Innovative Energy Systems and Technologies

https://iest.cultechpub.com/iest

Cultech Publishing

Article

Prediction of Energy Efficiency in a Thermal Storage Wall System by the Modified Model

Seyed Hossein Hashemi*

Energy Systems Engineering, Faculty of Engineering and Applied Science, University of Regina, Regina, Canada

*Corresponding author: Seyed Hossein Hashemi, shn081@uregina.ca

Abstract

The Trombe wall system is a paradigmatic example of passive solar construction, providing thermal control of internal spaces through the efficient utilization of solar radiation. The temperature variability within the air channel is a critical parameter determining the system's functional effectiveness. This research introduces a refined thermal model to estimate the energy efficiency of a traditional Trombe wall, based on variables including incident solar radiation, ambient temperature near the wall face, and conditions at the glazing near the upper end of the channel. Furthermore, it employs the k-nearest neighbors (KNN), linear regression, random forest, and decision tree algorithms to predict system efficiency based on the aforementioned temperature metrics. Empirical results indicate that the KNN and random forest models achieved zero error in the initial test simulation, in stark contrast to the linear regression and decision tree methods, which exhibited errors of 0.2785 and 0.2291, respectively. Additionally, the modified thermal model demonstrated a strong agreement with experimental data, showing a deviation of less than 5% for room temperatures.

Keywords

Trombe wall, Machine learning, Solar energy efficiency, Building energy management, Energy storage systems

Article History

Received: 30 September 2025

Revised: 27 November 2025

Accepted: 09 December 2025

Available Online: 17 December 2025

1. Introduction

The last few decades have witnessed a significant rise in passive solar technologies, particularly the Trombe wall, which offers a promising solution for reducing energy consumption by using solar radiation for space heating [1,2]. The prominence of the Trombe wall stems from its ability to enhance energy efficiency in the built environment [2]. The relevance of this technology is further amplified by global concerns over the excessive use of fossil fuels and associated increases in carbon dioxide emissions [1].

The operational performance of a Trombe wall is directly influenced by its constituent materials. Empirical studies demonstrate that using thermally resilient bricks is more effective for maintaining temperatures than relying on wall thickness alone [1]. Moreover, integrating phase-change materials (PCMs) has been shown to improve the rate of energy conservation in such systems [3]. Supplementary features, such as photovoltaic panels, have also been incorporated to diversify system functionality by enabling electricity generation [4].

As the system primarily utilizes traditional construction materials, it is both environmentally sustainable and economical, helping to minimize reliance on conventional energy sources like natural gas [1]. The framework also suggests significant economic potential for achieving energy independence through the implementation of Trombe walls [2]. Consequently, numerous researchers have investigated the system's effectiveness in architectural applications [3,4].

Xiao et al. [5] investigated the effect of low-emissivity glass on Trombe wall ventilation in regions of China with high solar constants. They found that it reduced the heating demand by 61.4% compared to conventional wall designs and the cooling demand by 11.1% compared to a conventional Trombe wall, though it compromised ventilation effectiveness. Zhu et al. [6] developed an augmented Trombe wall with PCMs and natural ventilation, achieving a 13.52% reduction in energy consumption, optimized using TRNSYS-GenOpt (TRNSYS (Transient System Simulation) energy modeling software with the GenOpt (General Optimization)).

Friji et al. [7] researched the Trombe wall as an environmentally friendly residential heating system using computational fluid dynamics (CFD) analysis, incorporating a k-ε turbulence model and discrete ordinates (DO) radiation model. They determined the optimal cavity width to be 0.1 m, which validated the system's operation and paved the way for its refinement into a passive solar residential heating solution. Li et al. [8] proposed a two-layer PCM Trombe wall system designed to adapt to seasonal temperature variations.

Akbarzadeh et al. [9] investigated the combination of Trombe walls for passive solar heating. There was an emphasis on the requirement for improved design parameters for architects and designers. This experimental research involved analysis in terms of flow rates, temperature distribution, the effect of wall parameters such as the distance from the glass top surface of the wall to the ventilation hole, etc. Bevilacqua et al. [10] presented work on Trombe walls in residential structures. Appropriate ventilation resulted in reduced demands for 71.7% for ‘heating’ and 36.1% for ‘cooling’ in tropical climates. Similarly, in cold climates, ‘heating’ and ‘cooling’ demands reduced by 18.2% and 42.4%, respectively.

To improve the functionality of the Trombe wall in terms of thermal insulation in regions that mostly experience hot summers and cold winters, Long et al. [11], in their research work, proposed the use of a solar collector plate, thermal radiation reflection layer, and radiation panel. According to their research work performed in the Xiangtan atmosphere, the collector temperature is very effective in regulating the process of heat transfer/insulation. The temperatures in the system ranged from 84.8 °C to 49.1 °C.

Qi et al. [12], for instance, studied the energy-saving effect of a finning Trombe wall (TW) in combination with the floor-heated room in the city of Lanzhou in China by utilizing the ANSYS software. It was concluded that the effect of the optimized-finning TW was to increase the convective heat transfer coefficient by 7.77%, in addition to 8.25% energy savings in relation to a TW without fins.

Machine Learning (ML) is one of the recent methods used for the optimization and improvement of thermal systems [13-20], especially for thermal energy storage wall systems [21-23]. ML has emerged as a powerful tool for the modeling, optimization, and performance prediction of diverse thermal systems, as evidenced by recent research. Applications range from predicting the efficiency of photovoltaic-thermal collectors [13] and controlling battery thermal management in electric vehicles [14], to modeling indoor thermal response [15] and thermal comfort via heating, ventilation, and air conditioning (HVAC) systems [16]. This data-driven approach is also instrumental in optimizing hybrid solar-thermal systems [17], forecasting the behavior of phase change materials in thermal energy storage [18], analyzing solar distillation processes [19], and identifying the performance of solar thermal heating systems [20]. This comprehensive approach demonstrates the broad application of ML in improving energy efficiency and thermal performance, including in the context of thermal energy storage wall systems [21-23]. Bhamare et al. [21] concluded that the temperature variation in a cement wall system incorporating a PCM is lower. They also showed the ability of an artificial intelligence (LSTM) algorithm for the accurate estimation of wall performance. Çolak et al. [22] proposed an AI algorithm for the estimation of the performance of multi-function walls. The algorithm was trained on 57 datasets from experimental work. This algorithm is reliable enough to estimate wall performance with no more than 0.23% error and 99.917% accuracy [22]. Hashemi et al. [23], in their research work on the importance of energy optimization in buildings, used experimental results for the implementation of various ML algorithms. Various parameters like the heat flux, average absorber temperature, average temperature behind the Trombe wall, outside temperature, average temperature of the right glass, average temperature of the left glass, average front glass temperature, temperature of the top & bottom Trombe wall vents, & the temperature of the canal temperature are used for the analysis. These parameters are used to train four different ML algorithms on real samples. Following the trial on real samples, the algorithm is very successful. Table 1 compares the emphasis of the previous research work on the topic along with the emphasis of the current research work. It is clear from the table that though the research work on various modification ideas on the topic exists in plenty, no research work on the temperature difference between the wall and the glass worked directly in the ML algorithm. That is the intention of the current research work.

Table 1. Summary of literature focus and research gap identification.

Main Focus	**Consideration of Detailed Channel Temperature?**	**Ref.**
Integration of PCM; System optimization	No	[6]
CFD analysis; Air gap optimization	No	[7]
Double-layer PCM; Thermal comfort	No	[8]
New design with collector/reflection layer	No	[11]
Finned Trombe wall; Convective heat transfer	No	[12]
ML Algorithm for PCM wall thermal behavior prediction	No	[21]
AI model for multifunctional wall performance prediction	No	[22]
ML Algorithm for room temperature prediction in Trombe walls	No	[23]
Combining a modified thermal model with ML for a classic Trombe wall	Yes, uses temperatures near the wall and glass along the channel as a core input for energy efficiency of a Trombe wall system	Present Study

In the proposed research work, the emphasis is on analyzing the energy efficiency of the Trombe wall system on the basis of temperature variations around the wall and glass in the air channel, an aspect that was not pursued in the previous research work. This aspect is very important since the temperature difference between the wall and glass in the air channel is the main force behind the natural convection current and the flow of heat energy in the air channel. Modeling the temperature variations in the same way is very crucial in predicting the efficiency of the system in the actualsense. Ensuring the system's efficiency is another equally important aspect of the research work. To bridge the gaps in the previous research work, the proposed work aims to apply the concepts of both thermal analysis and machine learning for an inclusive analysis of the Trombe wall system.

2. Method

2.1 Model Development

Machine learning algorithms in combination with thermal equations provide an effective method for system and process optimization. This may occur in instances where experimental data is incomplete. Additionally, if some of the system parameters are not available in the experimental setup. Here, the variable of interest would be expressed by thermal equations for the purpose of model training. To model the heat transfer process in the thermal storage wall (with vent) and glass materials, we make use of the equations below [24-26]:

$$a_s \cdot Q_{solar} \cdot t_g = \varepsilon_{w\text{-}g}\, \sigma \left[\left(\frac{T_{w(x)}+273}{100}\right)^4 - \left(\frac{T_{g(x)}+273}{100}\right)^4\right] + h_{cw}\left(T_{w(x)}-T_{aw(x)}\right) + h_{i_w}\left(T_{w(x)}-T_{room}\right) \quad (1)$$

$$\varepsilon_{w\text{-}g}\, \sigma \left[\left(\frac{T_{w(x)}+273}{100}\right)^4 - \left(\frac{T_{g(x)}+273}{100}\right)^4\right] \pm h_{cg}\left(T_{g(x)}-T_{ag(x)}\right) = \varepsilon_2\, \sigma \left[\left(\frac{T_{g(x)}+273}{100}\right)^4 - \left(\frac{T_s+273}{100}\right)^4\right] + h_o\left(T_{g(x)}-T_o\right) \quad (2)$$

For modeling the air in the channel based on the temperature near the wall and glass, we use Equation 3 (i= w, g) [24,26]:

$$T_{ai(x)} = T_{i(x)} - \frac{T_{i(x)} - T_{room}}{e^{\left(\frac{h_{ci}\, b\, At\, I}{c\, G_i}\right)x}} \quad (3)$$

Based on the temperature near the wall and glass in the channel, the average air temperature can be written as:

$$T_{am} = \frac{(T_{aw}+T_{ag})}{2} \quad (4)$$

Unlike in other research works [27,28], in the current research energy efficiency is calculated considering the average temperature in the channel. This is different from the research works [27,28], where the temperature at the outlet is calculated by a specific model for the temperatures at the inlet and theoretical temperatures at the outlet. By contrast, the temperature at the outlet is also calculated in the current work by taking the average temperature of the values measured near the wall surface and glass at the top of the channel. This gives a more realistic representation of the values for the temperature of the air entering the room. This average temperature is based on the temperatures measured near the wall surface and glass at the top of the channel. Since in the current research work the air enters the room through the top vent, the equation used in the research work is given by

$$\eta=\frac{m\,c\ (T_{mv}\text{-}T_{in})}{QA}\times 100 \qquad (5)$$

In the given equation, Q, A, Tin, and c represent the solar radiation on the wall surface, the area of the Trombe wall, the room temperature based on entering the channel through the lower vent, & specific heat of the air respectively. Also, Tmv is the average temperature of the air in the vent at the top of the wall. The mass flow rate of the air passing through the vents of the Trombe wall is given by the equation:

$$\text{m} = V A_c\ \rho \qquad (6)$$

To calculate the air velocity in the channel (V), the following equation can be defined [29]:

$$v_a=\left[\frac{2\,\Delta p}{\rho\ \left(c_1\left(\frac{A_c}{A_i}\right)^2+c_2\frac{z}{w}+c_3\left(\frac{A_c}{A_o}\right)^2\right)}\right] \qquad (7)$$

2.2 Collection of the Experimental Data

Experimental data used in the current research was taken from the study by Rabani et al. [30], where they studied the heating ability of the new Trombe wall system proposed for the desert climate in Yazd, Iran. Parameters extracted from the reference work are mainly composed of the following:

(1) Data on the outdoor temperature and solar radiation levels.

(2) Geometric dimensions. Air channel width: 30 cm; size of the room: 3 m × 2 m × 3 m (internal); sizes of the upper and lower vents: 30 cm × 50 cm; properties of wall material: concrete thickness of 20 cm.

(3) Sensor data. Temperatures in various locations along the Trombe wall absorber and the back side of the wall; air temperatures in the channel and the top and bottom vents; atmospheric temperature.

These experimental results were used for the two main purposes in the current study:

(1) Validation & Simulation: The validation of the thermal model was performed by utilizing the geometric & operating parameters for simulation of the system's operations on different solar & temperature inputs.

(2) Machine Learning Training: Measured values of the outdoor temperature and solar radiation from [30] contributed to the input. The variations in temperature near the glass and wall inside the channel, together with the system's efficiency obtained from the thermal model analysis, contributed to the targets used for the ML algorithm's training. Moreover, for the purpose of training the machine learning algorithms, the temperature variations near the glass and wall in the channel, as well as the system efficiency predicted by the thermal model, were used. By doing so, the approach verifies that the models developed are based on realistic experimental scenarios. This improves the authenticity of the predictions.

2.3 Validation and Optimization

2.3. 1 Algorithm for the Computational Flow Chart

Figure 1 explains the flow chart for solving and optimizing the equations developed in this research through the computational process. This process starts by initializing the input values. This includes the number of time steps (n), the values for solar radiation (q), the value for outer temperatures (Te), and the initial room temperature (Tin). Arrays are also preallocated for the storage of temperature and energy values. A time loop starts for the computation of values for each time step. Variables are defined in each iteration. These involve the wall surface area, thickness of the air channel, and the specific heat values of the air. Other values are also defined. These involve the average temperature of the air (Tm), the velocity of the air (V), the mass of the air (m), and the convective heat transfer coefficient (hc).

At the heart of the process lie the definitions of the system of nonlinear equations for temperatures. Solutions for the temperatures (room temperature, wall temperature, glass temperature, and air temperatures) are stored in their respective arrays. Calculations for energy efficiency parameters follow. After the time loop process is finished, the outcome is revealed to the user through the display of relevant results. This is followed by the plotting of various graphs concerning the temperature and energy variations.

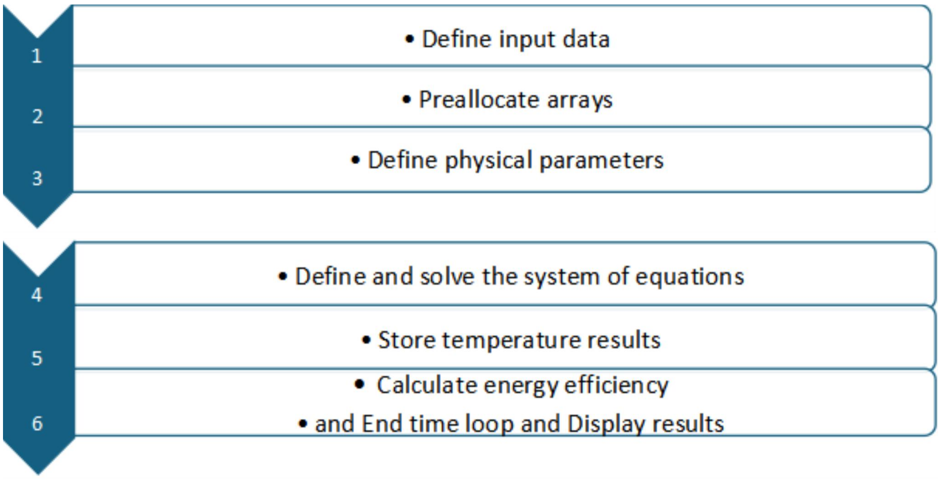

Figure 1. Flowchart for solving the equations defined in this study.

2.3.2 Predicting System Efficiency Based on Machine Learning Algorithm

In the current work, based on the outcomes of energy efficiency and temperature variations near the wall and glass in the channel, solar radiation, and outdoor temperatures, the combination of the results of thermal modeling and the application of machine learning algorithms (k-Nearest Neighbors, Random Forest, Linear Regression, and Decision Tree) is highlighted. This was also done in predicting room temperature but based on experimental outcomes used as the targeting variable. This approach not only enhances the estimation of thermal phenomena but also presents an effective method for energy efficiency analysis and room temperature estimation in building applications. In the current research work, the experimental data, geometry, and working parameters from the research by Rabani et al. [30] are used for validating the temperature variations and energy efficiency. Machine learning combines the strength of traditional thermal modeling. This allows for precision in the outcomes, rapid simulation processing, and self-stationed system optimization. Finally, it allows for intelligent system efficiency for designing complex thermal systems [1].

Four different machine learning algorithms are implemented for the prediction of room temperature in the Trombe wall system. The experimental data used for the analysis includes the outdoor temperature, solar radiation, among other geometrical parameters. Thus, the data points used for the analysis are given by the value of N for the experimental results.

(1) k- Nearest Neighbors

To develop the k-NN model, the `fitcknn` function in the Matrix Laboratory (MATLAB) platform was used by setting the value of the 'NumNeighbors' property to 1. However, the developed model was trained by utilizing the normalized input values (feature X) along with the known values of the room temperature (T). To check the estimation accuracy of the proposed model, both the predicted values and the experimental values were compared through graphical analysis. Additionally, the estimation error was also calculated.

(2) Linear Regression

Linear regression analysis was carried out by utilizing the `fitlm` function in MATLAB. This function was used to perform the regression analysis by means of the ordinary least squares method. Additionally, the regression was performed on the datasets by considering room temperature as the response variable. Predictions from the regression model were generated by utilizing the `predict` function.

(3) Decision Tree

The decision tree algorithm was also developed in MATLAB by utilizing the `fitrtree` function. By utilizing the input parameters and the response variable, the function developed a regression tree. After the regression tree was developed, the model was utilized in predicting room temperature values. By comparing the results to the experimental values, the model was evaluated for its predictive capabilities.

(4) Random Forest

The random forest model was generated by utilizing the MATLAB `TreeBagger` function for an ensemble of 90 trees. This ensemble model allows the collective use of various decision trees. Finally, the model was trained for the whole dataset by utilizing the `predict` function. Comparison analysis was performed through graphical representation and the calculation of the total error. This verifies the model's ability to effectively represent the intricate input parameters-room temperature relationship. Each of the models was tested on the same dataset and measures the same error metric (Mean Absolute Error) for comparing their ability to predict the behavior of the Trombe wall system.

3. Results and Discussion

3.1 Room and Duct Air Temperature Profile

Since energy stratification in buildings through solar energy utilization is very important, it is worth considering the application of machine learning algorithms to the Trombe wall system. We combined a thermal model with machine learning algorithms in this work to understand the air temperature changes in the air channel and how they affect the performance of the classic Trombe wall system (single wall and glass).

Room temperature changes as well as the temperatures close to the glass and the thermal storage wall within the air duct are presented in Figure 2. This figure indicates that as solar radiation increases, a very good temperature profile is created near the glass and wall, which consequently enhances the thermal efficiency of the room. When solar radiation is decreasing, the performance of the system goes down as well.

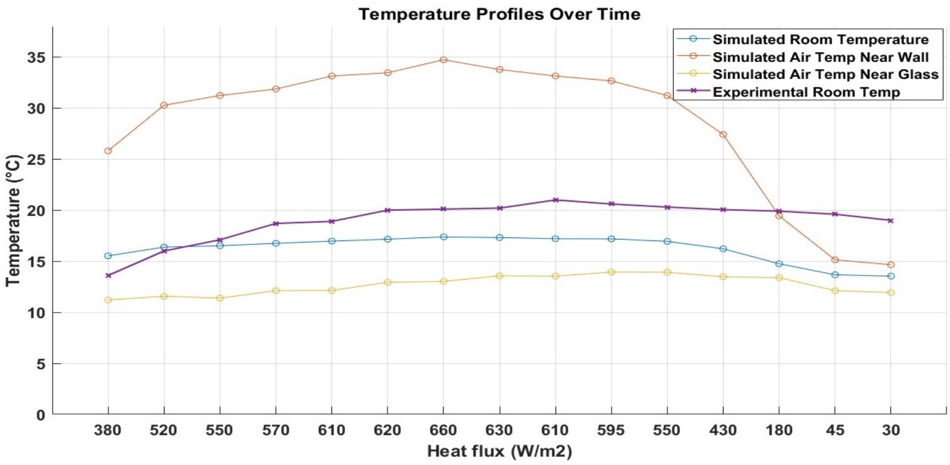

Figure 2. Temperature variations inside the room as well as nearby the glass and wall in the air channel of a Trombe wall system [30].

The room temperature in the figure gets to about 13.8 °C at a solar radiation of 30 W/m² and remains almost constant. This is also confirmed by the experimental results from the study by Rabani et al. [30]. As per the experimental data, from 17:30 onwards, when solar radiation significantly decreases and night is coming, a steep drop in room temperature is observed. For example, at 17:30 the room temperature is just about 19 °C, while at 23:45 it is around 15 °C.

The lack of experimental data on temperature changes near the wall and glass for training machine learning algorithms, as pointed out by earlier works, led to the training of four machine learning algorithms in this study. Inputs for these algorithms were solar radiation, outdoor temperature, and temperatures near the glass and storage wall (measured at distances from 0.5 to 2.5 meters through the air channel, starting from the bottom vent to the top vent). Room temperature (based on experimental results) was the target variable. By means of thermal equations, we estimated temperature changes near the glass and wall from the lower to the upper vent. These are the results displayed in Table 2 which shows that they are the input variables for the algorithms resulting in approximately 12 possible input variables. It should be noted that the findings presented in Table 1 are in agreement with the computations highlighted in Figure 2. In Table 2, Tnw and Tng are the abbreviations for the temperatures near the storage wall and glass, respectively.

Table 2. Temperature changes near the storage wall (Tnw) and glass (Tng) along with the air channel at different solar radiation levels (W/m^2) as calculated.

Heat flux (W/m^2)	T_{out} (°C)	x(0.5) T_{nw}	x(1) T_{nw}	x(1.5) T_{nw}	x(2) T_{nw}	x(2.5) T_{nw}	x(0.5) T_{ng}	x(1) T_{ng}	x(1.5) T_{ng}	x(2) T_{ng}	x(2.5) T_{ng}
380	-2.2	16.0828	18.4959	20.9286	23.3702	25.809	13.1996	12.698	12.198	11.6998	11.2053
520	2	16.9606	20.2624	23.5909	26.9313	30.268	13.2727	12.844	12.417	11.992	11.5698
550	1	17.1487	20.6409	24.1613	27.6943	31.224	13.2362	12.771	12.307	11.8461	11.3878
570	5	17.2741	20.8932	24.5415	28.2027	31.860	13.3823	13.064	12.746	12.43	12.1161
610	5.1	17.5249	21.3978	25.302	29.22	33.134	13.3859	13.0714	12.757	12.4447	12.1344
620	9.5	17.5876	21.5239	25.4919	29.474	33.452	13.5466	13.393	13.239	13.087	12.9354
660	10	17.8383	22.0285	26.2524	30.4911	34.725	13.5649	13.429	13.294	13.16	13.0265
630	13	17.6502	21.65	25.6819	29.728	33.770	13.6744	13.648	13.623	13.5978	13.5726
610	12.8	17.5249	21.3977	25.3017	29.2194	33.133	13.6671	13.634	13.601	13.5686	13.5362
595	15	17.4308	21.2084	25.0164	28.8378	32.655	13.7475	13.795	13.842	13.8898	13.9367
550	14.9	17.1487	20.6407	24.1608	27.6934	31.222	13.7438	13.787	13.831	13.8752	13.9185
430	12.5	16.3963	19.1266	21.8791	24.6415	27.401	13.6562	13.612	13.568	13.5248	13.4815
180	12	14.8287	15.9719	17.1244	18.2812	19.437	13.6379	13.575	13.513	13.4518	13.3904
45	5	13.9822	14.268	14.5562	14.8455	15.134	13.3822	13.063	12.746	12.4294	12.1152
30	4	13.8881	14.0787	14.2708	14.4637	14.656	13.3457	12.991	12.636	12.2833	11.9329

3.2 Prediction of Thermal Efficiency

Energy efficiency determinations based on the instrumental variables are depicted by Figure 3. As depicted, increased solar radiation is the major driver for the Trombe wall system's useful heat gain, the heat being supplied to the channel (considering both the wall and glazing) thus becoming more effective. But with drastically curtailed solar radiation, mostly in the late afternoon, the energy efficiency of the Trombe wall system goes down a lot. At such times, the useful heat from the air circulated in the channel becomes very small and the heat given off by the system comes mostly from the heat discharged by the wall itself during the night.

Moreover, when there is very little solar radiation (e.g., 30 W/m²), the heat that is effectively produced in the channel is greatly reduced, and both the channel and room temperatures stabilize at an equilibrium point. The enormous fall in energy efficiency as recorded in Figure 3 is due to the fact that according to Equation 5, Tm (the average air temperature at the top of the channel) is not substantially higher than the room temperature thus leading to an equilibrium between the average channel temperature and the room temperature. For instance, at 30 W/m² solar radiation, the room temperature is approximately 14 °C while the average air temperature at the top of the channel is nearly 11.93 °C. The tiny difference leads to very small heat transfer and consequently low system efficiency.

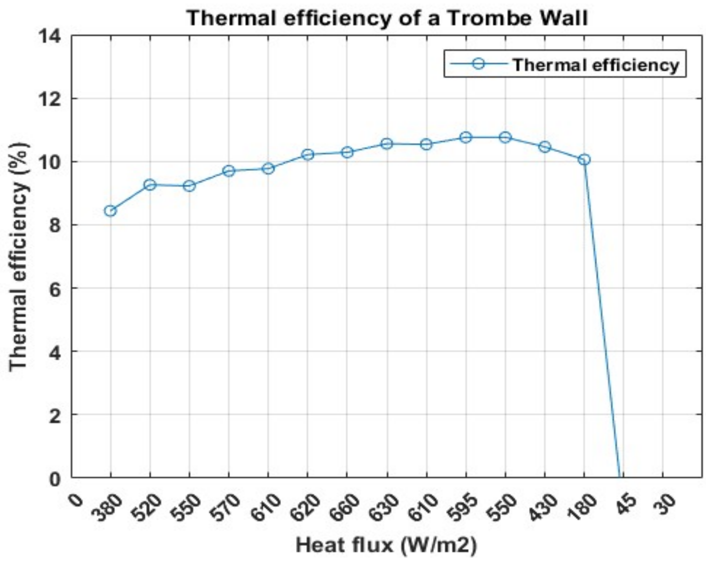

Figure 3. Prediction of thermal efficiency of a Trombe wall in this study.

3.3 Combining Machine Learning and Thermal Modeling for a Trombe Wall System

Figure 4(a) presents the thermal efficiency of a Trombe wall predicted by machine learning linear regression. The total error or the discrepancy between the prediction and the actual results is about 0.2785 meaning that the model has performed quite well. The linear regression algorithm results signify the error to be relatively low, hence the accuracy of the prediction of thermal efficiency is quite good. The algorithm may be appropriate for the systems in which a linear relationship between input variables and thermal efficiency of a Trombe wall exists. However, it might deteriorate its performance if there are non-linear patterns or complex interactions between variables in the data.

Figure 4(b) assesses the predicted thermal efficiency of a Trombe wall system using a decision-tree machine-learning algorithm with twelve inputs. The overall error of this model is approximately 0.2291, indicating that the decision-tree technique is less accurate than the linear-regression model in this case. The accuracy of predicting the thermal efficiency of a classical Trombe wall system using the k-nearest neighbor algorithm is shown in Figure 4(c). As depicted, the k-nearest neighbor regressor achieves a total error of zero, demonstrating an unusually high degree of accuracy. This performance suggests that the algorithm is particularly well-suited to the Trombe wall setup, likely because the data points for temperature measurements tend to form clusters based on the input variables.

Figure 4(d) shows the predicted thermal efficiency of a Trombe wall calculated using a random-forest algorithm. Similar to the k-nearest neighbors model, this method also achieves a total error of zero, indicating impressive precision and strong performance. Random forests are highly effective at capturing complex interactions and nonlinear patterns, which is likely why they perform well in this case. Moreover, they are more resistant to overfitting than a single decision tree, highlighting their strength in predicting the thermal performance of systems like Trombe walls, which are influenced by multiple factors. Figures 3a to 3d illustrate the target variable, which is the thermal efficiency of the Trombe wall. Input variables such as solar radiation and outside temperature were obtained experimentally.

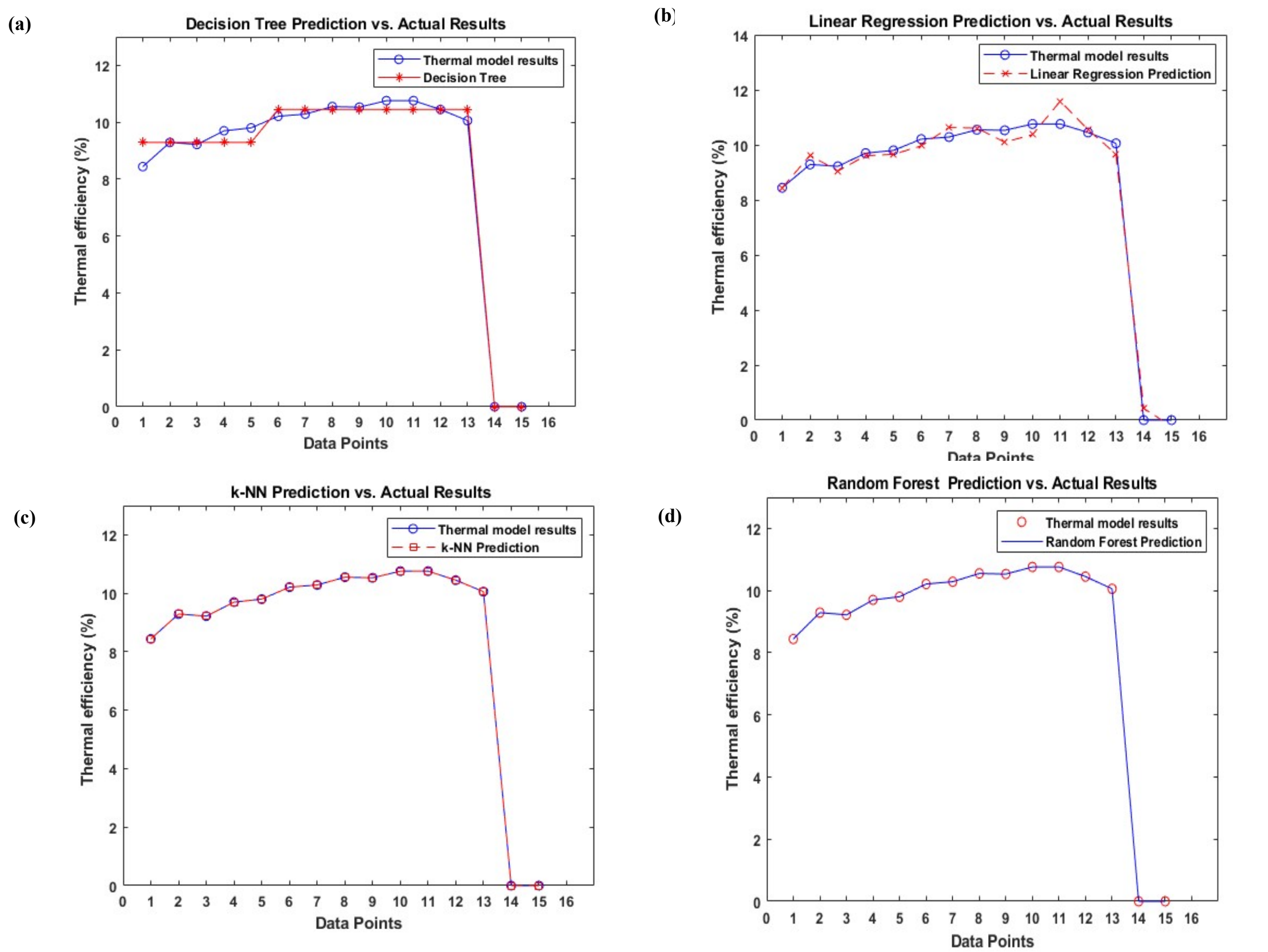

Figure 4. Predicted Thermal efficiency of a Trombe wall using: (a) linear regression algorithm; (b) decision tree algorithm; (c) k-nearest neighbor algorithm; (d) random forest algorithm.

4. Conclusion

This paper aimed to identify an accurate approach for predicting the energy efficiency of a classic Trombe wall system by combining a modified thermal model with machine learning. The modified thermal model, which determines the outlet-air temperature as a direct average of the temperatures around the wall and the glazing at the top of the channel, agrees well with experimental data; the calculated room temperatures are within five percent of the measured values, demonstrating the model's validity. The results were highly accurate when this thermal data was used to train machine learning algorithms. Specifically, both k-nearest neighbors and random forest algorithms demonstrated perfect predictive accuracy for thermal efficiency under the tested conditions. In contrast, the linear regression and decision tree algorithms had larger errors of 0.2785 and 0.2291, respectively, indicating their inadequacy in capturing the system's complex thermal behavior. The main outcome of this research is an effective hybrid model that can enhance the prediction of Trombe wall behavior, leading to more effective design and operational management to maximize solar energy utilization in buildings. A limitation of this work is that the model and machine learning analysis were developed and tested only on a classic Trombe wall setup (single wall and glazing). Its application to more advanced designs, such as those incorporating phase-change materials or fins, requires further study. Future work should focus on implementing the proposed framework in intelligent control systems that use IoT sensors and artificial intelligence to enable real-time monitoring and automatic regulation of ventilation for optimized energy savings. Additional efforts should also target the experimental optimization of thermal-storage materials, including nanomaterials in concrete, with validation through the simulation models developed in this research.

Data Availability Statement

The datasets used or analysed during the current study are available from the corresponding author upon reasonable request.

Conflict of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Generative AI Statement

The authors declare that no Gen AI was used in the creation of this manuscript.

References

[1] Meghdadi H, Khodadadi A. Theoretical analysis of Trombe wall performance: Evaluating key parameters for system efficiency. Innovative Energy Systems and Technologies, 2025, 1(1), 55-64. DOI: 10.64229/az1g5462

[2] Prozuments A, Borodinecs A, Bebre G, Bajare D. A review on Trombe wall technology feasibility and applications. Sustainability, 2023, 15(5), 3914. DOI: 10.3390/su15053914

[3] Duzcan A, Kara YA. Optimization of a multi-generation renewable energy supply system for a net-zero energy building with PCM-integrated Trombe wall. Journal of Energy Storage, 2025, 134, 117966. DOI: 10.1016/j.est.2025.117966

[4] Gao Q, Yang L, Shu Z, He J, Huang Y, Gu D, et al. Numerical and experimental study on the performance of Photovoltaic–Trombe wall in hot summer and warm winter regions: Energy Efficiency Matching and Application Potential. Buildings, 2024, 14(9), 2919. DOI: 10.3390/buildings14092919

[5] Xiao Y, Zhang T, Liu Z, Fukuda H. Thermal performance study of low-e glass Trombe wall assisted with the temperature-controlled ventilation system in Hot-Summer/Cold-Winter Zone of China. Case Studies in Thermal Engineering, 2023, 45, 102882. DOI: 10.1016/j.csite.2023.102882

[6] Zhu N, Deng R, Hu P, Lei F, Xu L, Jiang Z. Coupling optimization study of key influencing factors on PCM Trombe wall for year thermal management. Energy, 2021, 236, 121470. DOI: 10.1016/j.energy.2021.121470

[7] Friji K, Ghriss O, Bouabidi A, Cuce E, Alshahrani S. CFD analysis of the impact of air gap width on Trombe wall performance. Energy Science & Engineering, 2024, 12(10), 4598-612. DOI: 10.1002/ese3.1913

[8] Li S, Zhu N, Hu P, Lei F, Deng R. Numerical study on thermal performance of PCM Trombe Wall. Energy Procedia, 2019, 158, 2441-2447. DOI: 10.1016/j.egypro.2019.01.317

[9] Akbarzadeh A, Charters WW, Lesslie DA. Thermocirculation characteristics of a Trombe wall passive test cell. Solar Energy, 1982, 28(6), 461-468. DOI: 10.1016/0038-092X(82)90317-6

[10] Bevilacqua P, Benevento F, Bruno R, Arcuri N. Are Trombe walls suitable passive systems for the reduction of the yearly building energy requirements?. Energy, 2019, 185, 554-566. DOI: 10.1016/j.energy.2019.07.003

[11] Long J, Yongga A, Sun H. Thermal insulation performance of a Trombe wall combined with collector and reflection layer in hot summer and cold winter zone. Energy and Buildings, 2018, 171, 144-54. DOI: 10.1016/j.enbuild.2018.04.035

[12] Qi X, Wang J, Wang Y. Influence of a Built-in Finned Trombe Wall on the indoor thermal environment in cold regions. Energies, 2024, 17(8), 1874. DOI: 10.3390/en17081874

[13] Gharaee H, Erfanimatin M, Bahman AM. Machine learning development to predict the electrical efficiency of photovoltaic-thermal (PVT) collector systems. Energy Conversion and Management, 2024, 315, 118808. DOI: 10.1016/j.enconman.2024.118808

[14] Kurt E, Tunalı TE, Tavşancı G, Özgül E. Machine learning-based predictive control of thermal management system in battery electric vehicles. Thermal Science and Engineering Progress, 2025, 67, 104104. DOI: 10.1016/j.tsep.2025.104104

[15] Ye L, Ding Y. Comparative analysis of shallow and deep machine learning models for predicting indoor thermal response of flexible envelope system. Journal of Energy Storage, 2025, 126, 116997. DOI: 10.1016/j.est.2025.116997

[16] Penuela J, Hoosh SM, Kamyshev I, Bischi A, Ouerdane H. Indoor thermal comfort management: A Bayesian machine-learning approach to data denoising and dynamics prediction of HVAC systems. arXiv preprint, 2025. DOI: 10.48550/arXiv.2507.02351

[17] Yahya Z, Mahmoud AM, Ali V, Khan O, Parvez M, Yadav AK. MATERIAL selection and optimization for hybrid Solar-Thermal plume Systems: A machine learning approach to boost passive cooling and energy efficiency. Thermal Science and Engineering Progress, 2025, 104097. DOI: 10.1016/j.tsep.2025.104097

[18] Yan P, Wen C, Ding H, Wang X, Yang Y. The potential of machine learning to predict melting response time of phase change materials in triplex-tube latent thermal energy storage systems. Applied Energy, 2025, 390, 125863. DOI: 10.1016/j.apenergy.2025.125863

[19] Özcan Y, Gürdal M, Deniz E. Thermal behavior in solar distillation system using experimental and machine learning approach with scaled conjugated gradient algorithm. Desalination, 2025, 606, 118765. DOI: 10.1016/j.desal.2025.118765

[20] Bouguergour Y, Menhoudj S, Mokhtari AM, Dehina K, Zairi A, Mege R, et al. Experimental and machine learning-based identification of a solar thermal system for domestic hot water and direct solar floor heating. Case Studies in Thermal Engineering, 2025, 69, 105935. DOI: 10.1016/j.csite.2025.105935

[21] Bhamare DK, Saikia P, Rathod MK, Rakshit D, Banerjee J. A machine learning and deep learning based approach to predict the thermal performance of phase change material integrated building envelope. Building and Environment, 2021, 199, 107927. DOI: 10.1016/j.buildenv.2021.107927

[22] Çolak AB, Rezaei M, Aydin D, Dalkilic AS. Experimental and machine learning research on a multi-functional Trombe wall system. International Journal of Global Warming, 2024, 33(4), 404-415. DOI: 10.1504/IJGW.2024.139902

[23] Hashemi SH, Besharati Z, Hashemi SA, Hashemi SA, Babapoor A. Prediction of room temperature in Trombe solar wall systems using machine learning algorithms. Energy Storage and Saving, 2024, 3(4), 243-249. DOI: 10.1016/j.enss.2024.09.003

[24] Hashemi SH, Dinmohammad M, Hashemi SA. Evaluation of changes of room temperature according to Trombe wall system. Modeling Earth Systems and Environment, 2020, 2655-2659. DOI: 10.1007/s40808-020-00845-3

[25] Hashemi SH, Besharati Z, Babapoor A. Impact analysis of channel air temperature variations on composite Trombe wall using a theoretical model and GRG algorithm. Journal of Umm Al-Qura University for Engineering and Architecture, 2025, 16, 627-636. DOI: 10.1007/s43995-025-00143-y

[26] Piotrowski JZ, Stroy A, Olenets M. Mathematical modelling of the steady state heat transfer processes in the convectional elements of passive solar heating systems. Archives of Civil and Mechanical Engineering, 2013, 13(3), 394-400. DOI: 10.1016/j.acme.2013.02.002

[27] Irshad K, Algarni S, Islam N, Rehman S, Zahir MH, Pasha AA, et al. Parametric analysis and optimization of a novel photovoltaic trombe wall system with venetian blinds: Experimental and computational study. Case Studies in Thermal Engineering, 2022, 34, 101958. DOI: 10.1016/j.csite.2022.101958

[28] Dong X, Xiao H, Ma M. Thermal performance of a novel Trombe wall enhanced by a solar energy focusing approach. Low-carbon Materials and Green Construction, 2024, 2(1), 8. DOI: 10.1007/s44242-024-00039-5

[29] Chen ZD, Bandopadhayay P, Halldorsson J, Byrjalsen C, Heiselberg P, Li Y. An experimental investigation of a solar chimney model with uniform wall heat flux. Building and Environment, 2003, 38(7), 893-906. DOI: 10.1016/S0360-1323(03)00057-X

[30] Rabani M, Kalantar V, Dehghan AA, Faghih AK. Experimental study of the heating performance of a Trombe wall with a new design. Solar Energy, 2015, 118, 359-74. DOI: 10.1016/j.solener.2015.06.002