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Improving the control system of smart home automation

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Abstract:

Indoor temperature control systems are crucial for providing a comfortable indoor environment and achieving efficient energy utilization. With the continuous advancement of technology, various advanced technologies and methods have been applied to indoor temperature control systems to enhance their performance and efficiency. Base on the design of a simulated smart home system, the main thing is that, after the sensor data is collected (e.g. temperature), the power knob that controls the temperature is adjusted to get the desired temperature according to the user's needs, or energy efficiency. So the new parameters of this system will be given anew and can be obtained by calculations based on the laws of the physical world such as thermodynamics, or by training the algorithm according to the user's preferences. The core is the modelling of a discrete controller behind it, a second-order approximation of the control system. This article will discuss in detail the improvement methods of indoor temperature control systems.

Keywords: Indoor temperature control systems. Improvement. second-order approximation of the control system.

1. Introduction

Indoor temperature control systems are essential for providing a comfortable indoor environment and achieving efficient use of energy. As technology continues to advance, various advanced technologies and methods are being applied to indoor temperature control systems to enhance their performance and efficiency. In this paper, the enhancement methods of indoor temperature regulation systems will be discussed in detail.

1.1 Background

With the rapid development of the Internet of Things (IoT), Artificial Intelligence (AI), and sensor technologies, smart home systems are becoming part of the modern home. These systems are capable of monitoring and controlling the home environment through a variety of smart devices and sensors, thereby enhancing the convenience, comfort and safety of life. Currently, smart home systems are mainly divided into the following functional modules: environmental control, energy management and intelligent robots.

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This temperature control method can be extended to 2D and 3D heat transfer processes for transient control of sample surface/cross-section temperature field with one or two-dimensional distribution characteristics[1]. However, the current smart home system is not so 'smart' due to the current state of technology.

1.2 Disturbances and Implementation Challenges

External temperature variations: Weather changes can cause temperature swings that the system must compensate for.
Internal heat sources: Occupants, electrical appliances, and lighting contribute heat and must be factored into the control strategy.
Airflow dynamics: Ventilation and air leakage can introduce fluctuations that the controller needs to account for.
Other implementation challenges involve sensor noise and latency in temperature measurement due to the house's thermal inertia, meaning temperature changes are not instantaneous.

1.3 Disturbances and Implementation Challenges

The dynamic system of interest is the home environment, specifically the temperature inside the home. We can measure the temperature using a thermistor or thermocouple sensor strategically placed within the living area[2]. The system can be modeled as a thermal dynamic model, where the house is treated as a thermal mass that reacts to heat inputs (from the heating system) and external disturbances (outside temperature). We may model the open loop behavior by using principles of heat transfer, approximating it with a first-order transfer function like:

$$T(s) = \frac{K}{\tau s + 1} \tag{1}$$

Where $T(s)$ is the indoor temperature, K is the system gain, and τ is the time constant representing how quickly the house heats up or cools down in response to changes in heat input.

2. Current state of the technology

Environmental control: The environmental control module is mainly responsible for regulating the indoor temperature, humidity, lighting and other environmental parameters. Most existing technologies regulate the working status of devices based on preset schedules or simple sensor feedback, such as controlling the start and stop of air conditioners through temperature sensor feedback. While such systems improve living comfort to a certain extent, they lack deep learning of user behavioral habits, resulting in less efficient energy use.
Energy Management: The energy management module focuses on monitoring and optimizing the energy consumption of electrical devices in the home. Energy management (EM) systems, often inte grated with home automation systems, play an important role in controlling home energy con sumption[3]. Most existing smart home systems implement energy management based on timers, simple rule engines or manual settings, such as automatically switching off lights in unoccupied rooms or running energy-intensive devices during low tariff hours. Although such features can save energy to a certain extent, there is still much room for improvement, such as smarter device scheduling with more accurate energy consumption prediction.
Intelligent robots: Smart home systems cannot be separated from intelligent robots, such as intelligent sweeping robots that can automatically clean the home floor and avoid obstacles through sensors and path planning algorithms. Multiple cleaning robots can effectively co-operate to achieve common cleaning goals[4]. For some simple tasks, such as the adjustment of temperature knobs can also not be separated from the robot for end-to-end operation. Motion control, dynamics modelling and multi-sensor data fusion of intelligent robots cannot be separated from the controller design. For these tasks, motion control, dynamics modelling, and multi-sensor data fusion of intelligent robots are very important, and the implementation of these functions relies on the design of the controller. However, most of the current common motion controllers are continuous and cannot cope well with the problem of unsynchronised data sampling frequency and timestamps when dealing with data from different sensors, resulting in a significant decrease in control accuracy.

3. Improvement measures

Existing smart home control systems have made some progress in automation and intelligence, but there are still many areas that can be improved. In order to further enhance the efficiency, intelligence and user experience of the system, improvements can be made in the following areas:
By introducing Machine Learning (ML) models[5], smart home systems can analyse user behavioral habits and environmental changes in real time, so as to optimize the working state of the devices. For example, supervised learning can be used to predict users' temperature preferences at different times of the day, dynamically adjusting the air conditioner's set temperature to avoid unnecessary energy wastage; unsupervised learning can be used to de-

tect abnormal patterns in home electricity consumption, providing early warning of potential security risks.

Future smart home systems can focus more on personalisation and adaptive control[6]. By learning the user's daily habits, the system can automatically adjust the home environment and equipment operation strategy to provide more personalised services. For example, the system can adjust the temperature and light brightness of the bedroom according to the user's sleeping habits, or adjust the operation mode of the air conditioner according to seasonal changes to make the living environment more comfortable.

With the development of embedded systems, discrete controllers[7] show better adaptability and control accuracy in most cases. Compared to continuous controllers, discrete controllers are easier to integrate with digital systems, especially when dealing with data from different sensors, and are better able to cope with the problem of unsynchronised data sampling frequencies and time stamps. This makes the application of discrete controllers in smart home systems more promising.

Experiments were conducted in real buildings to validate the feasibility and effectiveness of the deep learning and model-based predictive control approach in real-world environments. This study presented a novel real-time indoor temperature control system based on occupant-centered monitoring using deep learning algorithms (i.e., Real-COMFORT) to optimize individual occupant thermal comfort and energy consumption based on a climate chamber experiment [8]. This method proved to be significantly better in terms of energy savings (40.56 per cent reduction in electricity consumption for cooling and 16.73 per cent reduction in electricity consumption for heating) and in terms of comfort for the inhabitants[9].

4. Definition and modelling analysis

The following is a definition and modelling analysis of the variables that may be involved in a smart home control system:

Input variable u(k): an input variable refers to a control signal or external influence received by the system at a specific point in time. For example, in a smart thermostat system, the input variable can be the power setpoint of a heater or air conditioner, indicating the control effort that the system wishes to exert. In addition, the external ambient temperature can also be considered as a perturbing input variable that affects the dynamic response of the system.

Output variable y(k): the output variable is the state or response of the system at a point in time. For example, in a room temperature control system, the output variable is the current room temperature. Output variables in a smart home system may also include the light intensity of the room, air quality, device status (e.g., light switch status), and so on.

State variables x1(k), x2(k): state variables are variables that describe the internal state of a system and are usually used to acquisition the dynamic behaviour of the system. In second-order systems, state variables can be used to represent the historical state of the system, such as the room temperature at the previous moment and the temperature at the previous two moments. These state variables determine the output of the system and respond to input signals.

System parameters, which reflect the characteristics and dynamic behaviour of the system. For example, and can represent the heat capacity and heat loss of a room, while b0, b1 and b2 represent the efficiency and response rate of a heater or air conditioner. These parameters are usually obtained through system identification or training based on historical data.

Perturbation variable d(k): a perturbation variable is an external factor that affects the system but is not under control, such as changes in the external temperature or fluctuations in the household electricity load. These perturbations may affect the output of the system, so the effects of the perturbations need to be considered when designing the control strategy.

Combining these variables, a second-order control system in a smart home can be used as follows

$$y(k)+a_1y(k-1)+a_2y(k-2)=b_0u(k)+ b_1u(k-1)+b_2u(k-2)+d(k) \tag{2}$$

With this model, smart home systems can dynamically adjust their control strategies in response to user needs and environmental changes. For example, a smart thermostat can use the model to predict trends in room temperature and automatically adjust the power of the air conditioner or heater according to user habits and changes in the outside temperature, thereby optimising energy use while ensuring comfort. In addition, by updating the model parameters in real time, the system can adapt to changes in the home environment and user behaviour to provide a more personalised service.

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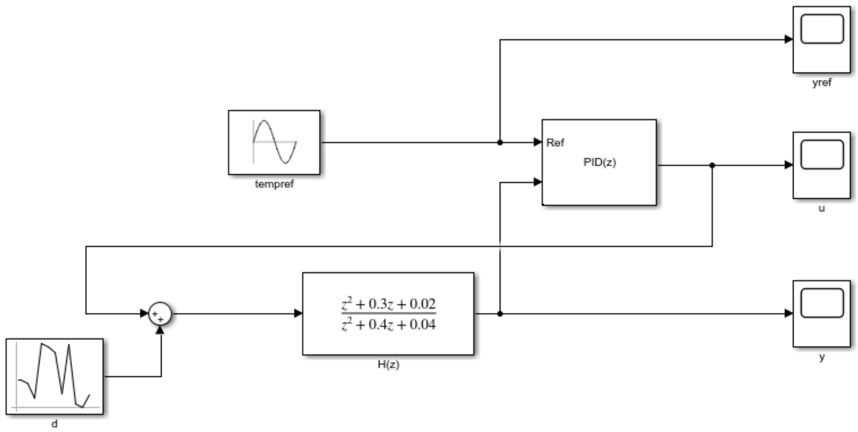

Fig. 1 Second-order control systems

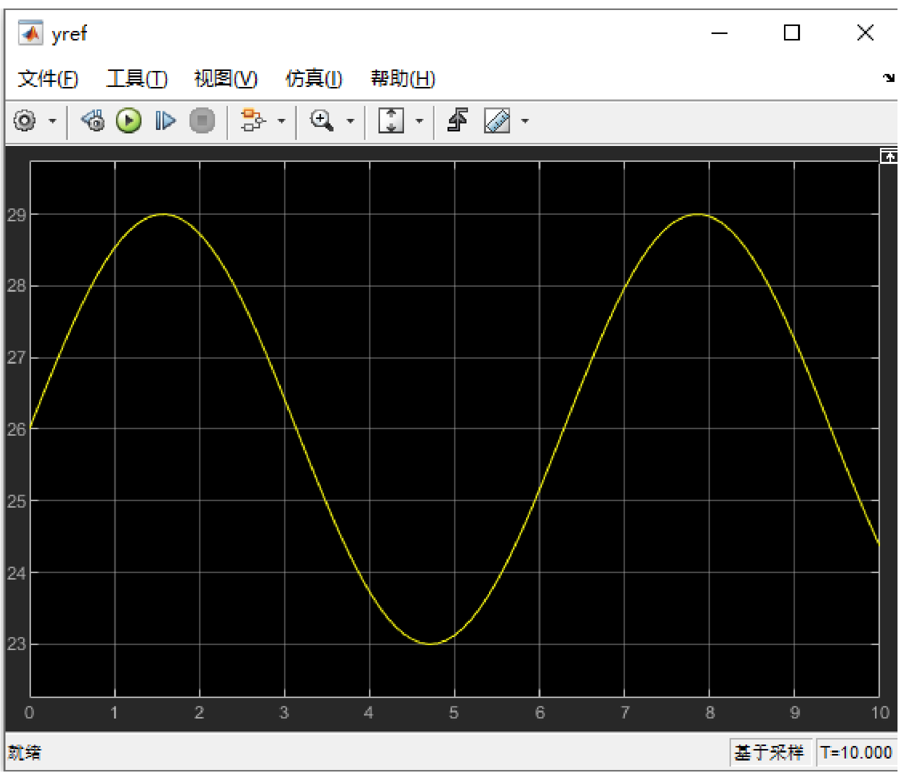

Fig. 2 System Desired Input

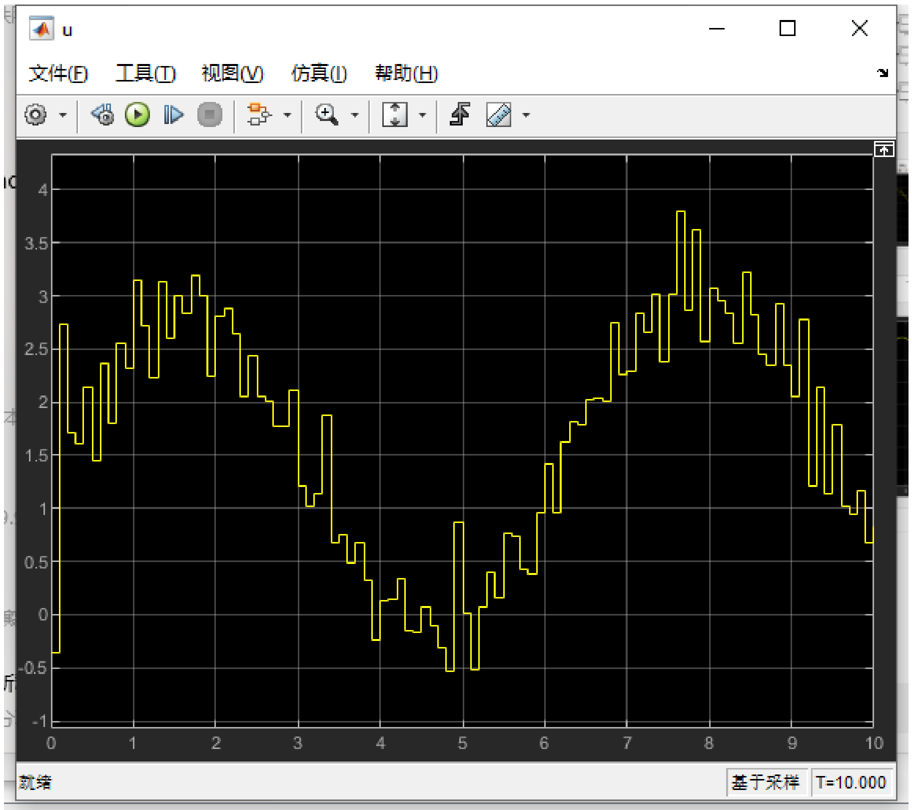

Fig. 3 System Input

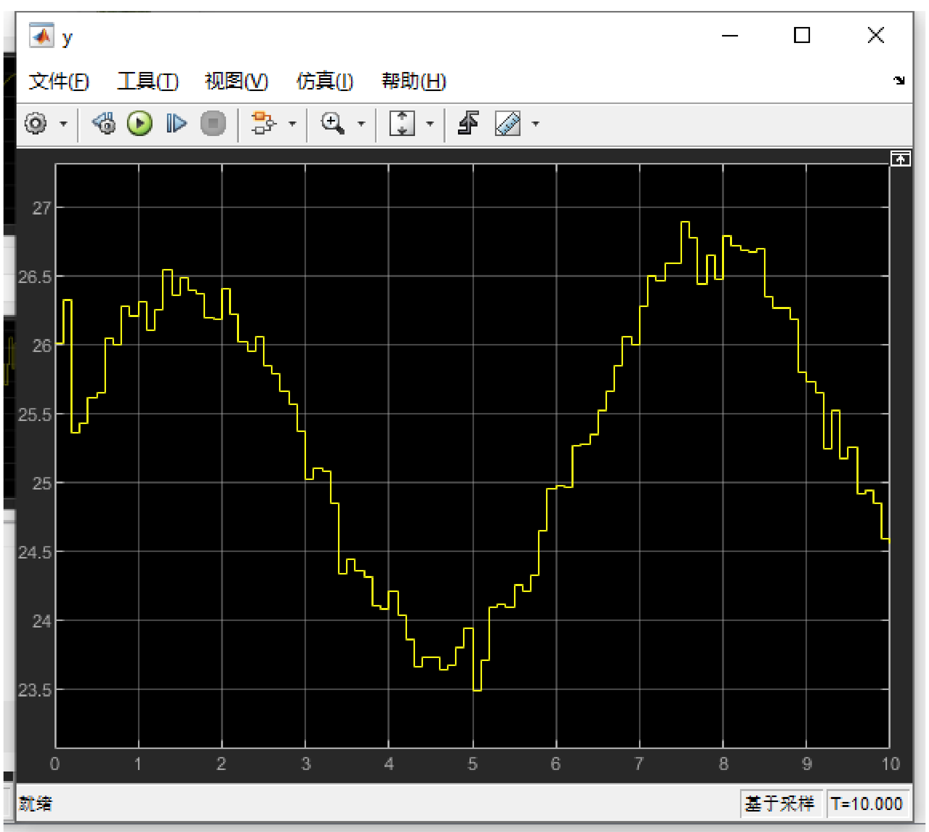

Fig. 4 system output

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As shown in Fig. 1, we simulate this second-order control system using simulink in matlab, and we are given a random set of system parameters to get the z transfer function of the system. The sampling period of this controller is set according to different situations, here a time step of 1ms is used, Yref is the desired input of the system (shown in Fig. 2), and the feedback of the system as a difference through the classical PID controller to get the system input, here the system input (shown in Fig. 3) is also an additional introduction of a white noise, and finally the system output (shown in Fig. 4).

5. Conclusion

Improving energy efficiency and comfort: By introducing adaptive control algorithms, predictive models and optimised control strategies, indoor temperature control systems are able to significantly reduce energy consumption while ensuring comfort.

Intelligent Trend: Using artificial intelligence and machine learning technologies, indoor temperature control systems are moving towards a more intelligent and personalised direction, which can better meet the needs of different users.

Most of the current systems still rely on preset control parameters and lack consideration of individual user needs. Future research could focus more on user involvement and optimise control strategies through user feedback and behavioural data[10].

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