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COOLING LOAD PREDICTION USING MACHINE LEARNING AND WEATHER PARAMETERS

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ABSTRACT

Cooling systems account for a substantial amount of end-use energy consumption in building sector. This system is responsible for removing the heat from the building to maintain the indoor temperature at a certain comfort level standard. Prediction of cooling load in a building is useful to design the HVAC system operation and energy management efficiently. This paper presents a method for predicting instantaneous building cooling load, relying on the inputs extracted from weather data and artificial neural networks. The data sets are generated by simulating cooling load at an educational building located in Indonesia for one year using Energy Plus software. The input parameters include dry-bulb temperature, relative humidity, wind speed, wind direction, horizontal infrared radiation rate, diffuse solar radiation rate, and direct solar radiation rate. Analysis of variance and Pearson coefficient of correlation was applied to analyze the relative contribution of individual input parameters on the cooling load. Both methods have consistently shown that the dry bulb temperature is the most influential parameters, while wind speed and wind direction have less significant effect on cooling loads. The result of this study indicates that the optimized ANN model with selected input parameters has successfully predicted the cooling load with coefficient of variation (CV) of 15.26%.

***Keywords**: Cooling load, Time delay, Machine learning, Prediction, Building*

1 INTRODUCTION

Energy demand in the building sector is nearly comparable to that of the industrial sector, accounting for 28 % of global energy consumption in 2022 (IEA, 2024) and contributing to approximately 30 % of CO_2 emissions (Rock et al., 2023). In most commercial and residential buildings, heating ventilating air conditioning systems (HVAC) represent up to 50% of the electrical load (Qi et al., 2012). Consequently, improving energy efficiency in the cooling sector is essential not only for reducing operating costs but also for mitigating climate change and meeting increasingly stringent carbon-reduction targets. It can be projected that without significant improvements in building energy efficiency, global energy demand from buildings could steadily increase, making this sector critical for achieving global climate goals.

Optimizing the cooling system can be achieved by selecting a refrigerant with high thermodynamic efficiency within the air conditioning (AC) system (Widagdo, 2010). Furthermore, accurately sizing the system capacity to match the cooling load is critical for ensuring both performance and energy efficiency. The cooling load of a building is a highly dynamic variable, governed by external temperature, humidity, solar radiation, building orientation, envelope characteristics, and occupancy patterns. Inaccurate cooling load prediction cause HVAC equipment to run either oversized (over-cooling) or undersized (under-cooling), leading to unnecessary energy waste and heightened greenhouse-gas emissions.

Accurately predicting building cooling loads remains a complex but critical task for building energy efficiency. The first step toward overcoming this challenge involves collecting data that are related with internal and external heat gain of building and developing robust mathematical models capable of cooling load estimation. Reliable cooling load estimation enables better optimization of air conditioning system operation.

Two main approaches for cooling load estimation are commonly employed: data-driven models and physical simulation. Data-driven methods, especially machine learning, are increasingly used to handle uncertainties in cooling load predictions. These models are believed to be capable of estimating cooling load without requiring deep technical details about building structures (Amasyali & El-Gohary, 2018). When design parameters change, they can rapidly and precisely estimate cooling load effectively, offering a fast and scalable solution.

In contrast, physical modeling relies on thermodynamic principles and employs tools such as TRNSYS, EnergyPlus, and DOE-2 to simulate building cooling load (Tao et al., 2008; Serale et al., 2018). While highly accurate, these tools require extensive input data, including material properties, HVAC system specifications, and construction details, making their implementation time-consuming and complex (Pham et al., 2020). Given these limitations, data-driven approaches such as machine learning offer a faster, more practical alternative.

Previous studies have explored the application of machine learning for predicting cooling loads under various scenarios and prediction cases (Yıldız & Beyhan, 2025; Zhang et al., 2025). However, accurately capturing the dynamic thermal behavior of buildings remains a significant challenge due to the thermal inertia of building materials such as walls that can delay the heat gain ~~while~~ penetrating the building. This paper presents a machine learning model designed to accurately predict the hourly cooling load of educational building in a tropical climate, specifically in Indonesia. The study investigates the incorporation of previous time step inputs into ANN model to better capture the dynamic characteristics of cooling load variation.

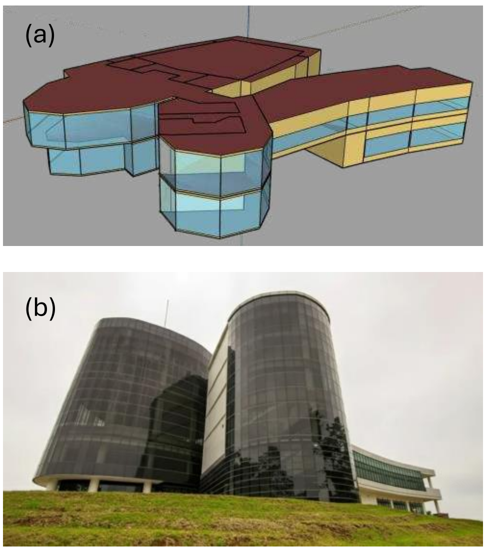

Figure 1 Photograph of Makara art center (a) Sketch-up model (b) Actual building

2. MATERIALS AND METHODS

2.1 Building description

The building under consideration is a 2-story educational structure located in Depok, Indonesia (Timotius et al., 2022). The total floor area is 24,000 m² with a 4-5 m floor to ceiling height. The building envelope is designed with window to wall ratio (WWR) of 40 % approximately. Moreover, the building is composed of 9 zones and mostly used as a virtual office building. The photograph of 3D building model from Sketch up together with its actual building is shown in Figure 1.

Table 1. Material and building construction (Timotius et al., 2022).

Construction	Materials	Thermal Conductivity (W/m·K)	Thermal Resistance (m²·K/W)
Interior Ceiling	100 mm lightweight concrete	0.53	
	Ceiling air space		0.18
	Acoustic tiles	0.06	
Interior Wall	19 mm gypsum board	0.16	
	Wall air space		0.15
Interior Floor	Acoustic tiles	0.06	
	Air space resistance		0.18
	100 mm lightweight concrete	0.53	
	Carpet pad		0.1
Interior Partition	25 mm wood	0.15	
Interior Window	Clear 3 mm glass	0.9	
Exterior Window	Theoretical glass	0.0133	
Interior Door	25 mm wood	0.15	
Roof	Roof Membrane	0.16	
	Roof Insulation	0.049	
	Metal Decking	45.006	
Exterior Wall	1 in. Stucco	0.69	
	8 in. concrete HW	0.17	
	Wall insulation	0.08	
	½ in. gypsum	0.16	

The specifications of building material and construction are shown in Table 1. During simulation, indoor temperature is set to 25 ˚C, following the thermal comfort standard (Badan Standardisasi Nasional, 2020). Standard weather data for Depok obtained from Meteonorm is used for this simulation. Moreover, the internal loads sourced from the occupants, lighting, and electrical equipment are neglected. Therefore, the cooling load simulation is based on outdoor conditions only.

Energy Plus software determines the cooling load primarily through a zone heat balance method, which accounts for all heat gains and losses in the building, including conduction, infiltration, internal gains, and solar radiation. The cooling load represents the heat that must be removed to maintain the desired indoor temperature. In addition, the air system model calculates how much cooling is supplied by considering air flow rates and supply air temperature. Together, these calculations dynamically balance the zone's thermal conditions and the system's cooling output to accurately simulate the building's cooling load.

Cooling load simulation was conducted over a full year. The input weather parameters and their respective ranges are presented in Table 2. In total, there are 8,760 hourly data points, each consisting of input-output pairs were utilized for model prediction and analysis.

Table 2. Range of weather data (Meteotest, 2025)

Symbol	Parameter	Range	Unit
A	Dry bulb Temperature	[21.6, 35.6]	°C
B	Relative Humidity	[37, 100]	%
C	Wind Speed	[0, 16.9]	m/s
D	Wind Direction	[0, 360]	deg
E	Horizontal Infrared Radiation Rate	[362, 464]	W/m^2
F	Diffuse Solar Radiation Rate	[0, 537]	W/m^2
G	Direct Solar Radiation Rate	[0, 977]	W/m^2

2.2 Feature analysis

Effective ANN models can be developed by selecting only significant parameters for the inputs. In this section the influence of each weather parameter on cooling load is analyzed. Two distinct statistical methodologies including Analysis of Variance (ANOVA) and Pearson's Correlation Coefficient are employed for the analysis.

ANOVA method assesses the statistical significance of differences between group means, evaluating the impact of each environmental parameter on cooling load. A higher F-value indicates a greater likelihood that variation in the cooling load is explained by the given parameter, suggesting a stronger influence (Sholahudin & Han, 2016). On the other hand, Pearson's Correlation Coefficient quantifies the strength and direction of a linear relationship between two variables (Sholahudin et al., 2023). A value closer to ±1 indicates a stronger linear correlation, implying that changes in the environmental parameter are linearly associated with changes in the cooling load. The equation for Pearson's Correlation Coefficient can be written in Eq. (1).

$$r = \frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{[n\sum x^2-(\sum x)^2][n\sum y^2-(\sum y)^2]}} \quad (1)$$

Where r represents the coefficient of correlation between variables x and y.

Before performing the feature analysis, all data sets are normalized in the range of [-1, 1], then the data are analyzed using ANOVA and Pearson's coefficient of correlation.

The ANOVA results are presented in Table 3. They show that Variable A, which represents dry-bulb temperature parameters, has the highest F-value, indicating that it is the most influential factor. In contrast, Variables C and D, which correspond to wind speed and wind direction, exhibit very low F-values, suggesting a comparatively minor effect on cooling loads.

Table 3. ANOVA results

Var	Sum of Square	Degree of freedom	Mean of square	F-value	P-value
A	3.84E+10	136	2.82E+08	24.72	0
B	4.13E+09	63	6.55E+07	5.73	0
C	2.43E+09	127	1.91E+07	1.68	0
D	4.37E+09	360	1.21E+07	1.06	0.21
E	6.30E+09	96	6.57E+07	5.75	0
F	1.64E+10	503	3.27E+07	2.86	0
G	5.71E+10	876	6.51E+07	5.70	0
Error	7.54E+10	6596	1.14E+07		
Total	1.43E+12	8759			

The linear relationship between each input variable and the cooling load output is illustrated in Figure 2. The results indicate that dry-bulb temperature has the highest coefficient, followed by wind speed and wind direction, which occupy the lowest positions and exhibit the least influence on cooling load.

Across both analytical methodologies, dry bulb temperature consistently emerges as the most significant environmental parameter affecting the building's cooling load. Its F-value of 24.72 is

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substantially higher than other parameters, and its correlation coefficient of 0.83 demonstrates a strong positive linear relationship. This finding is highly consistent, indicating that ambient air temperature fluctuations are the primary drivers of cooling load within the studied building. This aligns with general building physics principles, where sensible heat gain due to temperature differences constitutes a major component of cooling demand.

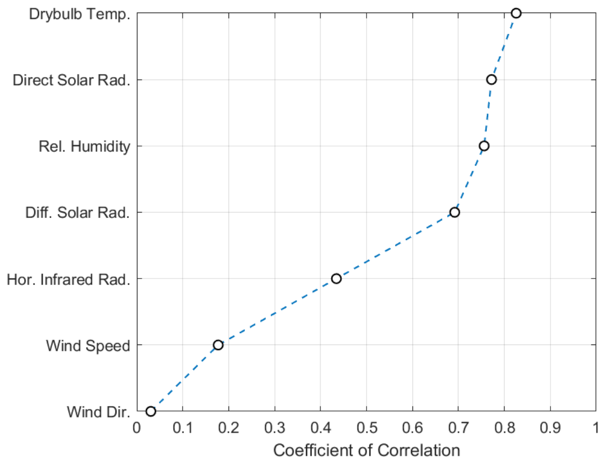

Figure 2. Coefficient of correlation of weather parameter

Conversely, wind speed and wind direction consistently rank at the bottom in both analyses, exhibiting low F-values (1.68 and 1.06, respectively) and weak correlation coefficients (0.18 and 0.03). This suggests that, for this specific building and its operational context, wind-related factors have a negligible impact on the cooling load. This could be due to factors such as low internal gains, a well-sealed building envelope limiting infiltration, or minimal reliance on natural ventilation strategies. Consequently, the ANN input set was partitioned into two configurations:

1. Full input set (all measured parameters)
2. Reduced input set (containing five variables after excluding the two wind-related parameters)

The reduction aims to achieve simpler ANN architecture with fewer inputs while preserving predictive capability. Nonetheless, an ANN trained solely on dry-bulb temperature is not sufficient to capture the cooling-load dynamics. Despite its high individual contribution, the cooling load is intrinsically nonlinear and affected by other statistically significant factors (shown by $p < 0.05$ in the ANOVA results). Therefore, involving the additional significant parameters is essential for robust and accurate cooling load prediction.

Table 4. Relative contribution of weather parameter to cooling load

Parameter	Ranking by ANOVA	Ranking by Pearson coefficient of correlation
Dry bulb Temperature	1	1
Direct Solar Radiation	2	4
Relative Humidity	3	3
Diffuse Solar Radiation	4	5
Horizontal Infrared Radiation	5	2
Wind Speed	6	6
Wind Direction	7	7

2.3 Artificial Neural network

An Artificial Neural Network (ANN) is a computational model inspired by the structure of the human brain. It consists of layers of interconnected neurons, where each connection has an associated weight. Each neuron receives one or more input signals, applies a weight to each input, adds a bias term, and then passes the resulting sum through an activation function. The output is then forwarded to neurons in the next layer.

The structure of ANN can be seen in Figure 3. It is composed of input layer, hidden layer, and output layer. The relationship between input and output is built through mathematical function that connects the neurons in each layer (Sholahudin et al., 2019). There are two types of ANN structures investigated in present study: static and time delay ANN models. The static ANN model uses current input variables without accounting for past information, essentially treating each time step independently.

In contrast, the dynamic or time-delay ANN model incorporates multiple past time-step inputs (delays) as additional features, enabling the network to learn temporal dependencies and dynamic behaviors in the output data (Sholahudin & Han, 2016). This architecture allows the time-delay model to more effectively capture trends and fluctuations influenced by previous states, improving prediction accuracy over the static model by modeling the temporal evolution of the cooling load with high precision.

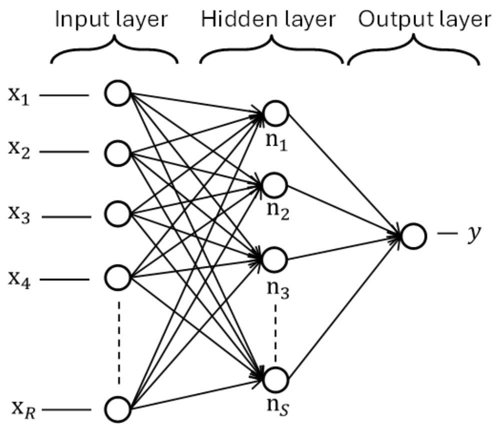

Figure 3. Structure of artificial neural networks

The accuracy of ANN model is measured by root means square error (RMSE) and coefficient of variation (CV).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

$$CV = \frac{RMSE}{\bar{y}} x\ 100\% \quad (3)$$

Where y_i and $\hat{y}_i$ represent the actual and predicted cooling loads. While $\bar{y}$ shows the average of actual cooling load.

3. RESULTS AND DISCUSSION

Several ANN models were developed using the datasets previously employed for ANOVA testing. Specifically, the data collected from January through November were allocated to the training set, whereas the simulated dataset for December was reserved for testing. Model optimization involved systematic exploration of input-parameter combinations, variation in the number of hidden neurons, and determination of the optimal number of time delay inputs. It is important to note that all evaluation on ANN performance is based on testing results.

3.1 Effect number of inputs

A comparison of the ANN model's performance in predicting cooling loads using seven and five input parameters is presented in Figure 4. The seven-input model incorporates all parameters listed in Table 4, while the five-input model excludes wind speed and wind direction variables identified as having minimal statistical significance in the ANOVA and linearity analysis.

Figure 4 shows the performance of ANN models that have been trained and tested in various numbers of neurons. Varying number of neurons is important because it affects the model's ability to learn complex patterns. Too few neurons may lead to underfitting, where the model is too simple to capture data trends. On the other hand, too many neurons can cause overfitting, where the model memorizes noise instead of generalizing. Finding the right number helps balance model complexity, improve performance, and ensure efficient training are the key steps in building effective neural networks.

According to Figure 4, the ANN model's performance, measured by RMSE, remains nearly unchanged when reducing the number of input parameters from seven to five across all neurons from 1 to 25. This indicates that the two excluded variables namely wind direction and wind speed, which showed low F-values in the ANOVA contribute minimally to cooling load prediction. The saturation of RMSE beyond 6 - 8 neurons suggests that excessive model complexity does not yield meaningful improvements, emphasizing the effectiveness of simpler architectures. Therefore, the five-input model achieves a favorable balance between predictive accuracy and computational efficiency, making it preferable for practical implementation. This supports the importance of data-driven feature selection to eliminate redundant inputs without sacrificing performance.

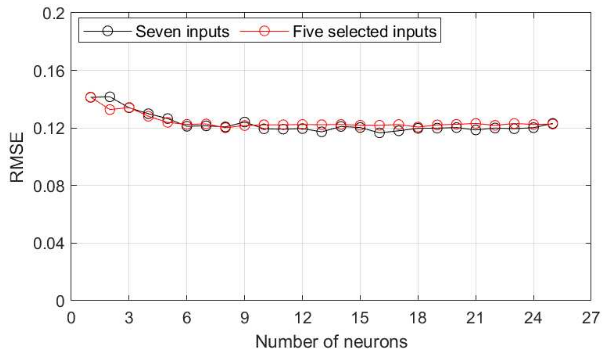

Figure 4. Comparison of ANN performance with different input groups

3.2 Effect number of time delay

Figure 5 illustrates the performance of ANN model as a function of the incorporated time-delay inputs. The models were trained using a series of input configurations that included one to four delayed inputs. As shown in the figure, the model with additional time-delay inputs yields a pronounced enhancement in prediction accuracy. This improvement reflects the model's capacity to capture the dynamic thermal behavior of buildings, namely thermal inertia, heat accumulation, and the delayed response to external conditions.

By integrating historical values of inputs such as indoor temperature and solar radiation, the time-delay ANN model learns temporal correlations that a static ANN cannot represent. The systematic reduction in RMSE with each added delay demonstrates that multi-step historical data substantially strengthen the model's ability to forecast cooling-load dynamics, particularly in humid-tropical climates where thermal conditions evolve gradually.

These results confirm that the inclusion of previous-step historical inputs is essential for accurate cooling-load prediction and substantiates the superiority of dynamic modeling approaches over static ones in practical building-energy applications.

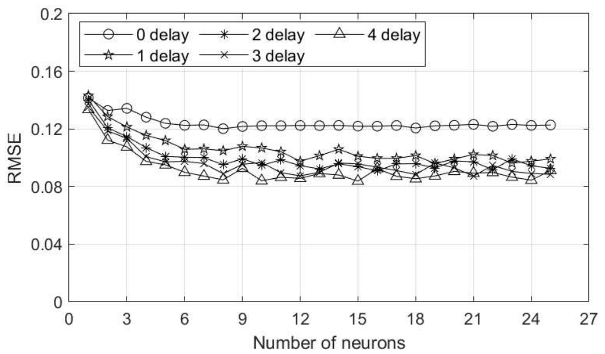

Figure 5. Effect of number of tapped delay inputs on prediction accuracy

3.3 Cooling load prediction by optimal model

Figure 6 presents the prediction results obtained using five selected input parameters, comparing (a) static ANN model and (b) time-delay ANN model with four time-delayed inputs. A comparative analysis reveals substantial performance differences between static and dynamic architectures. Both models were evaluated against simulated cooling load data generated by Energy Plus over a representative month in December, capturing the dynamic thermal behavior characteristic of building systems.

The static ANN model, which relies exclusively on instantaneous weather variables and employs an optimal configuration of eight neurons, exhibits notable limitations in representing the complex temporal evolution of cooling load. This particularly appeared during rapid transitions and peak load events. The model achieves a coefficient of variation (CV) of 21.25%, indicating moderate prediction error. As shown in Figure 6(a), systematic discrepancies are shown during sharp transients, most prominently a significant underprediction near the 200-minute mark, where the model fails to capture the full amplitude of the cooling load peak. This lagged response highlights the model's inability to consider the thermal inertia and heat accumulation within the building envelope. The cyclical pattern of these errors further emphasizes a fundamental constraint of static architectures when modeling systems governed by memory-dependent dynamics, wherein past thermal states critically influence present conditions.

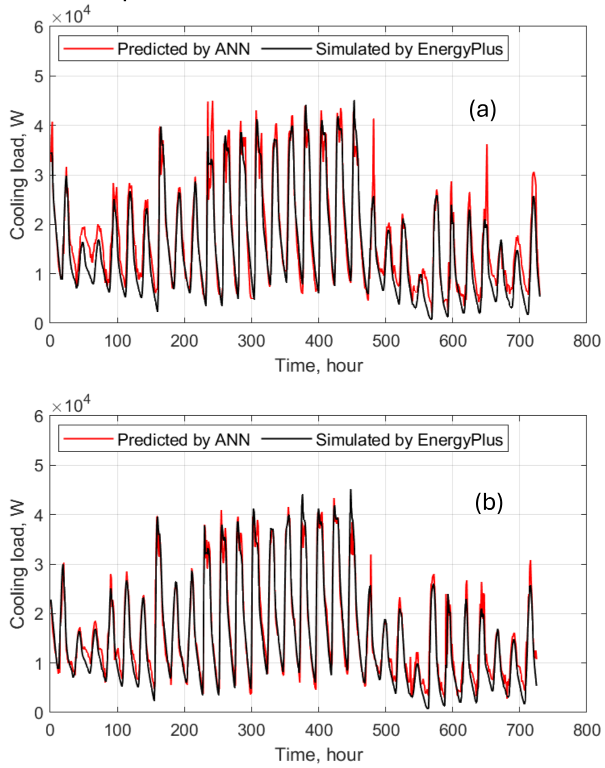

Figure 6. Cooling load prediction results (a) No-delay (b) 4-delay

In contrast, the time-delay ANN model, configured with four delayed inputs and an optimal number of twelve neurons (see Figure 6(b)), demonstrates improvements in predictive accuracy, achieving a CV of 15.26%. The model exhibits significantly enhanced agreement between predicted and simulated cooling loads across the entire evaluation period, particularly during peak demand and transient events. The improved performance is attributed to the model's inherent capacity to implicitly encode temporal dynamics by leveraging historical values of meteorological inputs, thereby capturing the delayed thermal response typical of building systems.

These findings bring significant implications for practical applications in building energy management. From a research standpoint, the results reinforce the necessity of incorporating temporal dependencies in machine learning models applied to building energy systems, aligning with established thermal dynamics principles that emphasize the role of thermal mass in delaying and smoothing thermal responses. From a practical perspective, the superior accuracy of time-delay architectures enables more robust model-predictive control (MPC) strategies, which can lead to reduced energy consumption, improved thermal comfort, and enhanced demand-response capabilities in intelligent building systems.

4. CONCLUSION

In this study, multiple ANN models were investigated to predict hourly cooling load in a building. A feature analysis employing analysis of variance (ANOVA) and Pearson's correlation coefficient was conducted to assess the relative significance of individual input variables on cooling load prediction. The results confirmed that among the seven input parameters, dry-bulb temperature, direct solar radiation, relative humidity, diffuse solar radiation, and horizontal infrared radiation exhibit the most substantial influence on cooling load prediction. In contrast, wind speed and wind direction were found to have negligible impact on model accuracy and were thus excluded from the input set without degrading prediction accuracy.

The inclusion of time-delayed inputs significantly enhanced model accuracy by enabling the capture of dynamic thermal behavior associated with building envelope thermal inertia. By including historical values of input parameters, the model effectively accounts for thermal mass effects, allowing it to simulate the delayed thermal response of building walls. As a result, the optimized time-delay ANN model achieved a coefficient of variation (CV) of 15.26%, demonstrating superior predictive performance compared to static configurations.

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