

**COOLING LOAD PREDICTION MODEL FOR
UNDERACTUATED ZONES USING A MULTI-
LAYER PERCEPTRON ARTIFICIAL NEURAL
NETWORK**

YADDARABULLAH

**ASIA e UNIVERSITY
2025**

COOLING LOAD PREDICTION MODEL FOR UNDERACTUATED
ZONES USING A MULTI-LAYER PERCEPTRON ARTIFICIAL NEURAL
NETWORK

YADDARABULLAH

A Thesis Submitted to Asia e University in
Fulfilment of the Requirements for the
Degree of Doctor of Philosophy

July 2025

ABSTRACT

This thesis addresses the complex challenge of predicting cooling load in under-actuated zones, where variability in occupant behavior and environmental conditions limits the effectiveness of traditional models. To enhance predictive performance, a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) was developed, integrating a Leaky ReLU activation function with a trainable bias term and scaled Glorot Uniform weight initialization. The model was trained and validated on a time-series dataset collected from a controlled environment. Optimal time intervals were identified using Polynomial regression, with mixed intervals proving most effective in capturing dynamic occupant patterns and their impact on cooling load. This configuration yielded the highest Kaiser-Meyer-Olkin (KMO) score of 0.6237, outperforming fixed intervals by 7.3% in representing occupant-related variability. A comprehensive feature engineering strategy was employed, incorporating sine-cosine transformations, lag features, interaction terms, and temporal attributes to enhance data representation. These features enabled the model to capture cyclic patterns, historical trends, and complex inter-feature relationships more effectively. The developed model achieved strong predictive performance, with an RMSE of 255.751, MAE of 131.845, and R^2 of 0.9962. Compared to the baseline, this reflects substantial error reduction and improved accuracy. Its stability was supported by a low R^2 standard deviation (0.0017), indicating strong performance across varying conditions. The novel contributions of this study include the integration of a trainable bias into the Leaky ReLU function with customized weight scaling, the use of empirically derived mixed time intervals, and the development of a context-aware feature engineering framework tailored for under-actuated zones. These innovations enhance the model's adaptability and generalizability, offering a reliable and scalable solution for occupant-centric cooling load prediction in modern HVAC systems.

Keywords: The under-actuated zone, occupant centric control, time interval analysis, polynomial regression, artificial neural network

APPROVAL

This is to certify that this thesis conforms to acceptable standards of scholarly presentation and is fully adequate, in quality and scope, for the fulfilment of the requirements for the Degree of Doctor of Philosophy.

The student has been supervised by: **Professor Ts Dr Aedah Abd Rahman & Associate Professor Ts Dr Amna Saad**

The thesis has been examined and endorsed by:

Professor Dr Megat Farez Azril bin Zuhairi

Asia e University

Examiner 1

Professor Dr Haryani binti Haron

Universiti Teknologi Mara

Examiner 2

This thesis was submitted to Asia e University and is accepted as fulfilment of the requirements for the Degree of Doctor of Philosophy.



.....
Professor Dr Siow Heng Loke

Asia e University

Chairman, Examination Committee

7 July 2025

DECLARATION

I hereby declare that the thesis submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy is my own work and that all contributions from any other persons or sources are properly and duly cited. I further declare that the material has not been submitted either in whole or in part, for a degree at this or any other university. In making this declaration, I understand and acknowledge any breaches in this declaration constitute academic misconduct, which may result in my expulsion from the programme and/or exclusion from the award of the degree.

Name: Yaddarabullah

A handwritten signature in black ink, appearing to be 'Yaddarabullah', written over a horizontal line.

Signature of Student:

Date: 7 July 2025

ACKNOWLEDGEMENTS

All praise and gratitude are due to Allah Subhanahu Wa Ta'ala, whose grace, guidance, and blessings have made it possible for me to complete this PhD journey. My deepest gratitude goes to my beloved family. To my parents, whose unwavering love, prayers, and support have provided a constant source of strength and inspiration throughout this journey. To my wife, whose patience, understanding, and encouragement have continuously sustained me during challenging times and whose belief in my work has been invaluable. To my son, whose joy and curiosity reminded me daily of the importance of learning and growth. I am also thankful to my extended family for their continuous encouragement and moral support, which was vital in completing this work.

I extend my heartfelt thanks to Universitas Trilogi for their steadfast support through a scholarship and for providing a conducive environment and essential facilities that enabled the successful execution of my research experiments. I am equally grateful to the Ministry of Education, Culture, Research, Technology, and Higher Education of the Republic of Indonesia, whose research funding from 2021 to 2024 was instrumental in supporting this study and in contributing to the advancement of knowledge in this field.

I would also like to express my profound appreciation to my colleagues at Universitas Trilogi, whose encouragement, insights, and collaboration greatly enriched my research experience and provided me with invaluable perspectives. A special acknowledgment goes to my students who served as research assistants; your dedication, hard work, and commitment were crucial to the progress and completion of this work.

TABLE OF CONTENTS

ABSTRACT	ii
APPROVAL	iii
DECLARATION	iv
ACKNOWLEDGEMENTS	vi
TABLE OF CONTENTS	vii
LIST OF TABLES	xi
LIST OF FIGURES	xv
LIST OF ABBREVIATIONS	xviii
CHAPTER 1 INTRODUCTION	1
1.0 Background of the Study	1
1.1 Problem Statement	6
1.2 Research Objectives	8
1.3 Research Questions	8
1.4 Significance of the Study	9
1.5 Operational Definition of Terms	10
1.6 Organization of Thesis	12
CHAPTER 2 LITERATURE REVIEW	15
2.0 Introduction	15
2.1 Building Operation	16
2.2 Cooling Load	18
2.3 HVAC Zone	22
2.4 Thermal Preferences	23
2.5 Occupant Behavior	25
2.6 Occupant Centric Control	26
2.6.1 Interactive Dimension	28
2.6.2 Individual Dimension	28
2.6.3 Temporal Dimension	29
2.6.4 Spatial Dimension	29
2.7 Feature Selection	29
2.8 Artificial Neural Network	33
2.9 Parameters	34
2.10 Weight Initialization	35
2.11 Activation Functions	36
2.11.1 Rectified Linear Unit	39
2.11.2 Leaky ReLU	40
2.11.3 Linear or Identify Function	41
2.12 Hyperparameters	41
2.12.1 Learning Rate	42
2.12.2 Epoch	42
2.12.3 Batch Size	43
2.12.4 Network Architecture	44
2.12.5 Optimization Algorithms	44
2.12.6 Regularization Techniques	45
2.13 Hyperparameter Tuning Methods	46
2.13.1 Grid Search	47

2.13.2	Random Search	48
2.14	Model Evaluation	49
2.14.1	Root Mean Square Error	49
2.14.2	Mean Absolute Error	50
2.14.3	R-Squared Score	51
2.14.4	Training Loss	52
2.14.5	Validation Loss	53
2.15	Related Works	53
2.15.1	Cooling Load in HVAC System	54
2.15.2	Occupants' Behavior Analysis in HVAC System	55
2.15.3	Cooling Load Prediction Model Based Occupancy	57
2.15.4	Research Trend of Cooling Load Prediction Model	68
2.16	Chapter Summary	69
CHAPTER 3 METHODOLOGY		72
3.0	Introduction	72
3.1	Case Study	72
3.2	Research Design	76
3.2.1	Research Model	77
3.2.2	Research Framework	79
3.3	Research Flow of First Research Objective	86
3.3.1	Data Collection and Pre-processing	87
3.3.2	Time Interval Measurement	87
3.3.3	Reliability Analysis	90
3.3.4	Validity Analysis	91
3.3.5	The Outcome of Appropriate Dataset	92
3.4	Research Flow of Second Research Objective	92
3.5	Data Collection Methods	93
3.5.1	Feature Engineering	93
3.5.2	Feature Normalization	98
3.5.3	Designing a Cooling Load Prediction Model Architecture	98
3.5.4	Proposed of Weight Scale Glorot Uniform Initialization	99
3.5.5	Proposed of Activation Function with Trainable Bias	101
3.5.6	Applying of Custom Weight and Activation Function	102
3.5.7	Hyperparameter Tuning Process	105
3.5.8	Feature Importance of Predictive Model	105
3.5.9	Model Evaluation and Validation	107
3.5.10	Model Improvement Analysis	108
3.5.11	Comparison with State-of-the-Art Methods	109
3.6	Experiment Setup	110
3.6.1	Scenario of Hyperparameter Tuning	112
3.6.2	Architecture of Baseline Model	113
3.6.3	Architecture of Advanced Model	114
3.6.4	Architecture of Developed Model	115
3.7	Dataset Features	116
3.7.1	Cooling Load Calculation	120
3.7.2	Group of Input Variables (Features)	121
3.8	Population and Sampling	122
3.9	Instrumentation	123
3.10	Experiment Tools	126

3.11	Data Collection Procedure	128
3.12	Research Ethics	130
3.12.1	Confidentiality and Anonymity	131
3.12.2	Ethical Considerations in Data Collection	131
3.12.3	Transparency and Honesty	131
3.12.4	Respect for Intellectual Property	132
3.12.5	Ethical Use of Technology	132
3.13	Chapter Summary	132
CHAPTER 4 RESULTS		134
4.0	Introduction	134
4.1	Dataset Description	134
4.1.1	Dataset of 5-Miute Interval	137
4.1.2	Dataset of 15-Minute Interval	139
4.1.3	Dataset of 30-Minute Interval	141
4.1.4	Dataset of 60-Minute Interval	142
4.2	Dataset Cleaning	143
4.2.1	Missing Values	143
4.2.2	Outlier Identification	145
4.3	Distribution of Variables	151
4.3.1	Number of Occupants	151
4.3.2	Activity of Occupant	153
4.3.3	Electronic Usage	155
4.3.4	Environmental Condition	156
4.3.5	Cooling Load	158
4.4	Time Interval Measurement	160
4.4.1	Polynomial Regression 2 nd Degree	160
4.4.2	Polynomial Regression 3 rd Degree	165
4.5	Dataset Reliability	169
4.5.1	Test-Retest Reliability	169
4.5.2	Cronbach Alpha	176
4.6	Dataset Validity	177
4.6.1	Dataset Mix-1	178
4.6.2	Dataset Mix-2	183
4.6.3	Dataset Mix-3	189
4.6.4	Exploratory Factor Analysis	195
4.7	The Output of Proper Original Dataset	197
4.8	Feature Engineering: Feature Transformation Techniques	198
4.8.1	Features of Engineering Dataset	198
4.8.2	Reliability	205
4.8.3	High Correlated Pairs and Variance Analysis	208
4.8.4	Validity	211
4.9	Feature Engineering Dataset Description	215
4.10	Comparison of Original and Feature Engineering Dataset	220
4.11	Feature Normalization	221
4.11.1	Original Dataset	221
4.11.2	Feature Engineering Dataset	223
4.12	Hyperparameter Selection	226
4.13	Features Importance of Predictive Models	228
4.14	Model Evaluation and Validation	230

4.14.1	Root Mean Square Error	230
4.14.2	R-Square Score	232
4.14.3	Mean Absolute Error	234
4.14.4	Training and Validation Loss	237
4.15	Model Improvement Analysis	239
4.15.1	Accuracy and Adaptability	239
4.15.2	Stability	242
4.15.3	Learning Curve	245
4.16	State-of the-Art Comparison	247
4.17	The Outcome of Cooling Load Prediction Model	249
4.17.1	Architecture of Cooling Load Prediction Model	249
4.17.2	Predictive Accuracy and Generalization	254
4.17.3	Impact of Feature Engineering	255
4.17.4	Impact of Weight Scale Factor	255
4.17.5	Impact of Activation Function with Trainable Bias	256
4.17.6	Practical Implications and Recommendations	256
4.18	Chapter Summary	257
CHAPTER 5 DISCUSSION AND CONCLUSION		259
5.0	Introduction	259
5.1	Limitations of Research	259
5.1.1	Clarity and Conciseness	261
5.1.2	Linking to the Literature	263
5.2	Implications of Research	266
5.3	Limitation of the Research	270
5.3.1	Scope and Limitation	270
5.3.2	Limitations of Time Interval Selection and Feature Analysis	272
5.3.3	Contribution to Methodology	273
5.4	Implications of the Research	274
5.5	Contribution of Research	277
5.5.1	Theoretical Contributions	277
5.5.2	Practical Contributions	278
5.5.3	Contribution to Methodology	279
5.6	Recommendation for Future Research	279
REFERENCES		283
APPENDICES		294
Appendix A		294
Appendix B		305

LIST OF TABLES

Table		Page
Table 1.1	Major Schemes of Relationships between PS, RO, and RQ	9
Table 2.1	Thermal Preferences of Occupant Activity	24
Table 2.2	Thermal Preferences of Electronic Usage	24
Table 2.3	Summary Table of Literature Review of Cooling Load Prediction Model	64
Table 3.1	Zone Specification at Universitas Trilogi Library	75
Table 3.2	Zone Occupant Profiling at Universitas Trilogi Library	76
Table 3.3	Alignment of Research Objectives Towards Research Outcome	81
Table 3.4	Comparison of Activation Function Outputs	104
Table 3.5	Model Experiment Scenario	111
Table 3.6	Scenario Overview of Models Architecture and Parameters	113
Table 3.7	Original Dataset Features	116
Table 3.8	Feature Engineering Variables	119
Table 3.9	Grouped Features	122
Table 3.10	Indicators of Occupant's Number	124
Table 3.11	Indicators of Occupant's Activity	125
Table 3.12	Indicators of Electronic Usage	125
Table 3.13	Indicators of Indoor Climate Condition	126
Table 3.14	Indicators of Outdoor Climate Condition	126
Table 3.15	Library Used in Python	127
Table 4.1	Dataset Description	137
Table 4.2	Outlier of Features	145
Table 4.3	Descriptive Statistics Before Outlier Capping	147

Table 4.4	Descriptive Statistics After Outlier Capping	148
Table 4.5	Polynomial Regression 2nd Degree of All Dataset	160
Table 4.6	Time Interval Based Polynomial Regression 2nd Degree of Zone 1	162
Table 4.7	Time Interval Based Polynomial Regression 2nd Degree of Zone 2	163
Table 4.8	Time Interval Based Polynomial Regression 2nd Degree of Zone 3	163
Table 4.9	Scenario of Time Interval Based Polynomial Regression 2nd Degree	164
Table 4.10	Polynomial Regression 3rd Degree of All Datasets	165
Table 4.11	Time Interval Based Polynomial Regression 3rd Degree of Zone 1	167
Table 4.12	Time Interval Based Polynomial Regression 3rd Degree of Zone 2	167
Table 4.13	Time Interval Based Polynomial Regression 3rd Degree of Zone 3	168
Table 4.14	Scenario of Time Interval Based Polynomial Regression 3rd Degree	169
Table 4.15	Test-Retest Reliability of Variables of Dataset Mix-1	171
Table 4.16	Test-Retest Reliability of Variables of Dataset Mix-2	173
Table 4.17	Test-Retest Reliability of Variables of Dataset Mix-3	175
Table 4.18	Cronbach Alpha Results of Groups of Variables	176
Table 4.19	Low-Variance Variables (Variance < 0.1) of Dataset Mix-1	178
Table 4.20	High-Variance Variables (Variance \geq 0.1) of Dataset Mix-1	179

Table 4.21	Output of Factor Loading Map of Dataset Mix-1	183
Table 4.22	Low-Variance Variables (Variance < 0.1) of Dataset Mix-2	184
Table 4.23	High-Variance Variables (Variance \geq 0.1) of Dataset Mix-2	185
Table 4.24	Output of Factor Loading Map of Dataset Mix-2	189
Table 4.25	Low-Variance Variables (Variance < 0.1) of Dataset Mix-3	190
Table 4.26	High-Variance Variables (Variance \geq 0.1) of Dataset Mix-3	190
Table 4.27	Output of Factor Loading Map of Dataset Mix-3	195
Table 4.28	Kaiser-Meyer-Olkin (KMO) Results Across Datasets	196
Table 4.29	Test-Retest Reliability of Variables of Feature Engineering Dataset	205
Table 4.30	Cronbach Alpha Results of Feature Engineering Dataset	207
Table 4.31	Low-Variance Variables (Variance < 0.1) of FE Dataset	209
Table 4.32	High-Variance Variables (Variance \geq 0.1) of FE Dataset	210
Table 4.33	Output of Factor Loading Map of FE Dataset	214
Table 4.34	Statistics Descriptive of Feature Engineering Dataset	218
Table 4.35	Result of Hyperparameter-Tuned of Models	227
Table 4.36	Result of RMSE Training Across Model and Cross Validation	231
Table 4.37	Result of RMSE Testing Across Model and Cross Validation	231
Table 4.38	Result of R2 Training Across Model and Cross Validation	233
Table 4.39	Result of R2 Testing Across Model and Cross Validation	233
Table 4.40	Result of MAE Training Across Model and Cross Validation	235
Table 4.41	Result of MAE Testing Across Model and Cross Validation	235
Table 4.42	Result of Training Loss Across Model and Cross Validation	237
Table 4.43	Result of Validation Loss Across Model and Cross Validation	237
Table 4.44	Improvement of RMSE Testing	240

Table 4.45	Improvement of MAE Testing	241
Table 4.46	Improvement of R2 Testing	242
Table 4.47	Stability of Model Performance	243
Table 4.49	Comparison with State-of-the-Art	247

LIST OF FIGURES

Figure		Page
Figure 2.1	HVAC Zone Plan	23
Figure 2.2	Occupant-Centric Control (OCC)	27
Figure 2.3	Feature Selection Strategies	31
Figure 2.4	Filter-Based Feature Selection Method	32
Figure 2.5	Architecture of Multi-Layer Perceptron	33
Figure 2.6	Activation Function	37
Figure 2.7	Activation Function for the Hidden Layers	38
Figure 2.8	Activation Function for the Output Layers	39
Figure 2.9	Example of Grid Search	48
Figure 2.10	Example of Random Search	49
Figure 2.11	Research Trend of Cooling Load Prediction Model	69
Figure 3.1	Layout of Universitas Trilogi Library	73
Figure 3.2	Layout of Student Corner Room	74
Figure 3.3	Research Model	78
Figure 3.4	Research Flow for First Research Objective (RO1)	86
Figure 3.5	Time Intervals of Cooling Load Prediction Model	89
Figure 3.6	Research Flow for Second Research Objective (RO2)	93
Figure 3.7	Architectural Diagram of Baseline Model with Original Dataset	114
Figure 3.8	Architectural Diagram of Advanced Model	115
Figure 3.9	Procedure of Data Collection	129
Figure 3.10	Internet of Things Diagram	130
Figure 4.1	CCTV Camera of Three Zones	136
Figure 4.2	Head of Dataset of 5-Minute Interval	138

Figure 4.3	Head of Dataset of 15-Minute Interval	139
Figure 4.4	Head of Dataset of 30-Minute Interval	141
Figure 4.5	Head of Dataset of 60-Minute Interval	142
Figure 4.6	Percentage of Missing Values	144
Figure 4.7	Comparison Before and After Outlier Capping	150
Figure 4.8	Number of Occupants for Each Day Across Zones	152
Figure 4.9	Number of Occupants for Each Day Across Zones	153
Figure 4.10	Electronic Usage for Each Day Across Zones	155
Figure 4.11	Environment Conditions for Each Day Across Zones	157
Figure 4.12	Cooling Load for Each Day Across Zones	158
Figure 4.13	Selected Features After Normalization of Dataset Mix-1	180
Figure 4.14	The Scree Plot of Dataset Mix-1	181
Figure 4.15	Factor Loadings Heatmap of Dataset Mix-1	182
Figure 4.16	Selected Features After Normalization of Dataset Mix-2	186
Figure 4.17	The Scree Plot of Dataset Mix-2	187
Figure 4.18	Factor Loadings Heatmap of Dataset Mix-2	187
Figure 4.19	Selected Features After Normalization of Dataset Mix-3	192
Figure 4.20	The Scree Plot of Dataset Mix-3	193
Figure 4.21	Factor Loadings Heatmap of Dataset Mix-3	194
Figure 4.22	Comparisons of KMO Measure Results of Datasets	197
Figure 4.23	Lagged Features and Rolling Statistics	201
Figure 4.24	Rolling Mean and Rolling Standard Deviation of Cooling Load	203
Figure 4.25	Interaction of Zone, Time Interval, and Day to Cooling Load	204
Figure 4.26	Elbow of Factor Loading Feature Engineering Dataset	212
Figure 4.27	Factor Loading Heatmap Feature Engineering Dataset	212

Figure 4.28	Head of Feature Engineering Dataset	215
Figure 4.29	KMO Comparison of Datasets	220
Figure 4.30	Original Dataset Features Before Normalization	222
Figure 4.31	Original Dataset Features After Normalization	223
Figure 4.32	Feature Engineering Dataset Features Before Normalization	224
Figure 4.33	Feature Engineering Dataset Features After Normalization	226
Figure 4.34	SHAP Values of Models	229
Figure 4.35	Learning Curve of Models	245
Figure 4.36	Architecture of Developed Model	251
Figure 4.37	Architecture of Cooling Load Prediction Model in Under-Actuated Zone	252

LIST OF ABBREVIATIONS

AHU	Air Handling Unit
ANN	Artificial Neural Network
API	Application Programming Interface
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BOS	Bayesian Optimization Search
BP	Back Propagation
CL	Cooling Load
CLF	Cooling Load Factors
CLTD	Cooling Load Temperature Differential
CNN	Convolutional Neural Network
CSV	Comma-Separated Values
ELUs	Exponential Linear Units
ETRs	Randomized Tree Regressors
GA	Genetic Algorithm
GD	Gradient Descent
GS	Grid Search
HVAC	Heating, Ventilation, and Air Conditioning
IEA	International Energy Agency
HAP	Hourly Analysis Program
IoT	Internet of Things
JSON	Javascript Object Notation

MAE	Mean Absolute Error
MLP	Multilayer Perceptron
MSE	Mean Square Error
OCC	Occupant Centric Control
ReLU	Rectified Linear Unit
RS	Random Search
SCL	Solar Cooling Load Factor
SGD	Stochastic gradient descent
SNI	Standard Nasional Indonesia
SVM	Support Vector Machine
SVR	Support Vector Regression
Tanh	Hyperbolic Tangent
TFM	Transfer Function Method
VAV	Variable Air Volume
Vents	Ventilations

CHAPTER 1

INTRODUCTION

1.0 Background of the Study

In contemporary building design, optimizing both energy efficiency and occupant comfort is intricately managed through Heating, Ventilation, and Air Conditioning (HVAC) systems. These systems, which are integral to sustaining indoor environmental quality, account for a substantial portion of a building's energy consumption. Within this context, HVAC zones are systematically classified into two principal types: fully-actuated zones and under-actuated zones (Brooks et al., 2015; Taheri et al., 2022). Fully-actuated zones are characterized by calculated cooling loads based on stable occupancy rates and controlled environmental parameters, making them ideal for spaces with predictable occupant presence and activity patterns, such as classrooms, offices, and auditoriums. In contrast, under-actuated zones refer to areas that lack dedicated cooling control and rely on shared HVAC systems, typically centralized air conditioning systems serving multiple ventilation zones within a building. This concept is commonly applied in large spaces with several ceiling ventilation outlets connected to centralized air conditioning systems, such as lobbies, libraries, restaurants, and corridors (Kong et al., 2022).

In Indonesia, many public buildings including libraries, university campuses, and government service halls utilize centralized HVAC systems with shared ventilation networks. These under-actuated zones are prevalent in tropical climates like Indonesia, where high humidity and fluctuating occupancy patterns make real-time cooling load regulation a persistent challenge. The complexity of under-actuated zones presented unique challenges for maintaining optimal cooling loads, as traditional

ventilation methods struggled to meet their dynamic demands. Effectively managing these zones requires sophisticated control strategies capable of adapting to constantly shifting conditions.

Among HVAC considerations, the cooling load a measure of required heat removal holds potential for substantial energy savings but is intricately influenced by factors including weather, design, and occupant behavior. In conventional HVAC systems with under-actuated zones, the control scheme for a zone is typically computed based on the average values of the cooling load measurements from the rooms, which can result in poor indoor climate control (Brooks et al., 2015; Taheri et al., 2022), especially in Indonesia where zone-level conditions can vary significantly due to uneven crowd densities or spatial layouts. This approach becomes problematic when climate conditions vary between areas within an under-actuated zone due to the fluctuating cooling load at different times and locations, largely influenced by occupant presence and activities. Additionally, the occupancy-driven cooling load in such zones introduces temporal variability, making it difficult to apply uniform cooling strategies across different time intervals and spatial areas (Wang et al., 2018; Ding et al., 2022). This variability affects thermal comfort and may have adverse effects on occupant health.

To ensure acceptable thermal conditions, Standard No. 55 developed by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) establishes guidelines for evaluating thermal environmental conditions for human occupancy. It specifies acceptable ranges of temperature, humidity, air velocity, and mean radiant temperature, while also considering clothing insulation and metabolic rate. This standard is widely recognized globally and serves as a key benchmark in HVAC system design, including in tropical and humid regions like

Indonesia. However, maintaining ASHRAE-compliant comfort in under-actuated zones remains a significant challenge due to fluctuating occupancy and uncontrolled airflow distribution. To address these challenges, Li & Yao (2020) emphasized the importance of assessing occupant presence and behavior at specific time intervals in under-actuated zones to optimize cooling load predictions.

Time intervals play a crucial role in under-actuated zones due to the cyclical nature of occupant behavior, which directly affects cooling load requirements over different periods, such as months, weeks, days, and specific times of day (Kim & Cho, 2022). Frequent changes in occupancy necessitate evaluating cooling load variations at specific intervals to effectively meet fluctuating demands. Accurate assessment of these variations enables HVAC systems to adapt to real-time cooling needs, ensuring optimal thermal comfort for occupants. Conditioned air is delivered from the Air Handling Unit (AHU) to each zone, with cooling load adjustments managed through Variable Air Volume (VAV) devices (Wei et al., 2022). However, current HVAC control systems heavily rely on temperature and humidity sensors with pre-configured setpoints, lacking real-time adjustments based on occupant behavior. This static control approach limits the system's ability to respond effectively to frequent fluctuations in occupancy and environmental conditions within under-actuated zones, leading to energy inefficiencies and inconsistent airflow volume regulation. Therefore, effective cooling load management must incorporate precise time interval analysis to dynamically adjust cooling strategies according to cyclical occupancy patterns.

To determine cooling load, engineers utilize specialized simulation software and design tools. These simulations are effective in replicating real-world conditions and assessing building design indicators (Moradzadeh et al., 2022). However, simulation-based methods are time-consuming and require expertise to operate. In response to

these limitations, machine learning models have emerged as a promising alternative for predicting cooling loads based on occupancy data. For instance, Kim et al. (2020) demonstrated that predictive models outperformed simulation tools in determining cooling load at a given time. Implementing cooling load-based control strategies enhances HVAC system efficiency and stability (Moradzadeh et al., 2022). Consequently, modern machine learning techniques have been increasingly adopted in cooling load prediction models (Gao et al., 2021).

Recent advancements in cooling load prediction have leveraged Multilayer Perceptron Artificial Neural Networks (MLP-ANNs) due to their ability to capture complex, nonlinear relationships in data (Moradzadeh et al., 2022). MLP-ANNs are particularly well-suited for scenarios involving limited datasets, as they can generalize patterns effectively without requiring large-scale data for training. Unlike deeper or more data-hungry architectures, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), MLP-ANNs can achieve high predictive accuracy with relatively fewer parameters, making them efficient and scalable for cooling load modeling in resource-constrained settings. This is especially relevant for applications in under-actuated zones, where collecting large volumes of labeled data is often impractical.

However, the effectiveness of MLP-ANN models is significantly influenced by activation functions, which determine the network's adaptability to dynamic environmental conditions and cyclical occupancy patterns across varying zones (Kulathunga et al., 2021). Furthermore, appropriate weight initialization plays a critical role in enhancing model convergence and stability, thereby improving predictive accuracy (Yang et al., 2023). Without proper initialization, models may suffer from vanishing or exploding gradients, which hinder the learning process and