



Journal of Materials and Engineering Structures

Research Paper

An efficient surrogate model for building energy consumption estimation considering global warming scenario: a case study in Tra Vinh

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ARTICLE INFO

Article history:

Received : 14 November 2024

Revised : 25 December 2024

Accepted : 27 December 2024

Keywords:

Building energy requirements

Machine learning

Optimization algorithms

Climate change

ABSTRACT

Climate change has emerged as a global challenge, profoundly affecting various sectors, including building energy. Rising temperatures lead to an increase in energy requirements, and the choice of building materials and orientation influences a building's energy efficiency. This paper aims to build a surrogate model for predicting energy demand through building materials. A case study of a two-storey residential house in Tra Vinh is conducted based on the RCP4.5 climate change scenario for 2050. Firstly, training datasets are generated under the assumed global warming scenario RCP4.5, considering various materials for walls and ceiling slabs. Then, a machine learning model is developed to forecast building energy consumption, with the number of hidden nodes, hidden layers, and training algorithm optimized based on a root mean squared error objective function. Additionally, building orientations are analyzed concerning the movement of the sun. The findings demonstrate the simplicity, efficacy, and application potential of the suggested approach in enhancing the efficiency of building energy analysis, offering valuable insights for sustainable building practices in the face of future climate change.

1 Introduction

Vietnam is among the countries most vulnerable to sea-level rise worldwide [1]. Climate change impacts are highly concentrated in Vietnam's two major river deltas, the Mekong River and the Red River [2]. As a province in the Mekong Delta River, Tra Vinh is considered highly vulnerable to the consequences of climate change [3]. Therefore, it is crucial to conduct studies aimed at mitigating the negative effects of climate on the sustainable development of Tra Vinh. Promoting

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low-carbon energy generation, including renewable and energy efficiency, is a key goal of environmental sustainability and resilience [1].

In the field of building construction, reducing CO₂ emissions is a critical concern throughout various phases, including construction (emissions from materials, transportation, and machinery), operation (emissions from energy consumption), as well as repair and demolition (emissions from materials, transportation, and machinery) [4, 5]. This current study focuses on calculating building energy consumption to identify design solutions that minimize energy demand. These solutions not only provide economic benefits but also contribute to environmental sustainability.

De Masi et al. proposed new design solutions for Italian temporary houses based on the energy performance requirements from 324 cases [6]. Taking into account the building materials, HVAC systems, geometric layout, and thermo-physical properties of the structure, they recommended the optimal solutions for different climate zones as well as building sizes. In a separate effort to optimize building energy consumption, authors in [7] manually examined 19 scenarios regarding the building dimensions and orientations. Their findings suggested that a building with a ratio of one to four could achieve the lowest energy requirements in Rasht city. Recently, artificial neural networks (ANN) and optimization algorithms have been increasingly being applied to enhance efficiency in various fields, including economics [8], civil engineering [9-12], and more. Therefore, some authors applied the advanced approach to energy requirement prediction [13-15]. However, research on building energy calculations that consider future climate change remains relatively limited. Mostafazadeh et al. [16] optimized life cycle costs and thermal discomfort, taking into account future climate change and rising energy prices. The results revealed that climate change significantly impacts building performance by altering external thermal loads. Building on a similar concept, the authors in [17] developed a new simulation-based optimization method for building energy consumption, taking into account the effects of both present and future weather data. The findings also revealed that the consequence of climate change varies depending on the construction area of the house. Therefore, considering future design solutions is crucial for sustainable development.

In addition, proper orientation enhances natural daylighting, reducing reliance on artificial lighting [18]. It also affects exposure to prevailing winds, optimizing natural ventilation and reducing mechanical cooling dependence. A properly oriented building can significantly reduce energy consumption over its lifespan [7, 19, 20]. Therefore, the building's orientation can be a potential solution to reduce energy requirements.

Therefore, this study aims to reduce the energy requirements for a two-story residential house by investigating various building materials, considering climate change with an RCP4.5 scenario in 2050. Additionally, the data obtained are utilized to develop a surrogate model for predicting energy needs. This surrogate model is based on a stochastic process, where the hyperparameters of an ANN are optimized. With optimized hyperparameters, the surrogate model can efficiently and accurately predict energy consumption. Furthermore, the study explores the impact of house orientation to provide a more comprehensive understanding of the building's energy demands concerning the sun's path.

2 Methodologies

The hyperparameters of an ANN are critical parameters that control the structure and learning process of the model. Generally, they must be set before the training process begins. Optimizing these hyperparameters can significantly enhance the performance of the ANN, but selecting the right values for these parameters is often challenging. Therefore, this study focuses on optimizing these hyperparameters using a stochastic process [21]. In this process, marine predator algorithm (MPA) in [22] is employed to optimize parameters, for instance, the number of hidden nodes, hidden layers, and the training algorithm. MPA is known for its strong global search capabilities and efficient exploration of the hyperparameter space, which helps in avoiding local minima and finding an optimal solution [23]. The root mean squared error (RMSE) is effective in developing a prediction model [24]. Therefore, an objective function using RMSE is presented as follows Eq. (1)

$$OF = \sqrt{\frac{\sum_{i=1}^N (y_{predict}^i - y_{target}^i)^2}{N}} \quad (1)$$

where N represents the number of observed data points. $y_{predict}$, y_{target} denote the estimated outputs and the desired targets, respectively.

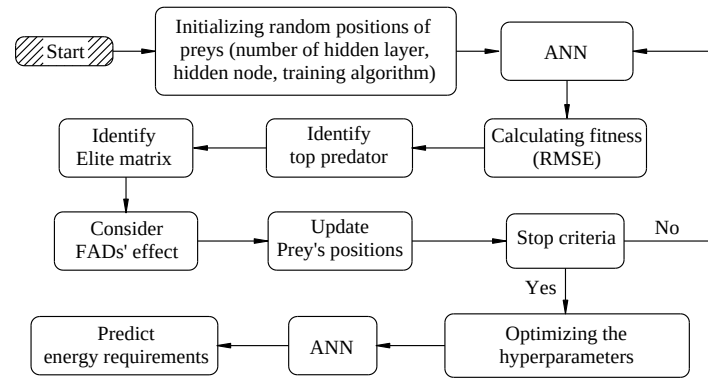


Fig. 1 – Operating principle of MPA-ANN for predicting energy requirements

Random values of the hyperparameters are treated as prey in the MPA. These initial values are then input into the ANN to calculate fitness using RMSE. The top predator and Elite matrix are constructed based on the obtained fitness values. To avoid local minima, the FAD's effect is incorporated into the optimization process before updating the prey's positions (i.e., the new hyperparameter values). Once the stopping condition is met, the process returns the optimized hyperparameters and the optimized model for predicting energy requirements, as shown in Fig. 1. Readers interested in the effectiveness of MPA can refer to [22], and [25] for further details.

3 Case study

3.1 Building information of the residential house

A two-storey house with a flat roof is used to analyse building energy requirements (see Fig. 2c). Details of the room in as-built drawings are presented in Fig. 2a and Fig. 2b. The heights of the first and second floors are 3.9m and 3.6m, respectively. The house was originally oriented to face south.

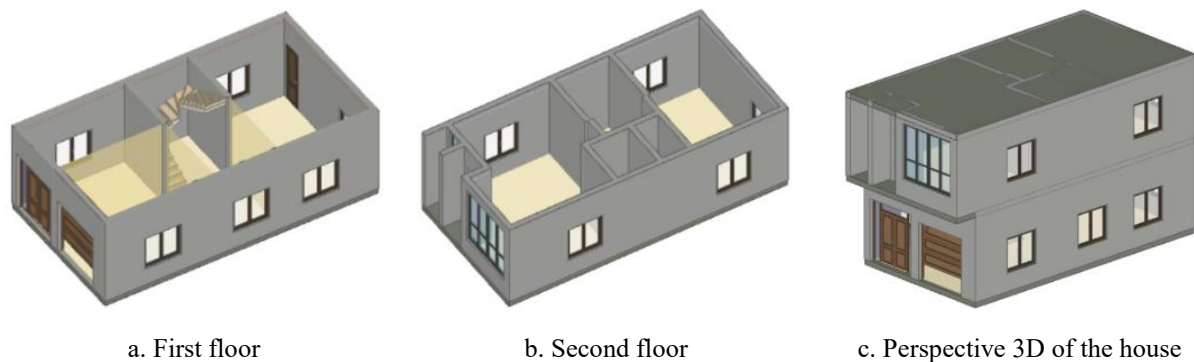


Fig. 2 – House details

The house features a living room, a garage, a kitchen, two bedrooms, and two bathrooms. The total area used for analyzing energy consumption is 141.54 m². Solid brick walls and ordinary concrete slabs are materials for walls and ceiling slabs. It is considered as the baseline model for comparison purposes. A constant indoor air temperature set point of 26°C is maintained to ensure residents' comfort. This means the cooling system is activated whenever the indoor temperature exceeds the set point. Besides, in this simulation, it is assumed the ventilation zone operates with natural ventilation, setting the outdoor airflow rate at a minimum value of 0.1 Vol/h, in the context of natural ventilation typically indicates low air exchange.

Using material properties in Table 1 and climate data in Fig. 4, the monthly energy requirement for the house is depicted in Fig. 3. It is observed that the building's energy requirement from March to July is higher in comparison with the other months. The total energy demand is approximately 40,535.83 kWh per year.

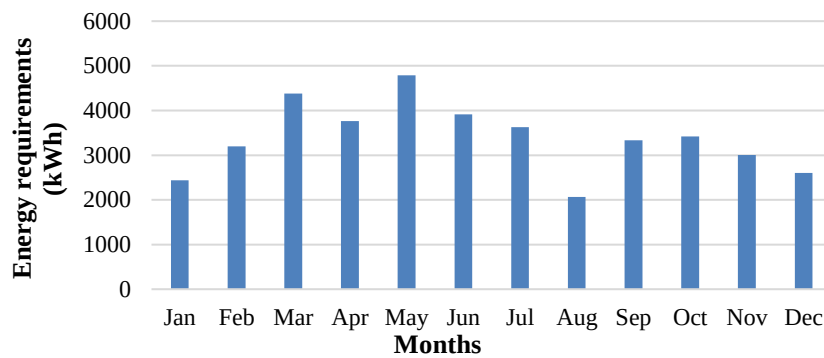


Fig. 3 – Variation in energy demand throughout the year for the original design.

3.2 Dataset collection for surrogate model

3.2.1 Climate change with a scenario of RCP 4.5

Representative concentration pathways (RCPs) are scenarios used to simulate various climate futures. The main RCPs are 2.6, 4.5, 6.0, and 8.5, representing different levels of greenhouse gases and their impact by the year 2100 [1]. The RCP4.5 scenario assumes moderate efforts to mitigate the influence of climate change on the environment. This study focuses on predicting energy requirements in 2050 under the RCP 4.5 scenario. To analyse the impact of weather changes on energy demands in a residential house at Tra Vinh, daily weather data such as temperature, and solar radiation are collected using Meteonorm software [26]. Effects of wind and shading are not considered in this study. The weather data during the January of 2050 is depicted in Fig. 4.

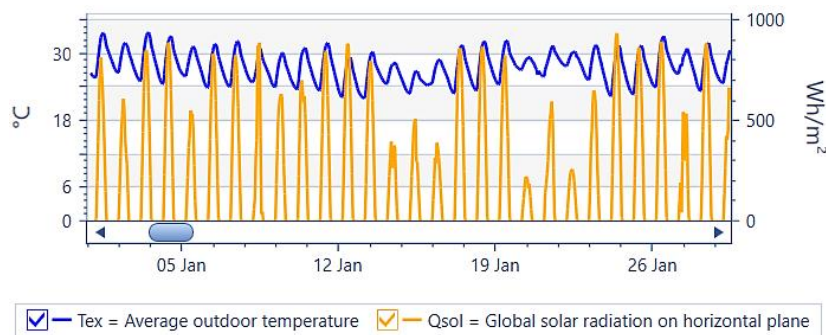


Fig. 4 – Predicted daily climate data during January of 2050

3.2.2 Materials

In this paper, several types of materials for walls and ceiling slabs are presented in Table 1. These materials are imported from the TerMus Plus library [27]. The insulation capacity of the building walls and ceiling slabs is simulated by the thermal transmittance or heat transfer coefficient (U-value, W/m^2K). This index is utilized to identify the heat gains in summer as well as the heat losses during winter.

Based on these materials, 50 models of the house were simulated in TerMus Plus to analyse the building energy demand over a year. The resulting energy requirements are in Fig. 5. It is evident that energy demand varies significantly with different materials. The findings show that using materials such as clay brick partition walls and reinforced steel concrete can reduce the energy requirement to 30,082 kWh. This represents a 25.8% reduction compared to the original design. Therefore, this combination can be considered the optimal material choice for the residential house under investigation.

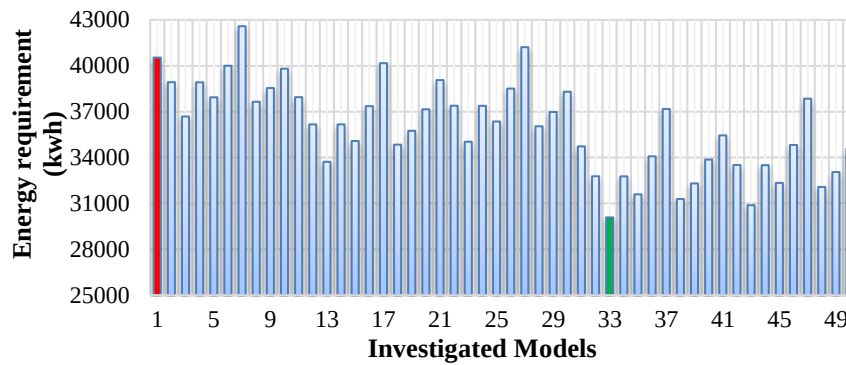


Fig. 5 – Relationship between building energy requirements and material types (red: original; green: optimized)

Table 1 – Materials used in the house models

Building elements	Materials	U-value*	Baseline	Label
Vertical envelope: 250 mm Wall (mortar included)	Solid brick wall	1.8397	x	W1
	Solid brick masonry cavity wall	1.4049		W2
	Clay brick partition wall	0.8853		W3
	Curtain wall with air gap	1.4003		W4
	Hollow brick cavity wall	1.1972		W5
	Concrete wall	1.6724		W6
	Reinforced concrete wall	2.4867		W7
	Insulated reinforced concrete wall	1.0556		W8
	Cavity wall composed of concrete block	1.2846		W9
	Tuff block masonry wall	1.632		W10
Horizontal envelope: 235 mm ceiling slab (mortar included)	Ordinary concrete slab	3.114	x	S1
	Reinforced concrete slab	2.1463		S2
	Light-weight concrete floor slab	2.599		S3
	Reinforced steel concrete	1.1243		S4
	Hollow-core slab	1.256		S5

Note: “*” U values (W/m²K) are extracted from TerMus Plus [27]

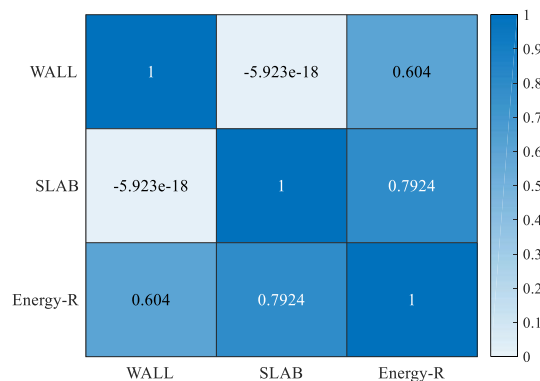


Fig. 6 – Correlation matrix between the investigated variables (wall, slab) and energy requirement

3.2.3 Surrogate model for energy demand prediction

As previously mentioned, the current paper aims to build a surrogate model for estimating energy requirements. Therefore, the collected data from 50 models are used as the training dataset. However, before constructing the machine learning model, the important variables in the training dataset are identified using a correlation matrix, as shown in Fig. 6. It

can be observed that both investigated variables are independent of each other, yet they have a significant impact on the output, namely the energy requirements.

Artificial neural networks (ANN) and MPA-ANN are employed to build the surrogate models. Hyperparameters for ANN and MPA-ANN, are presented in Table 2. Training algorithms, namely Bayesian Regularization backpropagation (trainbr), Scaled Conjugate Gradient (trainscg) and Levenberg Marquardt (trainlm) are investigated. The dataset is divided with 70% allocated for training, 15% for validation, and 15% for testing. The input parameters for MPA include 20 particles, 30 iterations, and 4 variables (1 for hidden layer, 2 for hidden nodes, 1 for training algorithm), respectively.

Table 2. Input parameters for prediction models

Model	Input node	Number of hidden layers	Hidden node	Training algorithm	Output node
ANN	2	2	10	trainlm	1
MPA-ANN	2	1 ÷ 2	1 ÷ 30	trainlm, trainbr, trainscg	1

After 30 iterations, a minimum value of the fitness converged to 7.86 as in Fig. 7. Corresponding to this fitness value, the optimized hyperparameters of MPA-ANN are 2 hidden layers with 12 and 13 hidden nodes for each and trainbr for the training algorithm. The performance of the optimized model is verified through several statistical metrics.

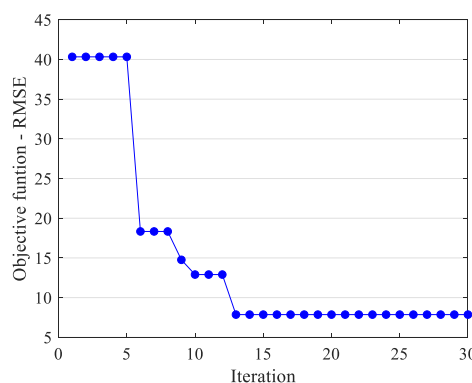


Fig. 7 – The evolution of the objective function using MPA-ANN

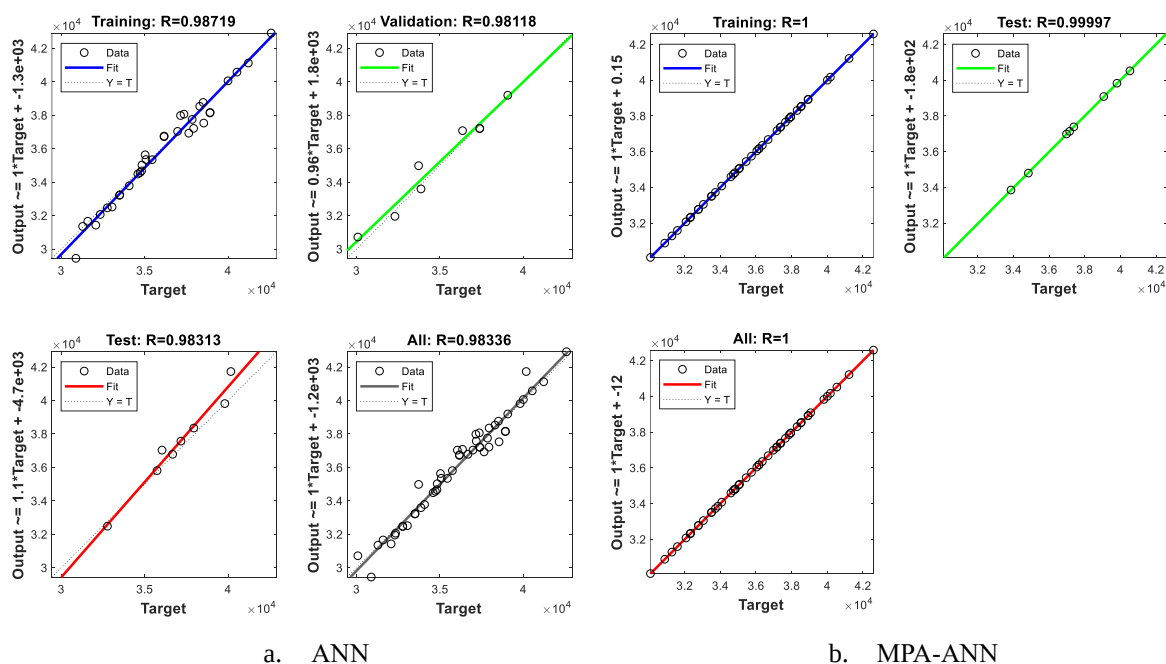


Fig. 8 – Regression plots

The first parameter is the correlation coefficient. A value closer to 1 indicates a stronger correlation between the targets and outputs. By using MPA to optimize the ANN's hyperparameters, this value is improved significantly, increasing from 0.9834 to nearly 1 (please see Fig. 8). Moreover, using MPA-ANN, most data points from both training and testing datasets closely follow the 45-degree line, indicating a good fit. In contrast, the points for the standard ANN are more scattered around this line, suggesting less accuracy. This demonstrates the improved stability and predictive performance of the MPA-ANN.

Table 3 – Statistical analysis of differences between targets and outputs

Model	RMSE	Mean	std	R ²	Adjusted R ²
ANN	560.30	−22.39	565.53	0.9670	0.9663
MPA-ANN	7.86	0.6652	7.91	1	1

Additional statistical metrics, such as root mean squared error (RMSE), average (mean), standard deviation (std), determination coefficient (R²), and adjusted R², are presented in Table 3. These metrics help confirm that the training process of MPA-ANN outperforms that of the standard ANN. Lower RMSE, mean, and std indicate better model performance and a lower prediction error on new data. The closer the R² and adjusted R² values are to 1, the better the model is at making predictions. Based on the results in Table 3 and Fig. 8, the proposed model demonstrates a low RMSE and high R² for both the training and testing datasets. This suggests that the proposed model has strong potential to generalize well from the training data to new, unseen data. As a result, the differences between predicted and actual values using MPA-ANN are consistently below 0.12%. In contrast, common errors when using the standard ANN range from 1% to 5% (see Fig. 9

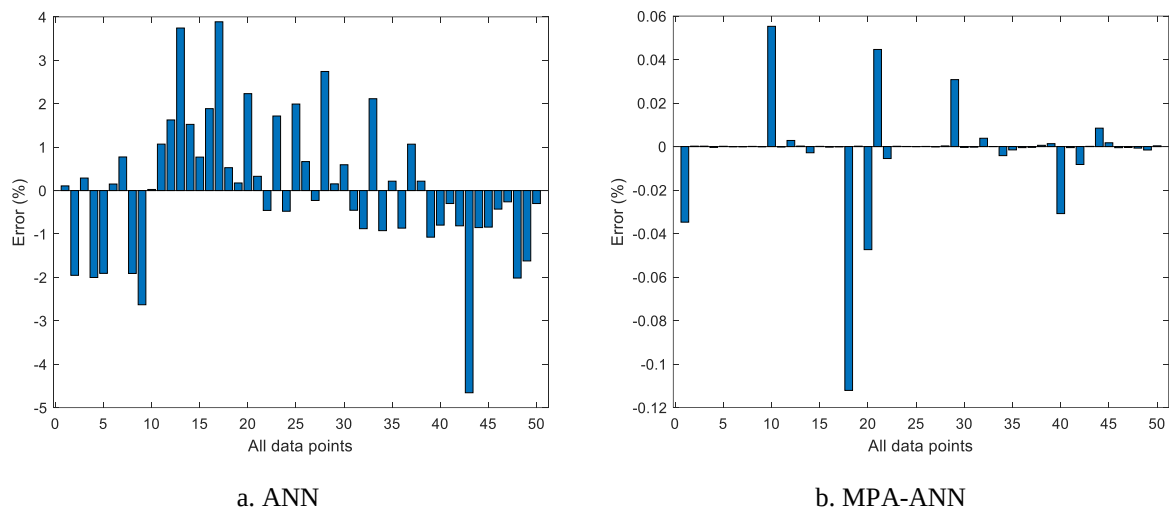


Fig. 9).

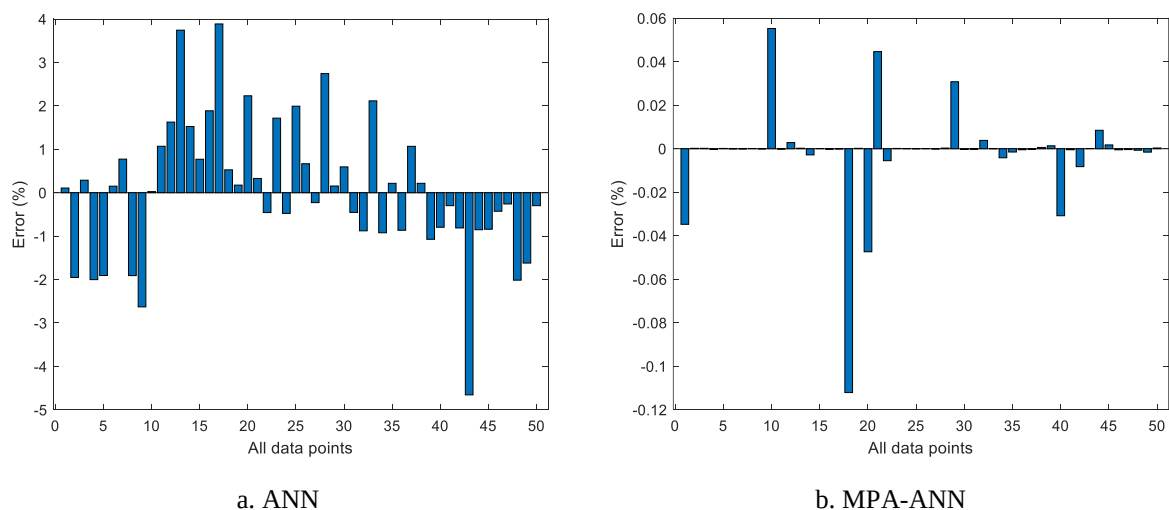


Fig. 9 – Errors between targets and outputs

Besides statistical metrics, MPA-ANN is used to predict energy requirements for several cases where wall and slab dimensions are modified as shown in Table 4. This data is created by varying the thickness of the walls or the ceiling slab or both. Using U-values as inputs, the trained models are employed to predict energy requirements.

Table 4 – Variations in the thickness of walls and ceiling slabs

Case	Wall	Thickness	U value	Slab	Thickness	U value
1	W10	250	1.632	S3	225	2.6348
2	W6	210	1.8904	S1	215	3.219
3	W3	220	0.9919	S3	235	2.599
4	W1	250	1.8397	S5	245	1.2413
5	W3	220	0.9919	S3	225	2.6348
6	W9	230	1.3542	S4	220	1.147

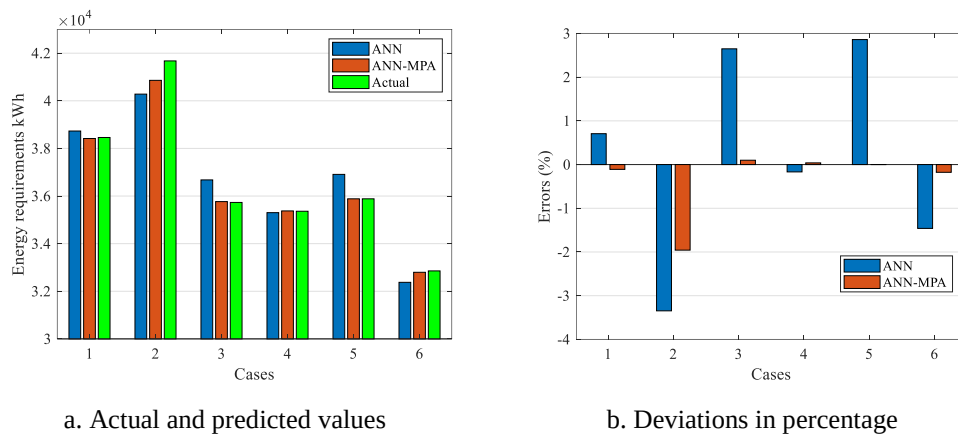
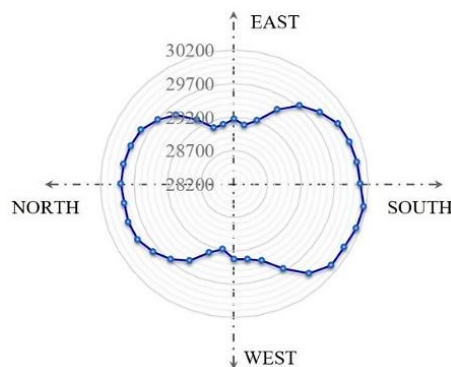
**Fig. 10 – Differences in energy requirements**

Fig. 10 presents a comparison between the two prediction models. The MPA-ANN model demonstrates superior performance in predicting energy demands compared to ANN. Most errors are smaller with MPA-ANN, with the majority being less than 0.17%, except for one case where the error is 1.96% (please see Fig. 10). In contrast, the observed errors using ANN fluctuate between 0.7% to 3.35%, with one exception of 0.17%. Therefore, MPA-ANN can be considered a reliable surrogate model for estimating energy needs, as an alternative to physical models.

**Fig. 11 – Relationships between energy requirement and building orientation**

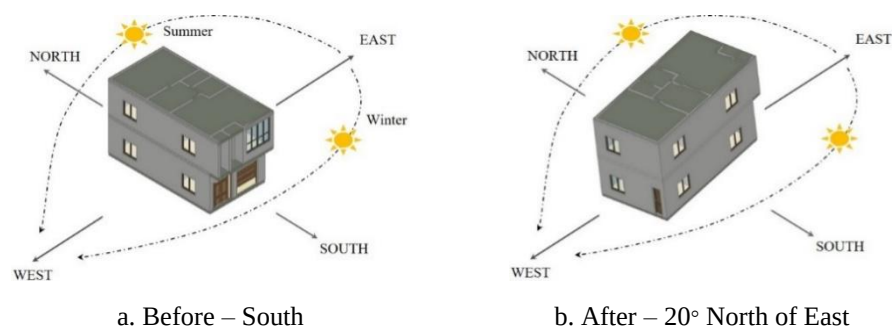


Fig. 12 – Building orientation and sun's path in Tra Vinh

3.2.4 Effect of building orientation

In addition to materials, house orientation also affects energy needs. To gain a comprehensive understanding of this impact, several orientation scenarios were analyzed. In the initial design (see Fig.12a), the house is oriented towards the south, which is considered 0° . By changing the orientation incrementally by 10° relative to the previous direction, the variation in energy demand is shown in Fig. 11. The building's energy demand is higher when oriented towards the south and north compared to the east and west orientations as in Fig. 11. The minimum energy requirement of 29,090.94 kWh is observed when the house is oriented 20° north of east (please see Fig. 12b). This energy demand is reduced by 3% compared to that of a south-facing house.

Fig. 12a shows the movement of the sun during summer and winter. According to the sun's path, the minimum energy demand can be explained by the fact that buildings with a longer side along the east-west axis can reduce solar gain compared to those oriented along the north-south axis. This configuration helps to minimize unwanted heat gain.

4 Conclusion

This study focuses on estimating energy requirements, considering the RCP 4.5 climate scenario in Tra Vinh and building orientation. The findings demonstrate that optimizing the hyperparameters of the surrogate model significantly improved the performance of conventional ANNs for predicting energy demands. Specifically, the differences between outputs and targets in the training dataset decreased from 5% to less than 0.12%. The effectiveness of the developed model in energy requirements estimation was validated through statistical metrics and several simulations, which achieved errors of less than 2%. Furthermore, optimizing material types and building orientation reduced the total energy demand by approximately one-third compared to the original design. In this study, the influence of material type on energy reduction proved to be substantially greater than that of building orientation, with reductions of 25.8% and 3%, respectively. Additionally, the study provides a comprehensive understanding of the influence of building orientation on energy requirements. Orienting the house along the east-west direction, compared to the north-south direction, was shown to reduce the building's energy needs.

Acknowledgments

This study is funded by the ITP Project 2024, Ghent University, Belgium: “A Research Training Programme on Machine Learning for Climate Change Mitigation in Buildings”

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