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Machine Learning based Home Energy Management System

T R Mani Chigurupati[1], SK Mahaboob Basha[2]
[1,2]Faculty,CSE Department,Holy Mary Institute of Technology and Science,Hyderabad
Email :tulasiratnamani.chigurupati@gmail.com[1],bashashaik1617@gmail.com[2],

***Abstract**:*

In this paper, we describe the machine learning and cooling system used in the smart home. In particular, we proposed a temperature controller based on machine learning and verified performance using real-time location data. With the experimental results, it is possible that the efficiency of the temperature control using the machine learning was verified. As a result of performance testing, the proposed system shows that there are variations in performance depending on the user's health pattern, and that the system works best if you have a particular lifestyle.

Keywords

Smart home, temperature control, smart home

1. Introduction

Recently, since the Internet of Things (IoT) solution was developed, a number of smart home based devices have been deployed on IoT. With these styles, smart home appliances that are user friendly and energy efficient are simultaneously studied [1]. In particular, the Google NestLab Thermostat sells more than 1 million units per year [2]. Also, AlphaGo is a representative example of the practical application of Reinforcing Learning among various machine learning approaches and has suggested new directions and opportunities for other researchers [3]. Watson's IBM Oncology is an example of applying machine learning to the medical field, and contributes significantly to the design of care designed for patients and preventive medicine through extensive data analysis [4]. 2 Normal Thermostat operates on a fixed algorithm or operates on an internal scale. These types of methods are unsatisfactory because they cannot reflect the diverse user needs and living conditions of the residents. In this paper, therefore, we propose a temperature control based on machine learning that can improve the quality of life and user satisfaction by studying the life patterns and temperatures desired by each user. The proposed method studies the lifestyles of real residents in terms of supervised learning and allows learning outcomes to be demonstrated in temperature control. To verify the performance, wintertime data of three sub-offices were used. Additional data for other seasons are collected and analyzed for better performance and accurate environmental analysis.

2. Temperature Control Model

The proposed system allows machine learning based on the user's life pattern (preferred temperature depending on each condition) and controls the cooling / heating devices of each content. However, it is difficult to determine whether user specific temperature preferences in all cases are possible. Therefore, the system has one week's time to learn the user's tendency and preference for temperature, and the user's temperature control results are used as training data during the study. The complete configuration of the system is shown in Figure 1.

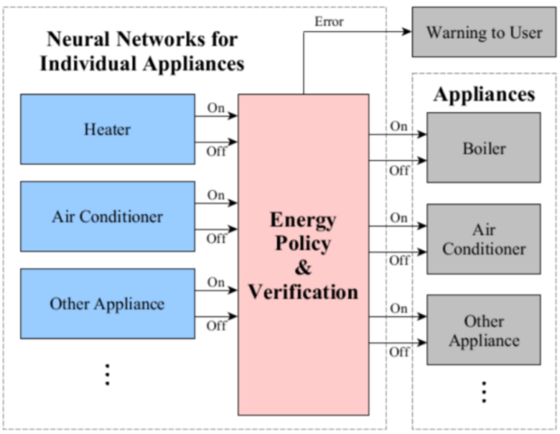

Fig. 1: Diagram of the overall system configuration

The left side of the diagram is a network connection that determines the need for each heating / cooling equipment and home operation. In these neural networks, machine learning is performed by retrieving various sensing data, and the need for the operation of individual devices is given based on learning outcomes. In the block in the middle of the program diagram, power policy and authentication functions are executed. When an enhanced neural network provides the demand for each application, it receives consistent results and determines the economic utilization of energy and resource efficiency. In addition, when device errors are detected, warning messages are issued to users. The block on the right is the part that directly controls the individual devices, and the part that starts and stops the devices themselves. In the installation phase, a total of six pieces of data are transmitted (a detailed list is shown in Table 1), and a hidden layer is made up of five layers. The output layer contains two output (On / Off) stages to judge the output of the output label. The Refresh Linear Unit (ReLU) is used as a function of the neural network, and it is described in (1) .

$$f(x) = \begin{cases} 0 & for\ x < 0 \\ x & for\ x \geq 0 \end{cases} \qquad (1)$$

The backpropagation method was used to study the hidden layer and the Defense Error Error (MSE) was used as a cost function

$$f_{COST}(\omega, b) = \frac{1}{2n}\sum_x \|y(x) - a\|^2 \qquad (2)$$

Table 1: Data for training and testing

	Data	Period
Training data	Time, weekday / weekend, temperature, humidity, CO2, PIR sensor data	2017.02.16. ~ 2017.02.22.
Test data		2017.02.23. ~ 2017.03.01.

By using the slope of the cost function the error is multiplied and read more hidden neurons. The machine learning process of this paper was performed using Python based 'Tensorflow', and the neural network model used was simplified in Fig. 2

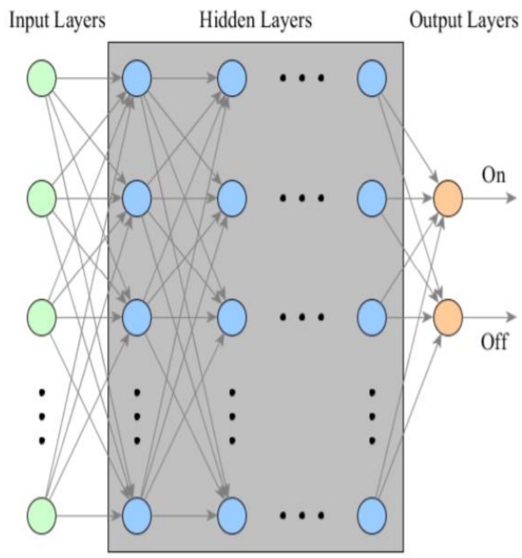

Fig. 2: Neural network model of temperature controller

3. Performance evaluation

To verify the effectiveness of the proposed method, data were collected at the 3 sub-offices in February, when several radio rays were used. Detailed data lists and times are listed in Table 1. In order to get the best performance, it is necessary to obtain a direct response to user temperatures. However, since it can cause user interference, indirect use has been used, in this paper. In other words, this reading is made up of details of the weekly workings of the user's computer. To apply this to machine learning, the optical temperature, which has the same standard deviation as the sensor obtained, was performed, and this temperature was fed as training data. The results of performance comparisons are summarized in Table 2. For all three offices, performance accuracy was above 80%, but in office 2, performance was lower than others, due to user's inappropriate lifestyle. Compared to other offices, user travel time is less stable, outdoor work is higher, and weekends are more active.

Table 2: Performance of the proposed system

Area (m2)	60.5	57.4	37.3
Residents (person)	4	3	4
Accuracy (%)	89.76	83.20	88.93

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4. Conclusion

In this paper, the construction and operation of a temperature controller based on machine learning of the smart home system is investigated. We also evaluated its effectiveness, using actual data obtained from small offices. In comparing performance, there is variability in performance depending on the user's health pattern, and performance shows a better outcome when the user has a particular lifestyle. In order to use a more accurate system, more data is needed, and it is important to show the user's purpose by analyzing the information received.

5. References

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