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Research article

Optimization of tertiary building passive parameters by forecasting energy consumption based on artificial intelligence models and using ANOVA variance analysis method

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Abstract: Energy consumption in the tertial sector is largely attributed to cooling/heating energy consumption. Thus, forecasting the building's energy consumption has become a key factor in long-term decision-making, reducing the huge energy demand and future planning. This manuscript outlines to use of the variance analysis method (ANOVA) to study the building's passive parameters' effect, such as the orientation, insulation, and its thickness plus the glazing on energy savings through the forecasting of the heating/cooling energy consumption by applying the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and the Long Short-Term Memory (LSTM) models. The presented methodology compares the predicted consumed energy of a baseline building with another efficient building which includes all the passive parameters selected by the ANOVA approach. The results show that the improvement of passive parameters leads to a reduction of heating energy consumption by 1,739,640 kWh from 2021 to 2029, which is equivalent to a monthly energy consumption of 181.2 kWh for an administrative building with an area of 415 m^2. While the cooling energy consumption is diminished by 893,246 kWh from 2021 to 2029, which leads to save a monthly value of 93.05 kWh. Consequently, the passive parameters optimization efficiently reduces the consumed energy and minimizes its costs. This positively impacts our environment due to the reduction of gas emissions, air and soil pollution.

Keywords: cooling/heating energy consumption; passive parameters; SARIMA models; LSTM models; ANOVA

1. Introduction

Currently, the Moroccan building sector is the second most energy-consuming sector, after the transport sector, which represents 4,000 Ktoe in 2020 [1]. Furthermore, the ratio of the consumed energy in the building sector increases successively during these years, and we expect that this ratio will continue growing in the future. Moreover, the worldwide energy crisis due to the war in Ukraine presents a serious issue in terms of the limited energy resources and its highest costs, which oblige different countries to think seriously about the optimization of buildings' energy efficiency plus reducing energy consumption and costs. Thus, it is important to forecast the building's energy consumption to improve its energy efficiency, which leads to conserving energy and reducing environmental pollution.

Forecasting energy consumption has become a key factor in long-term decision-making and future planning. Indeed, a reliable energy consumption prediction has a crucial role in the implementation of performant management energy systems. Nevertheless, the buildings' energy system is quite complex, whereas the main energy sources in buildings are electricity, cooling, heating, and hot water consumption. Furthermore, the building's energy consumption is affected by several factors, such as climatic conditions [2], the thermal-physical characteristics of the used buildings' materials[3–7], the occupants' behavior [8] and (HVAC) systems [9–12], the lighting systems, their efficiency, and schedules [13,14]. Because of this complex issue, accurate forecasting for analyzing the building's energy consumption is highly demanded.

Recently, many predictive approaches have been proposed and applied to overcome several problems in the building sector [15–20]. Moreover, many works have applied different Artificial Intelligence (AI) models for forecasting different interests. Newsham and Birt [21] improved an Auto-Regressive Integrated Moving Average with external input (ARIMAX) to predict electrical energy needs of an office, moreover, they have applied the occupancy dataset as an extrinsic predictor to develop it. Bilgili and Pinar have done a comparative study between SARIMA and LSTM Models to predict gross electricity consumption in Turkey, they have found that the two models are quite close to each other. And generally, the LSTM model provides more performance than the SARIMA model [22]. Blázquez-García et al. have used the Sarima models to predict the consumed energy of a green-elevator integrating batteries and photovoltaic, the results were validated by comparing the SARIMA models with the ANN and the GAM models. The SARIMA outperformed slightly better [23]. A Hybrid Artificial Neural Network (ANN) plus an Auto Regressive Integrated Moving Average (ARIMA) model was introduced by Wang and Meng [24] for predicting the consumed energy of the whole Chinese Hebei province. They selected the annual consumed energy datasets between 1980 and 2008 to improve and test the used model. Kandananond [25] applied ARIMA, ANN plus Multiple Linear Regression (MLR) model to forecast electrical energy needs in Thailand. The chosen datasets were determined between 1986 and 2010. The findings indicated that the MAPE equals 0.996% for ANN, while it’s respectively equal to 2.809% and 3.260% for ARIMA and MLR models. Wang et al. [26] Applied Long short-term Memory (LSTM) model to predict a periodic time series. They studied and analyzed a daily cooling system periodicity energy consumption through LSTM model. They deduced that the Lower-dimensional input instead of all presented variables minimizes the calculation cost, while minimizing the input variables diminishes the accuracy of this proposed model. Chujai et al. [27] presented the analysis of time series for the consumed electric energy of a residential building based on ARIMA and Auto Regressive Moving Average (ARMA) models. The selected data were collected from December 2006 until November 2010 for developing the proposed models. The findings showed that ARIMA model can perform the most appropriate predictions for the monthly and quarterly periods while the ARMA model presented the most suitable predictions for daily and weekly periods.

Inspired by those previous observations, the utilization of SARIMA and LSTM Models was applied in different domains [28–32]. In the energy efficiency sector, this paper examines SARIMA and LSTM models for predicting heating/cooling energy consumption the upcoming years. The proposed model in this research investigates the impact of improving the building’s passive parameters such as: orientation, insulation, and its thickness, plus the glazing on reducing the amount of the energy used. The selection process of those parameters was done using the Analysis of Variance method ANOVA. The adequate model is selected by comparing the statistical errors RMSE (Root Mean Square Error), MSE (Mean Square Error), MAE (Mean Absolute Error) and the Scatter Index SI.

In this work, a study was performed to show the impact of building’s orientation, envelope, and its thickness, plus the glazing on the forecasted heating/cooling energy consumed the next years by using SARIMA and LSTM models. The comparison was done by choosing two buildings. The base/reference building, and the efficient one contained the passive parameters selected by ANOVA approach.

This study presents a novel investigation, it is the first study using the statistical method ANOVA to select the building’s passive parameters that have an influence on the energy consumption. Plus, the contribution in the utilization of SARIMA and LSTM models to conduct a comprehensive comparative analysis of forecasted energy consumption between a reference building and an energy-efficient counterpart. By examining these parameters in tandem, the research offers a holistic understanding of their combined effects on energy use, providing valuable insights for optimizing building design and energy management strategies.

This study’s remaining sections are organized as follows: Section 2 provides an overview of the used architectures as well as a summary of the technique and method that was used, plus evaluation metrics that gauge the effectiveness of models are defined. The results and discussion are covered simultaneously in Section 3 and 4. The study's conclusions are presented in section 5 to conclude.

2. Materials and methods

2.1. Data description

In this research, our study is focused on two administrative buildings with an area of 415 m^2 and both are located in Errachidia city, Morocco. The buildings are composed of two floors, each one containing five offices, two secretariats, a hall, and stairs. The first building is the reference building and the second one is efficient. The first building’s main materials components are: The interior/exterior walls are composed of a single red brick layer with a thickness of 15 cm, plus a simple glazing for the windows. While for the efficient building, we have added a layer of airgap as insulation with a thickness of 5 cm inside the exterior walls. Also, we have changed the windows' simple glazing by double glazing with a medium of air gap.

The energy consumption datasets of the reference and the efficient buildings during cooling and heating operations were determined by using ECOTECT ANALYSIS software from January 2016 until December 2020 (Figures 1 and 2).

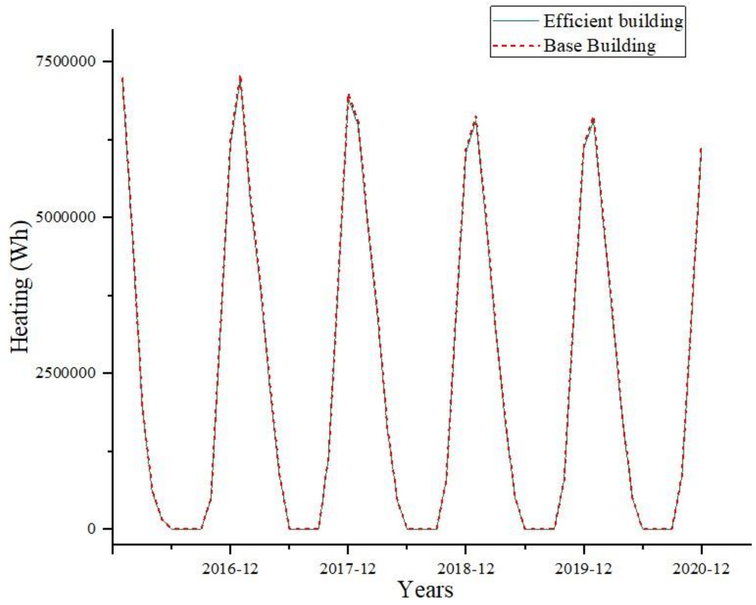

Figure 1. Heating energy consumption of the base and the efficient building (Wh).

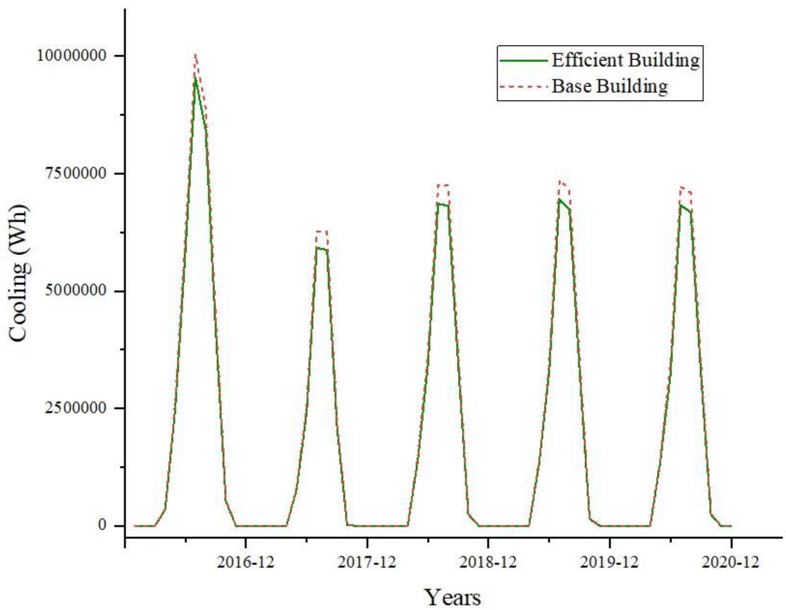

Figure 2. Cooling energy consumption of the base and the efficient building (Wh).

The simulations were performed by considering the occupants' behavior (Table 1) and the thermal-physical characteristics of an administrative building in its surrounding climatic conditions (Figures 3 and 4).

Table 1. Occupant's behavior.

	Office	Stairs	Secretariat	Hall
Clothing (clo)	1	1	1	1
Lightning level (Lux)	400	100	400	200
Occupant's number	2	3	1	5
Occupant's activity (W)	70	80	70	70

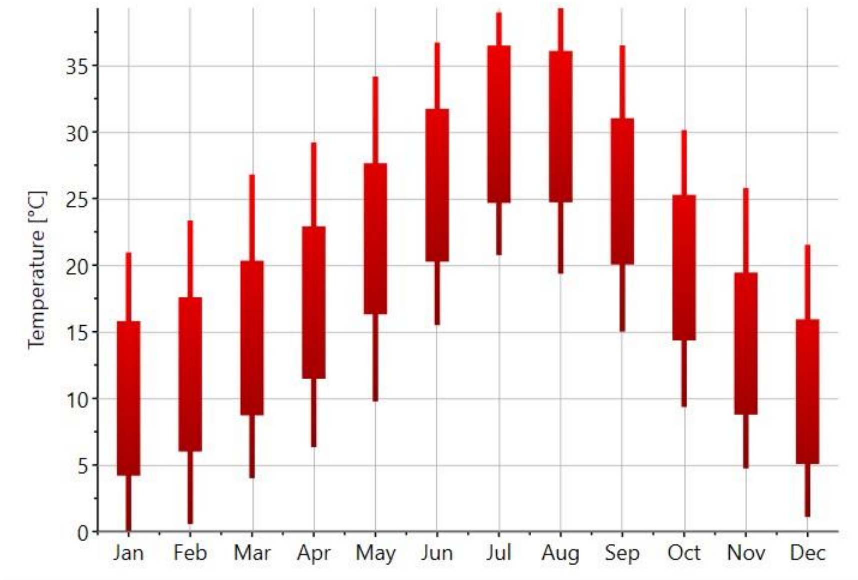

Figure 3. Temperature climatic conditions.

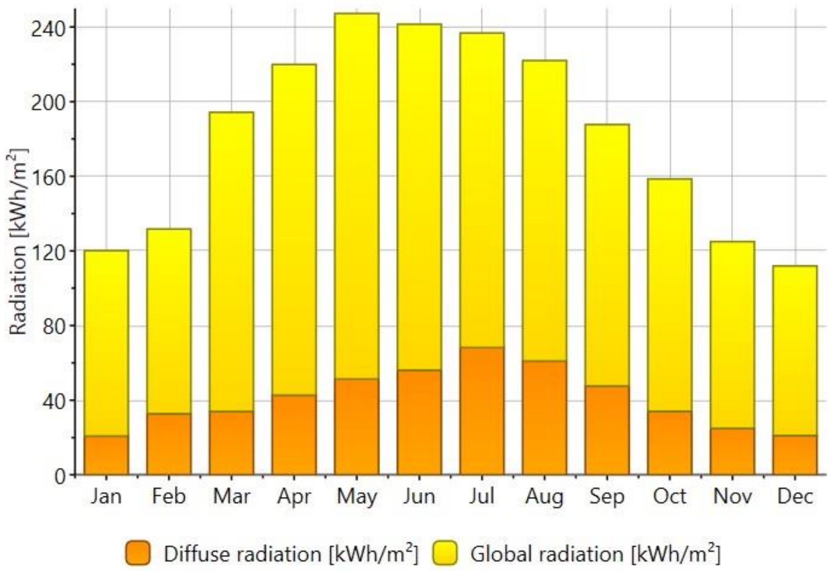

Figure 4. Radiation climatic conditions.

2.2. SARIMA model

First, the SARIMA model time series correlates non-seasonal and seasonal components, which is symbolized as SARIMA (p, d, q) (P, D, Q) s. While, the p is the order of the AR model, d is the degree of differentiation, q is the order of the MA model, P is the seasonal autoregressive order (AR) part, D is the seasonal difference order, Q presents the seasonal moving average order (MA), and s is the order of the seasonal component.

The AR process considers the previous observed measures up to an indicated maximum lag, plus the error term. The differentiation process is the integration part, which considers the data stabilization by removing the periodicity or the trend, but for MA path, it considers the last error terms that help for determining predictions.

The mathematical description of SARIMA model is presented as follow (Eq 1):

$$\varphi(B)\phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)\varepsilon_t + \theta_0 \quad (1)$$

Where the mathematical symbols/equations' meanings are described in Table 2.

Table 2. Mathematical symbols/equations' meanings.

Mathematical symbol/equation	Mathematical description
Y_t	Time series data
$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$	Order p of the autoregressive operator AR
$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p$	Order q of the moving average operator MA
$\phi(B^s) = 1 - \phi_1 B^s - \phi_2 B^{2s} - \cdots - \phi_P B^{Ps}$	Order P of a seasonal auto-regressive operator AR
$\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta_Q B^{Qs}$	Order Q of a seasonal moving average operator MA
ε_t	Time t error term
B	Backward shift operator
θ	Non-seasonal moving average coefficient
φ	Non-seasonal auto-regressive coefficient
Θ	Seasonal moving average coefficient
ϕ	Seasonal auto-regressive coefficient

2.3. LSTM models

The LSTM "Long Short-Term Memory" is a type of RNN "recurrent neural network" [33]. The LSTM can memorize the values of the previous steps, while these values can be used in the future.

The LSTM is a unit of three "gates" that compute domains that regulate the flow of information by performing specific actions with two outputs called states:

- Input gate: Controls the information's amount entering the input gate of a memory cell.
- Output gate: Use the sigmoid activation functions, it checks an amount of information flowing in the rest of the network (Eq 2).
- Forget gate: Chooses the state of the cell at the precedent instant and adaptively retains some of the information at the present time.
- Hidden state: Allows the LSTM to retain information over extended sequences, enabling it to understand and capture long-range dependencies within the data.
- Cell state: Allows weighting of the data that will combine with the input gate to update the state of the cell.

$$\sigma(x) = \frac{1}{1+e^x} \tag{2}$$

The input gate, output gate, and forget gate are represented by i_t, o_t, and f_t, respectively. The input data of the LSTM model at time t is x_t, the output data is h_t, c_t is the memory state, and $\tilde{c}_t$ is the intermediate value during computation. The LSTM memory block is described as follows (Eq 3):

$$\begin{cases} i_t = \sigma(W_i X_t + U_i h_{t-1} + b_t) \\ \tilde{c}_t = tanh(W_z X_t + U_z h_{t-1} + b_z) \\ f_t = \sigma(W_f X_t + U_f h_{t-1} + b_f) \\ c_t = i_t * \tilde{c}_t + f_t * c_{t-1} \\ o_t = \sigma(W_o X_t + oU_i h_{t-1} + b_o) \\ h_t = o_t * \tanh(c_t) \end{cases} \tag{3}$$

While W_i, U_i, W_z, U_z, W_f, U_f, W_o and U_o are weight matrices. b_t, b_z, b_f are bias vectors. X_t represents the present input. h_t and h_{t-1} are respectively the outputs at time t and at the precedent time t−1 (Figure 5). The hyperbolic tangent function is defined as follows (Eq 4):

$$tanh = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$

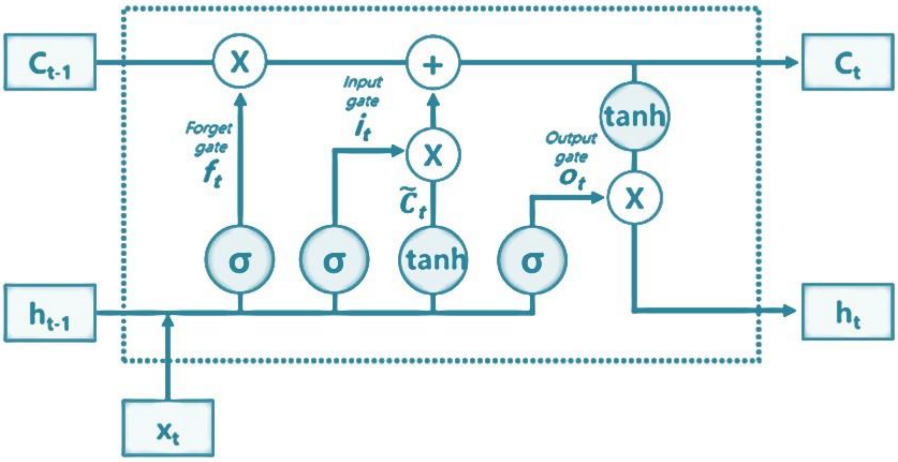

Figure 5. LSTM model architecture.

After generating the historical data, we will consider them as input data for the two models studied namely SARIMA and LSTM. The data from 2016 to 2019 are used as training set for these models, while the data from 2019 to 2020 are used as test set for SARIMA models. For the LSTM models, we will use six months as validation data and the next six months as test data.

The next step is to compare the statistical errors generated by the models of cooling/heating energy consumption, then select the one that generates the smallest values of RMSE (Root Mean Square Error), MSE (Mean Square Error) and MAE (Mean Absolute Error).

From Table 3, we notice that the RMSE values are quite high due to the order of heating/cooling energy consumption magnitude values. Therefore, we have calculated the dispersion index SI to properly compare the opted models to predict the energy consumption. We can see that the performant model for forecasting heating/cooling energy consumption is SARIMA model with dispersion indices of 5% and 7.3% respectively.

Table 3. Statistical errors generated by SARIMA and LSTM models.

Energy consumption	Models	Statistical errors				The best model
		MSE	RMSE	MAE	SI	
Heating	SARIMA	10927.13	104.53	70.12	0.05	SARIMA
	LSTM	13480.3	116.104	108.3	0.07	
Cooling	SARIMA	48486.35	220.19	142.52	0.073	SARIMA
	LSTM	51440.93	226.80	138.77	0.075	

2.4. ANOVA analysis method

The main propose of analyzing the variance through ANOVA method is to study the parameters that directly affect the energy needs during heating/cooling operations, namely the orientation, the envelope's insulation, the thickness of the insulation and the glazing. Then study the impact of these significant parameters on energy consumption by comparing the predicted energy of the reference building with that of the efficient building.

The methodology consists of using the ANOVA method to detect the parameters which have a significant effect on heating/cooling energy consumption. At next, we will generate a new database of the energy consumption of an efficient building by taking into consideration that it does contain the parameters selected by the method ANOVA. Finally, we will predict the energy consumption for the second time and compare it with that of the reference building to calculate the energy loss margin in Kilowatt hours for a single building in the south-east of Morocco. We have opted for the following passive parameters described in Table 4.

Table 4. Passive parameters selected by ANOVA method.

Passive parameter	
Orientation	South, east, north, west, south-east, south-west, north-east
Insulation	Air gap, hemp wool, glass wool, rock wool and polystyrene
Glazing	Single glazing, double glazing
Thickness	5 cm, 10 cm, 15 cm

The Table 5 presents the ANOVA analysis of variance to determine the influence of these parameters on energy consumption, we see that:

- For glazing and insulation, the difference between groups is significant for heating and cooling ($p = 0.000$). We can therefore conclude that glazing and insulation have an impact on energy consumption. Accordingly, The ANOVA analysis essentially reveals a convincing connection between glazing, insulation, and energy usage. An in-depth statistical study confirms that the observed changes in heating and cooling behaviors are not mere coincidences and support their direct influence on energy efficiency. This information has the potential to support better informed design and construction decision-making, fostering the development of a greener and more sustainable built environment.
- For orientation, the dataset was deliberately divided into eight separate groups, each of which contained a certain orientation configuration, to provide a comprehensive viewpoint. This strategic grouping made it possible to evaluate energy consumption patterns in detail over a

wide range of circumstances, which helped to clarify the function of orientation. The results of the statistical analysis were extremely significant, especially when it came to the area of heating energy use ($p = 0.000$). It strongly implies a link between heating energy consumption patterns and building orientation. The results highlight the fact that the deliberate differences in orientation protocols are fundamentally linked to the variations in heating energy usage. However, when examining the effect of orientation on cooling energy use, a more complex picture begins to take shape. The predicted cooling energy consumption p-value of 0.425 supports a different narration. Practically speaking, this means that even if orientation may not have a significant impact on cooling energy consumption, it still plays a crucial part in overall building design, even though its impact on heating is more evident.

- The thickness of the insulators presents a value of ($p = 0.045$) for the heating, which shows that this parameter influences the heating. While the difference between the three groups is however not significant for cooling ($p = 0.789$), we can therefore conclude that the thickness has no impact on the cooling energy needs. Which means that there is no correlation between increasing the insulation's thickness and reducing cooling energy consumption.

Table 5. Analysis of ANOVA variance.

		ddl	F	p-value
Glazing	Heating	1	27.256	0.000
	Cooling	1	544.058	0.000
Insulation	Heating	4	9.321	0.000
	Cooling	4	8.549	0.000
Orientation	Heating	7	20.632	0.000
	Cooling	7	1.010	0.425
Thickness	Heating	2	3.135	0.045
	Cooling	2	0.238	0.789

3. Results

First, the SARIMA (p, d, q) $(P, D, Q)_{12}$ model was established by python programming language, then, we have trained and tested that model by exploring the collected energy consumption data during the cooling/heating operations between January 2016 and December 2020, for the reference building plus the efficient one in Errachidia city, at the north-east of Morocco. The determination of the forecasted energy consumption by using SARIMA models was realized as follow:

Step 1: The first stage is reserved for checking the datasets stationarity. If stationarity is not satisfied and the series has trend or seasonal components, we should change it by using differencing.

In this study, we have differentiated the cooling/heating dataset of the two buildings once to make it stationary. Thus, the orders of seasonal and non-seasonal differences are respectively: $D = 1$ and $d = 1$.

Step 2: For the second stage, the orders (p, q, P, Q) of SARIMA models must be defined by using Akaike Information Criterion AIC "Eq 5".

$$AIC = 2K - 2\ln(L) \tag{5}$$

The smallest value of AIC for the cooling/heating datasets lead to the optimal combination of the orders (p, q, P, Q) for the reference building and the efficient one (Table 6).

Table 6 shows that the SARIMA (2,1,0) $(2,1,0)_{12}$ and SARIMA (0,1,2) $(2,1,0)_{12}$ models present, respectively, the minimum AIC values for heating of the reference building and the efficient building. The SARIMA (0,1,3) $(1,1,0)_{12}$ model generates significant results in terms of AIC for the cooling energy consumption of the two studied buildings. Therefore, these models are sufficient to forecast energy consumption during heating-cooling operations.

Step 3: In this last step, after selecting the best SARIMA model, we can now forecast heating/cooling energy consumption of the reference and efficient buildings from 2021 to 2029.

Table 6. AIC values of the cooling/heating data of the reference building and the efficient building.

Heating (p, d, q) (P, D, Q) s	AIC	Cooling (p, d, q) (P, D, Q) s	AIC
Reference building			
(1,1,1) $(0,1,0)_{12}$	1018.965	(1,1,1) $(0,1,0)_{12}$	1027.901
(0,1,0) $(0,1,0)_{12}$	1019.874	(0,1,0) $(0,1,0)_{12}$	1033.739
(1,1,0) $(1,1,0)_{12}$	1020.537	(1,1,0) $(1,1,0)_{12}$	1012.047
(0,1,1) $(0,1,1)_{12}$	1020.616	(0,1,1) $(0,1,1)_{12}$	1011.850
(1,1,1) $(1,1,0)_{12}$	1017.483	(0,1,1) $(0,1,0)_{12}$	1026.341
(1,1,1) $(2,1,0)_{12}$	1006.211	(0,1,1) $(1,1,1)_{12}$	1011.429
(1,1,1) $(3,1,0)_{12}$	1008.175	(0,1,1) $(1,1,0)_{12}$	1009.644
(2,1,1) $(3,1,1)_{12}$	1003.016	(0,1,1) $(2,1,0)_{12}$	1011.384
(2,1,0) $(2,1,0)_{12}$	999.264	(0,1,1) $(2,1,1)_{12}$	1013.079
(2,1,0) $(1,1,0)_{12}$	1007.760	(0,1,0) $(1,1,0)_{12}$	1031.949
(2,1,0) $(3,1,0)_{12}$	1001.089	(0,1,3) $(1,1,0)_{12}$	997.460
(2,1,0) $(2,1,1)_{12}$	1001.092	(0,1,3) $(0,1,0)_{12}$	1064.785
(2,1,0) $(1,1,1)_{12}$	1000.379	(0,1,3) $(2,1,0)_{12}$	998.625
(2,1,0) $(3,1,1)_{12}$	1003.090	(0,1,3) $(1,1,1)_{12}$	998.791
Efficient building			
(0,1,0) $(0,1,0)_{12}$	1018.948	(1,1,1) $(0,1,0)_{12}$	1023.168
(1,1,0) $(1,1,0)_{12}$	1019.571	(0,1,0) $(0,1,0)_{12}$	1029.908
(0,1,1) $(0,1,1)_{12}$	1019.525	(1,1,0) $(1,1,0)_{12}$	1007.250
(1,1,1) $(1,1,0)_{12}$	1016.500	(0,1,1) $(0,1,1)_{12}$	1007.022
(1,1,1) $(2,1,0)_{12}$	1005.131	(0,1,1) $(0,1,1)_{12}$	1007.022
(1,1,1) $(3,1,0)_{12}$	1007.101	(0,1,1) $(0,1,0)_{12}$	1021.752
(1,1,1) $(2,1,1)_{12}$	1007.100	(0,1,1) $(1,1,1)_{12}$	1006.721
(1,1,1) $(1,1,1)_{12}$	1007.614	(0,1,2) $(1,1,0)_{12}$	1000.754
(1,1,2) $(3,1,1)_{12}$	1002.472	(0,1,2) $(0,1,0)_{12}$	1025.151
(0,1,2) $(2,1,0)_{12}$	998.254	(0,1,2) $(2,1,0)_{12}$	1002.426
(0,1,2) $(1,1,0)_{12}$	1008.526	(0,1,3) $(1,1,0)_{12}$	992.857
(0,1,2) $(3,1,0)_{12}$	1000.070	(0,1,3) $(0,1,0)_{12}$	1059.570
(0,1,2) $(2,1,1)_{12}$	1000.071	(0,1,3) $(2,1,0)_{12}$	993.735
(0,1,2) $(1,1,1)_{12}$	999.511	(0,1,3) $(0,1,0)_{12}$	1059.570

4. Discussion

Figures 6 and 7 show the forecasting of the energy cooling and heating consumed for the reference building in red and the efficient building in green for eight years.

We note that the improvement of the passive parameters, namely the application of double glazing separated by an air gap for the windows, the insulation of the exterior walls by an air gap with a thickness of 5 cm, and the orientation to the south-east will allow us to save up to 893,246 kWh for the cooling consumed energy from 2021 to 2029, which leads to save a monthly value of 93.05 kWh for a single building with an area equal to 415 m^2. Moreover, it will ensure a significant decrease of the heating energy consumption by 1,739,640 kWh from 2021 to 2029, which is equivalent to a monthly value of 181.2 kWh for an administrative building with an area of 415 m^2.

These recommendations are very useful for building engineers and architects to exploit the building's passive parameters to achieve promising reductions in heating/cooling energy consumption. Therefore, this energy saving in the building sector reduces the emission of Carbon Dioxide CO_2, which leads to save the environment and reduce the pollution.

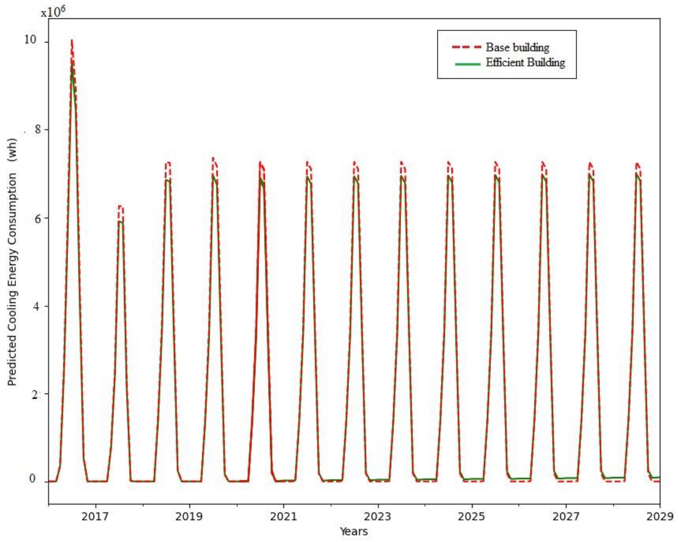

Figure 6. Forecasted cooling energy consumption by SARIMA models.

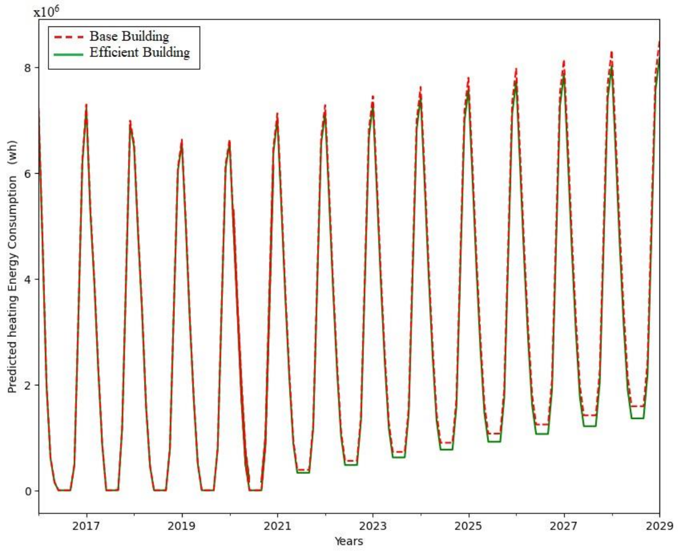

Figure 7. Forecasted heating energy consumption by SARIMA models.

5. Conclusions

In this work, we apply the variance analysis method (ANOVA) to study the effect of passive parameters on heating/cooling energy consumption which are the orientation, insulation and its thicknesses, and the glazing. This process concerns the use of SARIMA and LSTM models to forecast the energy consumption during heating and cooling operations of two different buildings existed in Errachidia city, Morocco. The analysis of the statistical errors generated by SARIMA and LSTM models shows that SARIMA model is more adequate and efficient for predicting energy consumption compared to LSTM model. This research also compares the predicted energy of a reference building with that of an efficient building which includes the proposed passive parameters generated by ANOVA method. The results show that by improving these parameters, the heating consumption reduced by 1,739,640 kWh from 2021 to 2029, which is equivalent to a monthly value of 181.2 kWh for an administrative building with an area of 415 m^2. While for the cooling energy consumption we could save up to 181.2 kWh from 2021 to 2029, which is equivalent to a monthly value of 93.05 kWh for a building with a surface equal to 415 m^2.

Finally, the optimization of passive parameters contributes efficiently to reduce energy consumption and costs for the future.

Use of AI tools declaration

The authors declare they have not used artificial intelligence tools in the creation of this manuscript.

Acknowledgments

We would like to thank every single author for his/her contributions.

Conflict of interest

The authors declare no conflict of interest.

Author contributions

Lamya LAIRGI and Rachid LAGTAYI conceived of the presented idea and performed the computations and the data acquisition. Yassir LAIRGI, Abdelmajid DAYA, Rabie Elotmani, Ahmed KHOUYA and Mohamed TOUZANI contributed to the interpretation of the results, provided critical feedback, and reviewed it critically. Lamya LAIRGI and Rachid LAGTAYI drafted and wrote this manuscript.

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Appendix

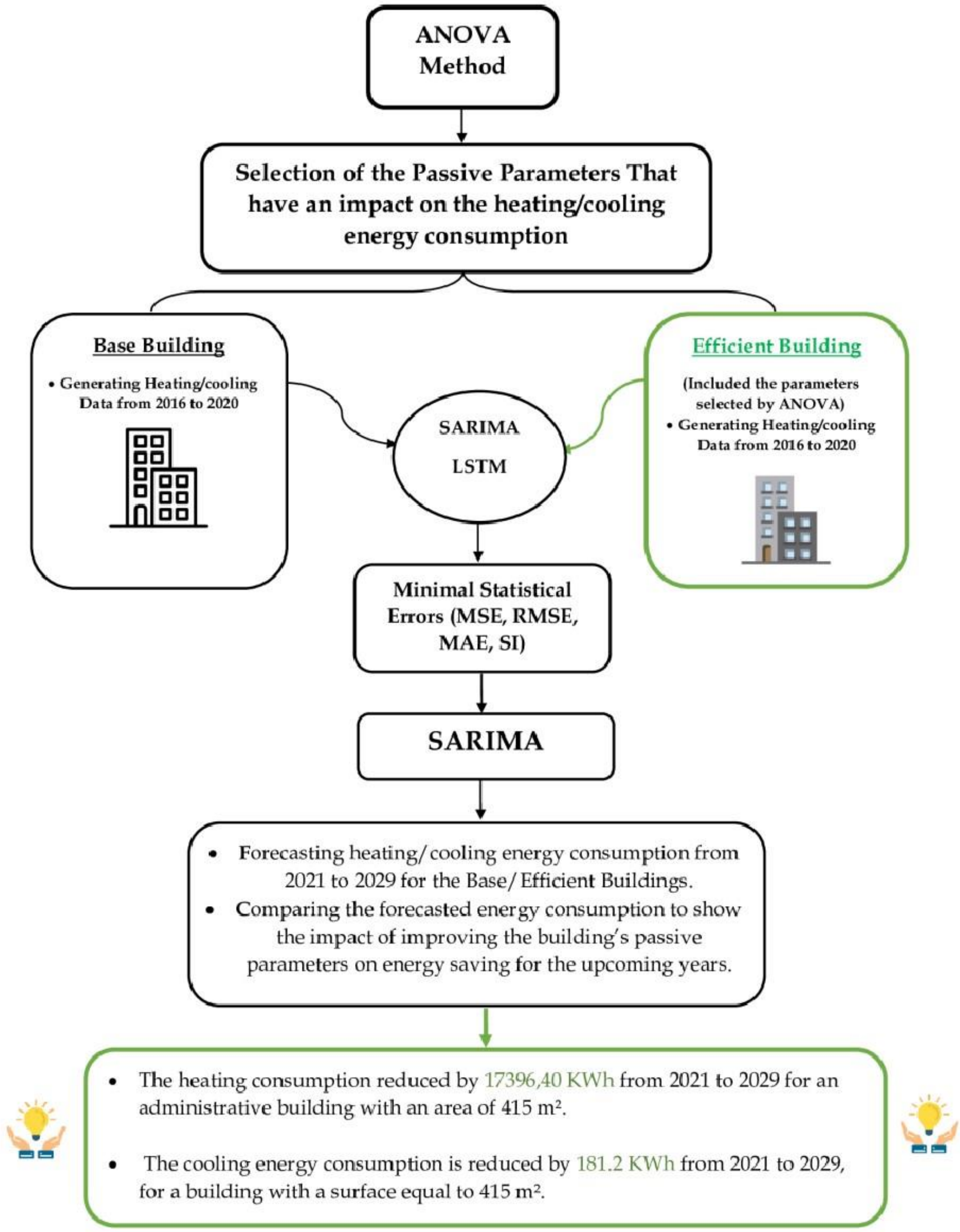

Figure A1. Graphical abstract.