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Indoor condensation prediction based on a surface temperature estimation

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Summary
Since indoor condensation occurs for a variety of complex reasons, it is difficult to find a fundamental solution to prevent it. Indoor condensation, which is caused by environmental changes (an increase in internal humidity or a low ambient temperature), is difficult to prevent in an occupied residential structure based on the design of the structure. In this paper, we propose a new model for predicting indoor dew condensation that occurs in a residential environment with IoT technology. First, a basic dataset in the condensation environment is collected through a test bed, and a surface temperature estimation method that uses the machine learning model used to evaluate the dataset. In addition to the surface temperature estimation technique, which achieves a low RMSE of 0.97 in the field test, an associated condensation time prediction algorithm is proposed. The proposed method is a new method for determining the intersection point between two temperature changes based on the real-time rate of change of the surface temperature and the dew point temperature. The high condensation prediction accuracy of the proposed method is experimentally demonstrated.

KEYWORDS
condensation prediction, dew condensation, IoT, linear regression, surface temperature estimation

1 | INTRODUCTION

Condensation is a phenomenon in which water droplets form on windows, inner walls, or ceilings due to a temperature difference between the inside and the outside of a building, as shown in Figure 1. In severe cases, children or the elderly can suffer from respiratory diseases due to mold that is caused by condensation.[1]

Indoor condensation has been one of the major problems in the field of architecture over the last decades, and various efforts have been made to minimize the damage that is caused by condensation. Until now, most of the solutions were to use structures that are robust against condensation or to design buildings using optimal materials and structures through various simulations prior to construction. Recently, studies on preventing condensation via various methods, such as new structures and ventilation systems,[3-6] were conducted. However, because the condensation is caused by indoor and outdoor temperature differences and indoor humidity changes that are due to the indoor living pattern, the approaches have not provided a satisfactory solution to the condensation problem.

Recently, smart home services and technologies have been developed for solving various problems in the home using IoT technology.[7-9] Several studies have attempted to solve the condensation problem by applying IoT technology.[6-8] This IoT-based condensation research uses wireless sensor nodes to sense the temperature and the humidity in real time in

FIGURE 1 Indoor condensation problem[2]

the room, transmits the data to the server, and predicts the dew point in the server based on the data. However, the research is still limited to studies on general aspects of predicting condensation according to the relationship between the surface temperature and the dew point.

It is highly difficult to find a comprehensive solution to the condensation problem because the materials that are used, the sizes of the structures, and the living patterns of the residents differ among problem instances. Two general solutions have been proposed, which specify the factors that should be considered in designing the building and how to prevent condensation after moving in. In the former case, interior and exterior materials that are resistant to condensation are used to construct and furnish the structure. In the latter case, it is necessary to analyze the life patterns of the residents and the real-time temperature changes inside and outside the building.

A more advanced algorithm is needed for predicting condensation based on real-time temperature changes, rather than simply detecting condensation based on the current temperature and humidity information. A recent study[10] aims at solving this problem by utilizing a computational intelligence technique.

In this paper, we present a prediction model that utilizes data from a minimal number of sensor nodes for real-time condensation prediction in a real environment. This study substantially contributes to the prediction of the future time at which condensation will occur, which has not been dealt with previously, rather than the prediction of the presence or absence of simple condensation.

The remainder of this paper is organized as follows: Section 2 presents the basic theories of condensation and the problems to be addressed in this paper. Section 3 introduces the related research and describes the differences from this study. Section 4 describes the procedure for acquiring the dataset experimentally, and Section 5 exploits a machine learning model to estimate the surface temperature based on the collected datasets. In Section 6, the proposed condensation time prediction algorithm is described in detail, and the experimental results are presented. Finally, the conclusions of this paper are presented in Section 7.

2 | PROBLEM FORMULATION

2.1 | Dew condensation basics

When the temperature of the air in a space or place exceeds the temperature of an object, dew forms on the surface of the object. The temperature at which this begins to occur is called the dew point, which depends on the relative humidity. To understand the occurrence of condensation, it is necessary to understand the temperature and the water vapor curve in the air. The water vapor curve[11] is a curve of the ratio of the amount of water vapor that is contained in the air to the maximum amount of water vapor (saturated water vapor) that the air can contain, which is expressed as a percentage. A relative humidity of 100% does not correspond to the space being filled with water but rather to the amount of water vapor that is present in the air being equal to the saturated water vapor of the current temperature. When the air is cooled gradually past a threshold temperature, the water vapor in the air condenses and dew is formed. This threshold temperature is called the dew point.

Condensation occurs due to changes in the state of humid air with a difference in temperature between the inside and the outside of the building. To analyze the condensation state, a psychrometric chart[12] can be used to show the detailed thermodynamic state of humid air. The psychrometric chart is a graphical representation of each state value of the moisture vapor partial pressure, absolute humidity, relative humidity, dry bulb temperature, wet bulb temperature, dew point temperature, specific volume, enthalpy and sensible heat ratio, among others. It is possible to calculate the dew point temperature from at least two pieces of information (typically, the relative humidity and the temperature, which can be collected through the sensors), and the presence or absence of condensation can be determined by comparing the surface temperature and the dew point temperature.

The psychrometric chart provides the most reliable information for determining the dew point temperature based on changes in the relative humidity in the air and the room temperature; however, it is cumbersome to manually calculate the dew point in the graph. Therefore, a dew point table[13] or a dew point index can be used to more effectively determine the condensation state.

The dew point table method provides a more efficient approach for determining the dew point temperature than manual calculation using the psychrometric chart. However, for computers to calculate the dew point temperature in real time from the temperature and the relative humidity change, a more generalized formula is needed. The Magnus formula[14] provides an estimate of the dew point that is based on the relative humidity and the surface temperature. However, because it requires complex calculations, a simple method for calculating the dew point is needed for embedded systems that have constrained resources, eg, in terms of the processor or memory. Equation (1), which was developed by Barenbrug,[15] provides a more efficient method that satisfies these requirements. This formula has already been applied in studies on condensation problems that are based on wireless sensor networks.[16,17] Thus, the dew point temperature can be easily calculated from only room temperature and relative humidity information.

$$\begin{aligned} &0^{\circ}\mathrm{C} < T_{surf} < 60^{\circ}\mathrm{C} \\ &1\% < RH < 100\% \\ &0^{\circ}\mathrm{C} < T_d < 50^{\circ}\mathrm{C}, \end{aligned}$$

where T_{surf} is the surface temperature in degrees Celsius; RH is the relative humidity; and T_d is the dew point temperature.

$$T_d = \frac{b \cdot \alpha(T_{surf}, RH)}{a - \alpha(T_{surf}, RH)}, \tag{1}$$

where

$$\alpha(T_{surf}, RH) = \frac{a \cdot T_{surf}}{b + T_{surf}} + \ln\left(\frac{RH}{100}\right),$$

and $a = 17.27$ and $b = 237.3°\mathrm{C}$ (a and b are constant).

2.2 | Problems with indoor condensation prediction

To confirm the presence or absence of condensation on the surface of an object, the dew point temperature is calculated via Equation (1), and the difference between the obtained value and the surface temperature is used to detect condensation. It is possible to detect condensation using a temperature sensor and a humidity sensor or a temperature and humidity integrated sensor and an IoT node that can perform the calculation in Equation (1). However, since condensation occurs on a variety of surfaces, such as windows, inner walls, and closets, in an indoor environment, it is costly to install many sensor nodes for the detection of condensation. In addition, this method confirms the presence of condensation after condensation has already occurred; hence, condensation has already progressed when its occurrence in the system is detected.

Therefore, the following requirements are imposed in this study:

1. Sensor nodes must not be installed directly in all areas where condensation might occur. The condensation environment of the whole room must be monitored with a minimal number of nodes.
2. Condensation must be predicted prior to its occurrence.
3. The time at which condensation will occur in the future must be predicted based on past and current changes in the environment.

In this paper, to satisfy these requirements, we propose a novel method for predicting the time at which condensation occurs that overcomes the problems that are discussed above.

3 | RELATED WORK

Kawahara et al[3] developed methods for predicting the dew condensation risk that utilize the humidity index (HI) and the temperature index (TI). In addition, they evaluated the humidity using the humidity index (HI), which is a dimensionless index, and the dew condensation frequency for DI window frames at several locations in Japan. Zhang et al[4] proposed an advanced model predictive control (MPC) system for ventilation systems. The proposed MPC method can be used to prevent indoor condensation by controlling the ventilation system. However, the proposed method is not a general solution for preventing indoor condensation because it relies on experimental results on radiant ceiling cooling. Kim et al[5] investigated the generation of indoor heat and humidity in the recent construction of small apartment buildings. Laukkarinen et al[6] studied the impacts of the properties of the exterior window surface on condensation. The objective of the study was to analyze the impacts of the window U-value and other factors on the occurrence of external condensation. A combined heat and moisture transfer model was created and used for the calculations.

Pande et al[16] proposed a system structure that collects and monitors environmental information in a greenhouse in real time using a wireless sensor network. Park et al[17] presented a wireless sensor network (WSN)-based automatic monitoring system for preventing dew condensation in a greenhouse environment. This study focuses on a system structure that calculates the dew point via the expression of Barenbrug based on indoor/outdoor temperature and indoor humidity information and monitors the condensation state of indoor crops in the greenhouse in real time. Choi[18] proposed a structure that is composed of a wireless node and a monitoring server for predicting condensation in a building. As in most similar studies, wireless sensor nodes that are equipped with temperature and humidity sensors are installed at various points in the room, the corresponding data are transmitted to the server, and the dew point is calculated at the server to determine the presence or absence of condensation. These studies measure the surface temperature by directly attaching the sensor to the surface of the area where condensation occurs and detect the condensation based on the acquired data.

Baghban et al[10] proposed two models, namely, least-square support vector machine (LSSVM) and adaptive neuro fuzzy inference system (ANFIS), for estimating the dew point temperature of air at atmospheric pressure. However, the models are inadequate for indoor condensation environments.

None of the studies that have been conducted provide a fundamental solution to the problems that are discussed in Section 3.2. In particular, the estimation of the condensation time is not considered, which is important in the current study.

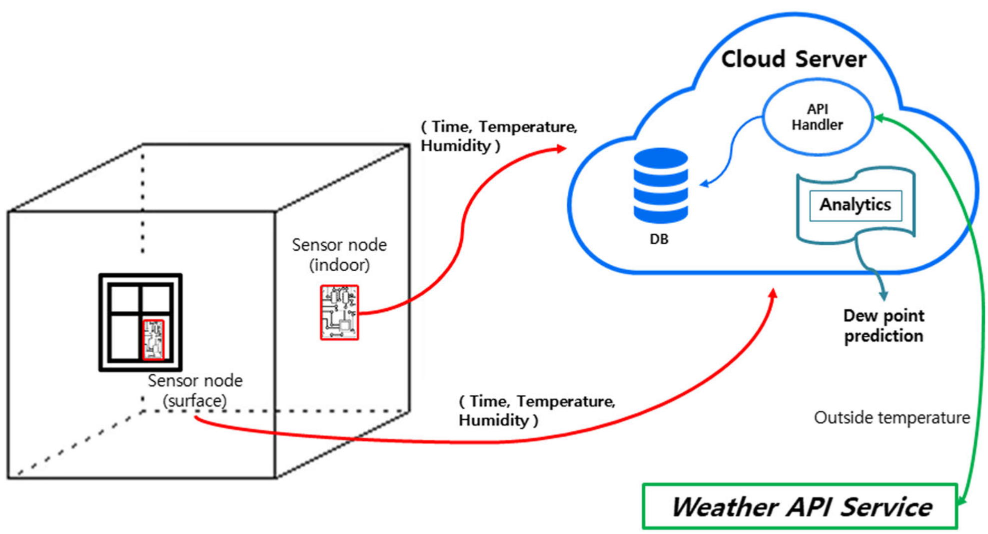

FIGURE 2 Test bed architecture for collecting indoor condensation datasets

4 | TEST BED FOR INDOOR CONDENSATION DATA COLLECTION

For analyzing the condensation in real households and collecting the necessary data, we constructed an indoor condensation test bed environment, as illustrated in Figure 2. Data collection in the room was conducted using a sensor node that was deployed by interfacing a DHT22[19] temperature/humidity sensor to Raspberry Pi 3.[20] As shown in Figure 3, the indoor test bed consists of an indoor sensor node for indoor temperature and humidity data collection and a surface sensor node for surface temperature and humidity collection. Each sensor node wirelessly connects to the cloud via Wi-Fi to transmit data every 10 minutes. In the cloud, the weather cloud API[21] service is executed to manage the external temperature information. The indoor test bed was installed in two rooms where condensation often occurs and data (indoor air temperature, indoor surface temperature, indoor air humidity, external temperature, and time) were collected every 10 minutes for 1 month; a total of 2139 data sets were collected. In the cloud, the dew point for each time was calculated based on the collected information and was compared with the surface temperature to determine the presence or absence of condensation; in addition, the actual condensation occurrence time was stored.

5 | SURFACE TEMPERATURE ESTIMATION

The indoor surface temperature, which strongly influences indoor condensation, depends on the difference between the indoor air temperature and the outdoor temperature. If the outdoor temperature is low and the indoor temperature is increased by heating, the difference between indoor and outdoor temperatures increases whereas the temperature of the indoor surfaces (windows, inner walls, etc) becomes lower than the indoor temperature due to the low outdoor temperature. In addition, one of the main objectives of this study is to minimize the number of sensor nodes that are used for condensation prediction. We do not deploy a sensor node to each surface where condensation occurs; instead, we use a single sensor node that collects room temperature and humidity to perform condensation prediction. One of the most important objectives is to estimate the indoor surface temperature from the collected indoor and outdoor temperatures (which are collected via API).

To realize this objective, we have developed a machine learning model for estimating the indoor surface temperature based on only the indoor air temperature and the outdoor temperature from the data sets that are collected from the test bed that is described in Section 4. Since the changes in the room temperature and the outdoor temperature are independent of each other, we can estimate the surface temperature using the following linear regression model:

$$T^{i}_{surf} = \alpha * T^{i}_{in} + \beta * T^{i}_{out} + c, \tag{2}$$

where T^{i}_{surf} is the surface temperature at time i; T^{i}_{in} is the indoor temperature at time i; T^{i}_{out} is the outside temperature at time i; and α, β, and c are the coefficients for the linear equation.

FIGURE 3 Sensor node installation (indoor and surface)

To determine the optimal values of α, β, and c, we learned the $T_{surf\text{-}real}$ values for the input (T_{in} and T_{out}) from the collected data sets. The difference between $T_{surf\text{-}real}$ and T_{surf} is analyzed by substituting the values of α, β, and c that were obtained via learning into Equation (2). Table 1 lists the values of the coefficients (α, β, and c) that were obtained via learning with training sets of various percentages of the 2139 data and the root-mean-square error (RMSE) results for each training set and test set. According to the results, the model with the 70% training set realized the best performance on both the training set and the test set. Figure 4 compares the measured actual surface temperature values ($T_{surf\text{-}real}$) and the estimated values (T_{surf}) for 6 days. According to the results, the mean error is less than 1° and the

TABLE 1 Linear coefficients and performances (RMSEs) under various training data set sizes

Training Data Percentage (Data Set Size)	Coefficients			RMSEs	
	α	β	c	Training	Test
40% (855)	0.66	0.20	3.03	0.94	1.00
60% (1283)	0.71	0.20	1.81	0.97	0.98
70% (1497)	0.70	0.20	1.86	0.97	0.99
90% (1925)	0.69	0.20	2.14	0.97	1.00

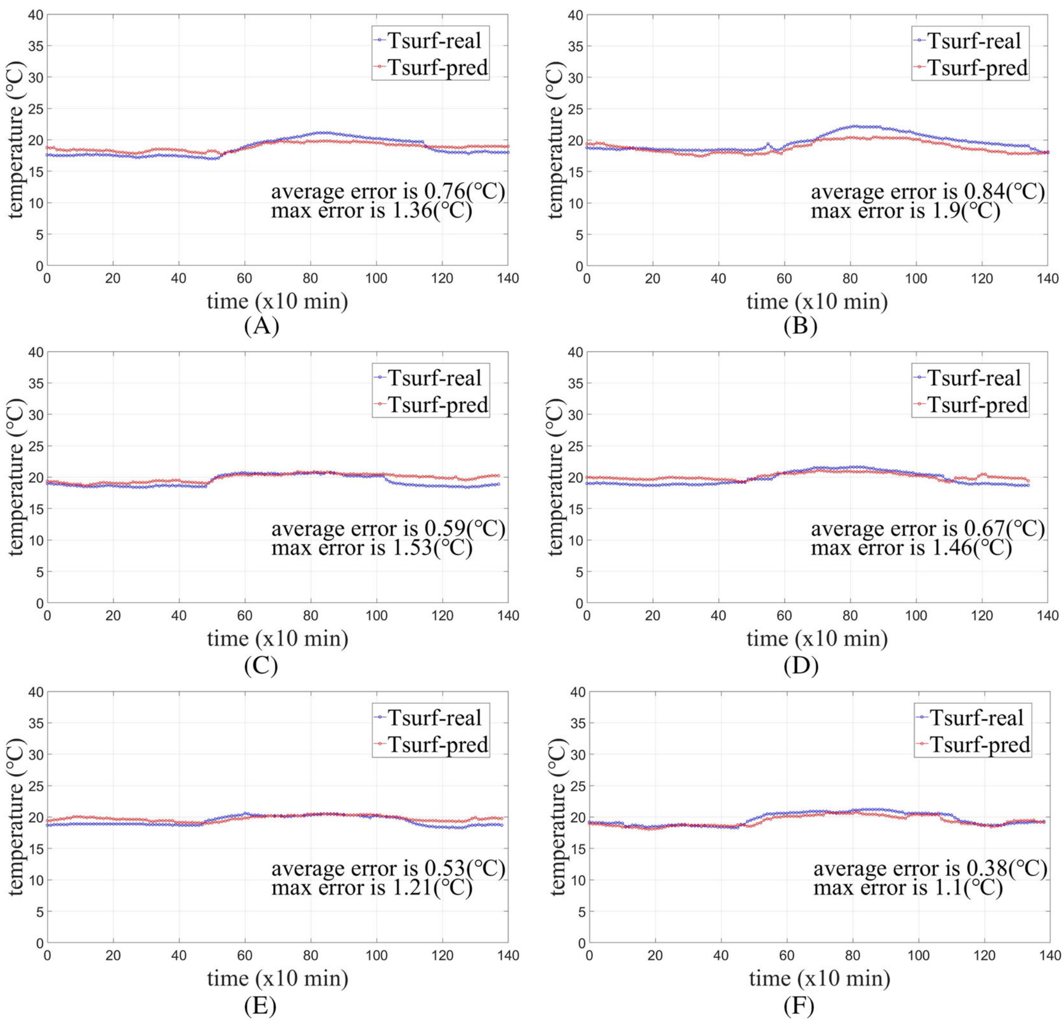

FIGURE 4 Real surface temperature vs estimated surface temperature (experimental results for 6 days)

maximum error is less than 2°. These results demonstrate that the proposed linear model that is learned from the dataset yields a value of T_{surf} that is close to $T_{surf\text{-}real}$.

6 | INDOOR CONDENSATION TIME PREDICTION

This section presents in detail the proposed algorithm for predicting the indoor condensation time. Figure 2 shows the test bed architecture for collecting datasets of internal surface temperature changes with respect to changes in the outdoor temperature and the indoor air temperature. However, to predict indoor condensation, only one indoor IoT module is installed in each room, as illustrated in Figure 5. The condensation prediction system module that is installed in each room periodically (in this experiment, every 10 minutes) senses the internal air temperature and the relative humidity and collects information on the current external temperature in real time through the weather API. Based on this information, we estimate the current surface temperature from the current outside temperature and the inside temperature value via the model that is described in Section 5. Based on the estimated surface temperature and the current humidity value, the current dew point is calculated via Equation (1) and the indoor dew condensation time is predicted.

6.1 | Indoor condensation time prediction algorithm

It is possible to judge the occurrence of indoor condensation based on the indoor surface temperature, namely, T_{surf}, and the dew point temperature, namely, T_{dew}. The proposed algorithm monitors the variation patterns of these two values and predicts the future condensation time based on recent changes. As illustrated in Figure 6, the proposed condensation time prediction algorithm determines the intersection points of two tangents at each point on the dew point change curve and the surface temperature change curve. First, T^i_{surf} at the current time i is calculated, and the equation of the line (the tangent of T_{surf}) that passes through points (i-1, T^{i-1}_{surf}) and (i, T^i_{surf}) is obtained. Likewise, T^i_{dew} at the current time i is determined, and the equation of the line (tangent of T_{dew}) that passes through points (i-1, T^{i-1}_{dew}) and (i, T^i_{dew}) is obtained. The condensation prediction time (τ^i_{pred}) at the current time (i) is obtained from the intersection point of these two lines. Since the condensation occurs from the moment at which T_{surf} and T_{dew} become equal, the intersection of the tangential equations of the two graphs (τ^i_{pred}) becomes more accurate as the condensation time nears and, eventually, τ^i_{pred} and the condensation point (at which T_{surf} and T_{dew} meet) become equal.

Figure 7 presents the pseudocode of the proposed condensation time prediction algorithm. First, in lines 1 to 3, the current room temperature and humidity information is stored as T_{in} and RH from the temperature sensor, and the humidity sensor and the external temperature of the current area is stored as T_{out} from the weather API via the Internet. Line 4 estimates the current surface temperature, namely, T^i_{surf}, via the linear model that was presented in Section 4. Here, *Coeff1*, *Coeff2*, and *Coeff0* represent α, β, and c, respectively, in Equation (2), and the optimal value that is obtained via the regression learning process is designated as a constant. Line 5 calculates the current dew point temperature (T^i_{dew}) via Equation (1) based on the estimated surface temperature (T^i_{surf}) and the current relative humidity value

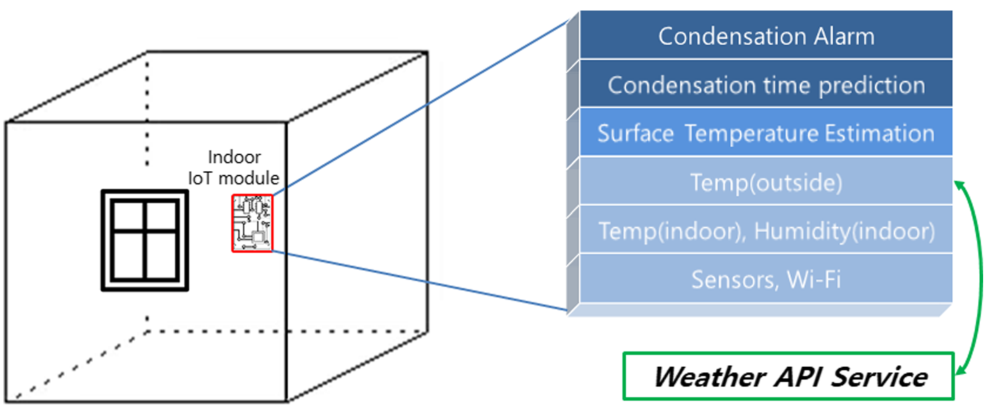

FIGURE 5 Deployment architecture of the condensation prediction system

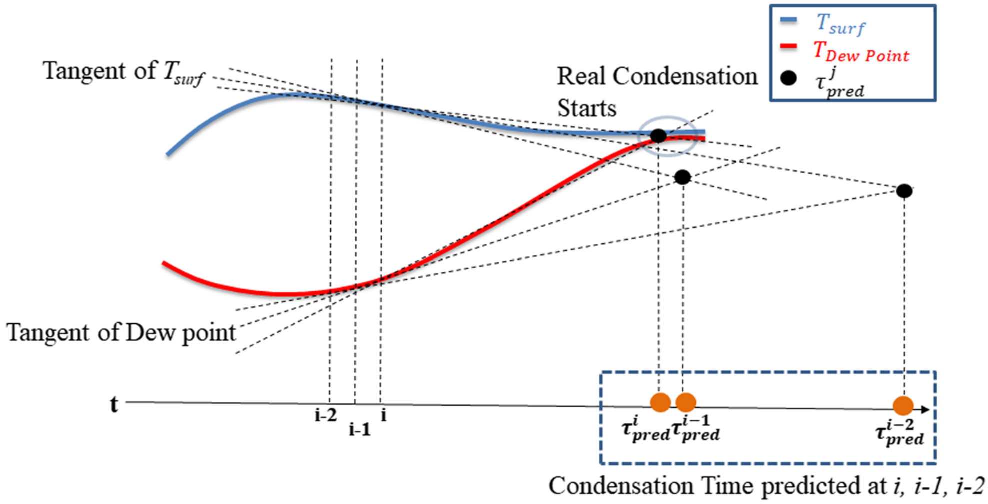

FIGURE 6 Basic strategy for condensation time prediction

Input : T_{in} , T_{out} , RH Output : τ_{pred}

Predict_condensation_time
1 $T_{in} \leftarrow$ Get_Indoor_Temp()
2 $T_{out} \leftarrow$ Get_Outdoor_Temp()
3 RH $\leftarrow$ Get_Indoor_RH()
4 $T^{i}_{surf} \leftarrow Coeff1 * T_{in} + Coeff2 * T_{out} + Coeff0$
5 $T^{i}_{dew} \leftarrow$calculate_dewpoint(T^{i}_{surf}, *RH*)
6 $Tangent^{surf} \leftarrow$ Find_tangent_of_surface_temperature(T^{i}_{surf}, T^{i-1}_{surf})
7 $Tangent^{dew} \leftarrow$ Find_tangent_of_dew_point(T^{i}_{dew}, T^{i-1}_{dew})
8 $T^{i-1}_{surf} \leftarrow T^{i}_{surf}$, $T^{i-1}_{dew} \leftarrow T^{i}_{dew}$
9 $\tau^{i}_{pred} \leftarrow$ calculate_intersection($Tangent^{surf}$, $Tangent^{dew}$)
10 if $| T^{i}_{dew} - T^{i}_{surf} | \leq$ con_bound
11 Then $\tau_{pred} \leftarrow \tau_{current}$
12 else
13 If $(\tau_{pred} < \tau_{current}) \,||\, (\tau_{pred} > \tau_{max} + \tau_{current})$
14 Then $\tau_{pred} \leftarrow \tau_{max} + \tau_{current}$
15 return τ_{pred}

FIGURE 7 Condensation prediction algorithm pseudocode

(*RH*). The tangent equation for the current surface temperature and the previous surface temperature and the tangent equation for the current dew point and the previous dew point are obtained in lines 6 and 7, respectively. In line 8, the current surface temperature and dew point are stored as previous data, and in line 9, the intersection of the surface temperature line and the dew point line is obtained. The time that corresponds to this intersection becomes the condensation prediction time (τ^{i}_{pred}). Line 10 is a condition on the current surface temperature, and the dew point that is used to determine whether condensation has occurred. If the condition is satisfied, the current time is the condensation prediction time; otherwise, line 13 determines whether the intersection of the two lines occurred in the past or at a point that exceeds the specified maximum. If this condition is satisfied, it is unlikely high that condensation will occur in the near future; hence, τ^{i}_{pred} is assigned the maximum value.

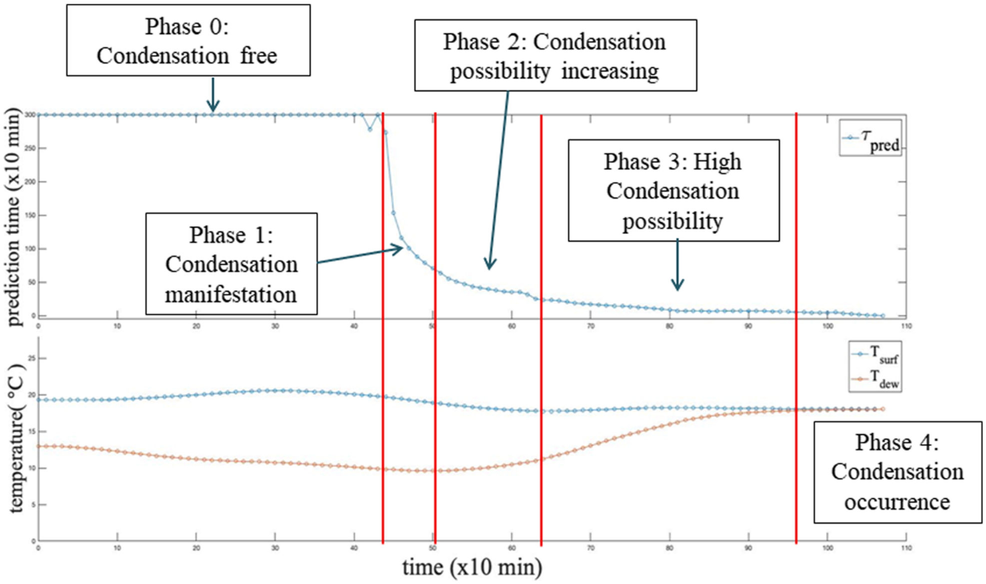

FIGURE 8 Condensation prediction phases

6.2 | Condensation prediction phases

Figure 8 shows a graph of the changes in the surface temperature and the dew point temperature in a room where condensation occurs and the condensation prediction time at each time is determined using the algorithm in Section 6.1. Based on the continuous prediction of dew condensation time, we found that the following five phases occur prior to condensation:

- Phase 0: Condensation-free
- Phase 1: Condensation manifestation
- Phase 2: Increasing condensation likelihood
- Phase 3: High condensation likelihood
- Phase 4: Condensation occurrence

In phase 0, no signs of condensation are observed. In phase 1, condensation manifestation is indicated by a sharp decrease in the prediction time. The proposed algorithm monitors the changes in the dew point temperature and the surface temperature in real time; hence, it might enter this phase when the dew point suddenly rises or the surface temperature decreases. In phase 2, the prediction time has been continuously decreasing since phase 1 and, eventually, falls below the phase 1 threshold. Hence, the likelihood of condensation is increasing. Additionally, if the prediction time continuously decreases below the phase 2 threshold, the system enters phase 3, namely, the likelihood of condensation occurring within a few hours is high. As a result, the predicted time value is close to 0 when condensation occurs; hence, in phase 4, condensation occurs. The proposed method can detect the signs of condensation in advance via the prediction of the condensation time and inform the user that the risk of condensation is increasing through the continuous steps.

6.3 | Experimental results

We constructed a test bed with the configuration that is illustrated in Figure 5 using the linear regression model that was proposed in Section 4 and conducted experiments for 1 month to predict the dew condensation time. In the proposed algorithm, the measurement error and the actual error range in Equation (1) are fixed to 1°C, and this value was used as the *con_bound* value in Figure 7. The indoor and outdoor temperatures and humidities were measured in 10-minute intervals. Based on these measurements, the surface temperature and the dew point were calculated every 10 minutes, and the prediction time was recorded. The presence of dew condensation was determined from the

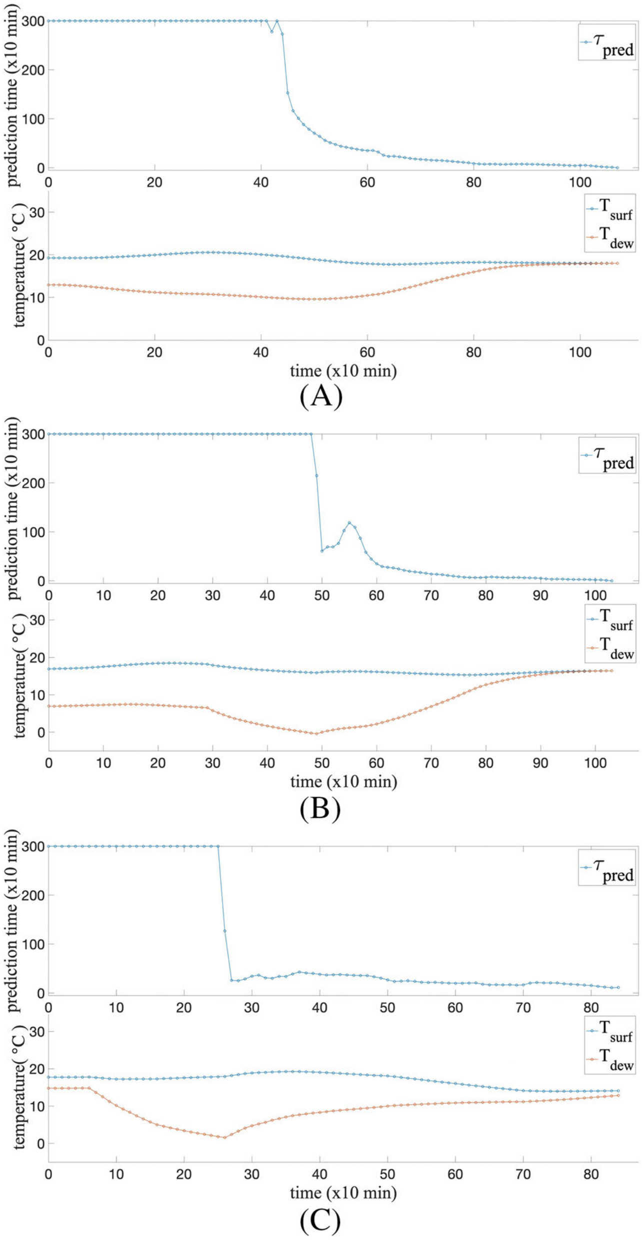

FIGURE 9 Condensation time prediction

difference between the dew point and the surface temperature. Figure 9A-C shows the changes in the surface temperature, dew point, and condensation prediction time for each of the 3 days during which condensation occurred during each of the experiments. In the case of condensation, as shown in Figure 8, each phase can be readily identified. The first warning was issued for the signs of phase 1 before 9 hours in case (a), before 6.5 hours in case (b), and before 10 hours in case (c). According to the results, the periods for phase 2 and phase 3 are clearly identified in the environment where condensation occurs.

We also analyzed the error in the condensation prediction time, which is plotted in Figure 10. The dew condensation time prediction error is defined as the time error between the predicted condensation time at the current time and the actual condensation occurrence time. As shown in the figure, the error is large in the period where no signs of condensation are visible. This is because the nonoccurrence of condensation corresponds to one of the following three scenarios: First, when the dew point temperature is falling or the surface temperature is rising, the intersection of the two tangents corresponds to a past time rather than a future time; hence, the predicted value is expressed as the maximum value, according to the algorithm in Figure 7. Second, when the difference between the dew point temperature and the surface temperature is large and there is little change in the two values, the two tangents do not intersect, namely, since no large change occurs in the current environment, the predicted value is represented by the maximum value, as in the

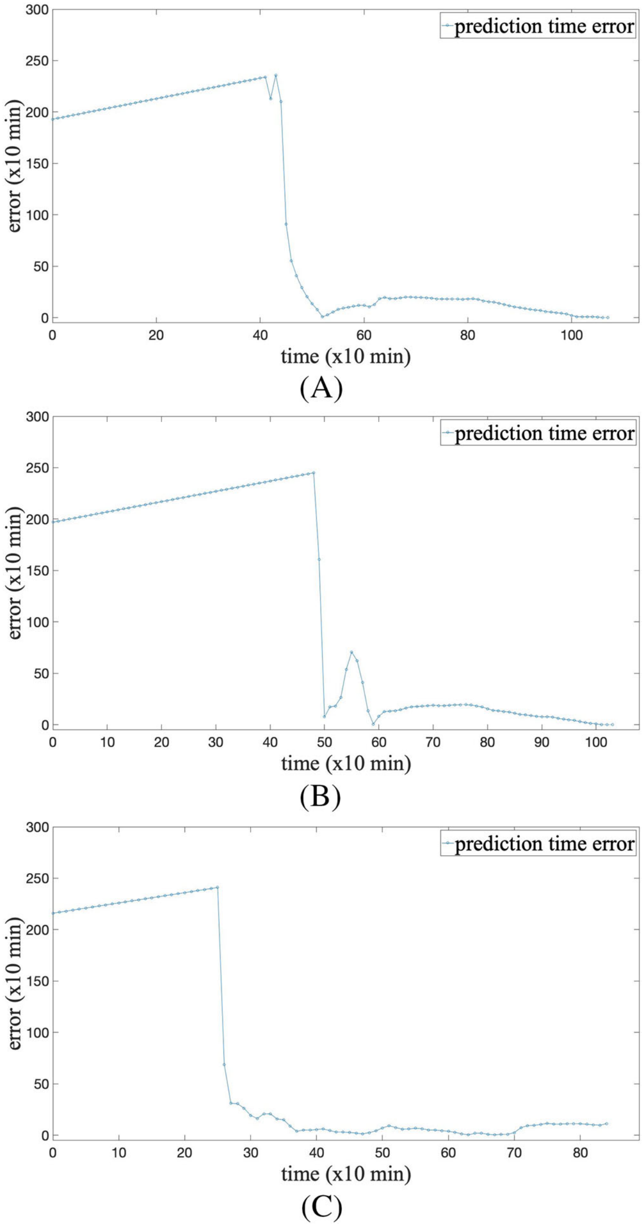

FIGURE 10 Prediction time error

algorithm in Figure 7. Finally, if the dew point temperature rise or the surface temperature drop slope is not large, then the two tangents intersect far into the future; hence, also in this case, the predicted value is expressed as the maximum value.

However, if a change occurs in an environment in which condensation occurs, the error of the predicted value drastically decreases. This corresponds to the point at which phase 1 is entered, as described in Figure 8. Up to the point at which condensation occurs, the prediction errors fluctuate due to the instantaneous environmental change. However, the error converges to zero. In the experimental results, the prediction error interval of less than 20 minutes was 2 hours for (a), 1 hour and 30 minutes for (b), and 1 hour for (c). Therefore, the proposed condensation prediction algorithm almost exactly predicts that condensation will occur after 2 hours with an error that is within 20 minutes.

7 | CONCLUSIONS

In this paper, we proposed a method for predicting the dew condensation time using a minimal number of IoT nodes. Our experimental results have demonstrated that the linear regression machine learning model that was used to estimate the surface temperature based on changes in the internal and external temperatures realizes high accuracy with 0.97 RMSE. Additionally, based on this surface temperature estimation approach, a new method for predicting indoor condensation time is proposed. The proposed method determines the likelihood that condensation will occur in the near future through five phases of condensation occurrence based on the predicted change in the dew condensation time by analyzing the surface temperature change and the dew point change in real time. Experimental results on a test bed demonstrated that it is possible to predict the occurrence of condensation within an error interval of 20 minutes after an average of 2 hours. Considering that the sampling period of each sensor is 10 minutes in this experiment, the precision of the slope of the tangent to the change can be increased by shortening the sampling period and the error interval can be substantially reduced. Nevertheless, the experimental results demonstrated that it is possible to detect the signs of condensation 10 hours prior to condensation by analyzing the condensation prediction time under the current environmental changes and to issue a warning. This is a highly important result for preventing condensation and the results and the methodology of this study are expected to substantially contribute to related research in the future.

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