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Predictive AC Control Using Deep Learning: Improving Comfort and Energy Saving

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***Abstract*— The growing global population and the availability of energy-hungry smart devices are critical factors in today's alarmingly high electricity usage. The majority of energy used in urban areas is consumed by buildings, with heating, ventilation, and air conditioning (AC) systems accounting for a significant amount of energy use. This project proposes an AC controlling algorithm that uses the Internet of Things sensors and a deep learning framework in temperature prediction to control a single AC unit. The algorithm consists of a Long Short-Term Memory (LSTM) model to predict the indoor temperature for the next *J* minutes. The highlight of this model is its capacity to predict the future temperature based on the predetermined AC status, whether it is switched on or off. The AC unit will be turned off if the *J*-minute predicted temperature is within the desired thermal comfort range, and it will be turned back on if the sensor readings exceed the upper pre-set threshold. The experiment is performed on the dataset collected by Chulalongkorn University Building Energy Management System (CU-BEMS). The LSTM prediction model developed using CU-BEMS data yields an average Root Mean Squared Error and Mean Absolute Error of 0.08 and 0.03, respectively. A half-day simulation is also performed in controlling the AC unit from 7:39 a.m. to 11:35 a.m. The proposed algorithm shows that 49.00% of the time, the AC unit can be turned off while the thermal range is maintained between 27ºC to 27.9ºC, providing a strategy for managing the AC unit and achieving energy savings.**

***Keywords*—Energy management; air-conditioner; deep learning; temperature prediction; thermal comfort.**

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I. INTRODUCTION

Energy optimization is an urgent requirement for modern society due to a limited quantity of energy supplies, increasing population growth, and increased energy use. Energy is a limited resource in nature that must be shared, has a significant cost, and is limited in supply. Therefore, it is necessary to create and install modern technologies in the home that can produce and use energy intelligently and efficiently, striking a balance between consumption and simplified comfort [1].

According to research, 90% of the energy used in Malaysia is in the form of electricity. The residential sector accounted for 44% of electricity usage in 2002, which continues to rise yearly. In 2020, the demand for electricity was anticipated to reach a peak of 23,099MW, with an increase in supply of 4 percentage points annually [2]. The Malaysia Energy Commission recently released data showing that, as of the end of December 2022, energy consumption had peaked at 19,183MW in May 2022 [3]. This shows that there is a yearly significant increase in electricity consumption, aligned with the rapid infrastructure development in Malaysia. Essentially, buildings consume more than 40% of energy in urban areas, with heating, ventilation, and air conditioning (HVAC) systems accounting for a considerable amount of energy consumption in many commercial buildings [4].

About 40–50% of the world's energy usage [5] and 30% of all CO2 emissions can be attributed to buildings [6]. Building energy consumption will inevitably rise as building density and urban population increase. The main approach of controlling interior thermal comfort is made possible by HVAC systems, and proper control of these systems impacts how comfortable a space feels to its occupants. The HVAC system is responsible for much of the building's energy consumption. Building energy-comfort-related control systems is thus required for smart building energy management [7].

An efficient HVAC system has a great ability to reduce energy consumption significantly. This is because an air-conditioner (AC) system is one of the appliances with high power consumption. In addition, the thermal storage capacity of buildings allows the change to the AC system's temperature setpoints without significantly inconveniencing building occupants. Finally, the advancement of building energy management systems has also made it possible to routinely regulate the AC systems remotely (i.e., turn ON/OFF, change temperature setpoints) [8] Therefore, it is crucial to develop an optimized energy AC control system to minimize energy usage which will lead to cost savings.

The existing HVAC system optimization solutions can be divided into two categories: building more energy-efficient hardware for the HVAC system [9] or developing various strategies to efficiently control the energy consumption of the existing HVAC system, with the latter receiving the majority of research attention. The optimal control of the HVAC system can be achieved by local control or supervisory control [10]. Examples of local control include applying rule-based control schemes or scheduling techniques by manipulating the 'ON' and 'OFF' states of the system or adjusting the setpoint temperature depending on the building needs [10], [11] The supervisory control, on the other hand, is to determine the optimal solutions that minimize the system's energy consumption of the system while ensuring the thermal comfort of the occupants [8].

As a result of recent advancements in the Internet of Things (IoT) and Artificial Intelligence, studies are now concentrating on using data-driven computational intelligence models to investigate the dynamic between the HVAC system and the environment. Esrafilian-Najafabadi et al. [12] proposed a rule-based (RB) HVAC control system using a multi-layer perceptron (MLP) network, a deep learning algorithm, for estimating dynamic preconditioning time in residential buildings. The control system uses current indoor temperature and weather data as inputs for the preconditioning-time machine learning model. It uses its results for the occupancy model to decide whether to set a temperature point to a comfortable level when there are occupants in the building or to set the temperature to decrease AC usage when there are no occupants. Godahewa et al. [13] proposed a global deep learning framework based on RNNs that can forecast the future indoor temperatures of a building using the current inside and outside temperatures, with the main goal of determining the optimal thermal setpoints and optimal time point to switch on the AC during the unoccupied period. The energy savings can be achieved by keeping the AC switched off for as long as possible.

Thermal comfort is the level of satisfaction with the environment experienced by the occupants [14]. Several models have been created recently to assess thermal comfort objectively. Shaw [15] presented the heat balance-based Predicted Mean Vote-Predicted Percentage Dissatisfied (PMV-PPD) model. The model aims to measure how hot or chilly the inhabitants feel regarding the environment. A variety of thermal comfort models built on machine learning algorithms were created with the quick development of machine learning. Zhou et al. [16] created a thermal comfort model with the capacity for self-learning and self-correction using the support vector machine (SVM) method. Liu et al. [17] suggested a model based on a back propagation (BP) neural network for predicting individual thermal comfort.

Baldi et al. [18] suggested a switching self-tuning approach to save energy while enhancing thermal comfort. Korkas et al. [19] proposed an EMS technique to alter the energy demand while considering occupancy data. They also suggested a distributed demand management system is flexible to various deviations (weather or occupancy) [20]. The study mentioned above was done to develop an adaptive optimization control approach. According to Wu et al. [21], residential HVAC systems use a hierarchical control method to offer primary frequency management. Watari et al. [22] utilized the MPC-based approach for energy management and thermal comfort. Zeng and Barooah [23] presented an adaptive MPC technique to reduce energy consumption for HVAC systems.

The abovementioned methods can all be categorized as model-based methods, given that a model of the HVAC's thermal dynamic environment is required. However, it is challenging to accurately estimate the thermal environment because of the many elements that influence it. Since model-free Reinforcement Learning (RL) has advanced significantly recently, several academics have used RL to address HVAC control issues. In Qiu et al. [24], building HVAC systems were optimized using Q-learning and a model-based controller to conserve energy. Brandi et al. [25], used deep reinforcement learning (DRL) to address the issue of the supply water temperature setpoint in a heating system, and a well-trained agent can reduce energy consumption by 5 % to 12%. Cost savings are the result of achieving energy savings through HVAC control optimization. Jiang et al. [26] suggest that DQN saves around 6% of total costs; without demand charges, it saves about 8%. Wei et al. [27] used a DRL-based algorithm to reduce overall energy costs while maintaining the target room temperature and adhering to deadlines for the workload in the data center. In order to maintain thermal comfort while conserving energy, Zenger et al. [28] implemented the RL algorithm. The DQN algorithm was used by the authors of Kurte et al. [29] to reduce energy use and maintain comfort (temperature). To optimize HVAC systems, Fu et al. [30] presented a distributed multi-agent DQN. It is crucial to have a viable control system to manipulate the HVAC system for cost and energy savings.

With this as a motivation, this project aims to create a viable system to predict indoor temperatures and control an AC unit by applying machine learning algorithms such as Long Short-Term Memory (LSTM) using a dataset that was collected by Chulalongkorn University Building Energy Management System (CU-BEMS) [31] The project will develop a LSTM predictive model that can predict future indoor temperatures subject to various AC statuses, whether it is turned on or off. The uniqueness of this prediction model compared to others in the literature is that future AC on-off settings are incorporated as inputs to the model, thus allowing a decision to be made between turning off the AC to achieve energy savings or keeping it running to maintain the required level of thermal comfort. The model will be trained and tested to ensure that it can predict indoor temperatures accurately. On top of that, a rule-based control system will be developed to control an AC unit to minimize energy usage while also maintaining a comfortable thermal level.

II. Materials and Methods

The proposed system design consists of two stages: the temperature prediction stage and the rule-based decision stage. The installed IoT sensors measure the indoor temperature in real-time. The measurements are then sent to the temperature prediction model to predict the temperature values for the block of subsequent *J* minutes when the AC is switched off. These predicted values are then utilized in the stage 2 rule-based decision model to determine whether to switch off the AC or not. A more thorough explanation of these two stages is provided below.

A. Temperature Prediction Model

Consider the indoor temperature collected as $\boldsymbol{T} = \{\boldsymbol{T_1}, \boldsymbol{T_2}, \dots, \boldsymbol{T_J}\}$, with $\boldsymbol{T_t}$ is the temperature measurement at time $\boldsymbol{t = 1, 2, \dots, J}$. The temperature prediction model intends to use the real-time temperature $\mathbf{T}$ to predict the temperature for $\boldsymbol{t = J + 1, J + 2, \dots, 2J}$. To accomplish this aim, the one-minute prediction model is first developed.

1) One-minute Prediction Model: The one-minute prediction model uses $\mathbf{T}$ to predict the temperature for the following minute at $\boldsymbol{t = J + 1}$. In order to be more precise, the model should be capable of predicting the temperature based on the AC status, whether it is on or off. As a result, in addition to the sensor readings on temperature, the prediction model must be informed by the time series of the AC on or off status. Thus, the input $\mathbf{T}$ is associated with the time series of AC status, which is defined as $\boldsymbol{S} = \{S_2, S_3, \dots, S_{J+1}\}$, with $S_i \in \{0 = \text{"on"}, 1 = \text{"off"}\}$.

For example, the temperature at time 1, T_1 is associated with the AC status at time 2, S_2; the temperature at time 2, T_2 is associated with the air conditioning status at time 3, S_3 and so on, until the last input is the temperature at time *J*, T_J, which is associated with the AC status at time $J + 1$, S_{J+1}. With this setting, the model can predict both the temperatures at time $J + 1$ based on the air conditioning status, S_{J+1}, whether it is switched off or on.

The neural network architecture applied here is LSTM, a classical neural network with memory cells that can store information about prior data [9]. The architecture of the model that was implemented in this suggested system is shown in Fig. 1. The three layers that make up the constructed neural network are the input layer, hidden layer, and output layer. The input layer, or "lstm_1_input," shows where a three-dimensional input is fed into the model. The three-dimensional inputs are made up of batch size, timesteps, and features. After the input layer, one LSTM layer with 64 hidden nodes is implemented and is named as "lstm_1". It is crucial to note that the output of the 'lstm_1' is a 2-dimensional layer. If the setting for the timestep is set to $\boldsymbol{J = 15}$. This implies that 15 data samples, or 15 minutes' worth of data, will be compiled as a list before being sent into the LSTM layer. Two dense or fully linked layers are added after the LSTM layer, with the first layer implementing the Rectified Linear Unit (ReLU), an activation function with eight hidden nodes, and the last layer employs the Linear activation layer, which has one hidden node.

2) J-minute Prediction Model: A J-minute prediction model is constructed to increase the usability of the model further so that the rule-based model in stage 2 could make a wise decision. This model aims to use *J*-minute sensor readings on temperature to predict the next *J*-minute of temperature with the planned setting on the AC status. The one-minute prediction model predicts one future temperature at $t = J$. This predicted value is then input into the model, which predicts the temperature at $t = J + 1$. The predicted values are fed back into the model iteratively until the entire *J*-minute temperature prediction is successful.

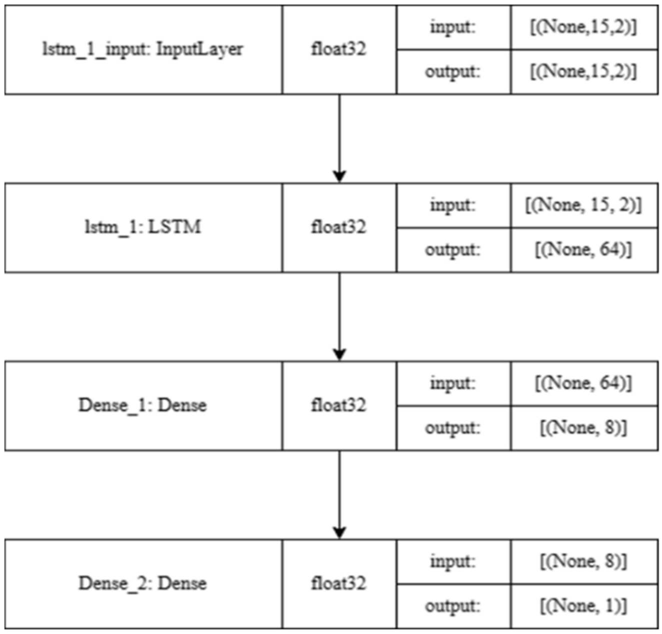


Fig. 1 Machine Learning Model Architecture

Fig. 2 visualizes the model's prediction flow when $\boldsymbol{J = 15}$. After predicting the one-minute indoor temperature at time $\boldsymbol{t = 16}$, the predicted indoor temperature will then be the last point in the input sequence to predict the temperature at $\boldsymbol{t = 17}$. The procedure is repeated by recycling the predicted temperature as the input to the one-minute prediction model until the temperatures at $\boldsymbol{t = 16, 17, \dots, 30}$ are obtained.

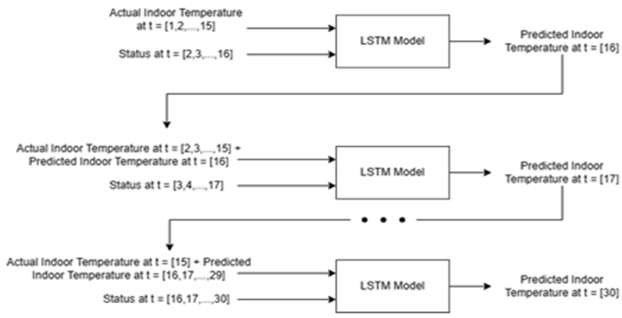


Fig. 2 Flow diagram for 15-minute prediction model

B. Rule-based Decision Model

The *J*-minute prediction model allows the temperature for the next *J* minutes to be projected ahead of time at $t = J$. Most notably, the model can predict the future *J*-minute temperature depending on various preference settings on the AC status within this time period. These predictive temperatures become important indications for decision-making in the stage 2 rule-based model. Once the *J*-minute sensor readings are available, the data will be used to predict the next *J*-minute temperature, and a decision to switch on or off the AC will be made. Fig. 3 depicts the detailed flow of the rule-based model.

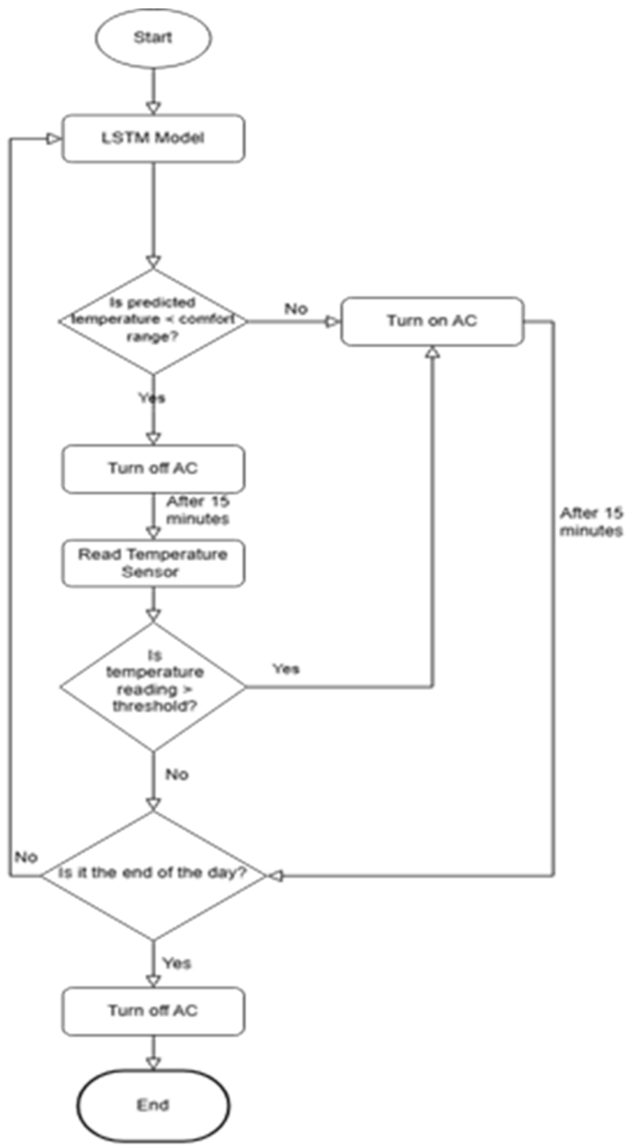


Fig. 3 Flow Diagram for the proposed system

Assume that $J = 15$. When the AC is turned on for the first time at the beginning of the day, the IoT temperature sensor will read the first 15 minutes of indoor temperatures. These 15-minute data are fed into the prediction model, which predicts the next 15 minutes of indoor temperatures with the AC status set to 0, indicating that the AC unit is presumed to be switched off for the next 15 minutes. The AC will be switched off if the predicted temperatures satisfy a predetermined thermal comfort range. Otherwise, the AC will continue to run for another 15 minutes before repeating the prediction and decision-making process. If the AC is turned off, the sensor will keep track of the indoor temperature and will promptly turn on the AC if the real-time temperature hits the threshold.

III. Results and Discussion

To assess the effectiveness of the suggested system, a simulation is performed on the dataset collected by the CU-BEMS. The data collected are from an office building on the university campus called the Chamchuri 5 building. This seven-story building has sensors such as Energy Monitoring Units (EMU), digital meters, multi-sensors, and gateways. The data is collected at a one-minute interval (1,440 data points/day) for 184 days during the second half year of 2018. However, for the purpose of this research project, the dataset of Floor 6 in Zone 1 in 2018 is used as it provides the most complete range of data sequentially.

Data preprocessing is required here as the electricity consumption of the AC must be converted to a new column of data called status, **S**. The status column, **S** provides when the AC is turned on or off during the day. As a result, whenever the electricity consumption of the AC on Floor 6 rises more than 0, a value of 1 is added to the corresponding status **S** to indicate that the AC is turned on, whilst a value of 0 shows that the AC is turned off.

A. Performance of the Prediction Model

1) Performance of the One-Minute Prediction Model: The one-minute prediction model uses 70% of the data for training, 20% for testing, and 10% for validation. Fig 4. shows the learning curve of the model.

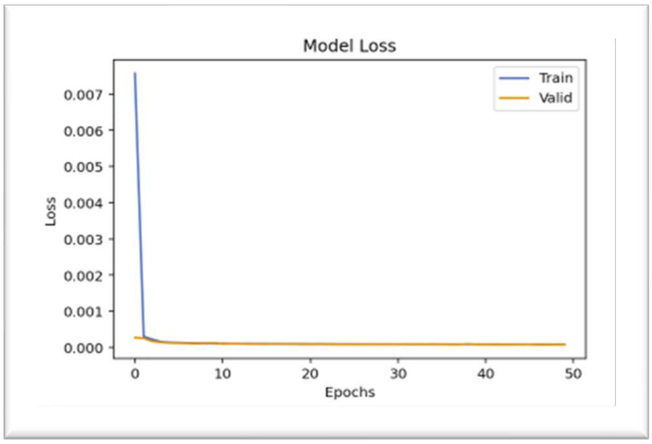


Fig. 4 One-minute training and validation loss curve

It is noted that the training loss initially has a bigger loss than the validation loss, which then steadily declines during the epochs to help interpret the learning curve for model less. The training loss curve begins to flatten as the epoch values approach 4, and this input persists through the conclusion of training, indicating that the training loss will not go down if more training data is added. The validation loss curve starts off at a relatively low value and meets the training loss curve at the same value. This is most likely due to the nature of the dataset given. The simplicity of the dataset makes the model learn faster as time goes on, leading to the validation loss flats out much more easily than the training loss curve. The model achieved a Root Mean Squared Error (RMS) of 0.08 and a Mean Absolute Error (MAE) of 0.03 during validation. The model is considered to have performed successfully for this research.

2) Performance of the 15-minute Prediction Model: To evaluate the prediction, the average RMSE of the following four case studies will be inspected. Table I shows a simplified view of the case studies mentioned below.

- Case Study 1: Using 15 minutes of indoor temperature when the AC status is off, predict the next 15 minutes of indoor temperature when the AC status is off.

- Case Study 2: Using 15 minutes of indoor temperature when the AC status is off, predict the next 15 minutes of indoor temperature when the AC status is on.
- Case Study 3: Using 15 minutes of indoor temperature when the AC status is on, predict the next 15 minutes of indoor temperature when the AC status is on.
- Case Study 4: Using 15 minutes of indoor temperature when the AC status is on, predict the next 15 minutes of indoor temperature when the AC status is off.

To evaluate the performance of the 15-minute prediction model, 30% of the validation dataset, which contains 30321 rows of data, is split into the four case studies mentioned above. Table II shows a total of 770, 30, 199, and 31 sets of time series data sets that match the criterion specified for Case Studies 1, 2, 3, and 4, respectively.

TABLE I
CASE STUDIES FOR THE PREDICTIVE MODEL

Case Study	AC Status for past 15 minutes	AC Status for next 15 minutes
1	OFF	OFF
2	OFF	ON
3	ON	ON
4	ON	OFF

Table II also provides the average RMSE achieved for each case study, which are 0.1600, 0.1591, 0.1621, and 0.1627, respectively. The low RMSE indicates that the predicted values closely reflect the actual values; this is supported by Table III, which compares the predicted and actual temperatures for one block of data set in each case study.

TABLE II
AVERAGE RSME FOR EACH CASE STUDY

Case Study	Total Tests Used	Average RMSE
1	770	0.1600
2	30	0.1591
3	199	0.1621
4	31	0.1627

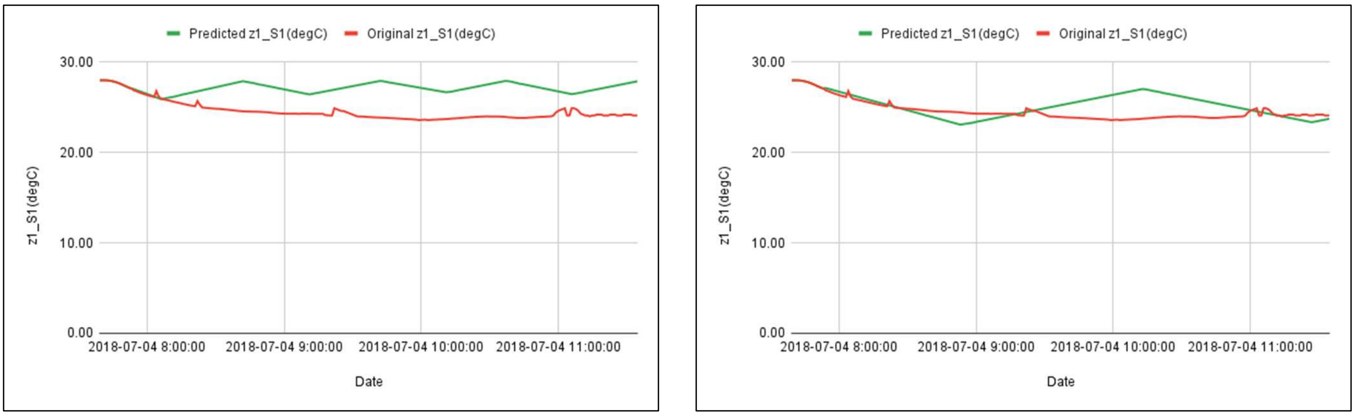
B. Half-day Simulation

A half-day simulation is used to assess the system's performance. The data used is the morning session on the date 4th July 2018. The system was applied when the AC was first switched on at the start of the day. The period for this application was between 7:39 a.m., when the AC was first switched on, to 11:35 a.m., when the AC was switched off due to lunch break. The following two rules for this simulation are considered in the stage 2 rule-based model.

- Rule 1: The thermal comfort threshold is set between 27ºC to 27.9ºC.
- Rule 2: The thermal comfort threshold is set between 24ºC to 27ºC. This proposal accommodates a larger range of thermal comfort.

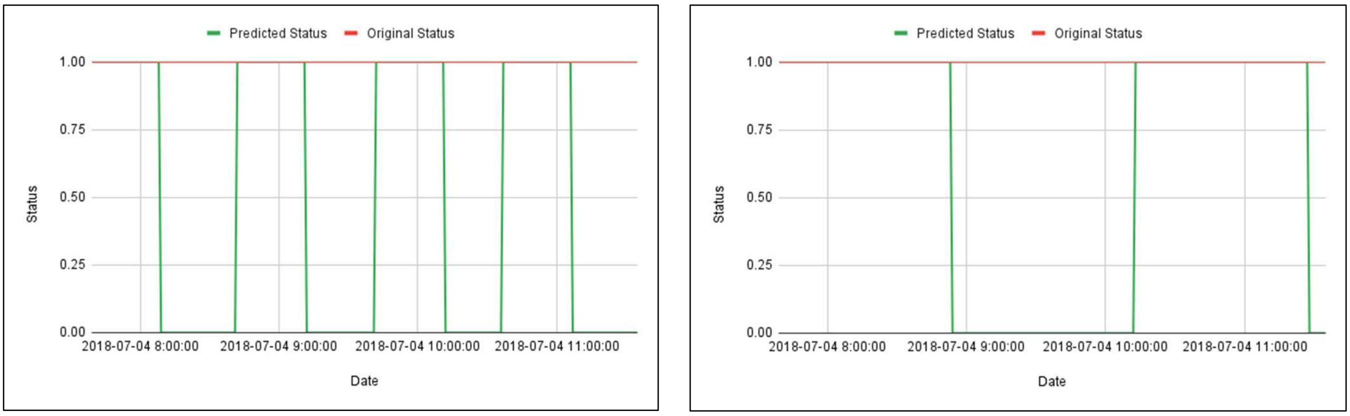
TABLE III
AN EXAMPLE OF ONE DATA SET: A COMPARISON OF ACTUAL AND PREDICTED DATA
CASE STUDY 1 (b) CASE STUDY 2 (c) CASE STUDY 3 (d) CASE STUDY 4

	Minute	Actual Temperature	Predicted Temperature	Status		Minute	Actual Temperature	Predicted Temperature	Status
(a)	1	27.66	27.66923332	0	(b)	1	26.80	26.12154198	1
	2	27.67	27.66899872	0		2	26.20	26.47855568	1
	3	27.67	27.67881203	0		3	25.96	26.15678215	1
	4	27.68	27.67875099	0		4	25.90	26.93669128	1
	5	27.68	27.68855476	0		5	25.84	25.82159805	1
	6	27.69	27.68852997	0		6	25.79	25.82159805	1
	7	27.00	27.69841576	0		7	25.74	25.77142906	1
	8	27.71	27.70853996	0		8	25.69	25.72114944	1
	9	27.72	27.71867371	0		9	25.64	25.67146873	1
	10	27.73	27.28845600	0		10	25.59	25.62241364	1
	11	27.73	27.73900986	0		11	25.54	25.57387924	1
	12	27.74	27.73905373	0		12	25.50	25.52569771	1
	13	27.75	27.74897766	0		13	25.45	25.48807907	1
	14	27.75	27.75908279	0		14	25.41	25.4399147	1
	15	27.76	27.75902367	0		15	25.37	25.40223312	1
	Minute	**Actual Temperature**	**Predicted Temperature**	**Status**		**Minute**	**Actual Temperature**	**Predicted Temperature**	**Status**
©	1	27.84	27.83755875	1	(d)	1	24.38	24.41259193	0
	2	27.84	27.87552643	1		2	24.40	24.45662117	0
	3	27.83	27.83707428	1		3	24.43	24.48226738	0
	4	27.82	27.83318367	1		4	24.46	24.51368523	0
	5	27.79	27.81324577	1		5	24.50	24.55085182	0
	6	27.77	27.77457237	1		6	24.56	24.60104561	0
	7	27.73	27.73576546	1		7	24.62	24.67090416	0
	8	27.69	27.68123817	1		8	24.70	24.74183655	0
	9	27.63	27.62484932	1		9	24.79	24.8273863	0
	10	27.57	27.55656052	1		10	24.89	24.92112732	0
	11	27.49	27.48905563	1		11	24.99	25.02149963	0
	12	27.42	27.41132545	1		12	25.80	25.12037468	0
	13	27.34	27.34070015	1		13	25.18	25.54359055	0
	14	27.26	27.26573944	1		14	25.28	25.38897896	0
	15	27.17	27.19246674	1		15	25.37	25.41068268	0



(a) (b)

Fig. 5 Indoor Temperature for simulation of a half-day operation: (a) Scenario based on Rule 1 (b) Scenario based on Rule 2



(a) (b)

Fig. 6 AC status for simulation of a half-day operation: (a) Scenario based on Rule 1 (b) Scenario based on Rule 2

The above settings indicate that the AC will be switched off whenever the predicted temperature falls below the lower threshold. When this happens, the model will use an IoT temperature sensor to measure the current indoor temperature and switch on the AC when the temperature hits the upper thermal comfort threshold.

Rules 1 and 2 simulation results are compared to a block of data in the original dataset in which the AC operates continuously from 7:39 a.m. to 11:35 a.m. The first 15-minutes of temperature readings from the beginning of the day at 7:39 a.m. are sensor readings from the original data and are consistent for all situations. However, the subsequent temperatures in the simulation after the first time the AC is turned off, are the predicted temperatures from the developed prediction model in stage 1.

The temperature values for all scenarios are depicted in Fig. 5, and the AC status of on/off for both Rule 1 and 2 scenarios are provided in Fig. 6(a) and Fig. 6(b). When Fig. 5 and 6 are compared, it can be observed that, as expected, the temperatures rise when the AC is turned off and drop when it is on. Table 4 provides detailed statistics of this simulation. For simulation of Rule 1, the maximum indoor temperature was 27.93 ºC while the minimum predicted indoor temperature was 25.92 ºC, and the average predicted temperature achieved was 27.16 ºC. The corresponding temperatures for simulation of Rule 2 are 27.14 ºC, 23.09 ºC and 25.23 ºC, respectively. This indicates that the proposed model is able to keep the temperature within the comfort range to ensure comfortability of the occupants whilst also saving energy usage by switching off the AC at the pre-set upper limit. In contrast, the original data keeps the AC on throughout the entire period of the experiment.

Table IV also shows the difference in operating in efficiency. The Rule 1 scenario turned off the AC 49.00% of the time whilst the Rule 2 scenario turned the AC off 36.70% of the time. The Rule 1 scenario turned the AC off a higher number of times than the Rule 2 scenario since the Rule 1 scenario set a higher value for the thermal comfort range, so less energy is needed to keep the room temperature within the required range. This signifies that the AC does not need to be turned on 100% of the time as it was in the original data to have a comfortable temperature for an indoor working environment.

IV. CONCLUSION

A deep learning framework for AC control is developed. The proposed framework consists of a predictive model which uses the historical indoor temperature to predict the future *J*-minute of indoor temperatures. The highlight of this predictive model is its capability of predicting the future indoor temperature based on different AC status, it is turned on turned off at any given future minute. In our work, the proposed rule-based model simply used the prediction model to predict the future temperature if the AC is off for the entire duration. The proposed model is straightforward but effective in generating the required savings in the half-day simulation.

TABLE IV
STATISTICS OF HALF-DAY SIMULATION FOR RULE 1 AND RULE 2

	Rule 1 Scenario	**Rule 2 Scenario**
Max Predicted Temperature	27.93	27.14
Min Predicted Temperature	25.92	23.09
Average Predicted Temperature	27.16	25.23
Total minutes AC is turned OFF	117	87
Total minutes AC is turned ON	120	150
Total Duration (Minutes)	237	237
Percentage of savings	49.00 %	36.70%

Performance of the proposed model is tested on the CUBEM dataset. A half-day operation to minimize the AC usage while also keeping a steady thermal comfort level. For thermal comfort range from 27.0 ºC to 27.9 ºC, 49.00% of the time the AC was turned off during the simulation, the average indoor temperature was 27.16 ºC, aligning with the required comfort range. The flexibility of the proposed predictive model provides various possibilities to design various possibility algorithms to control the AC for energy savings intelligently. A more sophisticated decision-making model that fully exploits the predictive model can be studied in the future.

A prediction model with high accuracy necessitates having a large dataset to train a neural network. Studying and using a more sophisticated neural network architecture like the bi-directional LSTM can enhance the model performance. In this situation, the network can better understand the data's trend and hence enhance forecast accuracy. To improve the trend of the prediction, the model can also be trained in stateful mode.

On the other hand, the system can be further improved by including more features in the model, such as outdoor temperature, and energy consumption. It is expected that the outdoor temperature may affect the indoor temperature cooling curve and the consumed energy. The addition of these features is expected to provide a better understanding of the energy consumption related to the temperature set points. Besides that, the developed predictive model can be incorporated with an optimization model to determine the real-time optimal schedule in AC operation so that the minimal operating cost can be determined precisely.

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