated the superiority of the RF algorithm compared to the RT and the support vector regressor (SVR) methods.

Mba et al. [20] demonstrated that ANN is a powerful modeling tool for hourly forecasting of indoor temperature and other thermal parameters in modern buildings one day to one month in advance using only the twelve last indoor and outdoor air temperature and relative humidity values. Özbalta et al. [31] developed ANN and multiple regression models to predict the daily indoor temperature and relative humidity in an educational building. The study showed that the ANN successfully predicted the thermal parameters and outperformed the multiple regression model. Considering the capacity of the ANN method to deal with time-series data, it has also been used in [32] to predict the indoor temperature in an institutional building. The study highlighted the importance of selecting the relevant input parameters and a suitable training algorithm to improve the prediction results. Potočnik et al. [33] conducted short-term prediction of indoor temperature using three ML methods (NN, autoregressive models with exogenous inputs (ARX), and extreme learning machine models ((ELM)). The NN model achieved the best prediction. Results also showed that the use of future weather data improves prediction performance. Qi et al. [21] showed that using SVR effectively predicts the indoor temperature of an office building and that it is more accurate than BPNN. The study carried out by Mateo et al. [34] confirmed the validity of several linear (autoregressive methods and robust multiple linear regression) and non-linear techniques (ELM and non-linear autoregressive exogenous multilayer perceptron) for predicting indoor temperature. Paul et al. [35] used an approach combining the Internet of Things (IoT) and ML methods to predict the indoor temperature in a smart building. Results showed that the RF, SVM, and NN methods gave accurate results. Aguilera et al. [36] showed the accuracy of a thermal model based on a DT algorithm using the weather data and occupants' feedback to predict the indoor temperature.

The gray box model involves both physical and black-box modeling [37]. This approach is based on the thermal modeling of buildings by analogy with an electrical resistance-capacity circuit [38]. The buildings are modeled by a set of dynamic differential equations representing the phenomenon of conduction, convection, and capacitive phenomenon. Several scholars used this approach in research about building energy efficiency. Berthou et al. [17] tested the capacity of four gray box models to predict heating and cooling demands of a multi-zone occupied office building to determine the best model architecture. The results showed that a second-order model was able to well represent the thermal behavior of the office building. Cui et al. [3] developed a hybrid model to predict the average temperature in two-story houses. Tests conducted on the 24 h data horizon gave satisfactory results. Ogunsola et al. [39] created a time-series model to estimate the indoor temperature's real-time cooling load. Two gray box models were combined for the building envelope and the internal thermal mass. The relevance of the model was checked on light, medium, and heavy constructions. A reasonably high degree of precision was obtained for the studied cases.

The studies mentioned above focused on using either the machine learning technics or the gray box approach for the thermal building modeling. This paper presents a comparison of the performances of a set of data-driven models in these two categories.

The remainder of this paper is organized as follows: Section 2 outlines the research methodology and material; Section 3 presents and discusses the prediction results., Section 4 summarizes the conclusions and highlights the primary outcome of this research.

2. Methodology and Materials

2.1. Methodology

This research aimed to compare the ability of different ML algorithms and a gray box model to predict indoor temperature. During this investigation, data on the thermal environment were first collected from a heating experiment in a closed room in the LGCgE laboratory using an intelligent monitoring system. The recorded datasets served as a basis for the development and training of ML algorithms, and the evaluation of their predictive performance in terms of root mean square error (RMSE) and coefficient of determination (R^2). For detailed information about the dataset see the Supplementary Materials.

A gray box model was also established and compared to the ML algorithms to cover the statistical and hybrid aspects of data-driven modeling.

Figure 1 summarizes the methodology applied in this study. More explicit descriptions of the experiment, intelligent algorithms, and evaluation criteria are presented below.

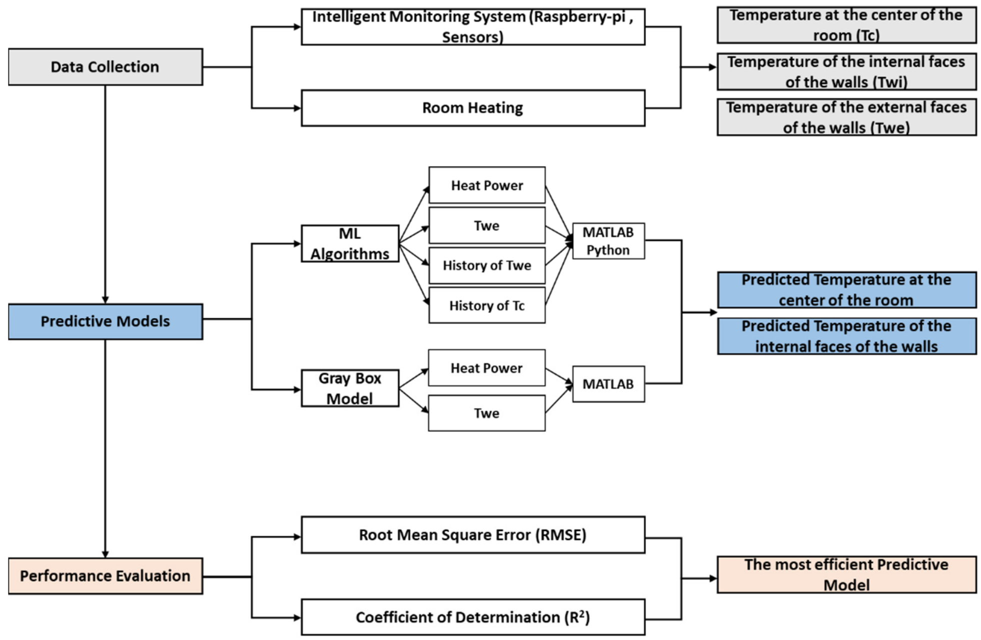

Figure 1. Research Methodology.

2.2. Material

The study was conducted in an unoccupied closed room in the LGCgE Laboratory at Lille University. The closed room has an area of 9 m^2 and a height of 2.3 m. It is furnished and does not have a facade or windows (Figure 2).

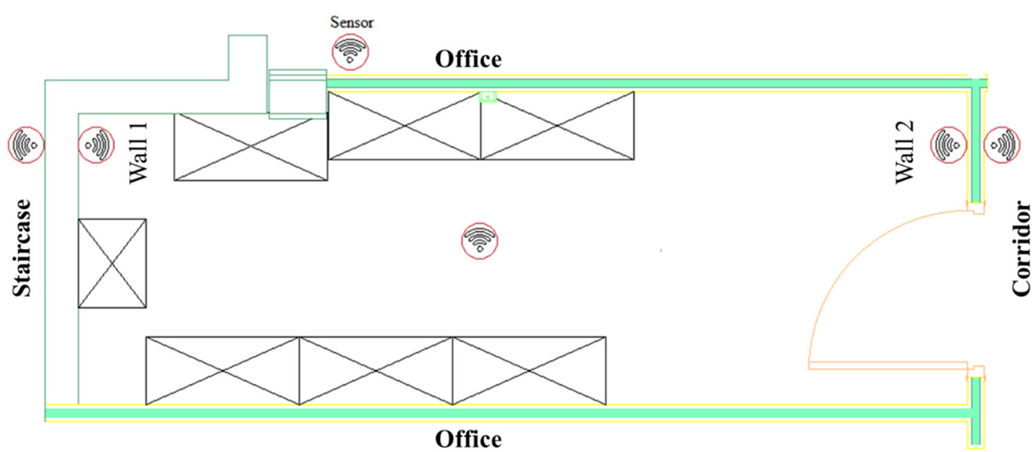

Figure 2. Reference room in LGCgE laboratory.

To model the thermal environment of the room, an intelligent monitoring system composed of a wireless network sensor connected to a micro-computer (Raspberry-pi) was implemented.

The main objective of these sensors was to track indoor comfort parameters. They provided measurements of four environmental variables: temperature, humidity, luminosity, and noise (THLN). In our work, we focused on the temperature readings. Sensors were installed as shown (Figure 2) on the internal and external faces of the walls of the room and another sensor was suspended at the center to assess the indoor temperature. A standard methodology for monitoring cannot be found in the scientific literature. Therefore, the number of sensors and their positions were based on empirical approaches

[40]. However, several studies have developed models to determine the optimal location of sensors to control energy consumption and thermal comfort [41–43]. In this research, the position of the thermal sensors was determined based on a study carried out in the LGCgE laboratory about the optimal sensor position that can provide representative data of the indoor room environment. Therefore, a sensor was suspended through a wire in the center of the room at a height of 1.5 m above the ground. The position of the sensors recording the temperature of the internal and external faces of the walls was determined based on the manufacturer's recommendations [44]. Two sensors per wall were installed on the internal and external faces of the walls in a neutral zone at the same height above the ground (1.5 m).

Reliability analysis of the sensors was carried out before their use. A set of sensors was located at the same position. Based on the obtained temperature profiles, these were classified into four groups (Figure 3). The maximum temperature difference between these groups, shown in Figure 4 (0.4 °C), did not exceed the precision range set at 0.4 °C. These results confirm the reliability of the sensors and their use in the experiments carried out.

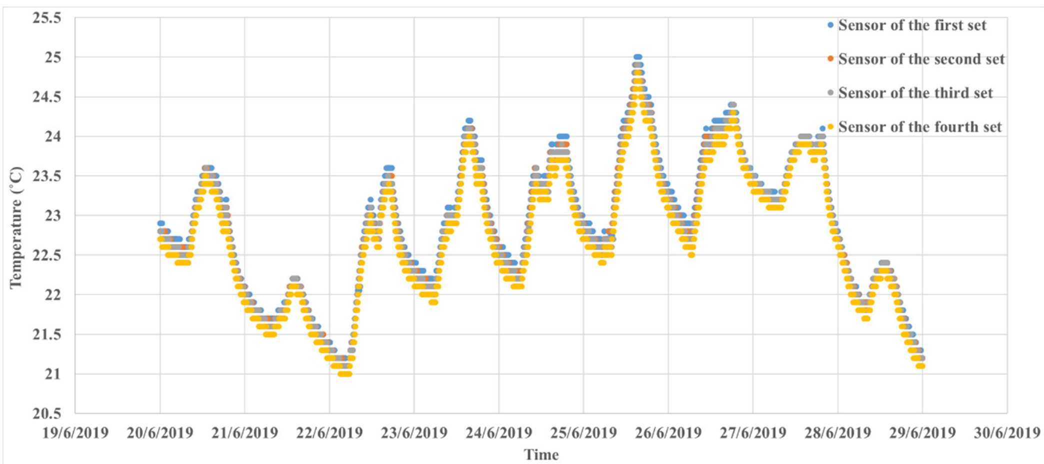

Figure 3. Recorded data by groups of sensors located at the same position.

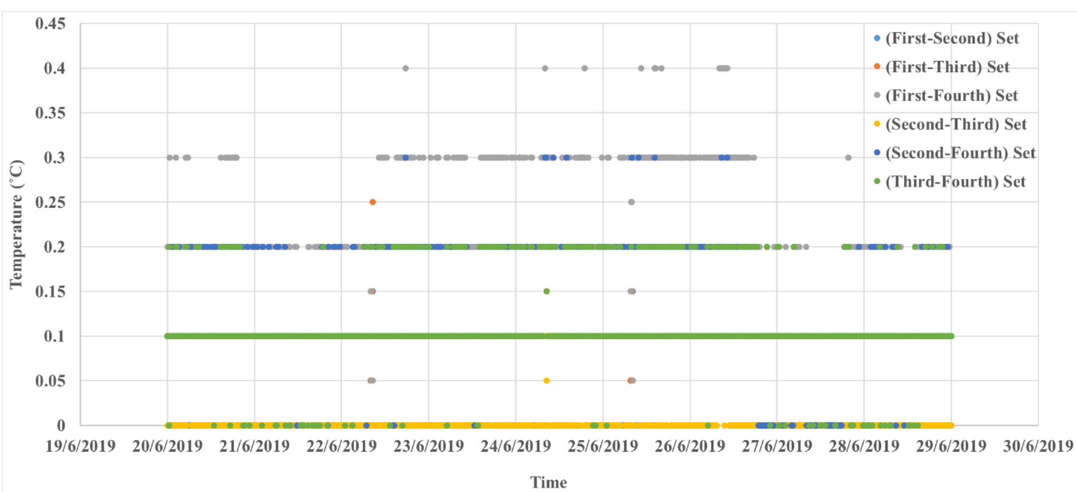

Figure 4. Temperature difference for the groups of sensors located at the same position.

The closed room was heated using a 2000 W power radiator for several hours. The temperatures at the center and on the walls, recording measurements at an interval of 10 min during the experiment, served as a dataset for the applied thermal algorithms.

Data were checked before their use in numerical modeling for the identification of missing data or abnormal values. Missing data were identified easily since data were recorded at a given time interval. Abnormal values were identified if they exceeded maximum expected values. In these two cases, data were identified and reported as unacceptable data. Since our experiments were conducted in controlled conditions, collected data were exempt from missing data or abnormal values. In the future, techniques based on machine learning will be used to identify and treat missing data and abnormal values.

The variation of these parameters, as well as the heating period, are illustrated in Figure 5.

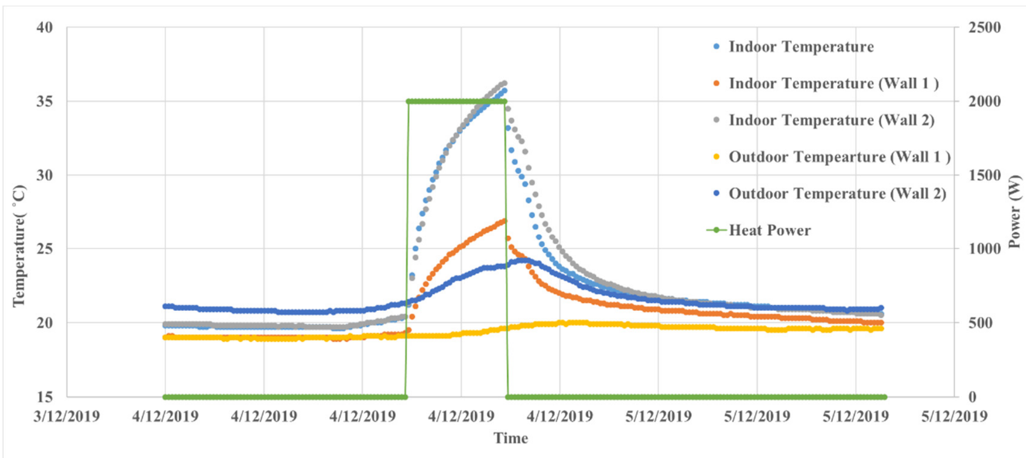

Figure 5. Recorded parameters of the heating experiment.

2.3. Selection of Predictive Models

In this study, a set of AI-based algorithms and a gray box model were compared to identify the most suitable model to predict the indoor temperature of the room. Furthermore, these models were evaluated according to their forecast accuracy and their performance. A detailed description of the adopted models will be presented below.

2.3.1. ML Methods

A variety of ML algorithms are found in the literature. Some of these algorithms (Table 1) have been frequently used and have shown reliable results in predicting buildings' thermal and energy variables.

Table 1. Machine learning-based thermal prediction.

Reference	Predicted Variables	ML Algorithms	Input Variables	Data Source	Key Finding	Performance Evaluation
[9]	Building energy needs	Multiple linear regression (MLR)	Cooling and heating degree day, external temperature, shape factor, opaque surface, and surface of glazed component	Non-residential building stock	MLR is a promising alternative in the field of building energy performance	Mean absolute error (MAE), mean square error (MSE), RMSE, R^2, mean absolute percentage error (MAPE)
[22]	Energy consumption	MLP, LR SVM, GB RF	Meteorological data, temporal data, appliances,	Two story building	MLP outperforms all other models	R^2, RMSE, MAE, MAPE

			and light energy consumption			
[45]	Indoor temperature	MLP, radial basis function (RBF), group method of data handling (GMDH)	Solar irradiation, environmental temperature, outdoor relative humidity, wind speed, working hours, and occupancy	Laboratory of a university	MLP achieved the highest estimations	Coefficient of correlation, RMSE
[46]	Next day daily peak demand and consumption	MLR, RF MLP, boosting tree (BT) SVR, K-nearest neighbors (K-NN), multivariate adaptive regression splines (MARS) autoregressive integrated moving average (ARIMA)	Building power consumption, meteorological data, time of observations,	High-class skyscraper	The ensemble model produces better generalization performance	MAPE, RMSE, MAE, R^2
[47]	Comfort index	LR, DT, RF, GB, naive Bayes (NB), Logistic regression (LoR) ANN, SVM K-NN adaboost (AB)	Indoor environment, meteorological data, personal factors, building information	ASHRAE global thermal database	RF model has shown better prediction accuracy	MSE, R^2 accuracy
[48]	Heating and cooling loads	RF,ET,GB	Building features	12 buildings typologies	Tree-based ensemble learning is able to accurately model and predict building loads	MSE, MAE, MAPE
[49]	Hourly HVAC energy consumption	ANN, RF	Meteorological data, time of observations, number of guests for the day, number of rooms booked	Hotel in Spain	Both models have comparable predictive power	Mean absolute percentage deviation (MAPD), median absolute deviation(MAD), MAPE, coefficient of variation of root mean square error (CV-RMSE),R^2
[50]	Heating energy consumption	RF, GB SVR extreme gradient boosting (XGB)	Meteorological data, occupancy data, time of day, historical heating consumption	Residential quarter	XGB exhibits the optimal efficiency RF exhibits optimal average accuracy The robustness of RF is the highest	RMSE,MAPE MAE,CV-RMSE

An artificial neural network (ANN) is a system whose functioning is inspired by the neurons of the human brain. Multi-layer perception (MLP) is the most popular structure among the forwarding propagation methods in ANN and has been the subject of several types of research. MLP has an input layer, an output layer, and a hidden layer in which each neuron is connected to the mentioned layers. This architecture has been used as a powerful method to predict the indoor temperature and energy consumption of buildings [22,45,51] and assess the occupants' thermal comfort [52,53]. This research started with an MLP model with one hidden layer and four neurons. This number was selected after a set of tests conducted with several neurons ranging from 4 to 10. The study conducted in [51] also supports this number. The training process was carried out by considering the Levenberg–Marquardt algorithm, which has proven to be effective with convergence towards a minimal root mean square [52,53]. The transfer function sigmoid was used for the hidden layer, while a linear transfer function was used for the output layer. Several tests were carried out to obtain a reliable prediction. These tests were characterized by similar training times. The best prediction was obtained for a test with 32 epochs and four neurons in the hidden layer. Appendix A summarizes the different tests conducted to estimate the number of neurons and to obtain the best prediction performance.

Multiple linear regression (MLR) is a mathematical regression method that extends simple linear regression. It has demonstrated its ability to solve complex problems, in particular a building's energy balance and energy planning [9], daily peak demand and consumption [46], and annual energy consumption [54].

A decision tree (DT) is a technique based on partitioning the dataset into groups in the form of a flowchart. This technique has been widely used in predicting buildings' energy consumption [14,55] and user comfort indices [47], as well as modeling buildings' energy demands [56].

Ensemble learning has also been applied in monitoring building energy performance, especially bagging and boosting algorithms.

Random forest (RF) and extra trees (ET) are representative techniques of the bagging family, which combine a multitude of decision trees. These algorithms have proven their efficiency in predicting a building's cooling and heating loads [48] and energy consumption [49,57], as well as personal thermal comfort [58,59].

Gradient boosting (GB) and extreme gradient boosting (XGB) methods also belong to the ensemble learning method. Their basic idea is to combine several simple models called weak learners to obtain a strong model with an improved prediction error. These methods appeared as a promising alternative in the domain of building energy efficiency. Several studies have confirmed their effectiveness in predicting energy consumption [50,60] and building energy loads [48,61], establishing predictive energy models [62] as well as detecting faults in HVAC systems [63].

These supervised ML algorithms were selected in this research due to their popularity. The dataset was divided into two subsets to train and test the chosen algorithms. The 70% and 80% training proportions are most often used in the literature [46–48,64,65]. To determine the most appropriate ratios for the dataset, values ranging from 50% to 80% were tested in this study. The results confirmed the use of the two proportions mentioned above. Similar performances in terms of RMSE and R^2 were observed for these proportions (see Appendix B).

ANN modeling was conducted using the neural network toolbox in MATLAB-based software, considering a dataset divided into 70% for training, 15% for validation, and 15% for testing. All the other algorithms were developed based on the python statistical computation language. The hyper-parameters were maintained at their default values, considering a dataset distribution of 70% for training and 30% for testing.

The input and output variables used for the models are summarized in Table 2. The temperature history is a matrix of parameters with a difference of 30 min between its different columns. For example, if the temperature was recorded at a time t, the history corresponds to t-0.5h, t-1h, t-1.5h, and t-2h.

Table 2. Input and output parameters of the ML methods.

Input Parameters	Output Parameters
Heat Power	Indoor Temperature (at the center)
Outdoor Temperature Wall 1	
Outdoor Temperature Wall 2	Indoor Temperature Wall 1
Outdoor Temperature History Wall 1	
Outdoor Temperature History Wall 2	Indoor Temperature Wall 2
Indoor Temperature History	

The accuracy of these forecasting models was evaluated, and their performances were compared based on the following criteria:

The root mean square error (RMSE) that can provide information on the magnitude of the deviations [3,65,66]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n}} \tag{1}$$

The coefficient of determination (R^2) that can be a measure of the adequacy between the predicted and the observed data [16,52,55]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{2}$$

where $\hat{y}$ is the predicted vector, y is the reference vector, and n is the number of parameters.

2.3.2. Gray Box Model (GBM)

Hybrid models have been the subject of numerous studies. They have been widely used in the field of predictive control [67–69] as well as in the area of predicting building thermal load [70,71] and indoor temperature forecasting [3]. The most common method for creating this model is applying a resistance-capacity (RC) form based on physical and statistical approaches [38,72–74]. The thermal resistance R represents the component to resist the heat flux, and the thermal capacity C describes its storage capacity.

In this work, a simplified (RC) model (Figure 6) was developed to thermally model the considered room.

(T_1, T_2) are the respective outdoor and indoor temperatures of the first wall, (T_5, T_4) the respective outdoor and indoor temperatures of the second wall, and T_3 the indoor air temperature. Q_h is the heat source power.

[Q_h T_1 T_5] and [T_2 T_3 T_4] represent the RC model's input and output vectors, respectively.

The model's parameters (R_1, C_1), (R_2, C_2), and (R_3, C_3) respectively designate the thermal resistance and capacity of the first wall, the indoor air, and the second wall.

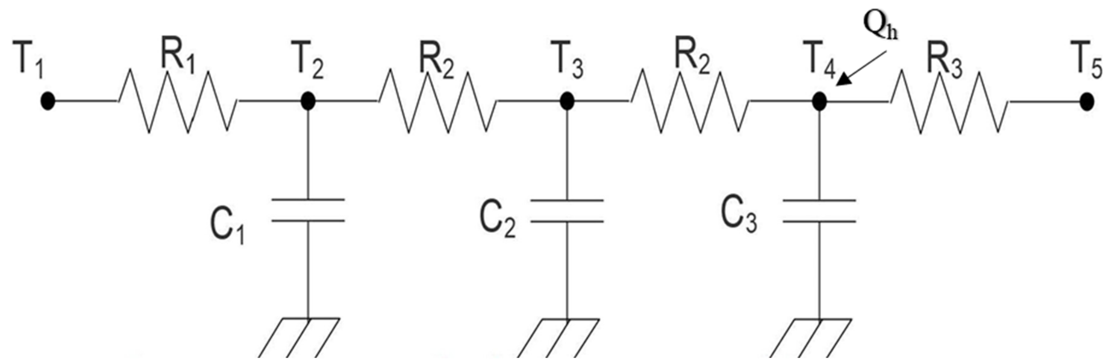

Figure 6. 3R3C room model.

The model can be expressed as a linear stochastic differential equation written into a matrix form for state-space representation by applying Kirchoff's balance laws to the circuit [75]. In addition, it includes a state equation and an output equation:

$$\begin{Bmatrix} \dot{T} = AT + BU \\ Y = CT + DU \end{Bmatrix} \tag{3}$$

The T vector contains the node temperatures, U the controllable inputs and disturbances, Y the measured output; A, B, C, D matrices have the RC parameters to be identified.

As for the parameters of the models, they are determined using the grayest function in MATLAB. The initial values of (R_2, C_2) and (R_1, R_3) were selected by applying the French thermal code (RT 2005-2012), while those of (C_1, C_3) were estimated based on the equations characterizing the walls mentioned in the building thermal code [66,76] (see Appendix C).

3. Results and Discussion

The tested algorithms' performance has been evaluated using the coefficient of determination (R^2), and the root mean square error (RMSE). The obtained values are illustrated in Table 3. This part focuses on the results of the prediction of the temperature at the center of the room only, since similar results were obtained for the prediction of the temperature of the internal faces of the walls.

Table 3. Prediction performance of predictive models.

ML Algorithms	RMSE	R^2
ANN	0.081	0.99965
MLR	0.332	0.99415
DT	0.268	0.99618
RF	0.295	0.99539
ET	0.159	0.99864
GB	0.218	0.99748
XGB	0.229	0.99721
GBM	0.842	0.96237

The used ML algorithms have been sorted in decreasing order based on their performance in each experiment, in other words, by increasing RMSE and decreasing R^2, as shown in Figure 7.

The proposed algorithms have shown their efficiency in the prediction of the indoor temperature of the room, given the values of the performance indices (RMSE <1 and R^2 > 0.8) [47,77]. Even though these algorithms seem powerful, they do not all have the same prediction accuracy. In fact, the best result for predicting the indoor temperature was provided by the ANN (RMSE = 0.081 and R^2 = 0.99965) and ET (RMSE = 0.159 and R^2 = 0.99864) algorithms. Boosting algorithms (GB and XGB) have shown fairly close performance. DT, RF, and MLR were less high performing than the previous algorithms despite the acceptable values of the performance criteria.

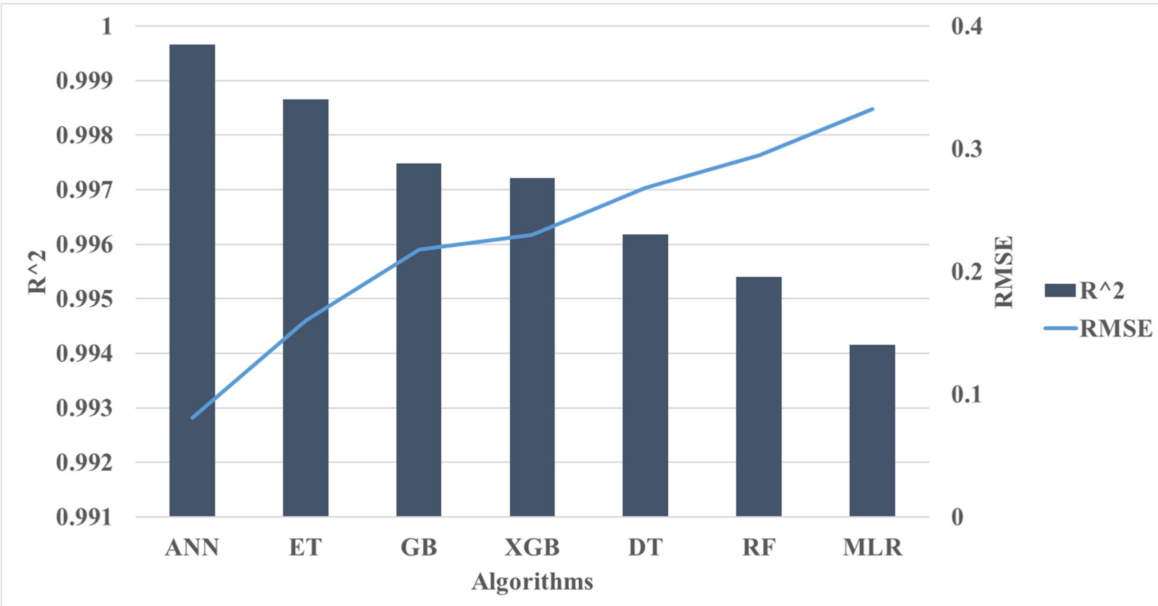

Figure 7. Performance criteria of ML algorithms (RMSE and R^2 coefficient).

The RC model also exhibited acceptable values of performance criteria (RMSE <1 and R^2 > 0.8). These are compared to those of the ML algorithms in Figure 8, which illustrate the ranking of the gray box model against the lower- and the best-performing ML algorithms. This figure shows that the AI-based algorithms outperformed the gray box model in predicting the indoor temperature. The lower-performing algorithm MLR (Figure 6) showed improved performance criteria values (RMSE = 0.332 and R^2 = 0.99415) compared to those of the RC model (RMSE = 0.842 and R^2 = 0.96237).

The results of this research were compared to other investigations in the literature. [65] compared the performance of 20 families of ML methods in predicting the indoor temperature of an intelligent building. The ET algorithm provided the best performances. This research partially agrees with this study: the ET method was among the best performing methods, but the ANN model outperformed the ET method. Wang and Chen [78] compared three data-driven models, a linear black-box model (ARX), a non-linear black-box model (ANN), and a gray box model in predicting the indoor temperature of a single-zone house. The performance of the gray box model was intermediate between the other two models. Our research also confirms the improved performance of the ANN and the linear black-box models over the gray box model. Indeed, in our study, even the simple MLR model outperformed the gray box model.

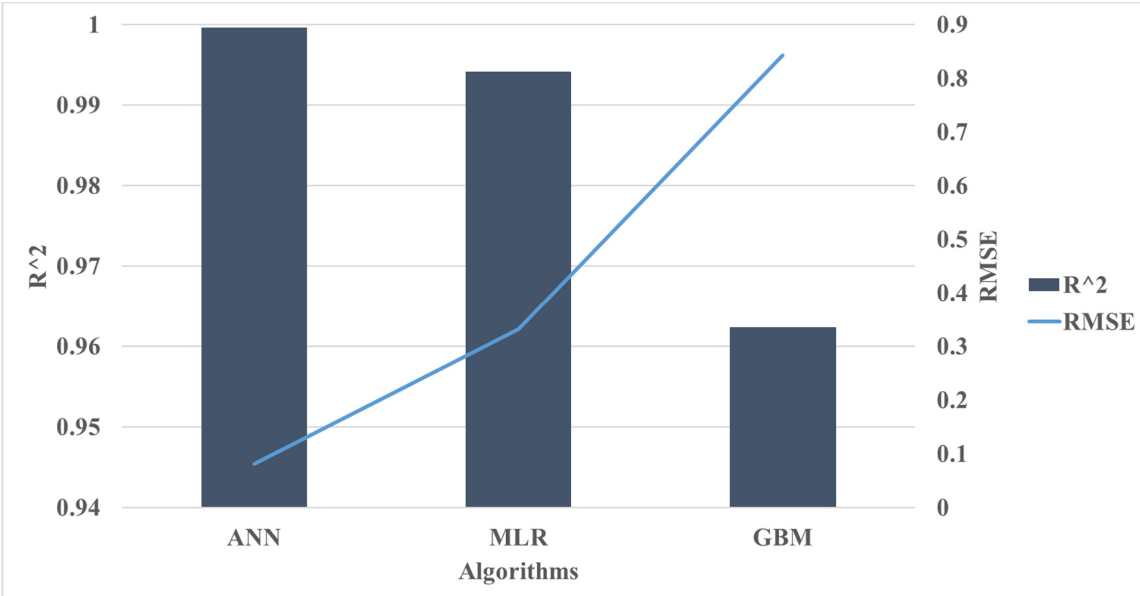

Figure 8. Data-driven models' performance comparison.

Our study compared the two aspects of the data-driven approach (black and gray box models) on their abilities to provide a reliable prediction of indoor temperature. It employed emerging predictive models in a straightforward manner using a limited number of input parameters necessary to achieve accurate prediction results. The obtained results were based on a heating experiment conducted in a closed room in a laboratory environment. This comparison is helpful as it provides a preliminary idea of the most relevant model in indoor temperature prediction that can be employed in energy system management strategies aimed at improving the energy performance of existing buildings.

Although the obtained results are exciting and some are confirmed by other research, this research has some limitations, which are related to the conditions of the experimentation. Indeed, the prediction of the indoor temperature was limited to the use of the following input parameters: heat power, outdoor wall temperatures, and indoor temperature history. In the future, this approach could be generalized by integrating additional input parameters such as the occupants' behavior and the building exposure. The case study in this work was done in a room that was unoccupied and has no facade. This can be viewed as a limitation of this study due to the additional input parameters, whose influence on the models needs to be investigated. The use of variables related to the occupancy and exposure of the room might be necessary to establish a more generalized approach.

4. Conclusions

Forecasting indoor temperature in buildings constitutes a central task in the optimal energy control in buildings and ensuring comfort and health conditions for users. This prediction combines technical parameters such as building characteristics and their energy system, environmental parameters such as the outdoor temperature and humidity, and social parameters. Considering these techno-social issues in the thermal modeling of buildings requires advanced methods such as machine learning methods. In addition, the consideration of complex building assets and the integration of unstructured data such as those recorded by cameras requires the use of Big Data tools. This paper contributes to the first objective by comparing AI-based technics and a gray box model to predict indoor temperature. This subject is helpful for the assessment of thermal comfort conditions and for reducing energy consumption.

The analysis was conducted on temperature datasets collected in a closed room of the LGCgE laboratory at Lille University using MATLAB and python statistical computation language simulations.

The adopted models exhibited a favorable prediction capacity in terms of root mean square error (RMSE < 1) and coefficient of determination ($R^2 > 0.8$). Among these models, ANN and ET emerged as the most suitable algorithms for indoor temperature forecasting, thus surpassing the other ML algorithms and the gray box model. These algorithms were followed by the boosting algorithms that exhibited approximately similar behavior. This research shows that a simple AI-based model could provide accurate forecasting of indoor temperature. It also offers an idea of the effective predictive models to be used in energy management strategies.

However, more efforts should be considered in the future to improve the research findings. In addition, this research should be extended to other data collected from other experimentations operating under various conditions with additional parameters such as occupancy and buildings' exposure. The use of these different data will help generalize the results of this research and their use in practical applications.

Furthermore, we suggest extending this research to the prediction of the operative temperature. Indeed, although the air temperature is the commonly used parameter in the control of energy systems, the international standards use the operative temperature for the thermal comfort control.

Supplementary Materials: The supplementary dataset can be seen at www.mdpi.com/article/10.3390/fi13100242/s1.

Author Contributions: Conceptualization, L.R, I.S.; methodology, L.R, I.S.; validation, L.R., I.S.; formal analysis L.R. Investigation, L.R. writing—original draft preparation, L.R. writing—review and editing, L.R., I.S.; supervision, I.S., H.M., F.H.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not Applicable, the study does not report any data.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Prediction performance of ANN based on the number of epochs and neurons.

Neurons	Epochs	RMSE	R^2
4	12	0.274	0.996
	16	0.311	0.99487
	18	0.244	0.9968
	22	0.222	0.99738
	26	0.143	0.99891
	29	0.142	0.99893
	32	0.081	0.99965
	37	0.117	0.99927
	43	0.179	0.99829
	54	0.41	0.9911
	59	0.257	0.99648
	62	0.1	0.99946
	82	0.211	0.9976
	94	0.095	0.99952
	139	0.191	0.9981
5	9	0.327	0.99433
	11	0.244	0.99685
	15	0.219	0.99745
	21	0.351	0.99349
	26	0.172	0.99843
	30	0.279	0.99587

	41	0.0806	0.99965
	57	0.146	0.99886
	61	0.251	0.99665
	87	0.326	0.99436
6	11	0.303	0.99513
	16	0.165	0.99854
	20	0.158	0.99866
	25	0.152	0.99878
	28	0.148	0.99883
	34	0.358	0.99317
	43	0.235	0.99705
	73	0.151	0.99879
	81	0.231	0.99714
	159	0.311	0.99487
7	13	0.291	0.9955
	17	0.085	0.99961
	20	0.206	0.99774
	24	0.317	0.99467
	28	0.175	0.99836
	32	0.181	0.99826
	49	0.218	0.9974
	91	0.121	0.99921
	120	0.11	0.99935
8	15	0.278	0.9959
	19	0.265	0.99627
	23	0.234	0.99711
	33	0.167	0.99851
	41	0.229	0.99722
	55	0.352	0.9934
	69	0.213	0.9976
	74	0.123	0.99919
	111	0.239	0.99697
9	14	0.135	0.99903
	19	0.12	0.99923
	25	0.229	0.99722
	28	0.217	0.9975
	38	0.282	0.99578
	43	0.243	0.99684
	55	0.131	0.9991
	73	0.166	0.99853
10	12	0.165	0.99854
	14	0.089	0.99957
	19	0.161	0.99831
	27	0.277	0.99591
	31	0.265	0.99627
	53	0.266	0.99623
	66	0.178	0.99831
	72	0.3202	0.99456

Appendix B

Table A2. Prediction performance based on training proportion.

	50%		60%		70%		80%	
	RMSE	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**
ANN	0.248	0.99672	0.235	0.9971	0.081	0.99965	0.059	0.99981
MLR	0.347	0.99359	0.336	0.99398	0.332	0.99415	0.331	0.99419
DT	0.52	0.98561	0.332	0.9945	0.268	0.99618	0.237	0.99702
RF	0.395	0.99171	0.353	0.99337	0.295	0.99539	0.278	0.99589
ET	0.198	0.99791	0.166	0.99852	0.159	0.99864	0.139	0.99898
GB	0.297	0.99531	0.269	0.99614	0.218	0.99748	0.191	0.9981
XGB	0.304	0.9951	0.282	0.99578	0.229	0.99721	0.219	0.99743

Appendix C

The heat balance at each node of the room model is described using the following set of first-order differential equations.

$$C_1 \frac{dT_2}{dt} = \frac{T_1 - T_2}{R_1} + \frac{T_3 - T_2}{R_2} \tag{A1}$$

$$C_2 \frac{dT_3}{dt} = \frac{T_2 - T_3}{R_2} + \frac{T_4 - T_3}{R_2} \tag{A2}$$

$$C_3 \frac{dT_4}{dt} = \frac{T_3 - T_4}{R_2} + \frac{T_5 - T_4}{R_3} + Q_h \tag{A3}$$

The initial values of (R_1, C_1), (R_2, C_2), and (R_3, C_3) were determined using the following equations:

$$R_2 = \frac{1}{h_{\text{int}} \times S_{\text{int}}} \tag{A4}$$

where h_{int} is the coefficient of internal convection, and S_{int} is the internal exchange surface.

$$C_2 = \rho_{air} \times C_{air} \times V_{\text{int}} + Mob \times S_h \tag{A5}$$

where ρ_{air} is the air density, C_{air} air mass capacity, V_{int} indoor air volume, *Mob* is the impact of the furniture on the air capacity, and S_h is the heated surface.

$$R_1, R_3 = \left(R_{si} + \frac{e}{\lambda} + R_{se} \right) \times \frac{1}{S} \tag{A6}$$

where R_{si} and R_{se} are the wall's inner and outer surface resistances, respectively, e is the depth of the wall, S its surface, and λ its thermal conductivity.

$$C_1, C_3 = m \times C_p \tag{A7}$$

where m is the mass of the wall and C_p is its specific heat.

References

1. Zamora-Martínez, F.; Romeu, P.; Botella-Rocamora, P.; Pardo, J. Online learning of indoor temperature forecasting models towards energy efficiency. *Energy Build.* **2014**, *83*, 162–172, doi: 10.1016/j.enbuild.2014.04.034.
2. Zamora-Martínez, F.; Romeu, P.; Botella-Rocamora, P.; Pardo, J. Towards energy efficiency: Forecasting indoor temperature via multivariate analysis. *Energies* **2013**, *6*, 4639–4659, doi:10.3390/en6094639.
3. Cui, B.; Fan, C.; Munk, J.; Mao, N.; Xiao, F.; Dong, J.; Kuruganti, T. A hybrid building thermal modeling approach for predicting temperatures in typical, detached, two-story houses. *Appl. Energy* **2019**, *236*, 101–116, doi: 10.1016/j.apenergy.2018.11.077.
4. Ruano, A.E.; Crispim, E.M.; Conceição, E.Z.E.; Lúcio, M.M.J.R. Prediction of building's temperature using neural networks models. *Energy Build.* **2006**, *38*, 682–694, doi: 10.1016/j.enbuild.2005.09.007.
5. Ferreira, P.M.; Ruano, A.E.; Silva, S.; Conceição, E.Z.E. Neural networks based predictive control for thermal comfort and energy savings in public buildings. *Energy Build.* **2012**, *55*, 238–251, doi: 10.1016/j.enbuild.2012.08.002.
6. Álvarez, J.D.; Redondo, J.L.; Camponogara, E.; Normey-Rico, J.; Berenguel, M.; Ortigosa, P.M. Optimizing building comfort temperature regulation via model predictive control. *Energy Build.* **2013**, *57*, 361–372, doi: 10.1016/j.enbuild.2012.10.044.
7. Zhao, Y.; Genovese, P.V.; Li, Z. Intelligent thermal comfort controlling system for buildings based on IoT and AI. *Future Internet* **2020**, *12*, 30, doi:10.3390/fi12020030.
8. Li, X.; Wen, J. Review of building energy modeling for control and operation. *Renew. Sustain. Energy Rev.* **2014**, *37*, 517–537, doi: 10.1016/j.rser.2014.05.056.
9. Ciulla, G.; D'Amico, A. Building energy performance forecasting: A multiple linear regression approach. *Appl. Energy* **2019**, *253*, 113500, doi: 10.1016/j.apenergy.2019.113500.
10. Amasyali, K.; El-Gohary, N.M. A review of data-driven building energy consumption prediction studies. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1192–1205, doi:10.1016/j.rser.2017.04.095.
11. Jain, R.K.; Damoulas, T.; Kontokosta, C.E. Towards data-driven energy consumption of multi-family residential buildings: Feature selection via The Lasso. *Comput. Civ. Build Eng.* **2016**, 1675–1682, http://dx.doi.org/10.1061/9780784413616.208.
12. Ferracuti, F.; Fonti, A.; Ciabattoni, L.; Pizzuti, S.; Arteconi, A.; Helsen, L.; Comodi, G. Data-driven models for short-term thermal behaviour prediction in real buildings. *Appl. Energy* **2017**, *204*, 1375–1387, doi:10.1016/j.apenergy.2017.05.015.
13. Liu, Z.; Wu, D.; Liu, Y.; Han, Z.; Lun, L.; Gao, J.; Jin, G.; Cao, G. Accuracy analyses and model comparison of machine learning adopted in building energy consumption prediction. *Energy Explor. Exploit.* **2019** , *37*, 1426–1451 . doi:10.1177/0144598718822400
14. Wei, Y.; Zhang, X.; Shi, Y.; Xia, L.; Pan, S.; Wu, J.; Han, M.; Zhao, X. A review of data-driven approaches for prediction and classification of building energy consumption. *Renew. Sustain. Energy Rev.* **2018**, *82*, 1027–1047, doi:10.1016/j.rser.2017.09.108.
15. Bourdeau, M.; Qiang Zhai, X.; Nefzaoui, E.; Guo, X.; Chatellier, P. Modeling and forecasting building energy consumption: A review of data-driven techniques. *Sustain. Cities Soc.* **2019**, *48*, 101533, doi:10.1016/j.scs.2019.101533.
16. Ahmad, M.W.; Reynolds, J.; Rezgui, Y. Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees. *J. Clean. Prod.* **2018**, *203*, 810–821, doi:10.1016/j.jclepro.2018.08.207.
17. Berthou, T.; Stabat, P.; Salvazet, R.; Marchio, D. Development and validation of a gray box model to predict thermal behavior of occupied office buildings. *Energy Build.* **2014**, *74*, 91–100, doi:10.1016/j.enbuild.2014.01.038.
18. Mahesh, B. Machine learning algorithms—A review. *Int. J. Sci. Res. IJSR* **2018**, *9*, 381–386, doi:10.21275/ART20203995.
19. Jordan, M.I.; Mitchell, T.M. Machine learning: Trends, perspectives, and prospects. *Science* **2015**, *349*, 255–260, doi:10.1126/science.aaa8415.
20. Mba, L.; Meukam, P.;Kemajou, A. Application of artificial neural network for predicting hourly indoor air temperature and relative humidity in modern building in humid region. *Energy Build.* **2016**, *121*, 32–42, doi:10.1016/j.enbuild.2016.03.046.
21. Qi, C.;Wang, W.; Wang, S.Application of indoor temperature prediction based on SVM and BPNN. In Procedings of the 27th Chinese Control and Decision Conference CCDC 2015, Qingdao, China, 23–25 May 2015; pp. 2883–2887, doi:10.1109/CCDC.2015.7162418.
22. Chammas, M.;Makhoul, A.; Demerjian, J. An efficient data model for energy prediction using wireless sensors. *Comput. Electr. Eng.* **2019**, *76*, 249–257, doi:10.1016/j.compeleceng.2019.04.002.
23. Cotrufo, N.; Saloux, E.; Hardy, J.M.; Candanedo, J.;Platon, R. A practical artificial intelligence-based approach for predictive control in commercial and institutional buildings. *Energy Build.* **2020**, *206*, 109563, doi:10.1016/j.enbuild.2019.109563.
24. Moon, J.W. Comparative performance analysis of the artificial-intelligence-based thermal control algorithms for the double-skin building. *Appl. Therm. Eng.* **2015**, *91*, 334–344, doi:10.1016/j.applthermaleng.2015.08.038.
25. Sholahudin, S.; Hwataik Han. Simplified Dynamic Neural Network Model to Predict Heating Load of a Building Using Taguchi Method. *Energy* **2016**, *115*, 1672–1678, https://doi.org/10.1016/j.energy.2016.03.057.
26. Li, Q.; Meng, Q.; Cai, J.; Yoshino, H.; Mochida, A. Predicting hourly cooling load in the building: A comparison of support vector machine and different artificial neural networks. *Energy Convers. Manag.* **2009**, *50*, 90–96, doi:10.1016/j.enconman.2008.08.033.
27. Li, Q.; Meng, Q.; Cai, J.; Yoshino, H.; Mochida, A. Applying support vector machine to predict hourly cooling load in the building. *Appl. Energy* **2009**, *86*, 2249–2256, doi:10.1016/j.apenergy.2008.11.035.
28. Paterakis, N.G.; Mocanu, E.; Gibescu, M.; Stappers, B.; Van Alst, W. Deep learning versus traditional machine learning methods for aggregated energy demand prediction. In Procedings of the 2017 IEEE PES Innovation Smart Grid Technologies Conference Europe(ISGT-Europe), Turin, Italy, 26–29 September 2017; pp. 1–6, doi:10.1109/ISGTEurope.2017.8260289.

29. Yu, Z.; Haghighat, F.; Fung, B.C.M.; Yoshino, H. A decision tree method for building energy demand modeling. *Energy Build.* **2010**, *42*, 1637–1646, doi:10.1016/j.enbuild.2010.04.006.
30. Wang, Z.;Wang, Y.; Zeng, R.; Srinivasan, R.S.; Ahrentzen, S. Random Forest based hourly building energy prediction. *Energy Build.* **2018**, *171*, 11–25, doi:10.1016/j.enbuild.2018.04.008.
31. Özbalta, T.G.; Sezer, A.; Yildiz, Y. Models for prediction of daily mean indoor temperature and relative humidity: Education building in Izmir, Turkey. *Indoor Built Environ.* **2012**, *21*, 772–781, doi:10.1177/1420326X11422163.
32. Afroz, Z.; Shafiullah, G.;Urmee, T.; Higgins, G. Prediction of Indoor Temperature in an Institutional Building. *Energy Procedia* **2017**, *142*, 21860–21866, doi:10.1016/j.egypro.2017.12.576.
33. Potočnik, P.; Vidrih, B.; Kitanovski, A.; Govekar, E. Neural network, ARX, and extreme learning machine models for the short-term prediction of temperature in buildings. *Build. Simul.* **2019**, *12*, 1077–1093, doi:10.1007/s12273-019-0548-y.
34. Mateo,F.; Carrasco,J.J.; Sellami,A.; Millan-Giraldo,M.; Dominguez,M.; Soria-Olivas,E. Machine learning methods to forecast temperature in buildings. *Expert Syst. Appl.* **2013**, *40*, 1061–1068, http://dx.doi.org/10.1016/j.eswa.2012.08.030.
35. Paul, D.; Chakraborty, T.; Datta, S.K.; Paul, D. IoT and machine learning based prediction of smart building indoor temperature. In Procedings of the 2018 4th International Conference on Computer and Information Sciences ICCOINS, Kuala Lumpur, Malaysia, 13–14 August 2018; doi:10.1109/ICCOINS.2018.8510597.
36. Aguilera, J.J.; Andersen, R.K.; Toftum, J. Prediction of indoor air temperature using weather data and simple building descriptors. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4349, doi:10.3390/ijerph16224349.
37. Foucquier, A.; Robert, S.; Suard, F.; Stéphan, L.; Jay, A. State of the art in building modelling and energy performances prediction: A review. *Renew. Sustain. Energy Rev.* **2013**, *23*, 272–288, doi:10.1016/j.rser.2013.03.004.
38. Brastein, O.M.; Sharma, R.;Skeie, N.-O. Sensor placement and parameter identifability in grey-box models of building thermal behaviour. In Proceedings of 60th SIMS Conference on Simulation and Modelling SIMS 2019, Västerås, Sweden, 12–16 August 2019; Volume 170, pp. 51–58, doi:10.3384/ecp2017051.
39. Ogunsola, O.T.; Song, L.; Wang, G. Development and validation of a time-series model for real-time thermal load estimation. *Energy Build.* **2014**, *76*, 440–449, doi:10.1016/j.enbuild.2014.02.075.
40. Hong, D.; Ortiz, J.; Whitehouse, K.; Culler, D. Towards automatic spatial verification of sensor placement in buildings. In Procedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings, BuildSys 2013, Roma, Italy, 11–15 November 2013, doi:10.1145/2528282.2528302.
41. Yanti, R.J.; Faridah, Mustika, I.W.; Ariananda, D.D.; Utami, S.S. Analysis of Gaussian process to predict thermal sensor placement for controlling energy consumption on the educational building. *AIP Conf. Proc.* **2020**, *2223*,050006-1:12 doi:10.1063/5.0000923.
42. Borggaard, J.; Burns, J.; Zietsman, L. On using LQG performance metrics for sensor placement. In Proceedings of the 2011 American Control Conference, San Francisco, CA, USA, 29 June–1 July 2011; pp. 2381–2386, doi:10.1109/acc.2011.5991462, doi:10.1109/acc.2011.5991462.
43. Campana, J.P.; Schuss, M.; Mahdavi, A.; Morini, G.L. Effects of the room temperature sensor position and radiator sizing on indoor thermal comfort and energy performances. *E3S Web Conf.* **2019**, *111*, doi:10.1051/e3sconf/201911101006.
44. Borier, O.M.; Kazanci, O.B.; Olesen, B.W.; Khovalyg, D. Which sensor type at which location should offices with south orientated window choose to improve comfort and reduce energy consumption? *J. Phys. Conf. Ser.* **2019**, *1343*, doi:10.1088/1742-6596/1343/1/012147.
45. May Tzuc, O.; Livas-García, A.; Jiménez Torres, M.; Cruz May, E.; López-Manrique, L.M.; Bassam, A. Artificial Intelligence Techniques for Modeling Indoor Building Temperature under Tropical Climate Using Outdoor Environmental Monitoring. *J. Energy Eng.* **2020**, *146*, doi:10.1061/(ASCE)EY.1943-7897.0000649.
46. Fan, C.; Xiao, F.; Wang, S. Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques. *Appl. Energy* **2014**, *127*, 1–102014, 127, 1–10, doi:10.1016/j.apenergy.2014.04.016.
47. Luo, M.; Xie, J.; Yan, Y.; Ke, Z.; Yu, P.; Wang, Z.; Zhang, J. Comparing machine learning algorithms in predicting thermal sensation using ASHRAE Comfort Database II. *Energy Build.* **2020**, *210*, 109776. doi:10.1016/j.enbuild.2020.109776.
48. Papadopoulos, S.; Azar, E.; Woon, W.L.; Kontokosta, C.E. Evaluation of tree-based ensemble learning algorithms for building energy performance estimation. *J. Build. Perform. Simul.* **2018**, *11*, 322–332, doi:10.1080/19401493.2017.1354919.
49. Ahmad, M.W.; Mourshed, M.; Rezgui, Y. Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption. *Energy Build.* **2017**, *147*, 77–89, doi:10.1016/j.enbuild.2017.04.038.
50. Wang, R.; Lu, S.; Li, Q. Multi-criteria comprehensive study on predictive algorithm of hourly heating energy consumption for residential buildings. *Sustain. Cities Soc.* **2019**, *49*, 101623. doi:10.1016/j.scs.2019.101623.
51. Attoue, N.; Shahrour, I.; Younes, R. Smart building: Use of the artificial neural network approach for indoor temperature forecasting. *Energies* **2018**, *11*, 1–12, doi:10.3390/en11020395.
52. Chan, S.Y.;Chau, C.K. Development of artificial neural network models for predicting thermal comfort evaluation in urban parks in summer and winter. *Build. Environ.* **2019**, *164*, 106364. doi:10.1016/j.buildenv.2019.106364.
53. Deng, Z.; Chen, Q.Artificial neural network models using thermal sensations and occupants' behavior for predicting thermal comfort. *Energy Build.* **2018**, *174*, 587–602, doi:10.1016/j.enbuild.2018.06.060.
54. Mottahedi, M.; Mohammadpour, A.; Amiri, S.S.;Riley, D.; Asadi, S. Multi-linear Regression Models to Predict the Annual Energy Consumption of an Office Building with Different Shapes. *Procedia Eng.* **2015**, *118*, 622–629, doi:10.1016/j.proeng.2015.08.495.

55. Capozzoli, A.; Grassi, D.; Causone, F. Estimation models of heating energy consumption in schools for local authorities planning. *Energy Build.* **2015**, *105*, 302–313, doi:10.1016/j.enbuild.2015.07.024.
56. Attanasio, A.; Piscitelli, M. S.; Chiusano, S.; Capozzoli, A. ; Cerquitelli, T. Towards an automated, fast and interpretable estimation model of heating energy demand: A data-driven approach exploiting building energy certificates. *Energies* , **2019** , *12*,1273, https://doi.org/10.3390/en12071273.
57. Ahmad, M.W.; Mouraud, A.; Rezgui, Y.; Mourshed, M. Deep highway networks and tree-based ensemble for predicting short-term building energy consumption. *Energies* **2018**, *11*, 3408. doi:10.3390/en11123408.
58. Farhan, A.A.; Pattipati, K.; Wang, B.; Luh, P. Predicting individual thermal comfort using machine learning algorithms. In Proceedings of the IEEE International Conference on Automation Science and Engineering, Gothenburg, Sweden, 24–28 August 2015; pp. 708–713, doi:10.1109/CoASE.2015.7294164.
59. Liu, S.; Schiavon, S.; Das, H.P.; Jin, M.;Spanos, C.J. Personal thermal comfort models with wearable sensors. *Build. Environ.* **2019**, *162*, 106281, doi:10.1016/j.buildenv.2019.106281.
60. Touzani, S.; Granderson, J.;Fernandes, S. Gradient boosting machine for modeling the energy consumption of commercial buildings. *Energy Build.* **2018**, *158*, 1533–1543, doi:10.1016/j.enbuild.2017.11.039.
61. Seyedzadeh, S.; Pour Rahimian, F.; Rastogi, P.; Glesk, I. Tuning machine learning models for prediction of building energy loads. *Sustain. Cities Soc.* **2019**, *47*, 101484, doi:10.1016/j.scs.2019.101484.
62. Chakraborty, D.; Elzarka, H. Advanced machine learning techniques for building performance simulation: A comparative analysis. *J. Build. Perform. Simul.* **2019**, *12*, 193–207, doi:10.1080/19401493.2018.1498538.
63. Chakraborty, D.; Elzarka, H. Early detection of faults in HVAC systems using an XGBoost model with a dynamic threshold. *Energy Build.* **2019**, *185*, 326–344, doi:10.1016/j.enbuild.2018.12.032.
64. Chaudhuri, T.; Soh, Y.C.; Li, H.; Xie, L. A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings. *Appl. Energy* **2019**, *248*, 44–53, doi: 10.1016/j.apenergy.2019.04.065.
65. Alawadi, S.; Mera, D.; Fernández-Delgado, M.; Alkhabbas, F.; Olsson, C.M.; Davidsson, P. A comparison of machine learning algorithms for forecasting indoor temperature in smart buildings. *Energy Syst.* **2020**, 1–17. doi:10.1007/s12667-020-00376-x.
66. Attoue, N.; Shahrour, I.; Mroueh, H.;Younes, R. Determination of the optimal order of grey-box models for short-time prediction of buildings' thermal behavior. *Buildings* **2019**, *9*, 198, doi:10.3390/buildings9090198.
67. Sarabi, S.; Ploix, S.; Le, M.H.; Dang, H.A.; Wurtz, F. Assessing the relevance of reduced order models for building envelop. In Proceedings of BS 2013 13th Conference of International Building Performance Simulation Association, Chambéry, France, 26–28 August 2013; pp. 3538–3545.
68. Ha, D.L.; Ploix, S.; Zamai, E.; Jacomino, M. Realtimes dynamic optimization for demand-side load management. *Int. J. Manag. Sci. Eng. Manag.* **2008**, *3*, 243–252, doi:10.1080/17509653.2008.10671051.
69. Candanedo, J.A.; Dehkordi, V.R.; Lopez, P. A control-oriented simplified building modelling strategy. In Proceedings of BS 2013 13th Conference of International Building Performance Simulation Association,Chambéry, France, 26–28 August 2013; pp. 3682–3689.
70. Fumo, N.;Rafe Biswas, M.A.Regression analysis for prediction of residential energy consumption. *Renew. Sustain. Energy Rev.* **2015**, *47*, 332–343, doi:10.1016/j.rser.2015.03.035.
71. Xu, M.; Watanachaturaporn, P.; Varshney, P.K.; Arora, M.K. Decision tree regression for soft classification of remote sensing data. *Remote Sens. Environ.* **2005**, *97*, 322–336, doi:10.1016/j.rse.2005.05.008.
72. Wang, Z.;Chen, Y.; Li, Y. Development of RC model for thermal dynamic analysis of buildings through model structure simplification. *Energy Build.* **2019**, *195*, 51–67, doi:10.1016/j.enbuild.2019.04.042.
73. Belić, F.; Hocenski Ž.;Slišković, D. Thermal modeling of buildings with RC method and parameter estimation. In Proceedings of the International Conference on Smart Systems and Technologies SST, Osijek, Croatia, 12–14 October 2016; pp. 19–25, doi:10.1109/SST.2016.7765626.
74. Steindl, G.; Kastner, W.; Stangl, V. Comparison of data-driven thermal building models for model predictive control. *J. Sustain. Dev. Energy Water Environ. Syst.* **2019**, *7*, 730–742, doi:10.13044/j.sdewes.d7.0286.
75. Viot, H.; Sempey, A.; Mora, L.;Batsale, J.C.; Malvestio, J. Model predictive control of a thermally activated building system to improve energy management of an experimental building: Part II—Potential of predictive strategy. *Energy Build.* **2018**, *172*, 385–396, doi:10.1016/j.enbuild.2018.04.062.
76. Tsilingiris, P.T. Parametric space distribution effects of wall heat capacity and thermal resistance on the dynamic thermal behavior of walls and structures. *Energy Build.* **2006**, *38*, 1200–1211, doi:10.1016/j.enbuild.2006.02.007.
77. Attoue, N. *Smart Technology for Building Heating Optimization: Indoor Temperature Forecasting*; Lille University: Lille, France, 2019.
78. Wang, Z.; Chen, Y. Data-driven modeling of building thermal dynamics: Methodology and state of the art. *Energy Build.* **2019**, *203*, 109405. doi:10.1016/j.enbuild.2019.109405.