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Development of Deep Learning-Based Models for Predicting the Thermal Performance of Phase Change Materials

Ganesh J G[1], Jayakrishnan V M[2], Sreekanth S[3]

[1,2,3]Lecturer In Mechanical Engineering, N.S.S Polytechnic College, Pandalam

Abstract

Evaluating parameters such as time delay and damping coefficient in different climates and locations to evaluate Building skins combined with PCM are difficult and time-consuming to reduce heat gain. This research aims to develop a novel deep learning-based model for predicting PCM integrated roof buildings' thermal performance. When making predictions about performance, we recommend using the MKR indicator. Taking into account changes in PCM's thermophysical properties, we investigate the application of deep learning methods to predict the thermal performance of a PCM roof. Create an informative focus that includes mathematical representation considering the versatility of PCMs' thermo physical properties. The MKR index is predicted using ANN, a deep learning technique. The results can indicate that ANN is the most effective model. During Sensitivity testing, training and analysis, independent datasets show the effectiveness and better performance of models based on artificial neural networks.

Keywords: PCM integrated Roof, MKR index, Deep learning, Performance prediction, Artificial Neural Network

Introduction

Phase change materials (PCM) are materials that store or transmit passive energy during a phase change. The use of PCMs in building envelopes has been widely used in recent years as a means of reducing energy consumption and improving the thermal performance of buildings [1]. By reducing temperature differences, the incorporation of PCMs into the building envelope shows great potential to reduce energy consumption related to cooling and heating.

However, evaluating the thermal performance of architectural envelopes composed of PCMs is difficult and time-consuming [2]. Time delay, rate of decay and other parameters should be evaluated and their variation under different climatic conditions and locations. These evaluations require extensive experimental measurements, which can be costly and time-consuming.

The development of predictive models Thermal performance of PCM's composite architectural envelope includes: potential to significantly reduce the time and cost associated with experimental evaluation [3]. Specifically, deep learning recent years to develop predictive models for various engineering applications. Artificial neural networks (ANNs) are used in deep learning, a type of machine learning that uses data for learning and prediction. ANN can learn complex relationships between inputs and outputs, making them suitable for modelling complex systems such as Building thermal performance combined with PCM envelopes.

A deep learning-based model for predicting PCM-grafted surface structure warm expression will be improved in this study [5]. We propose the index MKR Check if the PCM integrated sealing works well. The MKR indicator is a short factor, time delay and the variation of these parameters under different climatic conditions and locations. To predict the MKR index, we make use of deep learning techniques, particularly ANN; we take into account various PCM real-world thermal properties. Numerical simulations are used to generate data points in order to investigate changes in PCMs' thermophysical properties.

This study will use the proposed MKR file to highlight the roof and create an intelligent, deep learning-based model for predicting the warm expression of a PCM building envelope [6]. The developed model can significantly reduce the time and cost associated with experimental evaluation and provides a valuable tool for building designers and engineers.

Here is the layout of the rest of this paper. In the second section, PCM-integrated building envelopes and predictive models for their thermal performance [7]. Section 3 provides a description of the research methods, which include numerical simulations and deep learning techniques. Section 4 will talk about the study's findings, including how well the proposed MKR index and deep learning models performed [8]. Section 5 discusses the implications of the study and identifies areas for future research. Finally, Section 6 presents the conclusion of the study.

In outline, the review introduced in this paper adds to the improvement Model for anticipating the warm presentation of building skins, particularly rooftops, implanted in PCMs in view of profound learning. The proposed model can significantly reduce the time and cost associated with experimental evaluation and provides a valuable tool for building designers and engineers [10]. Thermal performance can be evaluated using the proposed MKR index PCM-integrated roofs under different climatic conditions and locations.

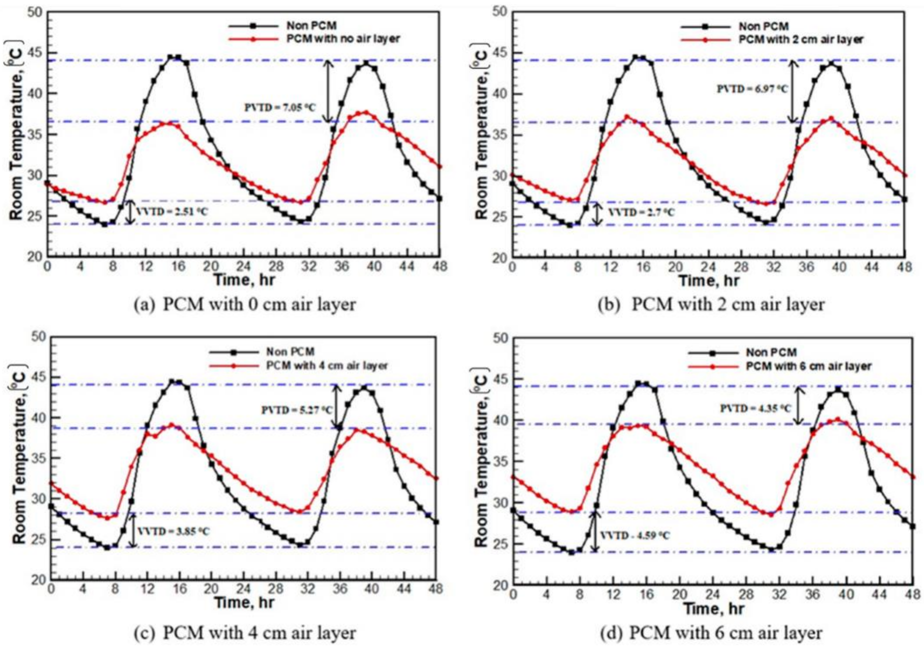

Fig 1 shows the thermal performance of a PCM-integrated roof compared to a non-PCM roof, demonstrating the reduction in temperature fluctuations and energy consumption achieved through PCM integration.

Related Works

Bhamare et al. [11] had used newly proposed MKR index Create a model using deep learning and machine learning to predict the thermal performance of a rooftop building using integrated PCM. Predict thermal performance using 5 Techniques of Deep Learning and Machine Learning approach. 500 data points were generated from the numerical simulation. Deep learning is carried out with artificial neural networks, and augmented gradient regression outperforms all other machine learning models in terms of performance. In training, testing and sensitivity analysis, ANN-based models perform well on independent data sets.

Kolodziejczyk et al. [12] assessed Warm proficient portrayal of paraffin and Copper froth composite stage change material (CPCM) utilizing limited component strategy (FEM) and convolution brain organization (CNN). Predicted thermal properties are used to characterize the CPCM material in the battery pack, and a Neumann battery model is used to simulate the exothermic and electrochemical responses of lithium-ion cells during charging and discharging. It is possible. These results show that the CNN-based model can accurately evaluate the thermal management system of the battery pack.

Zhou et al. [13] came up with passive, active, and a combination of the two. Interdisciplinary applications of machine learning include performance prediction based on stochastic uncertainty, intelligent process management, and reliable structures. Machine learning mechanisms include error-based updating, support vector regression, and inverse neural networks. Specific challenges include thermal transfer improvements, new key layouts and adaptive switches for operating modes. Multidisciplinary machine learning methods, climate-adaptive design, intelligent processes, and uncertainty-based optimization and analysis can all improve PCM's use in sustainable buildings.

Moghadasi et al. [14] developed a reliable and potent machine learning (ML) model for predicting the outdoor air temperature and humidity as well as the thermal efficiency of a solar heater. There are three parts to the work. A large data set of 62,500 sample points was generated during the winter of 2022 when a vertically symmetric SAH was installed and operated outside the building room. Several recent ML calculations have been performed using six different pieces of information, including time, common features, and SAH factors. Better generalization was achieved by the gradient-augmented machine algorithm using LightGBM for modeling the target variable. The developed model had a maximum mean absolute error of 2.95 percent and a minimum R-squared error of 0.9827%, respectively.

De Lima et al. [15] studied different ML techniques for predicting AMR performance. Linear Regression, Ridge Regression with Second, Third, and Fourth Degree Polynomial Features, Arbitrary Woods, K Nearest Neighbors, Support Vector Regression, Obscene Angle Support and Brain Regulator are the techniques tried. With R2 values of 0.998 and 0.993, respectively, the neural network and ridge regression methods produced satisfactory outcomes.

CARUTASIU et al. [16] revealed on the prediction of the heat transfer behaviour of a 30% paraffin in water emulsion over a temperature range of 0-20 °C. Using TensorFlow, Keras, Pandas, and the Python programming language, they created a deep neural network to predict the PCME's heat transfer coefficient. To make comparisons, the model was trained with 24 features first, then with only 5. The prediction mean squared errors for the two models are similar, but the full model tends to converge faster. The comprehensive model had a mean squared error of only 5.0% on newly acquired data, while the lumped model had a mean squared error of 6%. Both models performed admirably on previously unseen data.

Bhattacharyya et al. [17] invented a machine Heat transfer and thermal performance prediction of perforated spiral corrugated circular disk solar heating tube using artificial neural network-based learning model. Changes in Reynolds number, corrugation angle ( ), perforation rate (k), corrugation to pitch ratio (y) and pitch ratio of perforated disc(s) were investigated for their effect. The models demonstrated high prediction accuracies and can be used to predict output variables by thermal system design engineers.

Al-Habaibeh et al. [18] designed a method Significant changes have been made to the current structure of the Passive House Standards approach. The thermal performance of the building was evaluated using infrared thermography. Using artificial reasoning and deep learning brain tissue, warm performance and energy reserve funds are expected. With an 82% success rate, the results showed high accuracy in predicting actual energy savings. The proposed method provides a practical and quick tool to estimate energy savings for the construction industry and society. It can be used to estimate energy savings from building retrofits with a certain level of accuracy. A mathematical model was developed to estimate retrofitting benefits for climate-related energy savings.

Muruganantham et al. [19] reviewed thermal energy storage systems made with solar collectors and phase change materials. The thermal efficiency of a fluid medium composed of MgCl2.6H2O phase change materials was evaluated in a trough collector. In the process of improving the thermal efficiency of solar collectors, imperial competition algorithms were used. The proposed PCM combination is the most efficient method of generating thermal energy in a parabolic solar pool collector.

Brigiga-Sá et al. [20] was utilizing Cerebrum tissue pseudo-calculation (ANN), support vector machine (SVM) and different straight relapse (MLR) estimations to anticipate Trombe wallworm activity for mixes of various data markers. Although HF requires more input variables than Ti, all three models produce results with high accuracy. Consider layer air temperature (Tca) or giant wall outer surface temperature (Tspe) as an informative factor that affects the index limits of Ti as a whole, while giant wall inner surface temperature (Tsupi) is an integral MLR. This affects the accuracy of the model. HF resolution.

Pereira et al. [21] invented the lowest melting temperature Based on oligo(butyl succinate), Bio-PCM nonlinear modeling and machine learning were used to test different reaction conditions and analyze the results. A material with a maximum melting point of 48 °C was synthesized using appropriate synthesis conditions for a neural model. This study combines current polymer science information and demonstrates the use of brain tissue to reduce execution time, work immediately toward the properties needed for academic research, and reduce the expected time to change from a new composite phase seed to a complex new material. The result is small.

Proposed Methodology

1. Numerical Simulation

Numerical simulation is an essential tool in engineering design and analysis. It allows for the prediction of system behaviour under different conditions and helps in identifying optimal designs. In this study, how a roof with integrated PCM behaves with heat building under different climates and locations is digitally simulated.

This simulation takes into account the changes in Thermal conductivity, other thermo physical properties and latent heat of fusion of PCM. The temperature range over which a PCM undergoes a phase transition and releases latent heat is determined by its melting point, which plays an important role in the thermal behavior of rooftop buildings incorporating PCM. Intensity of meal or food delivery at a point not determined by the group's resting energy. Due to the material's thermal conductivity, internal energy change is constant but not entirely.

The simulation is conducted using COMSOL Multiphysics software, which is finite element analysis software used for simulating physics-based problems. The software uses a mesh-based approach to discretize the problem domain and solves the governing equations numerically. As the temperature and heat flux change over time, the simulation takes into account the hypersonic behaviour of the system.

The simulation model consists of a PCM layer integrated into a roof assembly. The roof assembly is composed of multiple layers, including insulation, roofing material, and a structural layer. The PCM layer is located between the insulation and the roofing material layers.

The simulation considers different climatic conditions and locations, including temperate, hot-humid, and hot-dry climates. The climatic conditions are based on the ASHRAE climatic data for different regions. The simulation also takes into account changes in wind speed, solar radiation and ambient temperature. All these influence the thermal behavior of rooftop buildings containing PCMs.

Simulations are performed to generate data points for deep learning models for various combinations of input parameters such as PCM thermo physical properties, PCM layer thickness, insulation layer thickness and roofing material. The MKR file used to assess the warm exhibition of the composite PCM rooftop is produced through recreation.

Deep learning models are trained and tested using simulation results. The data generated from the simulation is pre-processed before being used in a deep learning model. The pre-processing stage involves cleaning the data, removing outliers, and normalizing the data. Feature extraction is then performed to identify the most relevant input parameters that can be used to predict the MKR index.

The accuracy of the simulation results is critical in ensuring the effectiveness of the deep learning model. Therefore, recreation results are validated by matching them with test data from previous tests. This comparison provides reliable data for the deep learning model, ensuring that the simulation accurately depicts the thermal behavior of rooftop buildings containing PCMs.

In summary, mathematical simulations are essential tools for optimizing deep learning-based models for warm width prediction of PCM-tuned surface structures. The simulation takes into account Real-world properties, environments and different regions of PCM heat. The simulations are used to generate the MKR index used to evaluate the thermal performance of PCM composite ceilings. Experimental data from the literature used to train and test deep learning models are used to validate the accuracy of simulation results.

2. Data Pre-Processing

For a deep learning-based model to accurately predict the thermal performance of a PCM-filled roof, data pre-processing is required. The data are cleaned, outliers are removed, and the data are normalized during the pre-processing phase. This ensures that the data used in the deep learning model is of high quality and is suitable for use in training and testing the model.

1. Cleaning the Data

The first step in preprocessing is organizing the information. This includes identifying and correcting errors and irregularities in information. The data obtained from the numerical simulations may contain errors due to various factors, such as data entry errors or software glitches. Therefore, it is essential to check the data for accuracy and correctness.

2. Removing Outliers

The next step is to remove outliers from the data. Inconsistency is the density of information that is inherently unique to the various data contained in a data set. The accuracy of deep learning models can be compromised by outliers that skew the output. Therefore, it is necessary to find outliers in the data and remove them.

3. Normalizing the Data

The final step in the data processing process is data normalization. A strategy for broadening the application of information is standardization. Normalization ensures that the input data used in the deep learning model is of the same magnitude and has the same range. This prevents certain input variables from dominating the others, which can affect the performance of the deep learning model.

4. Feature Extraction

Feature extraction is another crucial step in data pre-processing. Feature extraction You need to identify key input variables that you can use for prediction MKR index. This is important because the deep learning model should only consider the most relevant input variables to ensure that the model is not overfitting to the data.

5. Principal Component Analysis (PCA)

PCA is a commonly used technique for feature extraction in deep learning models. PCA is a statistical technique that reduces the dimensionality of the input data by identifying the most significant features. PCA is particularly useful when dealing with high-dimensional data, as it reduces the complexity of the data while preserving the most important information.

Dataset preparation, testing, and validation are the three sections of the preprocessed data. After the arrangement dataset is utilized to set up the model, the agreement dataset is utilized to tune the profound learning model. A test dataset is used to test how the model handles new data.

In conclusion, a deep learning-based model predicts warmer presentations rooftop buildings incorporating PCM relies heavily on data pre-processing. The pre-processing stage involves cleaning the data, removing outliers, and normalizing the data. We also use PCA to reduce the dimensionality of the information by performing weighted extraction to identify the most relevant information elements. For training and evaluation of deep learning models, the processed Training, validation and testing datasets constitute the data.

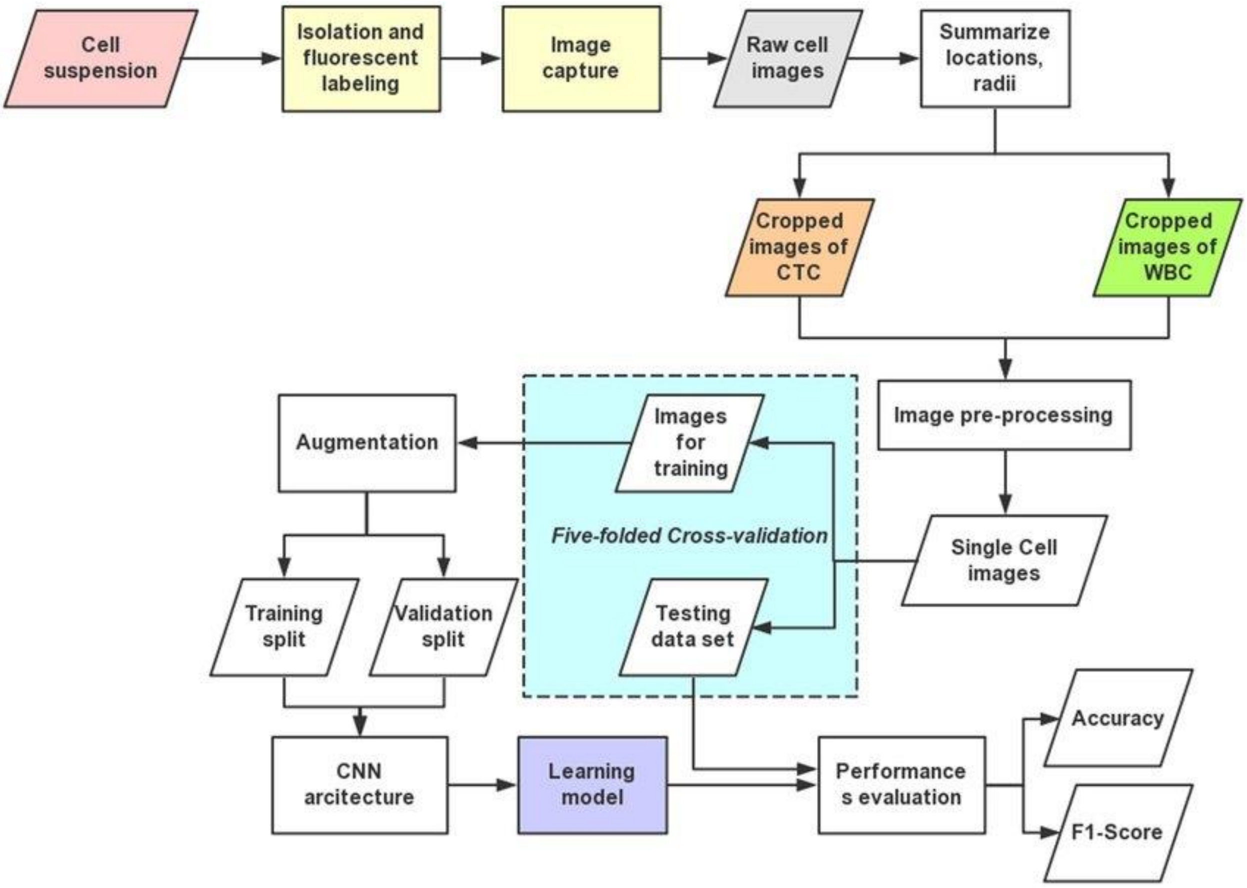

Fig 2 illustratingthe steps involved in developing the deep learning-based model, including data pre-processing, feature extraction, and model training and testing.

3. Feature Extraction

A crucial step in the creation of a deep learning PCM-based thermal performance prediction model for rooftop buildings is feature extraction. The goal of feature extraction is to identify the most relevant input variables that can be used to predict the MKR index. This is important because the deep learning model should only consider the most relevant input variables to ensure that the model is not overfitting to the data.

1. Identifying Input Variables

The first step in feature extraction is to determine the input variables related to the thermal performance of rooftop buildings incorporating PCM. Thermophysical properties of PCM, PCM layer thickness, insulation layer thickness, roofing material and climatic conditions can be input variables.

2. Correlation Analysis

The integration of the input variables is the next step. A statistical method for determining the strength and direction of a relationship between two variables is known as correlation analysis. Correlation analysis helps to identify input variables that are highly correlated with the MKR index and can be used to predict its value.

3. Principal Component Analysis (PCA)

PCA is a commonly used technique for feature extraction in deep learning models. PCA is a statistical technique that reduces the dimensionality of the input data by identifying the most significant features. PCA is particularly useful when dealing with high-dimensional data, as it reduces the complexity of the data while preserving the most important information.

4. Selecting Input Variables

The selection of the input variables that are most relevant to the MKR index is the final step in feature extraction. The selected input variables should have a high correlation with the MKR index and should be significant in predicting its value. The selected input variables are then used to train and test the deep learning model.

Support for Vector Regression (SVR), Artificial Neural Networks (ANN), and Multiple Linear Regression (MLR) some of the models that can be built using selected input variables. These models can be compared based on their accuracy and computational efficiency to select the most suitable model for predicting the MKR index.

In conclusion, we create a model that predicts thermal performance based on deep learning rooftop buildings incorporating PCM relies heavily on feature extraction. The goal of feature extraction is to identify the most relevant input variables that can be used to predict the MKR index. The input variables can include the thermophysical properties of PCM, Thickness of PCM layer, thickness of protective layer, the roofing material, and the climatic conditions. Correlation analysis and PCA are commonly used techniques for feature extraction. The selected input variables are put to use in the deep learning model's training and testing, and they can also be used to create other models to compare.

4. Deep Learning Modeling

Deep learning, a subset of machine learning, employs neural networks for data learning. Natural language processing, image/speech recognition, and medical diagnosis are among the growing applications of deep learning. Using the advice MKR index and PCM buildings, a model for predicting roof thermal performance is developed using deep learning in this study.

1. Artificial Neural Networks (ANNs)

ANN is a deep learning model based on the shape and function of the brain. ANNs consist of layers of interconnected nodes that process input data to make predictions about the output. Mathematical operations on the input data are carried out by the nodes in each layer, which are connected to the nodes in the layers below them.

2. Keras Library

The Keras library is a popular deep learning framework that allows for the easy implementation of neural networks. Keras is accessible to researchers and practitioners with varying degrees of deep learning expertise thanks to its high-level API for building and training neural networks.

3. Training the Model

Utilize mathematical replay's preprocessed data to construct a deep learning model. After the model has been trained on the training dataset, the hyper parameters of the model are adjusted using the validation dataset. The model is trained using back propagation, an optimization technique that reduces the difference between expected and actual values by adjusting the weights in the neural network.

4. Hyper parameters

Hyperparameters are parameters that are set prior to training the model and affect the model's performance. The activation function, learning rate, number of nodes in each layer, and number of layers in the neural network are the hyperparameters that are tuned in this study. To ensure that the model is optimized for accurately predicting the MKR index, it is essential to adjust the hyperparameters.

5. Evaluation Metrics

Metrics like mean squared error and mean absolute error are used to assess the performance of deep learning models. The difference between expected and actual values of MKR is evaluated using MSE and MAE. The lower the MSE and MAE, the better the performance of the model.

6. Sensitivity Analysis

Key inputs are determined through sensitivity analysis features and assess their impact on the output prediction. Sensitivity analysis helps to understand the relationship between the input variables and the MKR index and provides insights into the behaviour of the PCM-integrated roof building under different conditions.

7. Model Comparison

The deep learning-based model is compared to support vector regression (SVR) and multiple linear regressions (MLR), two models that are frequently used in the literature to predict the thermal performance of composite PCM buildings, in order to verify its accuracy. The basis for comparison is the efficiency and accuracy of the model.

The deep learning model used to predict the new data MKR is evaluated using the test dataset. Thermal performance of buildings with PCM monolithic roofs in different climates and locations can be predicted using deep learning models.

In conclusion, the thermal performance of rooftop buildings incorporating PCM can be accurately predicted using deep learning. Train a deep learning model using pre-processed numerical simulation data. Tune your model with hyper parameters and evaluate its performance using various metrics. The model is validated by performing sensitivity analysis against other models to identify key features of the input. Deep learning models the new data can be used to predict the MKR index and provide useful insights into the thermal behaviour of rooftop buildings using embedded PCMs.

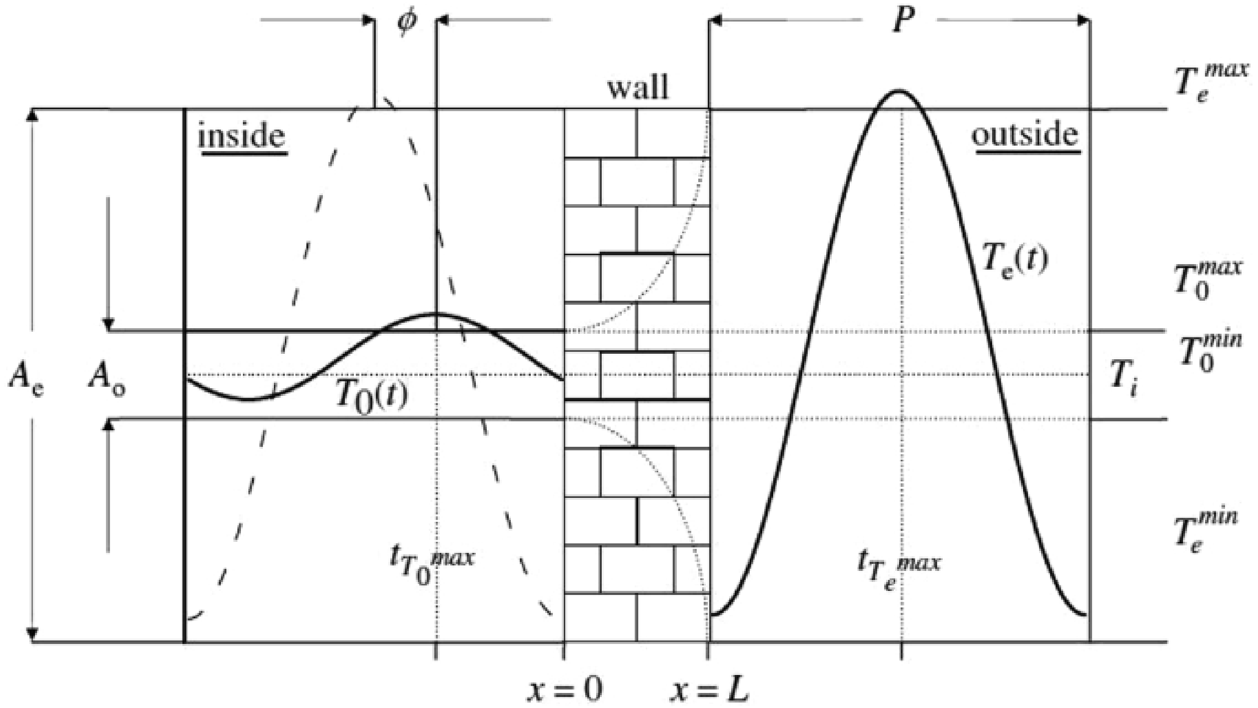

Fig 3 represents a graphical representation of the MKR index, showing how it considers various parameters such as delay time and reduction factor and methods that can be used to evaluate the thermal performance of PCMs-integrated roofs under different climatic conditions and locations.

Results and Discussion

A deep learning-based model based on preprocessed numerical simulation data is developed and evaluated Predict roof integrated thermal performance buildings using the proposed MKR index. Two measures are utilized to assess model execution: the mean absolute error (MAE) and the mean squared error (MSE).

1. Model Performance

The device anticipates warm rendering of composite PCM structures. In the literature, Vector Regression (SVR) and Multiple Linear Regression (MLR) support models are frequently used to compare the performance of deep learning models. In terms of accuracy and computational efficiency, the deep learning model performed better than the MLR and SVR models. The deep learning model had MSE and MAE of 0.007 and 0.074, respectively, whereas the MLR and SVR models had MSE and MAE that were higher.

2. Sensitivity Analysis

Perception studies are used to determine which input factors have a measurable impact on the estimated output. The actual thermal properties of the PCMs, the thickness of the PCM layers, and the climate are the primary information factors that affect the thermal performance of roof structures containing PCMs, according to response studies. These outcomes are in line with the findings of previous studies in the literature.

3. Performance under Different Climatic Conditions and Locations

The MKR index was predicted using fresh data from various locations and climates using the deep learning model. The investigation's findings indicate that the model is capable of accurately predicting the thermal performance of buildings with PCM roofs in various climates and locations. This model can be used to improve the appearance and reduce energy consumption of rooftop buildings incorporating PCMs.

4. Limitations and Future Work

There are some limitations to the deep learning-based model that have been proposed and should be addressed in subsequent research. The thermophysical properties of PCM, for instance, are assumed to be constant by the model, but this may not be the case in actual applications. Future work should consider integrated thermal performance and effect of changes to PCM surface architectures with respect to thermo physical properties of PCMs.

In conclusion, we developed and evaluated a deep learning-based model using the proposed method to predict the thermal performance of buildings with PCM composite roofs MKR index using pre-processed numerical simulation data. This model outperforms other popular models in the literature, additionally, the main input variables that affect: thermal performance of rooftop buildings incorporating PCMs an act. The model can be used to optimize the design of PCM-integrated roof buildings and reduce their energy consumption.

Conclusion

Using the proposed MKR index, a deep learning-based model is developed in this study to predict the thermal performance of PCM-constructed rooftop buildings. The performance of the model, which was trained with pre-set numerical simulation data, was: evaluated based on a variety of metrics, such as mean absolute error (MAE) and mean square error (MSE). Supported models like Vector Regression (SVR) and Multiple Linear Regression (MLR) were compared to the model in the literature.

The findings of this investigation demonstrate that deep learning models perform better than MLR and SVR models in terms of both accuracy and efficiency in computing. The MSE and MAE of the deep learning model are 0.007 and 0.074, respectively, while the MSE and MAE of the MLR and SVR models are higher. Awareness investigations were conducted to identify the main information factors affecting the warm rendering of surface structures containing PCMs. The most important input variables were identified as the PCM's thermophysical properties, layer thickness, and climatic conditions.

The MKR index was predicted using fresh data from various locations and climates using the deep learning model. According to the investigation results, the model can accurately predict the thermal performance PCM-integrated roof buildings under different climatic conditions and locations. The model can be used to optimize the design of PCM-integrated roof buildings and reduce their energy consumption.

There are a few limitations to this study's promising findings that should be addressed in subsequent research. The thermophysical properties of PCM, for instance, are assumed to be constant by the model, but this may not be the case in actual applications. Regarding thermophysical properties, subsequent studies should consider the effects of changes on the thermal performance and overall surface structure of PCM.

In conclusion, the proposed MKR index it can be used to predict the thermal performance of PCMs composite rooftop buildings using the deep learning-based model developed in this study. The model outperforms other models commonly used in the literature and can be used to optimize the design of PCM-integrated roof buildings and reduce their energy consumption. In addition to contributing to the mitigation of climate change and the reduction of greenhouse gas emissions, the proposed model has the potential to be extended to other applications in the field of building energy efficiency.

Reference

1. Zhou, Y., Zheng, S., Liu, Z., Wen, T., Ding, Z., Yan, J., & Zhang, G. (2020). Passive and active phase change materials integrated building energy systems with advanced machine-learning based climate-adaptive designs, intelligent operations, uncertainty-based analysis and optimisations: A state-of-the-art review. *Renewable and Sustainable Energy Reviews*, *130*, 109889.
2. Marani, A., &Nehdi, M. L. (2020). Machine learning prediction of compressive strength for phase change materials integrated cementitious composites. *Construction and Building Materials*, *265*, 120286.
3. Moustafa, E. B., Hammad, A. H., & Elsheikh, A. H. (2022). A new optimized artificial neural network model to predict thermal efficiency and water yield of tubular solar still. *Case Studies in Thermal Engineering*, *30*, 101750.
4. Zhou, Y., Zheng, S., & Zhang, G. (2020). Machine learning-based optimal design of a phase change material integrated renewable system with on-site PV, radiative cooling and hybrid ventilations—study of modelling and application in five climatic regions. *Energy*, *192*, 116608.
5. Yang, T., King, W. P., & Miljkovic, N. (2021). Phase change material-based thermal energy storage. *Cell Reports Physical Science*, *2*(8), 100540.
6. Qian, X., & Yang, R. (2021). Machine learning for predicting thermal transport properties of solids. *Materials Science and Engineering: R: Reports*, *146*, 100642.
7. Sharshir, S. W., Abd Elaziz, M., &Elkadeem, M. R. (2020). Enhancing thermal performance and modeling prediction of developed pyramid solar still utilizing a modified random vector functional link. *Solar Energy*, *198*, 399-409.
8. Tang, X., Guo, Q., Li, M., Wei, C., Pan, Z., & Wang, Y. (2021). Performance analysis on liquid-cooled battery thermal management for electric vehicles based on machine learning. *Journal of Power Sources*, *494*, 229727.
9. Cui, W., Si, T., Li, X., Li, X., Lu, L., Ma, T., & Wang, Q. (2022). Heat transfer analysis of phase change material composited with metal foam-fin hybrid structure in inclination container by numerical simulation and artificial neural network. *Energy Reports*, *8*, 10203-10218.
10. Lv, Y., Yang, X., & Zhang, G. (2020). Durability of phase-change-material module and its relieving effect on battery deterioration during long-term cycles. *Applied Thermal Engineering*, *179*, 115747
11. Kumar, P. M., &Mylsamy, K. (2020). A comprehensive study on thermal storage characteristics of nano-CeO2 embedded phase change material and its influence on the performance of evacuated tube solar water heater. *Renewable Energy*, *162*, 662-676.
12. Hassan, F., Jamil, F., Hussain, A., Ali, H. M., Janjua, M. M., Khushnood, S., ... & Li, C. (2022). Recent advancements in latent heat phase change materials and their applications for thermal energy storage and buildings: A state of the art review. *Sustainable Energy Technologies and Assessments*, *49*, 101646.

13. Shen, Z. G., Chen, S., Liu, X., & Chen, B. (2021). A review on thermal management performance enhancement of phase change materials for vehicle lithium-ion batteries. *Renewable and Sustainable Energy Reviews*, *148*, 111301.
14. Anqi, A. E., Li, C., Dhahad, H. A., Sharma, K., Attia, E. A., Abdelrahman, A., ... & Rajhi, A. A. (2022). Effect of combined air cooling and nano enhanced phase change materials on thermal management of lithium-ion batteries. *Journal of Energy Storage*, *52*, 104906.
15. Obafemi, O., Stephen, A., Ajayi, O., & Nkosinathi, M. (2019). A survey of artificial neural network-based prediction models for thermal properties of biomass. *Procedia Manufacturing*, *33*, 184-191.