Improving Energy Efficiency In Climatic Test Chambers With Deep Learning and Absolute Humidity Methods

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***Abstract*— Climatic test chambers are devices used to simulate environmental conditions for the testing and verification of products in various industries. However, these chambers can consume significant amounts of energy, resulting in high operating costs and environmental impacts. Therefore, the need to optimize the energy efficiency of climatic test chambers while maintaining their performance is becoming increasingly important. In this paper, we will discuss the control method for humidity testing by calculating the use of the LSTM algorithm instead of the classical control method PID to control climatic test chambers to improve energy efficiency and the control method based on absolute humidity instead of relative humidity. In particular, we harness the power of artificial neural networks to reduce energy consumption and improve control of climatic test chambers based on various input parameters such as temperature, humidity, and test duration. By changing the control methods, we aim to increase efficiency and make it more suitable and efficient for smart grid systems.**

Keywords—Climatic controlled room, efficiency, deep learning, Absolute Humidity Control.

I. Introduction

Climatic test chambers are devices used in various industries to simulate environmental conditions for testing and validation of products. However, such chambers can consume significant amounts of energy and result in high operating costs and environmental impacts.[1] [2]Therefore, optimizing the energy efficiency of climatic test chambers, but maintaining their performance, is becoming increasingly important. In this paper, we will discuss the use of the LSTM (Long Short-Term Memory) algorithm to improve the energy efficiency of climatic test chambers and the control method of humidity testing based on absolute humidity instead of relative humidity [1,2]. In particular, based on various input parameters such as temperature, humidity and test time, we will present a control method to reduce energy consumption and improve control of climatic test chambers by harnessing the power of artificial neural networks [3]. With the obtained efficiency, we pave the way for its use in smart grid systems with less energy consumption [4,5].

To evaluate the performance and reliability of these test chambers, temperature, humidity, and other factors need to be accurately controlled. Traditionally, humidity control is usually based on relative humidity (RH) values. Relative humidity is the ratio of ambient water vapor to the water vapor carrying capacity of the air, usually expressed as a percentage (%RH) [1]. However, temperature and humidity control based on relative humidity may involve irregularities and difficulties in the operation of humidification /dehumidification systems, where humidity is expressed differently under different temperature and pressure conditions and operated accordingly, thus reducing energy efficiency.

Absolute humidity (AH) control has emerged as an alternative method of humidity control [6]. Absolute humidity refers to the actual water vapor content of a unit volume of air and is usually expressed in grams of water vapor/kilogram of air. Absolute humidity control is recognized as a more accurate and reliable humidity control method than relative humidity control. In addition, absolute humidity control can perform more consistently under different test conditions as the target temperature humidity values are achieved with more realistic control.

In this paper, we highlight the absolute humidity control method and deep learning methods to improve the energy efficiency of climatic test chambers. It will examine how the conversion from traditional relative humidity control to absolute humidity control can improve energy saving and performance. Furthermore, the impact of deep learning methods, such as the use of artificial neural networks and the LSTM algorithm, on the humidity and temperature control of climatic test chambers will be discussed. By highlighting the potential of climatic test chambers to optimize energy efficiency, this study can contribute to the adoption of a more sustainable approach in future smart grid systems.

II. Climatic Test Chambers

Climatic test chambers are specialized test equipment used in various industries to simulate and control environmental conditions to evaluate the performance, durability, and reliability of products under different climatic scenarios [7,8].

Fig. 1. Example of Climatic Test Chamber

These chambers are designed to simulate real-world conditions and create controlled environments with precise temperature, humidity, sunlight, vibration and other environmental parameters to evaluate how products respond to different climates. Climatic test chambers are widely used in industries such as automotive, aerospace, electronics, pharmaceuticals and food processing to conduct accelerated aging tests, durability tests, performance tests and quality assurance checks [9].

A climatic test chamber is an enclosed, insulated room that allows precise control of temperature, humidity, light and other environmental factors to create various climatic conditions such as extreme cold, high temperature, low or high humidity for testing purposes. These chambers are used to evaluate the performance, reliability and durability of products under different climatic scenarios. It helps manufacturers to identify potential problems and improve product quality before they go to market.

The main purpose of climatic test chambers is to enable accurate and consistent testing of products under different climatic scenarios by creating controlled environments that simulate real-world conditions in a repeatable and controlled manner. These chambers enable manufacturers to test how their products perform in extreme and extreme conditions, assess their resistance to changes in temperature, humidity, light, vibration, etc., examine their behavior under different climatic scenarios and identify potential design flaws or weaknesses.[10]

The refrigeration system of climatic chamber is based on a vapor compression refrigeration cycle that includes a refrigeration compressor, a condenser, an evaporator, and an expansion valve. The refrigeration compressor compresses the gaseous refrigerant to high pressure and temperature levels. The compressed gas then comes into contact with ambient air or water in the condenser, where it loses its heat and turns into a liquid.

The liquid refrigerant evaporates as its pressure drops in the expansion valve, absorbing heat and cooling the environment in the process. The vaporized refrigerant returns to the compressor and completes the cycle. This cycle helps the climatic cabinet to always maintain the desired temperature and humidity conditions. Figure 3 shows an example of a cascade cooling system schematic.

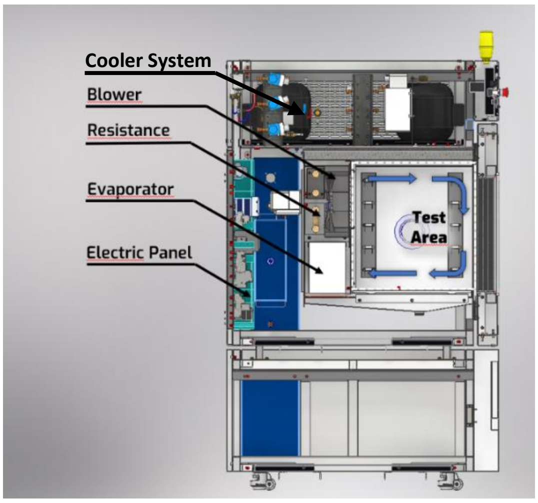

Fig. 2. Internal structure of the climatic test chamber.

The heating system of air-conditioned cabins is usually provided using electric heating elements. The heating elements directly heat the air inside the cabin to reach the desired temperature levels. The resistances are controlled by thermostats or controllers such as PLC to control the temperature inside the climatic cabinet.[12] Figure 2 shows the internal structure and component layout of a climatic cabinet.

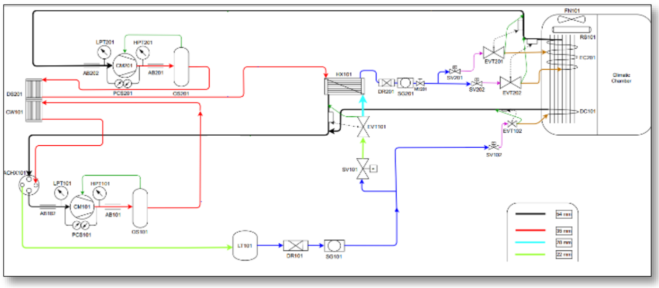

Fig. 3. Example of a cooling system schematic.

The humidification system of air-conditioned cabinets controls humidity levels with data from humidity sensors, usually by adding water vapor or spraying water. The humidification system humidifies the air inside the cabin to achieve the desired humidity levels. Humidification equipment such as ultrasonic humidifiers, steam boilers or steam generators can be used to add water vapor. Sensors continuously monitor the humidity levels inside the climatic cabinet and add water vapor when humidity drops, ensuring the desired humidity conditions.[13]

The most used **dehumidification systems** are refrigeration-based dehumidification systems. These systems typically send cold fluid to the evaporator in the test volume to remove moisture from the air. By cooling the air to below the dew point temperature, it condenses the moisture into water. This reduces the humidity inside [14].

III. Material and Method

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is widely used in various areas of machine learning and deep learning, including time series analysis, speech recognition and natural language processing. LSTM overcomes this limitation by using a more complex architecture involving memory cells with gating mechanisms, allowing it to capture long-range dependencies and more effectively learn patterns in sequential data. The LSTM architecture includes gates such as the input gate, output gate and forget gate, which regulate the flow of information and enable the model to selectively hold or forget information from previous time steps. This makes LSTM particularly well suited for tasks that require modeling sequences with long-term dependencies, such as time series data used in climatic test chambers.

To improve energy efficiency and climate operations, the LSTM method has been widely used in many areas, such as building energy management systems, smart grids, and climate prediction. For example, in Zhang et al.'s (2020) study, LSTM was used to predict a building's cooling load, which resulted in more effective energy management and HVAC regulation.[18] Similarly, in the study by Liu et al. (2019) [19], LSTM is used for prediction of electricity consumption in a smart grid, facilitating demand side management and peak load savings. In the context of climatic test chambers, LSTM can be used to model and predict temperature, humidity, and other climatic variables, enabling more accurate and efficient control of the test chamber environment.

Using LSTM in the proposed deep learning approach to improve energy efficiency in climatic test chambers, the model can effectively capture temporal dependencies and patterns in the data, leading to improved energy management strategies and reduced energy consumption. This study aims to use an LSTM model trained with a PID controller instead of PID control to realize parameter-independent temperature control [15].

The study process includes determining the time series target temperature set points, generating the data set, extracting the features, designing, and training the LSTM model, and evaluating the model performance [16]. Among deep learning models, recurrent neural network (RNN) models are known to be suitable for learning time series data. The LSTM network consists of input, multiple hidden and output layers and the memory cells of the hidden layers play an important role in learning the data.

The data set to be used for the learning process is first created with input-output data from the designed PID controller. In order for the data set not to cause training errors and to operate with high accuracy, the temperature control system controlled by the existing PID controller must successfully reach the target temperature values. Therefore, a target temperature prescription was created using random values in a certain range to test the PID controller. The PID test recipe in Figure 4 was used to generate the training data for the model.

Before proceeding with the machine learning system, it is necessary to test it with the existing dynamics of the system. Therefore, in the randomly generated target temperature graph, the temperature range is defined in 5 steps in the range of 20-60 °C.

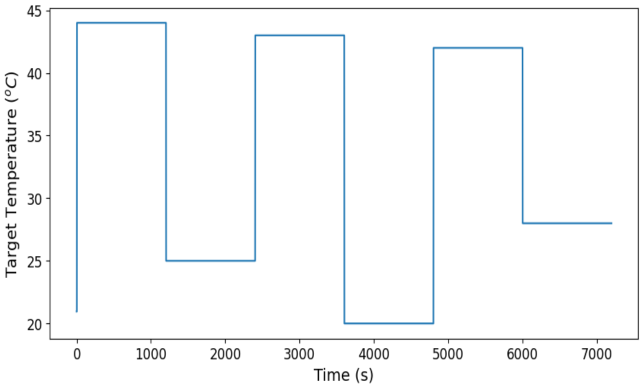

Fig. 4. Example of a randomized target temperature/time graph.

The prescription consists of a period of approximately 120 minutes. This test recipe was tested with the existing PID controller software. The test results showed that the PID-controlled software captured the target temperatures appropriately. Figure 4 shows the operating performance of the PID controller output on the pre-generated test recipe.

The three parameters indicated in the graph are RP, CT and TT respectively. In the created system, RP (Resistance Power) is the percentage representation of the resistance output power. CT (Current Power) represents the current temperature value of the PID controlled system in °C. TT (Target Temperature) parameter shows the target temperature (°C) value on the recipe.

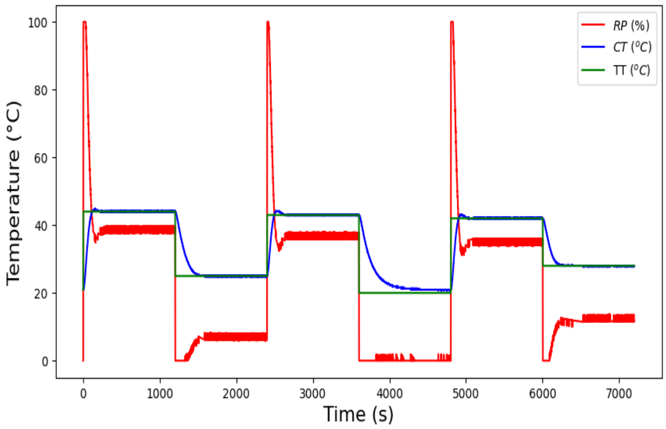

Fig 5. Test graph with PID control software

The results obtained with the PID-controlled software were used to train and test the LTSM-controlled software. The control software modeled using an LSTM neural network developed with Tensorflow and Keras libraries was integrated into the controller. The other 5-step test recipe was run again.

Table 1 shows the values of the methods and optimum parameters used in LSTM control.

TABLE I. OPTIMUM PARAMETER VALUES

No	*Parameter*	*Value*
1	Batch_size	128
2	validation_split	0,2
3	epochs	300
4	optimizer	adam
5	Model	Sequential
6	Return sequence	True

The model performance obtained as a result of training with the specified parameters is shown in the graph in Figure 6. Error values decreased over time to minimum levels.

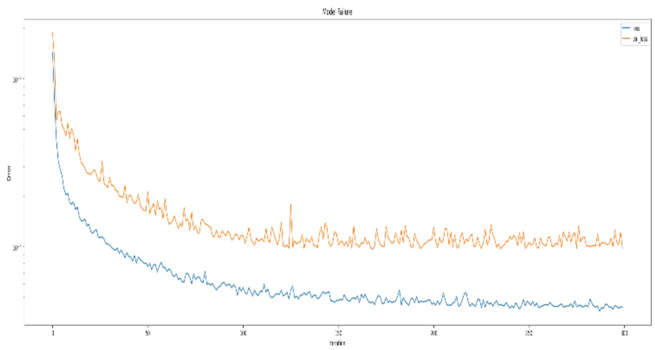

Fig 6. LSTM Training performance graph.

A test recipe was created again with LSTM controlled software. like the previous recipe, it consists of 120 minutes and 5 randomized steps in Figure 6.

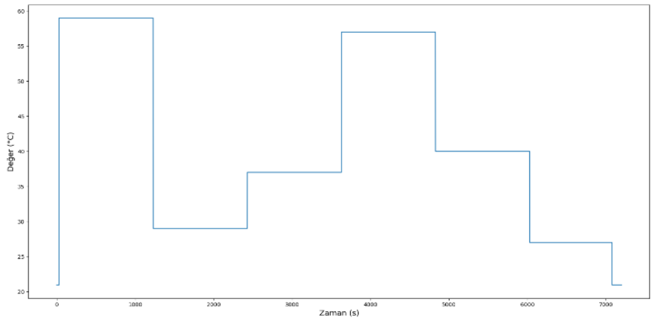

Fig 7. New test recipe graph.

First, we test the test recipe only with PID controlled software. The test results are as follows in Figure 8. Temperature control tolerance is in the range of ±2 °C.

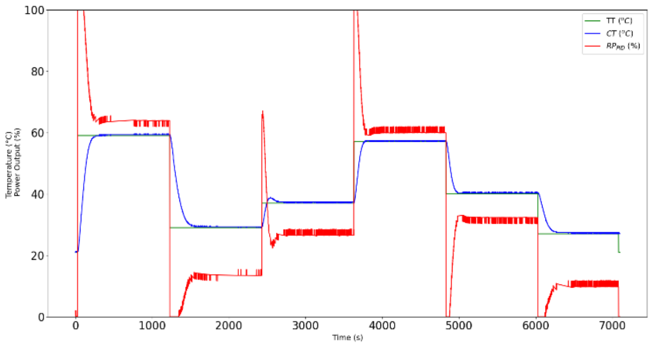

Fig 8. New test recipe result using PID.

The same test recipe was performed again with the LSTM controlled software. the results are shown in Figure 9.

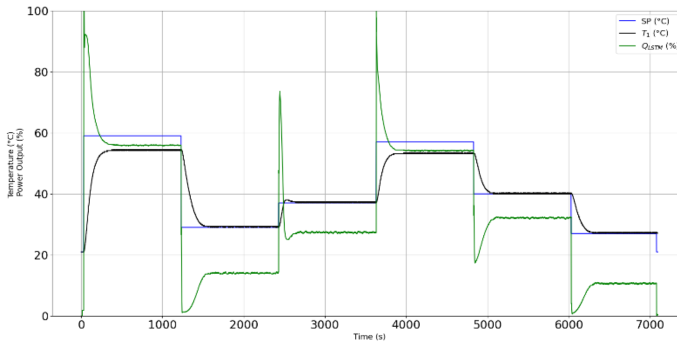

Fig 9. LSTM test performance graph

The test results of the LSTM network model realized in the last stage independently of the PID controller are presented in Figure 9. The test output shows that the LSTM network successfully reaches the temperature setpoints. In addition, when we examine the resistance outputs; it has worked at lower powers compared to PID and by using the output at optimum power, it shows that it both increases energy efficiency and provides more successful control in achieving the target. The investigations on air-conditioned cabinets reveal that the LSTM-based neural network model achieves significant success in temperature control and can be integrated into different cabinets independently of PID parameters.

There are many control methods for humidity control in climatic chambers, the most common of which is the feedback control method with PID. Depending on the humidity reading inside the chamber, dehumidification or humidification systems are operated.

Since the test condition is a certain relative humidity value at a certain temperature, feedback is used in almost all systems by reading the relative humidity. If the reading is different from the target value, the system reacts accordingly. During step transitions in the test jams, the humidity target suddenly changes and the system is controlled according to the new humidity. A simple humidity test recipe is described in Table 2.

TABLE II. SAMPLE OF HUMIDITY TEST RECIPE.

Step No.	Target Temperature °C	Target Humidity %RH
Step 0	50	50
Step 1	60	40
Step 2	70	30
Step 3	40	40
Step 4	70	30
Step 5	30	30

When moving from step 0 to step 1, the relative humidity value decreased from 50%Rh to 40%Rh in the current control method. The control software starts the dehumidification system for this drop demand. This decision is incorrect because the required amount of water vapor (Absolute Humidity) has increased from 41.6 g/m^3 to 51.9 g/m^3. Therefore, the system should operate the humidification system instead of dehumidification.

Because of this wrong decision, a high-powered dehumidification system worked unnecessarily and the amount of water vapor (absolute humidity) available in the test volume decreased. Therefore, the humidification system will run longer than it should, and the test efficiency will be significantly reduced, and the duration of the test will be prolonged. Table 3 provides a summary of the operating requirements for dehumidification and humidification systems in a relative humidity-controlled system.

TABLE III. HUMIDITY TEST RECIPE IN CONVENSIONAL METHOD.

Step	Temp °C	Hum. %RH	Dehumidifier behavior during stage change.	Humidifier behavior during stage change.	Is the operation right or not?
0	50	50	N/A	N/A	N/A
1	60	40	Opened	Closed	NOT
2	70	30	Opened	Closed	NOT
3	40	40	Closed	Opened	NOT
4	70	30	Opened	Closed	NOT
5	30	30	Closed	Closed	NOT

The relative humidity equation in the traditional control software is as in Equation 1.[21]

$$RH = \frac{100\exp\left(1.8096+\frac{17.269\,T_W}{273.3+T_W}\right)-7.866*10^{-4}*P(T-T_W)(1+\frac{T_W}{610})}{\exp(1.8096+\frac{17.269\,T}{273.3+T})} \quad (1)$$

Here Tw is the wet bulb temperature (°C), T is the dry bulb temperature (°C) and P is the station level pressure (hPa).

Using two thermometers, the relative humidity inside the cabin is measured indirectly.

Wet-bulb temperature Tw is the temperature at which water (liquid or solid), by evaporating into moist air at dry bulb temperature t and humidity ratio W, can bring air to saturation adiabatically at the same temperature Tw while total pressure P is constant.

If pressure is not known, the following table of standard pressures can be used as a first guess. Standard Sea level 1013.25 hPa, or 1 atmosphere 9atm), or 29.92 inches of mercury. [20]

TABLE IV. PRESSURE AND ALTITUDE TABLE.

Station Altitude (m)	0-250	251-500	501 - 750	1001 - 1250	1251 - 1500
Pressure (hPa)	998.3	969.0	940.4	912.5	885.2

Given an accurately measured station level pressure, the calculated relative humidity is expected to differ by 3% from the value calculated using a pressure in the table above.

The equation for calculating absolute humidity (grams/m[3]) using the relative humidity equation integrated into the control software is as in equation 2.

$$AH = \frac{6.112 * exp\left(\frac{17.269\,T}{273.3+T}\right) * RH * 2.1674}{273.15+T} \quad (2)$$

The temperature (T) given in the equation is expressed in degrees Celsius, the relative humidity (RH) in % and e (exp) in natural logarithm base 2.71828. [20]

After the new equation is integrated into the software, the new behavior of the behavior in Table 3 according to the new algorithm is as shown in Table 4.

TABLE V. HUMIDITY TEST RECIPE IN USING ABSOLUTE HUMIDITY EQUATION METHOD.

Step	Temp °C	Hum %RH	AH grams/m3	Dehum. behavior during stage change.	Hum. behavior during stage change.	Is the operation right or not?
0	50	50	41,6	N/A	N/A	N/A
1	60	40	52,3	Closed	Opened	RIGHT
2	70	30	59,9	Closed	Opened	RIGHT
3	40	40	20,5	Opened	Closed	RIGHT
4	70	30	59,9	Closed	Opened	RIGHT
5	30	30	9,1	Opened	Closed	RIGHT

Before and after the change of control method, a 25°C 50% RH test was performed in a climatic test chamber. Relative humidity-controlled test result is shown in Figure 10.

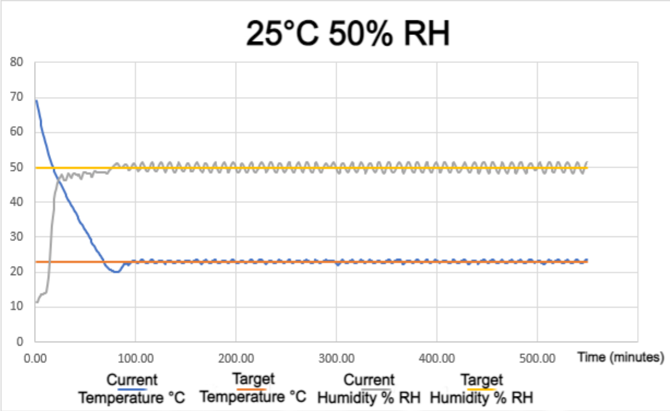

Fig 10. Test result using Relative Humidity based controller.

Absolute humidity-controlled test result is shown in Figure 11.

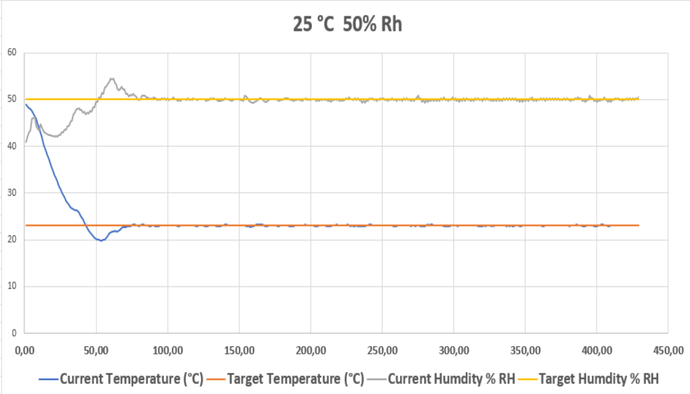

Fig 11. Test result using Absolute Humidity based controller.

IV. RESULTS

When we compare the two test results, the number of fluctuations in the humidity value in the relative humidity-based control is quite high and the value range is measured as ±4%RH. In the absolute humidity-based control, the fluctuation in the humidity value was measured as ±1 %RH. No fluctuation was observed as a result of the test.

The absolute humidity-based control increased the power efficiency and test accuracy. In climatic test chambers, the accuracy of temperature and humidity distribution, control system stability and adequacy of system performance are of great importance for successful testing. Therefore, the developed control systems need to be optimized with all parameters. In this study, an innovative LSTM-based deep neural network model that is independent of parameters and can reach the temperature values in the optimum time, as an alternative to the current PID control algorithm's success in temperature control, and absolute humidity control software has been developed instead of the relative humidity control algorithm. The LSTM network is trained with the outputs obtained from a designed PID system. The designed PID control system is a successful system that can control the temperature outputs and resistance output levels proportionally. Firstly, the PID system and then the developed LSTM network model were tested on a test recipe containing randomly generated target temperature setpoints.

The LSTM network was trained and tested with various hyperparameters to determine the optimal parameters. The results are shown on graphs comparing the performance of the LSTM network and the PID system. The LSTM network control system, operated independently from the PID system, gave successful results on different test prescriptions. By changing the humidity control method, the dehumidification and humidification systems are operated at the right time, preventing unnecessary energy consumption and preventing the systems from working more than necessary due to improper control. Experiments on different test recipes prove that both models give successful results.

V. Conclusion

Nowadays, artificial intelligence and deep learning applications are being successfully used in many fields and are becoming increasingly widespread. The learning capabilities of deep learning algorithms can be seen as an important innovation, especially for eliminating some deficiencies in control systems. The control system developed in this direction can be trained with a high-dimensional data set and tested in real systems and contribute to obtaining the optimum solution.

In addition, switching from the traditional relative humidity-based control used in humidity test chambers to the more complex absolute humidity-based control can extend the product life and obtain more stable test results by ensuring that the system equipment operates only when needed. However, it can be difficult to achieve sufficient optimization of a detailed model within a given period of time due to the optimization process requiring long computational times. For this reason, experimental results should be compared with calculations to make optimal choices. Considering all these studies, it is seen that developing an innovative control system based on deep learning will make significant contributions to the industry and the literature. The use of innovative control systems based on deep learning and absolute humidity methods can play a crucial role in improving the energy efficiency of climatic test chambers, which can lead to more efficient and effective use of these chambers in smart grid systems. This can ultimately contribute to a more sustainable energy future by reducing energy waste and increasing the overall energy efficiency of the grid.

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