Harnessing Machine Learning and Meta-Heuristic Algorithms for Accurate Cooling Load Prediction

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***Abstract*—Precisely calculating the cooling load is essential to improving the energy efficiency of cooling systems, as well as maximizing the performance of chillers and air conditioning controls. Machine learning (ML) has better capabilities in this area than conventional techniques and regression analysis, which are lacking. ML models are capable of automatically recognizing complex patterns that are influenced by various factors, including occupancy, building materials, and weather. They enable responsive predictions that enhance energy optimization and efficient building management because they scale well with data and adapt to changing scenarios. This research acknowledges the difficulties presented by the intricacies of energy optimization while exploring the intricate world of cooling load systems. To solve these issues, in-depth research and creative approaches to problem-solving are needed. The Weevil Damage Optimization Algorithm (WDOA) and the Improved Manta-Ray Foraging Optimizer (IMRFO) are two meta-heuristic algorithms that are seamlessly combined with the Gaussian Process Regression (GPR) model in this study to increase accuracy. Previous stability tests have provided extensive validation for the cooling load data used in these algorithms. The research presents three different models, each of which offers important insights for precise cooling load prediction: GPWD, GPIM, and an independent GPR model. With an RMSE value of 1.004 and an impressive R^2 value of 0.990, the GPWD model stands out as the best performer among these models. The remarkable outcomes demonstrate the outstanding precision of the GPWD model in forecasting the cooling load, highlighting its applicability to actual building management situations.**

Keywords*—Building energy; cooling load; machine learning; Gaussian Process Regression; Improved Manta-Ray Foraging Optimizer; Weevil Damage Optimization Algorithm

I. Introduction

The imperative for energy conservation has garnered significant attention from scholars, given the staggering volumes of energy consumed across diverse applications. A substantial proportion of this energy is attributable to the global building sector, where the effective management of a crucial parameter, cooling load (CL), assumes pivotal importance. The Ventilation and Air Conditioning (HVAC) systems wield the responsibility of regulating these loads, a task heavily reliant on a multifaceted interplay of variables, including building characteristics, utilization patterns, and prevailing climatic conditions [1], [2]. HVAC systems, in addition to managing loads, are engineered to enhance indoor air quality and comfort. Achieving sustainable energy consumption hinges on adopting a judicious approach, such as the rigorous evaluation of energy performance through building energy testing (EPB) and the deployment of sophisticated HVAC models [3].

Presently, global energy consumption levels are alarmingly high, with projections suggesting a continued upward trajectory. This surge is often attributed to humanity's ever-increasing aspirations for improved living standards [4], [5]. Notably, Europe alone accounts for almost 40% of total energy consumption within buildings, underscoring the magnitude of the challenge [6]. In 2013, global energy consumption reached a staggering 12,928.4 million tonnes, with the lion's share supplied by fossil fuels. Just five years prior, in 2008, the world consumed a colossal 474 Exajoules (EJ) of energy, with fossil fuels remaining the primary source [7]. Global electricity consumption experienced a substantial surge of 70% between 1990 and 2008, underscoring the mounting energy demands. Building sector figures are particularly significant, as they constitute approximately 40% of global energy consumption and contribute to 30% of global CO_2 emissions [8].

Due to the severe challenge posed by cooling loads, HVAC systems come to the fore. Typically, sensors and automation technology are harnessed to compute these loads. However, even advanced commercial Building Management Systems (BMS) at times struggle to predict cooling loads with the requisite accuracy. The complexity of this forecasting task is attributable to a web of interconnected factors, including a vast array of appliances and the need for building customization to meet the evolving demands of the population. This confluence of challenges underscores the pressing need for more robust and accurate load forecasting models that can empower engineers and scientists to better evaluate sustainability concerns during the construction phase of buildings [9], [10].

A. Literature Review

Research into HVAC regulations and best practices has brought organizations like ASHRAE to the fore. ASHRAE's core mission revolves around advancing the knowledge and practice of cooling, ventilation, air conditioning, refrigeration, and associated human factors to meet the ever-expanding needs of the public [11]. The HVAC systems, in particular, play a transformative role in regulating the indoor environment, wielding significant influence over a building's overall energy consumption. Thus, the accurate prediction of cooling loads is pivotal in the quest to preserve energy. Researchers have embarked on substantial efforts to forecast the cooling loads of buildings. Their pursuit has culminated in the deployment of diverse machine learning (ML) algorithms that have proven to be effective in predicting these loads. For instance, Deb et al. [12] successfully employed artificial neural networks (ANN), which are particularly useful when dealing with nonlinear patterns that elude conventional analysis. Similarly, Khayatian et al. [13] harnessed ANN to forecast energy performance, exemplifying the versatility and adaptability of this approach. In tandem, Moradzadeh et al. [14] contribute to the field by predicting heating and cooling loads with Support Vector Regression (SVR) and Multilayer Perceptron (MLP) models. Notably, the MLP method achieves an outstanding R-value of 0.9993 in predicting Heating Load. This research introduces an advanced methodology that utilizes artificial neural networks and ML applications, specifically MLP and SVR techniques, for forecasting heat and cool loads and optimizing the consumption of energy in residential buildings. These technological strides collectively affirm the transformative potential of advanced computational methods in elevating the precision and efficiency of predictions the energy consumption of residential building.

The application of ML in predicting cooling loads has opened up a realm of possibilities for enhancing energy efficiency in the building sector [15]. ML can sift through vast datasets, identify intricate patterns, and optimize HVAC system operations [16]. Through continuous learning and adaptation, these algorithms can adapt to changing building dynamics, further enhancing energy conservation efforts [17]. One notable advantage of ML is its ability to account for nonlinear relationships and complex interactions among variables. Traditional methods of load prediction often struggle with these complexities, leading to less accurate results [18].

Furthermore, ML models can continually refine their predictions as new data becomes available. This adaptability ensures that the HVAC system's performance remains optimized over time, even as building usage patterns and climate conditions evolve [19], [20]. The use of ML, such as artificial neural networks, offers a sophisticated approach to optimizing HVAC system operations, ultimately reducing energy consumption and environmental impact. As global energy consumption continues to rise, innovative solutions like ML must be embraced to mitigate the environmental footprint of the building sector and ensure a more sustainable future [21].

The primary aim is to forecast the cooling load of buildings utilization real-world dataset accurately that demonstrates energy usage patterns. Gaussian Process Regression (GPR) is employed as a simulation method to achieve this objective. To improve the efficiency of the GPR model, the Improved Manta-Ray Foraging Optimizer (IMRFO) and Weevil Damage Optimization Algorithm (WDOA) are chosen as hybrid models due to their unique advantages. These meta-heuristic algorithms are designed to optimize the GPR hyperparameters. Also, a perfect statistical analysis is carried out to assess the accuracy and reliability of each optimizer. The main goal of this research is to anticipate the cooling load demand of buildings precisely by combining sophisticated optimization algorithms with GPR. The selection of IMRFO and WDOA further enhances the effectiveness of the model as optimizers. Through a robust statistical analysis and the use of diverse performance metrics, this study aims to provide accurate and reliable predictions while enabling a comprehensive evaluation of the chosen optimizers' performance.

The research examines how integrating machine learning methods like GPR, IMRFO, and WDOA improves HVAC system performance. Key findings and methodologies are summarized in a Table I, demonstrating continuous improvement of predictions with new data. Advanced algorithms enhance GPR effectiveness through rigorous optimization. Statistical analysis confirms accuracy and reliability, supporting energy efficiency and sustainability in buildings.

TABLE I. THE EFFICIENCY AND WORK DONE SUMMARY

Aspect	Description
Machine Learning Benefits	Continuous refinement of predictions with new data
	Optimization of HVAC system operations with artificial neural networks
	Reduction of energy consumption and environmental impact
Research Methodology	Use of Gaussian Process Regression (GPR) for accurate cooling load forecasts
	Integration of Improved Manta-Ray Foraging Optimizer (IMRFO) and Weevil Damage Optimization Algorithm (WDOA) as hybrid models for GPR optimization
Performance Evaluation	Comprehensive statistical analysis to assess accuracy and reliability
	Evaluation of optimization algorithms (IMRFO and WDOA) effectiveness

II. MATERIALS AND METHODOLOGY

A. Data Gathering

This study focuses on the importance of reliable data for the successful implementation of strategies to predict cooling load requirements in buildings. The research utilizes a dataset consisting of 768 samples sourced from the study available at https://www.sciencedirect.com/science/article/abs/pii/S2352710223020351, which is crucial for training sophisticated models and evaluating the proposed strategies. The study utilizes a GPR model and considers eight key input variables related to cooling load production. These variables include relative compactness, surface area, roof area, wall area, orientation, overall height, glazing area, and glazing area distribution. Each variable has an impact on cooling requirements and is represented in a correlation plot (Fig. 1). Statistical values of these input parameters are provided in Table II. The study emphasizes the significance of these variables in understanding the dynamics of cooling load in buildings. It highlights the need for high-quality data and emphasizes the importance of intelligent model training and data analysis techniques to achieve research objectives [22], [23].

B. Gaussian Process Regression (GPR)

The framework for probabilistic regression used by GPR starts with a training dataset as its input $D = \{(y_w, x_w)\ ,\ w = 1,2,3,\dots,W\}$ of W couples of vector input $x_w IR^L$ and based on a dataset of training phase with output values (yn), GPR builds a model that can successfully generalize to the output distribution at new input locations. It is assumed that the output noise uncertainty is extremely, zero-mean, stationary, and normally distributed and is brought on by outside variables like truncation or observation errors [24].

$$y = f(x) + \delta, \quad \delta\ "W(0, s_{noise}^2) \tag{1}$$

TABLE II. THE STATISTICAL PROPERTIES OF THE INPUT VARIABLE OF COOLING

Variables		**Indicators**			
	Category	$\boldsymbol{Min}$	$\boldsymbol{Max}$	$\boldsymbol{Avg}$	$\boldsymbol{St.Dev.}$
Relative Compactness	Input	0.62	0.98	0.764	0.106
Surface Area	Input	514.5	808.5	671.7	88.09
Wall Area	Input	245	416.5	318.5	43.63
Roof Area	Input	110.25	220.5	176.6	45.17
Overall Height	Input	3.5	7	5.25	1.751
Orientation	Input	2	5	3.5	1.119
Glazing Area	Input	0	0.4	0.234	0.133
Glazing Area Distribution	Input	0	5	2.813	1.551
Cooling	Output	10.9	48.03	24.59	9.513

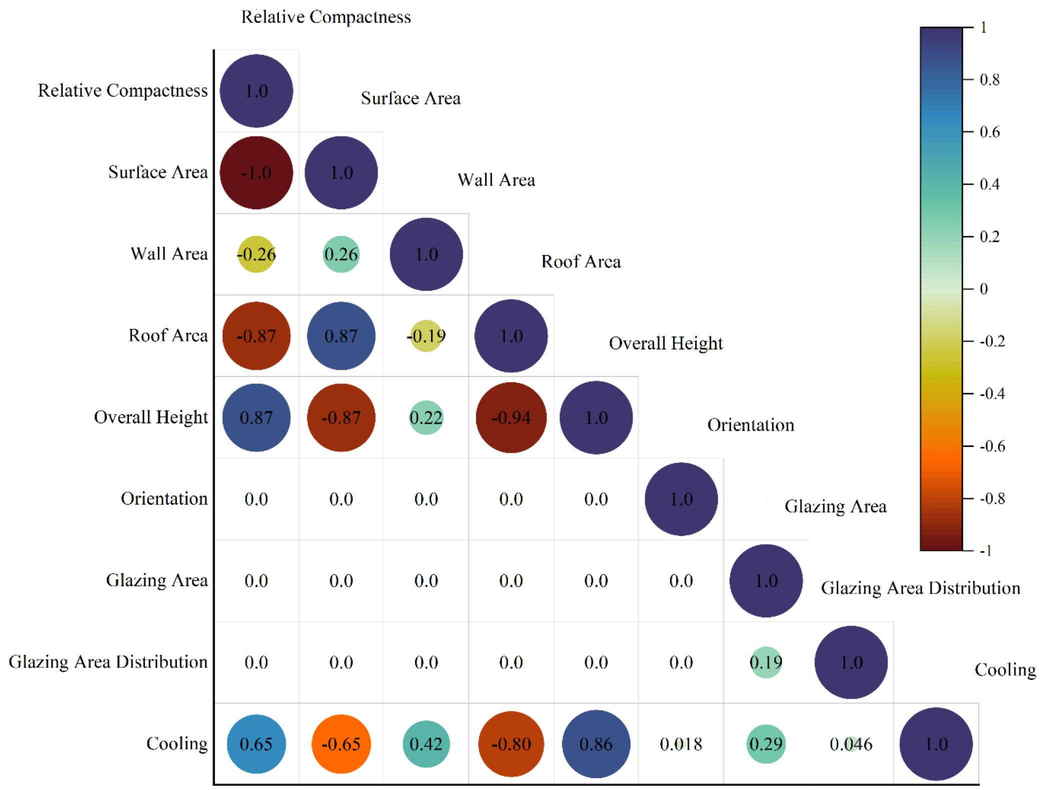

Fig. 1. The plot of correlation for the input and output variables.

GPR utilizes a Gaussian Process (GP) to represent the hidden parameters of f, with x serving as an index for these parameters. The goal is to limit the analysis to functions whose values are correlated in a Gaussian manner, which is achieved by using a Fixed Gaussian distribution for any limited set of $\{f(x_1), \ldots, f(x_k)\}$ with unique indices. In a Bayesian framework, this is akin to setting a GP prior over functions. By specifying the mean function $v(x)$ and the function of covariance $k(x, x')$, can conveniently define functions. This technique makes it simple to determine the function values of new inputs with a small amount of training data. The variance of the s_{noise}^2, is used to represent the noise in the model.

$$v(x) = E[f(x)], \quad k(x, x') = E[(f(x) - v(x))(f(x') - w(x'))] \tag{2}$$

The $E[.]$ denote expectation. Only the unseen region of the input space is relevant for the mean function selection, which is typically set to 0. The covariance function, which is regular and positive indeterminate by definition when assessed for any couple of points in input space, is the only factor that influences how the process behaves [25]. The function of covariance usually includes several hyperparameters, determining the earlier distribution of $f(x)$. The squared exponential of covariance function is commonly used in [26].

$$k(x, x') = q_1 \exp\left(\frac{\|x - x'\|}{2q_2}\right) \tag{3}$$

Here, k denotes a norm that is defined on the input space. It is worth noting that the covariance function decays rapidly as the distance of input pairs x and x' rises, indicating weak correlations between $f(x)$ and $f(x')$. There are three hyperparameters involved: q_1 specifies the $maximum$ allowable covariance, the correlation decay rate as points become farther apart is characterized by a positive hyperparameter, q_2, and q_3 is a hyperparameter that represents the variance s_{noise}^2 in Eq. (1), although it has not specifically been expressed in Eq. (2). A vector (q) is formed by grouping these hyperparameters, which are then considered as realization of random vector (Q). Based on the training data, the realization that offers the most appropriate for the dataset is chosen to make predictions. The inference procedure is easy if this assumes that the hyperparameters are already known. Denoting the vector of training latent variables as f and the vector of test latent variables as f^*, can obtain the following joint Gaussian distribution:

$$p(f, f^*) = W\left(0, \begin{bmatrix} k_{f,f} & k_{*,f} \\ k_{f,*} & k_{*,*} \end{bmatrix}\right) \tag{4}$$

The covariance matrix K is formed by calculating the covariance of the $i-th$ parameter in the group represented by the first subscript and the j_th parameter in the group represented by the second subscript ($*$ is used in place of f^* for short), using the function of covariance $k(.,.)$in Eq. (4) and the related hyperparameters [27]. The prediction framework is illustrated in Fig. 2.

C. Improved Manta-Ray Foraging Optimizer (IMRFO)

One of the effective metaheuristic methods for resolving optimization issues is the Manta Ray Foraging Optimisation Algorithm. Premature convergence, however, occasionally acts as a constraint. Two changes have been made to the Manta Ray Foraging Optimisation Algorithm to maximize its potential. The first entails integrating the algorithm with the widely recognized opposition-based learning (OBL) technique. Sometimes, the primary solution is in the opposite direction of the optimal solution, and the solution deviates from it. This may result in unsuccessful attempts at problem-solving or in more optimization efforts [28]. It is crucial to think about the worst-case scenario in such circumstances. As a result, the OBL technique was applied to the algorithm to produce more effective results, as follows:

$$\bar{x}_i^d = x_i^{max} + x_i^{min} - x_i^d \tag{5}$$

In this approach, $\bar{x}_i^d$ represents the opposite location of x_i^d, while x_i^{max} and x_i^{min} represent the maximum and minimum constraints, respectively. If $\bar{x}_i^d$ has better performance than its opposite location, which is denoted as x_i^d, then $\bar{x}_i^d$ is utilized instead of x_i^d.

The second change entails applying the self-adaptive technique, which permits the individual to adjust their size through variable adaptation. Optimizing for individual size is a critical component. First, this transformation is applied to update the primary individual size:

$$x_i^d(t) = 10 \times N \tag{6}$$

N, in this case, stands for the number of parameters. Then, the following formula determines the updated individual size for the next iteration:

$$\bar{x}_i^{d+} = round(x_i^d \times (1 + \delta)) \tag{7}$$

The adjustable parameter δ, which represents a random in range of -0.5 to 0.5, is used to modify the individual size in this context.

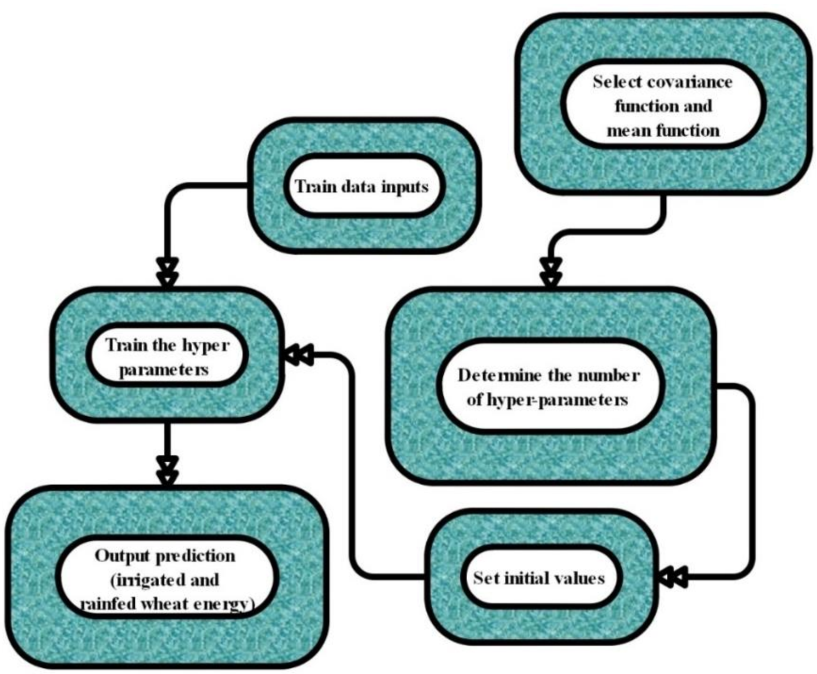

Fig. 2. Estimation framework of the GPR model.

Based on whether δ is positive or negative, the individual size either increases or decreases. If the updated individual size ($\bar{x}_i^{d+}$) is larger than the previous size ($\bar{x}_{i-1}^{d+}$), the current populations proceed to the subsequent iteration. In such cases, the remaining individuals are selected based on elitism. On the other hand, when $\bar{x}_i^{d+}$ is less than $\bar{x}_{i-1}^{d+}$, only the best individuals from the current population are carried forward to the subsequent iteration, and the remaining populations are discarded. It is set to the number of problem parameters if the updated individual size is less than the problem size.

D. Weevil Damage Optimization Algorithm (WDOA)

The Curculionidae superfamily of insects includes the large and diverse group of insects known as weevils. Their prominent snouts help to identify them. An estimated 97,000 species, they constitute one of the largest groups of organisms on the planet. While most weevil species are considered environmental nuisances, some, such as the boll, wheat, and maize weevils, are well known for seriously harming crops.. Weevils, despite their unfavourable image, are crucial components of many ecosystems as pollinators, decomposers, and animal prey [29]. The populations of weevils are generated randomly, resulting in n populations represented as $(W_1, W_2, \dots W_n)$. It is well known that weevils actively seek out the ideal conditions for breeding, which is frequently represented as a cost function. The following actions are taken until the condition for termination is satisfied [30].

- Take the strongest applicant out of the pool of applicants as a first step. Doing this, the best weevil is kept and can be utilized to create new weevil populations.
- Distribute the Fly Power Rate (ψ) and Snout Power Rate (φ) for each weevil to promote population diversity. This step involves assigning a value of φ and ψ to each weevil, representing their relative power levels. It is possible to diversify the weevil population and prevent any one individual from taking over by dispersing these values.
- Implement these tactics to increase the number of weevils. Retaining the best candidate and promoting population diversity by assigning values can both enhance the general quality and diversity of the weevil population.

Adopting measures such as distributing (φ) and (ψ) for each weevil provides a comprehensive understanding of their power levels. Each weevil's level of harm is determined by the Damage Decision Variable (DDV), where greater damage increases the weevil's chance of surviving. Performance and the mutation rate parameter, μ, in the Reproduction Environment Rate (RIR) are inversely correlated. Evolutionary algorithms typically sort the population and pass on the best individuals to the next generation to increase population diversity and quality [31].

$$WDOA = CF \sum_{i=1}^{n} \sum_{DDV=1}^{n} (W_i[\varphi, \psi] \times RIR\ of\ \mu \quad (8)$$

CF refers to the cost function. The pseudo-code for the $WDOA$ is presented as follows.

Algorithm 1. The pseudo-code of WDOA.

```
Creat a random set of Weevils: (W_1, W_2, ... W_n)
Calculate CF value (Cost function and sort best to worst)
While the termination criterion is not met
Continue the best individuals
        Calculate Fly Power Rate ψ and Snout power Rate φ for
each Weevils according to CF
Seeking for an environment with more food source
Choose W_i by probability with φ
Choose Wj by probability with ψ
Randomly choose a DDV from W_j
Change out random DDV W_j with W_i

Begin  Mutation μ
Choose a DDV in W_i with the probability of mutation rate (RIR)
If W_i DDV is selected
Change out Wi (DDV) with a randomly developed DDV
End if
End Mutation
Calculate the ESI value of new Weevils
Sort population (best to worst (cost))
Change out the worst with the preview development's best
Sort population (best to worst (cost))
End while
```

E. Efficiency Assessment Methods

This article uses a variety of metrics to assess the models, including the previously mentioned Fractional bias (FB), Correlation Coefficient (R^2), Mean Square Error (MSE), Index of agreement (IOA), and Root Mean Square Error ($RMSE$).

- Fractional Bias (FB): Fractional Bias calculates the average bias, the variation of predicted and observed values, relative to their average. An FB value close to 0 indicates that the predictions are unbiased, while a positive or negative value indicates overestimation or underestimation, respectively.
- Correlation Coefficient (R^2): The Correlation Coefficient, also known as the coefficient of determination, quantifies how well the predicted values correlate with the observed values. An R^2 value close to 1 demonstrates a great positive correlation, meaning the model explains most of the variability in the observed data. A value close to 0 indicates little to no correlation.
- Mean Square Error (MSE): Mean Square Error is the average of the squared differences between predicted and observed values. Lower MSE values indicate better model performance, as they show that the predictions are closer to the actual values. It is sensitive to outliers due to the squaring of errors.
- Index of Agreement (IOA): The Index of Agreement is a standardized measure of the degree of model prediction error, taking into account the range of observed values. IOA values range between 0 and 1, which 1 represent perfect agreement between the model predictions and the observed values.
- Root Mean Square Error (RMSE): The square root of the average of the squared discrepancies between the predicted and observed values is known as the root

mean square error. Similar to MSE, lower RMSE values indicate better model performance. RMSE is useful because it provides an error metric in the same units as the original data, making it easier to interpret.

During the training, validation, and testing phases, a high R^2 value determines that the algorithm performed suitable. Conversely, smaller MSE and RMSE values are better since they indicate less model error. These metrics are computed using Eq. (9–13).

$$R^2 = \left(\frac{\sum_{i=1}^{N}(h_i - \bar{h})(q_i - \bar{q})}{\sqrt{[\sum_{i=1}^{N}(h_i - h)^2][\sum_{i=1}^{N}(q_i - \bar{q})^2]}} \right)^2 \quad (9)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(q_i - h_i)^2} \quad (10)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N} q_i^2 \quad (11)$$

$$FB = \frac{1}{N}\sum_{i=1}^{N}\frac{2\times(q_i - h_i)}{q_i + h_i} \quad (12)$$

$$IOA = 1 - \frac{\sum_{i=1}^{N}(x_{i,q} - x_{i,h})^2}{\sum_{i=1}^{N}(|x_{i,h} - \overline{x_q}| + |x_{i,q} - \overline{x_q}|)^2} \quad (13)$$

Here, h_i and q_i refer to the predicted and experimental values, respectively. The mean values of the experimental samples and predicted are represented by $\bar{h}$ and $\bar{q}$, alternatively, and N demonstrates the number of samples being considered.

III. Results

A. Hyperparameter

Table III presents the results of the hyperparameter tuning for two models: GPWD and GPIM. Hyperparameters are critical settings that influence the training process and performance of machine learning models. For the GPWD model, the hyperparameters include 120 restarts, a length scale of 685.0302031, and an alpha value of 0.896335693. These values suggest a robust optimization process aimed at fine-tuning the model for high precision in cooling load prediction. On the other hand, the GPIM model is configured with 55 restarts, a length scale of 112, and an alpha value of 1.4. This set of hyperparameters indicates a different optimization strategy, potentially focusing on balancing computational efficiency and prediction accuracy.

The number of restarts in both models indicates multiple attempts to find the optimal solution, enhancing the reliability and stability of the models. The length scale parameter influences the model efficiency in generalizing across various scales of data, while the alpha parameter affects the model's noise tolerance, contributing to its robustness in varying conditions. The distinct hyperparameter values reflect the tailored approaches of each model to achieve optimal performance in forecasting cooling loads.

B. Evaluation of Models

The objective of this study was the prediction of cooling loud using three distinct models: GPR, GPWD, and GPIM. Model performance was assessed against experimental data, which was divided into training (70%), validation (15%), and testing (15%) phases. This division ensured an unbiased evaluation of the models. To comprehensively compare the algorithms employed five statistical metrics: R^2, RMSE, FB, IOA, and MSE.

During the training phase, the GPWD model exhibited exceptional predictive accuracy. It achieved the highest R^2 (0.990) and IOA (0.997) values, surpassing the other models. In comparison, the GPR model had slightly lower R^2 (0.971) and IOA (0.993) values. The GPWD model's superior performance was further highlighted by additional error indicators, such as the RMSE values ranging from 1.004 to 2.208, indicating lower errors compared to the GPR model. When considering the FB values during training, the GPWD model demonstrated the lowest value (-0.007), while the GPR model had the highest value (0.002). This suggests that the GPWD model provided a better fit to the data than the GPR model. Furthermore, in terms of MSE, the GPWD model excelled with a training value of 1.007, while the GPR model exhibited the highest value (2.658).

Overall, the results underscored the superiority of the GPWD model over the GPR and GPIM models, particularly during the training phase. Its high R^2 and IOA values indicate a strong ability to explain the variance in the dependent variable. Additionally, the lower RMSE and FB values, along with the lower MSE value, further support the GPWD model's superior performance. It is important to note that these findings are specific to the training phase and may vary across different phases or datasets. Further analysis and evaluation are necessary to validate the models' performance in real-world scenarios.

Nonetheless, the results obtained from this study highlight the potential of the GPWD model for accurate cooling load prediction. The developed models' results for GPR are represented in Table IV, and Fig. 3 displays the line plot for each metric.

This study compares how well hybrid models perform in the training, validation, and testing stages utilization the scatter plot shown in Fig. 4. Overall, the GPWD model shows minimal variation of predicted and observed values, indicating good accuracy. The performance of the GPR and GPIM models is similar, with slightly lower precision and higher inaccuracy, even though their data points are farther from the centreline. A wider dispersion of the data points suggests a slightly higher inaccuracy and lower precision when compared to the GPWD model.

TABLE III. Result of the Hyperparameter

Models	Hyperparameter		
	n_restarts	length_scale	alpha
GPWD	120	685.0302031	0.896335693
GPIM	55	112	1.4

TABLE IV. RESULT OF DEVELOPED MODELS FOR GPR

Model	Phase	Index values				
		RMSE	R^2	MSE	FB	IOA
GPR	Train	1.630	0.971	2.658	0.002	0.993
	Validation	2.208	0.955	4.874	0.024	0.988
	Test	1.782	0.970	3.177	0.032	0.991
	All	1.751	0.967	3.067	0.010	0.992
GPWD	Train	1.004	0.990	1.007	-0.007	0.997
	Validation	1.402	0.984	1.965	-0.003	0.995
	Test	1.443	0.980	2.081	-0.008	0.994
	All	1.145	0.988	1.311	-0.006	0.996
GPIM	Train	1.332	0.981	1.774	-0.006	0.995
	Validation	1.659	0.975	2.753	-0.005	0.993
	Test	1.839	0.966	3.384	-0.010	0.990
	All	1.470	0.978	2.162	-0.006	0.994

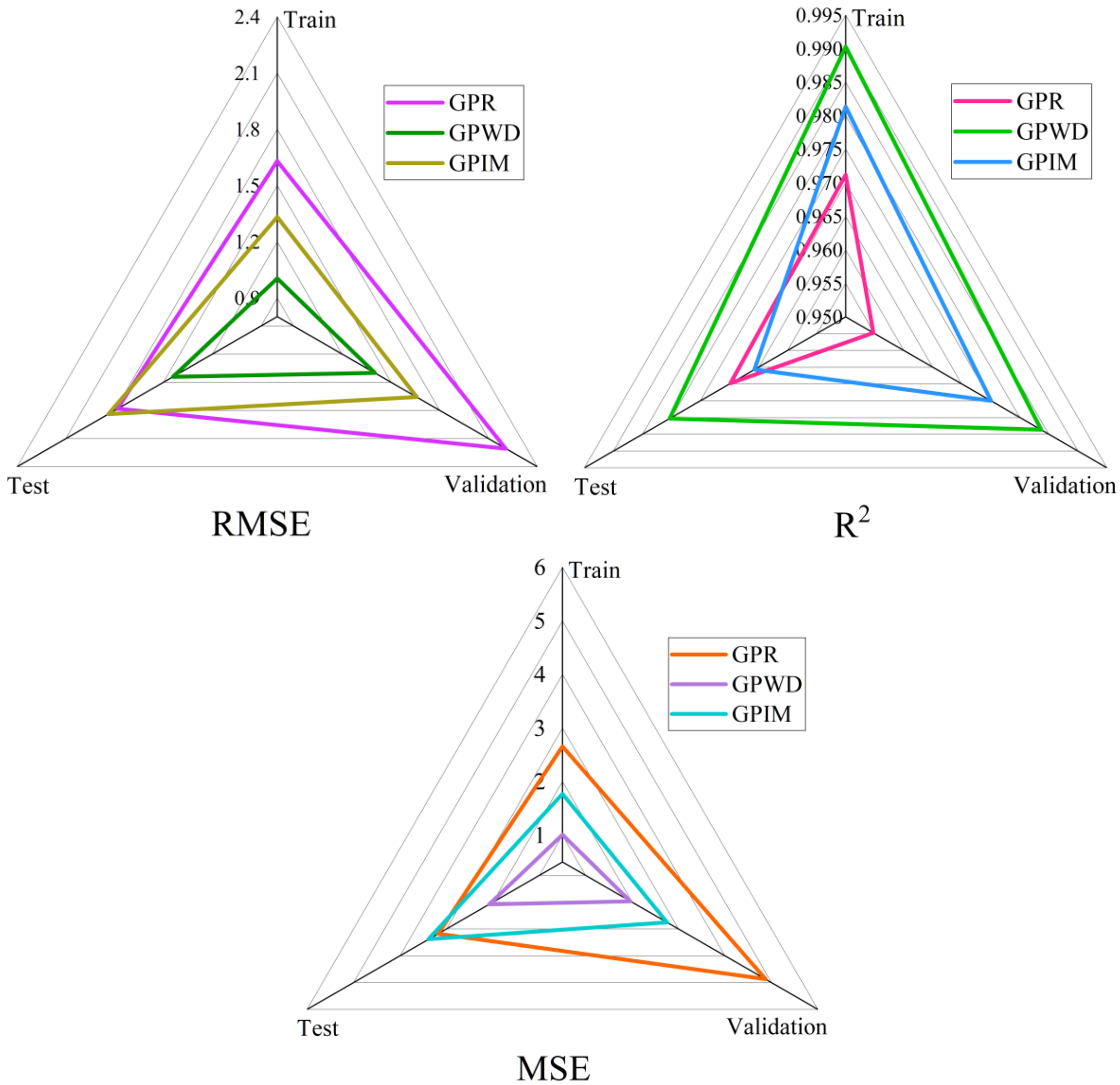

Fig. 3. The line plot for developed models' comparison according to metrics.

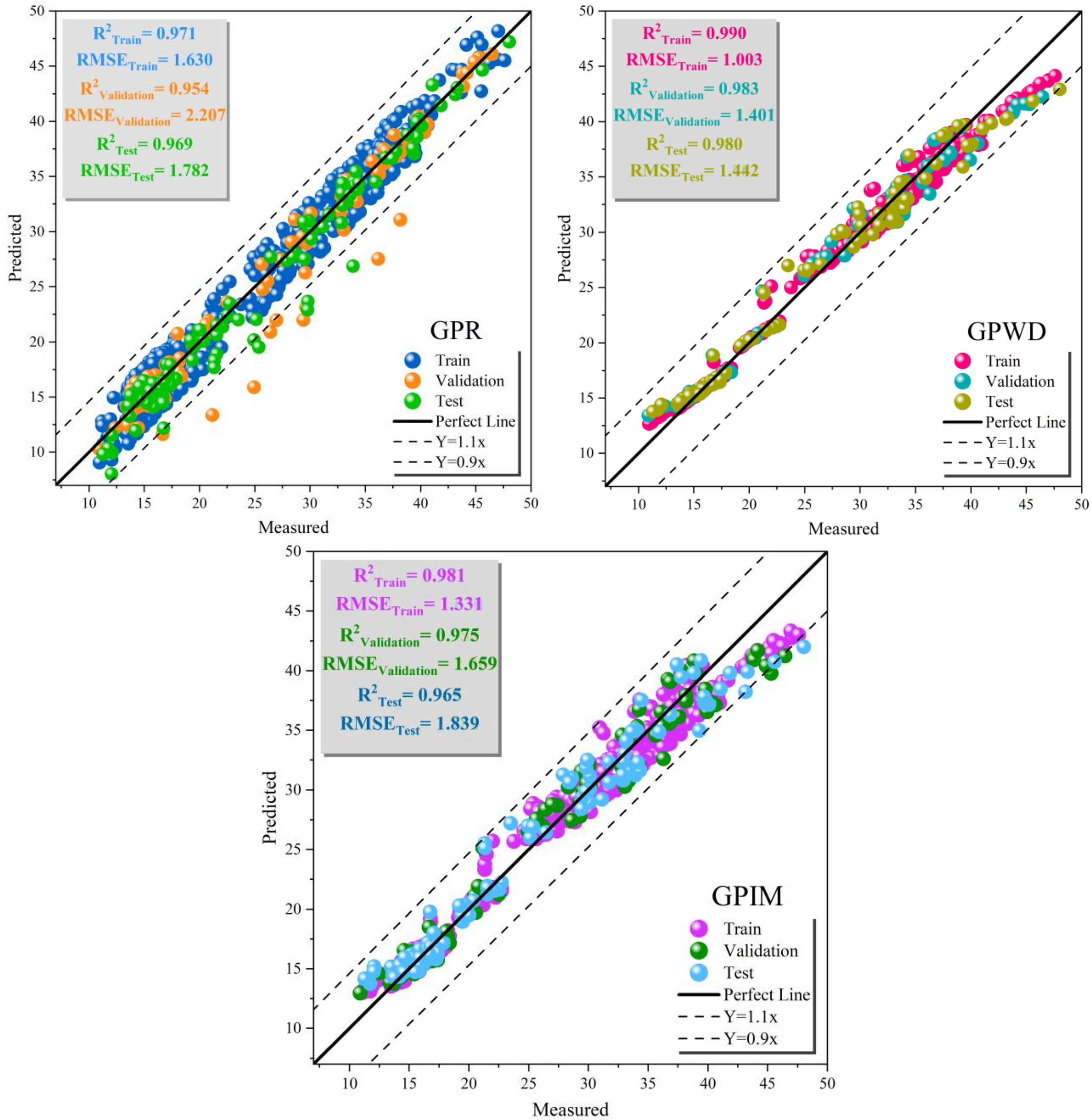

Fig. 4. Plotting the dispersion of evolved hybrid models.

In Fig. 5, a vertical drop line graph illustrates the percentages of error related with the created models. Notably, the GPWD model stands out with the lowest error of 23.18%. The graph indicates that the majority of values for GPWD are clustered around the 10% range. In contrast, the error percentages for GPR and GPIM exhibit a broader distribution, with a significant concentration of values higher than 36.85% and 25.79%, respectively. It is noteworthy that both the GPR and GPIM distributions are right-skewed, indicating a significant number of data points which increased rates of error. This results highlights the great accuracy of GPWD and effectively showcases the percentage of error distributions in developed models, as depicted in the plot.

The study shows the respective error percentages for the three models in Fig. 6, which is a box normal plot. The GPWD model showed remarkable performance, with errors under 10% and little dispersion. The GPR model's dispersion had a monotonous distribution with a topmost value of 20% and was constant across all phases. The GPIM model had the most significant differences between the models during the assessment stage, with one outlier data point accounting for more than 15% of the data.

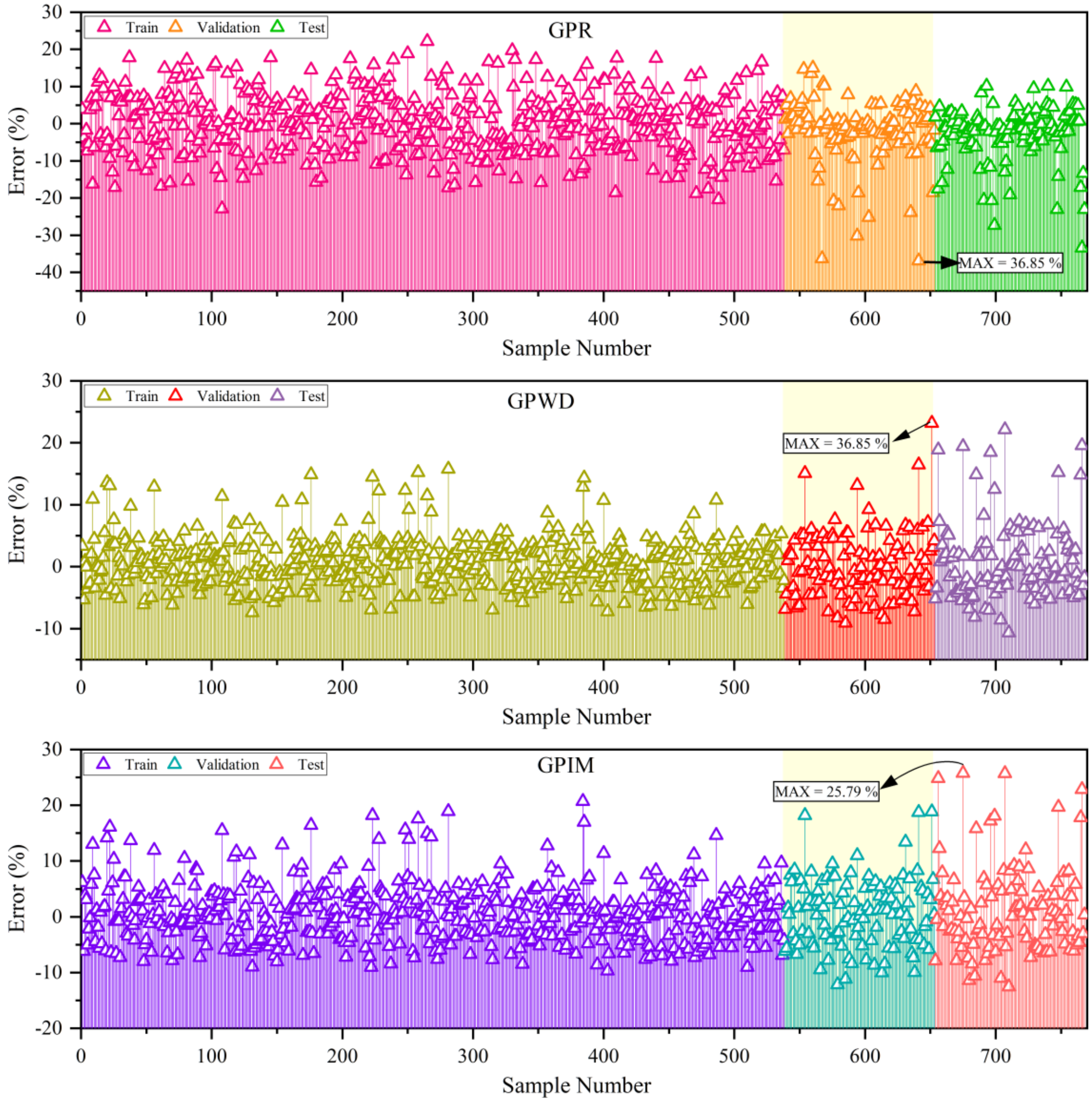

Fig. 5. The error percentage of the models is based on the vertical drop line plot.

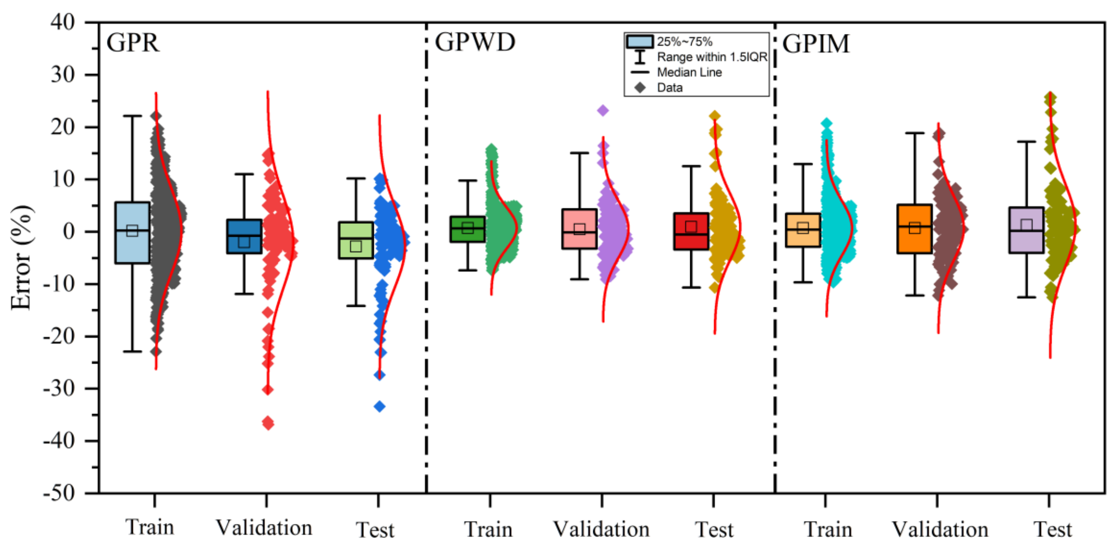

Fig. 6. The box normal plot errors of proposed models.

IV. Discussion

A. Comparison

Table V compares the best-performing models from the present study with those from related literature, highlighting their RMSE and R^2 values. The study by Moradzadeh et al. using the Support Vector Regression (SVR) model achieved an RMSE of 0.9887 and an R^2 of 1.7389. Roy et al. employed the Multivariate Polynomial Multiple Regression (MPMR) model, which resulted in an RMSE of 0.0791 and an R^2 of 0.99. Afzal et al. utilized the Particle Swarm Optimization with Grey Wolf Optimization (PSOGWO) model, attaining an RMSE of 1.9275 and an R^2 of 0.9590. In the present study, the GPWD model demonstrated an RMSE of 1.004 and an R^2 of 0.990. Despite the GPWD model not having the lowest RMSE, its high R^2 value signifies strong predictive accuracy and robustness. Comparing these results illustrates the competitive performance of the GPWD model against other advanced techniques in the literature, confirming its efficacy in forecasting cooling loads. The comparison underscores the potential of the GPWD model in achieving reliable predictions, essential for energy-efficient building management.

TABLE V. The Study Compares the Best-Performing Models Results with Related Literature

Articles	Index values		
	Models	*RMSE*	*R^2*
Moradzadeh et al. [14]	SVR	0.9887	1.7389
Roy et al. [32]	MPMR	0.0791	0.99
Afzal et al. [33]	PSOGWO	1.9275	0.9590
Present Study	GPWD	1.004	0.990

B. Limitation

Despite the promising results, this study has several limitations. First, a particular dataset was used to train and validate the models, potentially limiting their generalizability to other contexts or buildings with different characteristics. The dataset's scope and quality may influence the models' performance, necessitating further testing on diverse datasets. Second, the study focused primarily on a controlled environment, which might not capture the variability of real-world conditions, such as unexpected occupancy changes or extreme weather events. Additionally, while the integration of meta-heuristic algorithms with the Gaussian Process Regression model enhanced prediction accuracy, it also increased computational complexity, potentially posing challenges for real-time applications. Lastly, the study did not consider the economic aspects of implementing these advanced ML models in existing systems, which could impact their practical feasibility and adoption. Further research is needed to address these limitations and validate the models in various real-world scenarios.

V. Conclusion

To sum up, precise cooling load prediction is critical to enhancing the energy efficiency of cooling systems and maximizing the functionality of air conditioning controls and chillers. Within this field, machine learning (ML) models have become extremely powerful instruments, outperforming traditional methods and regression analysis because of their ability to identify complex patterns impacted by a variety of variables, including occupancy, construction materials, and meteorological conditions. Machine learning models provide dynamic forecasts that improve energy efficiency and enable effective building administration; they are data-scalable and scenario-adaptive. This research has shed light on the intricacies of cooling load systems, and the challenges entailed in energy optimization. To address these challenges, the study employed a comprehensive research methodology and innovative problem-solving approaches. The integration of the Weevil Damage Optimization Algorithm (WDOA) and the Improved Manta-Ray Foraging Optimizer (IMRFO), both meta-heuristic algorithms, with the Gaussian Process Regression (GPR) model was seamlessly executed to augment prediction accuracy. Rigorous validation, including stability tests, was performed on the cooling load data employed in these algorithms to certify the reliability of the outcomes obtained.

The study presented three distinct models: GPWD, GPIM, and an independent GPR model. Each model provided valuable intuitions for the exact prediction of cooling load. Among these models, the GPWD model exhibited exceptional performance, surpassing the others in terms of accuracy. Boasting an RMSE value of 1.004 and an impressive R^2 value of 0.990, the GPWD model demonstrated its prowess in forecasting cooling loads with remarkable precision, thereby indicating its practical applicability in real-world building management scenarios. The findings of this research underscore the superiority of ML models, particularly the GPWD model, in the prediction of cooling load. By harnessing complex algorithms and incorporating diverse factors, these models offer insights that contribute to energy optimization and efficient building management.

Nevertheless, it is essential to acknowledge that the results obtained in this study are specific to the dataset and training phase. Further analysis and evaluation are imperative to validate the performance of these models across different contexts and real-world scenarios. In conclusion, the study underscores the potential of ML models, particularly the GPWD model, in accurately predicting cooling load. This research contributes to the expanding body of information in the discipline of energy optimization and emphasizes the significance of leveraging advanced techniques to enhance the efficiency of cooling systems. Ongoing research and development efforts in this area are critical for advancing energy optimization and sustainable building management.

References

[1] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, and G. Brager, “Personal comfort models: Predicting individuals’ thermal preference using occupant heating and cooling behavior and machine learning,” Build Environ, vol. 129, pp. 96–106, 2018, doi: https://doi.org/10.1016/j.buildenv.2017.12.011.

[2] B. Sadaghat, S. Afzal, and A. J. Khiavi, “Residential building energy consumption estimation: A novel ensemble and hybrid machine learning approach,” Expert Syst Appl, vol. 251, p. 123934, 2024, doi: https://doi.org/10.1016/j.eswa.2024.123934.

[3] A. Speake, E. J. H. Wilson, Y. Zhou, and S. Horowitz, “Component-level analysis of heating and cooling loads in the U.S. residential

building stock," Energy Build, vol. 299, p. 113559, 2023, doi: https://doi.org/10.1016/j.enbuild.2023.113559.

[4] X. Li and R. Yao, "A machine-learning-based approach to predict residential annual space heating and cooling loads considering occupant behaviour," Energy, vol. 212, p. 118676, 2020, doi: https://doi.org/10.1016/j.energy.2020.118676.

[5] B. Sadaghat, A. Javadzade Khiavi, B. Naeim, E. Khajavi, A. R. Taghavi Khanghah, and H. Sadaghat, "The Utilization of a Naïve Bayes Model for Predicting the Energy Consumption of Buildings," Journal of Artificial Intelligence and System Modelling, vol. 1, no. 01, 2023.

[6] P. Markewitz, J. Marx, A. Schreiber, and P. Zapp, "Ecological evaluation of coal-fired Oxyfuel power plants-Cryogenic versus membrane-based air separation," Energy Procedia, vol. 37, pp. 2864–2876, 2013.

[7] G. E. Akpan and U. F. Akpan, "Electricity consumption, carbon emissions and economic growth in Nigeria," International Journal of Energy Economics and Policy, vol. 2, no. 4, pp. 292–306, 2012.

[8] S. S. Roy, P. Samui, I. Nagtode, H. Jain, V. Shivaramakrishnan, and B. Mohammadi-Ivatloo, "Forecasting heating and cooling loads of buildings: A comparative performance analysis," J Ambient Intell Humaniz Comput, vol. 11, pp. 1253–1264, 2020.

[9] A. Moradzadeh, A. Mansour-Saatloo, B. Mohammadi-Ivatloo, and A. Anvari-Moghaddam, "Performance evaluation of two machine learning techniques in heating and cooling loads forecasting of residential buildings," Applied Sciences, vol. 10, no. 11, p. 3829, 2020.

[10] C. Fan, F. Xiao, and Y. Zhao, "A short-term building cooling load prediction method using deep learning algorithms," Appl Energy, vol. 195, pp. 222–233, 2017.

[11] X. Xu, J. E. Taylor, A. L. Pisello, and P. J. Culligan, "The impact of place-based affiliation networks on energy conservation: An holistic model that integrates the influence of buildings, residents and the neighborhood context," Energy Build, vol. 55, pp. 637–646, 2012, doi: https://doi.org/10.1016/j.enbuild.2012.09.013.

[12] C. Deb, L. S. Eang, J. Yang, and M. Santamouris, "Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks," Energy Build, vol. 121, pp. 284–297, 2016, doi: https://doi.org/10.1016/j.enbuild.2015.12.050.

[13] F. Khayatian and L. Sarto, "Application of neural networks for evaluating energy performance certificates of residential buildings," Energy Build, vol. 125, pp. 45–54, 2016.

[14] A. Moradzadeh, A. Mansour-Saatloo, B. Mohammadi-Ivatloo, and A. Anvari-Moghaddam, "Performance evaluation of two machine learning techniques in heating and cooling loads forecasting of residential buildings," Applied Sciences, vol. 10, no. 11, p. 3829, 2020.

[15] A. Moradzadeh, B. Mohammadi-Ivatloo, M. Abapour, A. Anvari-Moghaddam, and S. S. Roy, "Heating and cooling loads forecasting for residential buildings based on hybrid machine learning applications: A comprehensive review and comparative analysis," IEEE Access, vol. 10, pp. 2196–2215, 2021.

[16] R. Chalapathy, N. L. D. Khoa, and S. Sethuvenkatraman, "Comparing multi-step ahead building cooling load prediction using shallow machine learning and deep learning models," Sustainable Energy, Grids and Networks, vol. 28, p. 100543, 2021.

[17] E. Abdelkader, A. Al-Sakkaf, and R. Ahmed, "A comprehensive comparative analysis of machine learning models for predicting heating and cooling loads," Decision Science Letters, vol. 9, no. 3, pp. 409–420, 2020.

[18] Z.-H. Zhou, Machine learning. Springer Nature, 2021.

[19] Q. Zhang, Z. Tian, Y. Ding, Y. Lu, and J. Niu, "Development and evaluation of cooling load prediction models for a factory workshop," J Clean Prod, vol. 230, pp. 622–633, 2019.

[20] T. Han, A. Siddique, K. Khayat, J. Huang, and A. Kumar, "An ensemble machine learning approach for prediction and optimization of modulus of elasticity of recycled aggregate concrete," Constr Build Mater, vol. 244, p. 118271, 2020.

[21] B. Mahesh, "Machine learning algorithms-a review," International Journal of Science and Research (IJSR).[Internet], vol. 9, pp. 381–386, 2020.

[22] J. Zhao, X. Yuan, Y. Duan, H. Li, and D. Liu, "An artificial intelligence (AI)-driven method for forecasting cooling and heating loads in office buildings by integrating building thermal load characteristics," Journal of Building Engineering, vol. 79, p. 107855, 2023, doi: https://doi.org/10.1016/j.jobe.2023.107855.

[23] C. Fan, Y. Liao, G. Zhou, X. Zhou, and Y. Ding, "Improving cooling load prediction reliability for HVAC system using Monte-Carlo simulation to deal with uncertainties in input variables," Energy Build, vol. 226, p. 110372, 2020.

[24] P. Mehdipour et al., "Application of Gaussian Process Regression (GPR) in estimating under-five mortality levels and trends in Iran 1990-2013, study protocol," 2014.

[25] C. E. Rasmussen and C. K. I. Williams, "Gaussian processes for machine learning (adaptive computation and machine learning) the mit press," Cambridge, MA, USA, pp. 69–106, 2005.

[26] B. Wang and T. Chen, "Gaussian process regression with multiple response variables," Chemometrics and Intelligent Laboratory Systems, vol. 142, pp. 159–165, 2015.

[27] Z. Y. Wan and T. P. Sapsis, "Reduced-space Gaussian Process Regression for data-driven probabilistic forecast of chaotic dynamical systems," Physica D, vol. 345, pp. 40–55, 2017.

[28] M. H. Hassan, E. H. Houssein, M. A. Mahdy, and S. Kamel, "An improved manta ray foraging optimizer for cost-effective emission dispatch problems," Eng Appl Artif Intell, vol. 100, p. 104155, 2021.

[29] S. Mousavi and S. Mirinezhad, "Weevil damage optimization algorithm and its applications," Journal of Future Sustainability, vol. 2, no. 4, pp. 133–144, 2022.

[30] S. Al-Megren, H. Kurdi, and M. F. Aldaood, "A multi-UAV task allocation algorithm combatting red palm weevil infestation," Procedia Comput Sci, vol. 141, pp. 88–95, 2018.

[31] S. Mousavi and S. Mirinezhad, "Weevil damage optimization algorithm and its applications," Journal of Future Sustainability, vol. 2, no. 4, pp. 133–144, 2022.

[32] S. S. Roy, P. Samui, I. Nagtode, H. Jain, V. Shivaramakrishnan, and B. Mohammadi-Ivatloo, "Forecasting heating and cooling loads of buildings: A comparative performance analysis," J Ambient Intell Humaniz Comput, vol. 11, pp. 1253–1264, 2020.

[33] S. Afzal, B. M. Ziapour, A. Shokri, H. Shakibi, and B. Sobhani, "Building energy consumption prediction using multilayer perceptron neural network-assisted models; comparison of different optimization algorithms," Energy, vol. 282, p. 128446, 2023.