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GRU와 IoT 기반의 지능형 온도 제어 시스템

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Intelligent Temperature Control System Utilizing Gated Recurrent Units and the Internet of Things

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[요 약]

현재의 온도 제어 시스템은 에너지 절약과 삶의 질 향상에 있어 점점 더 많은 과제에 직면해 있다. 기존의 지능형 온도 제어 시스템은 동적 조정 및 예측 기능이 부족하여 쾌적성과 에너지 효율성이 떨어진다. 본 논문에서는 IoT와 GRU를 통합하여 생활의 쾌적성을 높이고 에너지 사용을 최적화하는 지능형 온도 제어 시스템을 제안한다. 이 시스템은 IoT를 통해 실시간 데이터를 수집하고 GRU를 활용하여 사용자 행동 패턴과 환경 변화를 학습하고 에너지 절약 모드를 동적으로 조정하여 에너지 소비를 크게 줄이면서 쾌적함을 극대화한다. 실험 결과 이 시스템은 온도 예측 정확도를 개선하고 에너지 소비를 줄이며 사용자의 편안함을 향상시키는 것으로 나타났다. 미래의 지능형 홈 온도 제어 시스템을 위한 이론적, 실용적 토대를 마련했다. 몇 가지 한계에도 불구하고 이 시스템은 추가적인 최적화와 확장을 통해 스마트 홈 애플리케이션의 핵심 기술이 될 잠재력을 가지고 있으며, 스마트 홈 솔루션의 광범위한 채택을 위한 길을 열어줄 것이다.

[Abstract]

Existing temperature control systems are increasingly inadequate in addressing the dual demands of energy conservation and enhanced quality of life owing to their limited adaptability and predictive capabilities. Traditional intelligent temperature control systems, including earlier intelligent models, often lack dynamic adjustment and predictive mechanisms, leading to reduced user comfort and suboptimal energy efficiency. This paper proposes an intelligent temperature control system that integrates the Internet of Things (IoT) and gated recurrent units (GRUs) to enhance living comfort and optimize energy usage. The system collects real-time data through IoT sensors, utilizing the GRU to learn user behavior patterns and environmental fluctuations, dynamically adjusting energy-saving modes to maximize comfort while significantly reducing energy consumption. Experimental results demonstrate that the system improves temperature prediction accuracy, reduces energy consumption, and enhances user comfort. This research lays both theoretical and practical foundations for future intelligent home temperature control systems. Despite some limitations, with further optimization and scaling, this system has the potential to become a key technology in smart home applications, paving the way for broader adoption of smart home solutions.

색인어 : 사물 인터넷, 게이트 순환 유닛, 온도조절기, 에너지 절약, 스마트 홈
Keyword : Internet of Things (IoT), Gated Recurrent Unit (GRU), Temperature Control, Energy-Saving, Smart Home

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Ⅰ. Introduction

In recent years, with the rise of artificial intelligence and the Internet of Things (IoT), coupled with the push from the pandemic forcing more people to work from home, there has been an increasing demand for higher-quality home living. Many smart cities have seen a significant increase in demand for smart home applications[1]. IoT devices from some smart enterprises have gradually solved network application issues through the rise of low-power wide-area network (LPWAN) wireless communication solutions represented by NB-IoT, eMTC, and LoRa, further reducing consumption and costs[2]. However, improving people's quality of life while saving more energy remains a significant challenge.

Smart home temperature control systems play an essential role in improving the comfort of living environments and energy utilization efficiency. Under the influence of global greenhouse effects, temperature has become a crucial measure of comfort. More suitable temperatures can effectively enhance people's comfort. IoT can integrate various information -sensing devices and networks to achieve mutual connectivity among people, machines, and objects at any time and place. In smart home temperature control systems, people can control the home's temperature through IoT anytime and anywhere, such as turning on the air conditioner or heater before returning home to ensure a comfortable temperature. In recent years, much research has focused on using machine learning algorithms to analyze and predict user behavior patterns in order to optimize the operational efficiency of home automation systems. For example, a study by Zhang et al.[3] shows how deep learning models can be used to predict users' daily behaviors and automatically adjust the operation of home devices accordingly.

Gated recurrent unit (GRU) is a type of recurrent neural network that is more suitable for short-term environmental control tasks compared to traditional RNNs[4]. In smart greenhouse systems, the environment is relatively simple, and using GRU's computational efficiency can reduce the system's computational burden while maintaining good performance. The smart home temperature control system combining IoT and GRU can collect indoor and outdoor environmental data through sensors, quickly adjust the indoor environment based on GRU's predictions, analyze users' temperature control habits and patterns, learn users' personalized needs, and adjust temperature settings according to daily life patterns to improve comfort and energy-saving effects. Somporn Sirisumrannukul and others[5] demonstrated in their research on smart home cooling management systems that combine artificial intelligence and IoT with home energy management and complex backend infrastructure, which can maximize energy efficiency. They used various sensors, gateways, IoT devices, and servers to collect real-time data and used artificial neural networks (ANN) and particle swarm optimization (PSO) algorithms to complete an energy-saving smart home cooling system while maintaining user comfort.

Google's Nest system combines machine learning algorithms and IoT technology[6], learning users' preferences and daily habits, automatically adjusting the temperature, providing comfort, and reducing energy consumption.

This paper proposes an intelligent temperature control system based on GRU and IoT to achieve a more comfortable, energy-saving, and environmentally friendly home, thus improving people's quality of life. The purpose of the system is to combine IoT and GRU, collect indoor and outdoor environmental data through sensors, quickly adjust the indoor environment based on GRU's predictions, analyze users' temperature control habits and patterns, learn users' personalized needs, and adjust temperature settings according to daily life patterns to improve comfort and energy-saving effects.

This proposed model used the efficient time series processing of GRU[7], which is very helpful for adjusting temperature control systems to cope with environmental changes. Compared to LSTM, GRU's structure is simpler and has lower computational overhead, making it suitable for widespread home use. Additionally, GRU can process data quickly and respond promptly, which is crucial for achieving energy-saving effects through timely adjustments.

This system utilizes IoT devices to collect home environment data in real time, providing rich data inputs for the temperature control system. Users can also remotely control the system through mobile apps or cloud platforms, achieving more flexible temperature management[8].

The system has the following features: First, GRU can process the massive data collected by IoT and predict and adjust the temperature more accurately[9]. Second, GRU can learn users' habits and preferences, continuously optimize the plan through IoT feedback[10], to provide better and more personalized services. Third, Higher energy efficiency, the combination of GRU and IoT devices can optimize temperature control plans through real-time data, reducing energy waste. Fourth, Timely feedback, if data is significantly abnormal, it can promptly alert users to reduce potential losses. Fifth, The combination of GRU and IoT devices can be applied not only to standalone temperature control systems but also they optimize the overall home environment for smart home systems.

II. GRU and IoT in Smart Home Temperature Control

2-1 Status of GRU and IoT

Current smart temperature control systems can remotely control home temperature control devices through smartphones, adjusting the indoor temperature anytime and anywhere. Users can also use smart speakers, such as Amazon Alexa, Baidu's Xiaodu, and Xiaomi's Xiaoyi, to control the temperature with voice commands. Ecobee thermostats are equipped with remote sensors[11], which can detect the temperature conditions of different rooms and optimize the home's temperature control. While traditional smart thermostats were limited in their dynamic adjustment and predictive capabilities during their initial introduction, advances in artificial intelligence technology and machine learning algorithms have significantly improved these limitations in recent years. For example, modern smart thermostats such as Nest and Ecobee have the ability to learn user habits and adjust the temperature automatically. These systems are becoming increasingly sophisticated and use predictive algorithms to analyze your living patterns and environmental changes to maintain optimal room temperatures.

However, further research is still needed to improve their predictive performance in more complex environments and their ability to process real-time data. In particular, more sophisticated algorithms and technological advances are needed to enable real-time responses that take into account multiple variables and more accurate long-term predictions.

However, traditional smart temperature control systems rely more on preset schedules and simple rules for temperature adjustment[12], lacking dynamic adjustment capabilities and predictive abilities. Traditional smart temperature control systems also have limited data sources, relying solely on indoor temperature sensor data, which cannot fully reflect environmental changes. Moreover, data processing and response speed are relatively slow, unable to adjust the temperature in real time. In terms of energy utilization, traditional systems have fixed energy-saving modes, lack flexibility, and require users to make adjustments based on settings, leading to reduced comfort and energy waste.

Research on smart home temperature control systems currently focuses more on overall smart home control systems, without significantly improving comfort and energy savings in temperature control.

2-2 Previous Works of GRU and IoT

With the maturity of IoT technology and the development of artificial intelligence, people's pursuit of comfort and energy savings in daily life is increasing. Neural networks such as gated recurrent units (GRUs) can have efficient predictive performance in temperature control systems, but they don't always provide the best performance in all scenarios. While GRUs benefit from computational efficiency due to their simplified structure, other recurrent neural network models such as long short-term memory (LSTMs) may be more appropriate when dealing with more complex patterns or when long-term dependencies need to be considered. LSTMs are better at balancing long- and short-term memory, so there are situations where they can provide better performance than GRUs.

Therefore, when choosing a neural network in a smart temperature control system, it is important to determine the optimal model between GRUs, LSTMs, or other models depending on the specific environment and scenario. While GRUs can be advantageous in certain situations due to their simple structure and high efficiency, LSTMs or other deep learning models may be better suited for situations where more complex data or multiple environmental variables need to be considered. These advantages not only enhance the system's intelligence and efficiency but also provide more personalized and convenient user experiences, promoting the overall development of smart home systems.

Yilin Jiang and others[13] used model predictive control for pre-cooling simulations in their research. They used MPC agents with grey-box models to capture household thermal dynamics, reducing energy costs for cooling spaces during hot summers by 28.72%~51.31% and up to 60.32% during mild summers. This research illustrates the importance of temperature prediction in intelligent temperature control. Moon-Sun Shin et al.[14] proposed an IoT-based intelligent monitoring framework, using GRU and LSTM to measure the internal temperature of low-temperature refrigerators and the temperature of each component, ensuring high-precision detection and management of the low-temperature freezer's state to prevent sample spoilage. Experiments demonstrated the reliability of IoT-based intelligent monitoring frameworks using GRU and deep RNNs for temperature detection and prediction. Beatrice Faniyi and Zhenhua Luo[15] applied IoT to greenhouse systems for temperature control, as microclimates affect crop metabolism and yield, requiring detection and control to maximize yield and quality with minimal energy consumption, thereby maximizing profits. As an evolving environmental monitoring and control technology, IoT has been widely used in temperature measurement and has shown excellent performance.

Ⅲ. GRU Temperature Prediction

3-1 Overview

Existing smart temperature control systems use various technologies and methods to achieve temperature control, each with unique implementation methods and working principles. These systems generally use sensors to detect the environment then use preset patterns to adjust and control the temperature. For example, in smart thermostats, built-in temperature sensors can monitor indoor temperature, humidity sensors can monitor humidity, and Wi-Fi connectivity can feedback information to the user's smartphone application. Users can check the temperature and decide whether to adjust it, remotely controlling the thermostat and other temperature control devices to change the indoor temperature to a comfortable range. In summary, although smart thermostats, smart air conditioner controllers, smart floor heating control systems, smart windows, and shading systems have unique implementation methods and working principles, they all integrate IoT to feedback temperature information to users and trigger different scenarios based on user settings, such as sleep mode and away mode, automatically adjusting device operation status. Fig. 1 describes the traditional intelligent thermostat temperature control method.

To mitigate privacy and security risks associated with data collection through IoT devices, a robust data protection plan is essential. First, implement end-to-end encryption (E2EE) for data transmission, utilizing advanced encryption standards like AES-256 and RSA for secure key exchange, while also encrypting stored data using strong encryption methods to protect it from unauthorized access. Apply the data minimization principle to ensure only necessary data is collected, and use anonymization and pseudonymization techniques to safeguard user identities. Employ role-based access control (RBAC) to restrict data access to authorized personnel, and establish secure communication protocols like HTTPS and MQTT over TLS to protect data during transmission. Regularly rotate encryption keys and set reasonable data retention periods to minimize risks associated with long-term storage. Ensure transparency by allowing users to manage their data preferences and obtain informed consent, while conducting regular audits and maintaining logs of data access. Finally, deploy an intrusion detection system (IDS) for real-time monitoring and response to suspicious activities, and ensure timely updates and vulnerability patches for firmware and software to maintain system integrity. This comprehensive approach enhances user trust and significantly mitigates the risk of data breaches in a smart home context.

In this paper, we propose a smart home temperature control system combining GRU and IoT, which can effectively predict temperatures, learn user behavior patterns and environmental changes, and reduce user intervention. By collecting real-time data through IoT, the system proactively adjusts energy-saving modes based on real-time data and predictive models, ensuring comfort while minimizing energy consumption. Unlike existing systems, the proposed system includes a “user behavior prediction” module (using the GRU model). This module can predict the user's behavior patterns and adjust the temperature settings in advance. This prediction feature is not available in the existing system. In addition to temperature sensors, the proposed system introduces various sensors to fuse data to provide a more comprehensive view of the environment. This data is used not only to control the current temperature but also to predict and prepare for future changes in the situation.

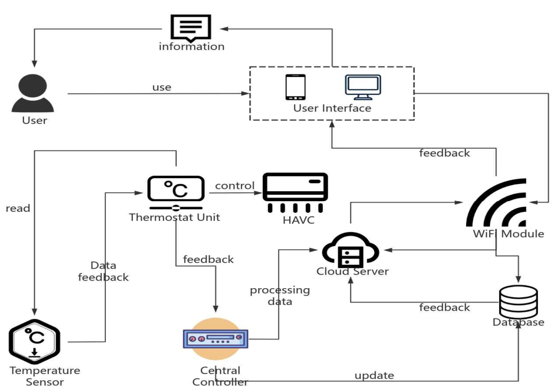

Fig. 1. Traditional temperature control method diagram

3-2 System Design

This section details the system architecture of the smart home temperature control system based on IoT and GRU technology. The system mainly consists of four parts:

① IoT Devices is consist of four parts:

- Temperature Sensors: These sensors continuously monitor the ambient temperature in real-time. They provide critical data to the system, allowing it to adjust the heating and cooling devices as necessary to maintain the desired indoor climate.
- Humidity Sensors: These sensors track the environmental humidity levels. The data they provide helps in fine-tuning the climate control, as humidity can significantly affect perceived temperature and comfort.
- Heating Devices: These include heaters and other similar appliances that increase the indoor temperature. They are activated or deactivated based on the temperature data and control strategies.
- Cooling Devices: Devices such as air conditioners. They work to reduce the temperature within the home when the system determines that cooling is necessary.

② Central Controller is consist of three parts:

- Processor: It is responsible for making real-time decisions based on the data received from the IoT devices and the predictive models provided by the cloud server.
- Communication Modules: Wi-Fi/Bluetooth modules for communication with cloud servers and other devices. This connectivity is crucial for data exchange and remote control.
- Real-Time Operating System (RTOS): The RTOS manages multitasking within the central controller, ensuring that all processes are executed efficiently and in a timely manner.

③ Cloud Server is consist of two parts:

- Data Storage: This component securely stores all sensor data, user preferences, and historical records. The data repository is essential for long-term analysis and for improving the system's predictive capabilities over time.
- GRU Model: A type of neural network that uses the historical data stored to predict future temperature trends. The GRU model helps in optimizing control strategies by predicting temperature changes and adjusting the heating or cooling devices accordingly.

④ User Interfaces is consist of two parts:

- Mobile App: Users can view and adjust temperature settings via smartphones. It offers a convenient way to interact with the system remotely.
- Web App: Provides system and historical data access through web interfaces.

This design ensures that temperature control system is both efficient and user-friendly, leveraging IoT and GRU technology to maintain optimal indoor conditions while allowing users to have full control over their environment.

1) Data Collection and Transmission

The data collection process is as follows: Temperature and humidity sensors periodically collect environmental temperature and humidity data (if the network connection is unstable, the sensors temporarily store the data locally). Sensors are distributed in key areas to ensure coverage of the required test environment. Then, sensors send the data to the central controller through wireless communication modules (we use the most common Wi-Fi). The central controller is the core node of data collection and transmission, responsible for aggregating sensor data.

To effectively address the critical concerns of data security and privacy in the system design that integrates IoT devices, a central controller, and a cloud server, it is essential to implement a comprehensive privacy protection strategy. Given that the collected data includes sensitive information such as temperature readings, real-time location data, and user behavior patterns, several key measures should be adopted. Firstly, robust data encryption protocols, such as AES-256, must be employed for both data in transit and at rest to ensure that unauthorized access renders the data unreadable. Additionally, privacy-preserving machine learning techniques like federated learning or differential privacy should be utilized, allowing for model training on decentralized data without exposing individual data points, thus enabling users to set parameters for data sharing.

Furthermore, the system should feature a user-friendly interface that allows individuals to manage their privacy settings, ensuring transparency regarding data collection and usage. Employing anonymization and pseudonymization techniques will further protect personal identifiers, reducing the risk of re-identification. Regular audits of data handling practices are necessary to maintain compliance with privacy regulations, while educational resources should be provided to users to raise awareness about data privacy. By incorporating these strategies, the system can effectively safeguard user data, foster trust, and ensure responsible handling of sensitive information in a smart home environment.

The central controller performs data cleaning, which includes handling missing values and detecting and filtering outliers. Missing values are generally handled using interpolation, mean imputation, and regression imputation methods, while outlier detection and filtering use statistical methods (e.g., standard deviation, interquartile range) or machine learning algorithms (e.g., isolation forest, DBSCAN). The data is then normalized, converting data with different dimensions into the same range (e.g., 0 to 1) to improve the effectiveness of subsequent machine learning model training. Finally, data format conversion is performed, converting raw data into a format suitable for model training and prediction, such as converting time series data into sliding window format for input into the GRU model.

The central controller uploads the processed data to the cloud server through an IoT gateway, using constrained application protocol (CoAP), which is more suitable for IoT environments. The cloud server receives and stores the data, preparing it for further processing and analysis. We chose Amazon S3 to store the massive sensor data, ensuring high data availability and scalability. The Fig. 2 illustrates how data collection and transfer are carried out in this system. This data transmission structure ensures data accuracy, transmission stability, and high quality, providing a better foundation for subsequent temperature predictions

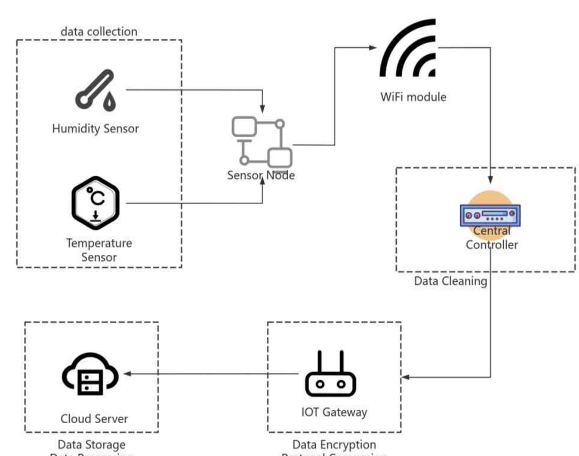

Fig. 2. Data transmission diagram

2) GRU Temperature Prediction Model

GRU is an improved type of recurrent neural network (RNN) that addresses the vanishing gradient problem in traditional RNNs when learning long-term dependencies by introducing gating mechanisms. Compared to traditional RNNs and other variants, GRU has a simpler structure and offers advantages in computational efficiency and handling long-term dependencies. In practical smart home temperature control systems, real-world data may be subject to many disturbances. GRU is capable of effectively processing and utilizing imperfect data, providing more stable temperature prediction and control.

The GRU model consists of three parts: the input layer, GRU units, and the output layer. The input layer receives time-series data, with each input sample comprising features from multiple time steps. In a temperature control system, the input data may include temperature and humidity data from the past N time steps. The GRU unit contains two primary gates: the update gate and the reset gate[4]. The update gate controls how much information from the hidden state of the previous time step needs to be passed to the current time step, while the Reset Gate controls how much of the previous hidden state needs to be reset. These gates allow GRU to effectively capture long-term dependencies in time-series data by controlling the flow and forgetting of information.

After data cleaning and normalization, historical data is segmented into fixed-length time windows, which serve as input features for the model.

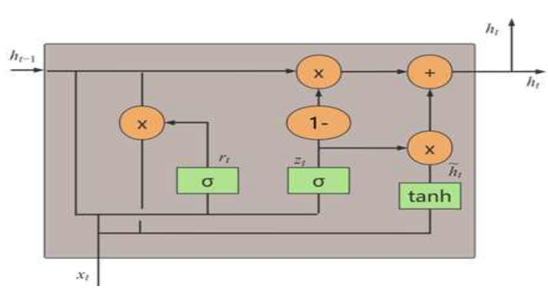

Fig. 3. GRU model

3-3 System Process

In the smart home temperature control system, the process is crucial to ensure accurate data collection and input, followed by temperature prediction using the GRU model, and finally, the generation of the overall temperature control policy. The overall process is shown in the Fig. 4.

The system process begins with sensors deployed in various locations collecting real-time environmental data such as temperature and humidity, which is then transmitted to the central server. The central server collects the sensor data, performs data collection and preprocessing, such as handling missing values, denoising, and normalization, and uses the preprocessed data to train the GRU model.

The GRU input layer receives time-series data, the hidden layer processes the time series, capturing long-term dependencies, and the fully connected layer outputs the predicted temperature values. The GRU model is then trained using the training dataset, and its performance is evaluated using the validation and test datasets, with hyper-parameters being adjusted and the model optimized.

The system continuously collects real-time data from IoT sensors, making ongoing predictions and adjustments. The trained GRU model is used to predict temperatures based on real-time input data. Temperature control strategies are generated based on the temperatures predicted by the GRU model, controlling related devices such as air conditioners and heaters to maintain the environmental temperature within the set range. The control strategy is then used to automatically adjust the heating, ventilation, and air conditioning (HVAC) system, and the system continuously monitors the effectiveness of the HVAC system, making real-time adjustments and optimizations.

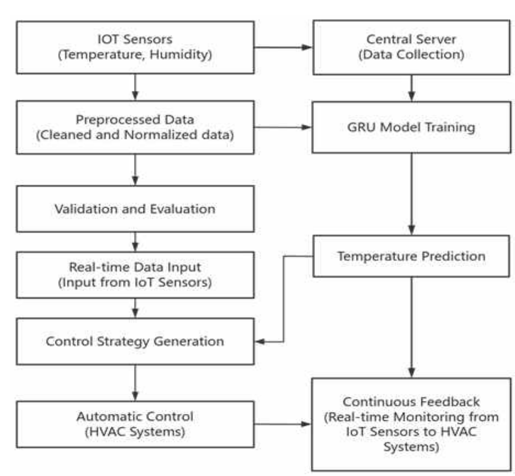

Fig. 4. Flow chart of GRU model in intelligent temperature control system

The system process generally includes several key steps, which are more vividly with a sequence diagram just like Fig. 5. In the system, IoT sensors collect data, which is then transmitted to the central controller. The central controller performs data preprocessing, and subsequently, the GRU model analyzes and processes the data to predict future changes. Based on this prediction, the system generates corresponding temperature control strategies to adjust the operation of the HVAC system. Finally, the system continuously collects real-time data for feedback, and the GRU model continuously self-adjusts and optimizes to ensure that the system always operates efficiently and stably.

IV. Evaluation and Result

4-1 Experimental Method

To evaluate the feasibility and performance of the system design, historical temperature and humidity data were collected from a smart home environment. The dataset covers a three-month period with hourly records of temperature and humidity. The experiment utilized a multi-layer GRU model, and the Adam optimizer was employed for model training. To further enhance the model's prediction accuracy, hyperparameters such as the number of hidden units and learning rate were tuned and optimized.

70% of the dataset was allocated to the training set, 15% to the validation set, and the remaining 15% to the test set. The model's predictive performance was evaluated using the test set, with metrics such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). To prevent the model from overfitting during training, regularization techniques such as L2 regularization and dropout were applied. In addition, cross-validation was employed to ensure the model's generalization performance, and early stopping was used to prevent overfitting during the training process.

4-2 Performance Evaluation

To provide a more comprehensive assessment of the GRU model's performance in the smart temperature control system, the GRU model was compared with other commonly used time-series prediction models, including a simple linear regression model and an LSTM model. The same dataset was used for training and evaluation, and metrics such as MSE, RMSE, and MAE were calculated. Additionally, we introduced R^2 and Mean Absolute Percentage Error (MAPE) to evaluate the models from a broader perspective:

- R^2 : A value closer to 1 indicates that the model better explains the variability of the data.
- MAPE : Reflects the average relative error between the predicted and actual values, helping to measure the prediction accuracy of the model.

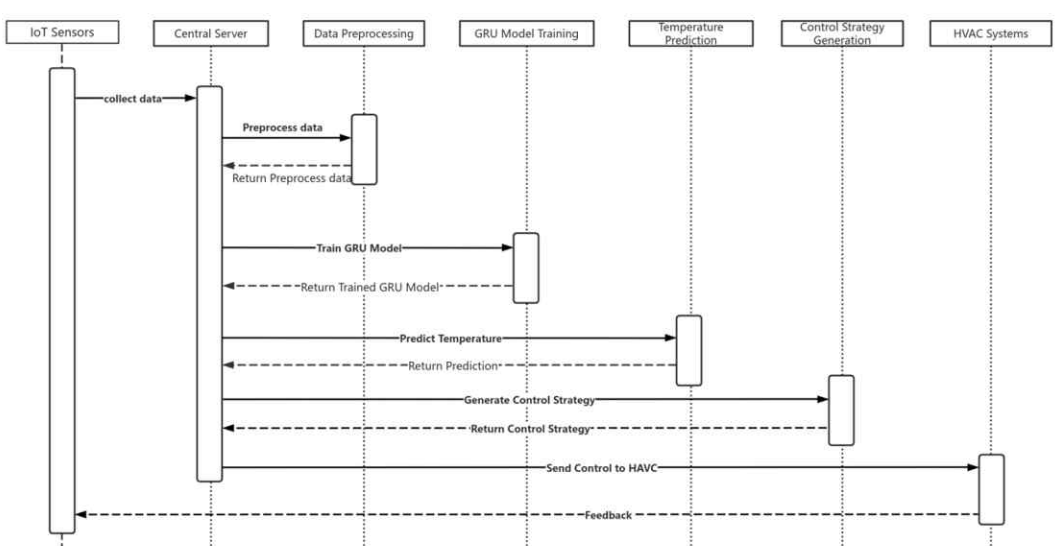

Fig. 5. Intelligent temperature control system sequence diagram

Table 1. Performance evaluation table of three models

Model	MSE	RMSE(R²)	MAPE
Linear Regression	1.11	1.06	0.88
LSTM	0.50	0.73	0.36
GRU	0.45	0.76	0.32

As shown in Table 1, the MSE for the simple linear regression model was 1.11, RMSE was 1.06, and MAE was 0.88, with an R^2 of 0.65 and a MAPE of 12.4%, indicating that this model struggles to capture the complexity of temperature changes. The LSTM model had an MSE of 0.50, RMSE of 0.73, MAE of 0.36, R^2 of 0.85, and MAPE of 4.7%, performing better than the linear regression model. The GRU model achieved an MSE of 0.45, RMSE of 0.76, MAE of 0.32, R^2 of 0.87, and MAPE of 4.3%, excelling in high-precision predictions and capturing temporal dependencies, while also being more computationally efficient compared to the LSTM. To provide a more intuitive comparison between the predicted and actual values, we plotted line charts that visualize the performance of the three models.

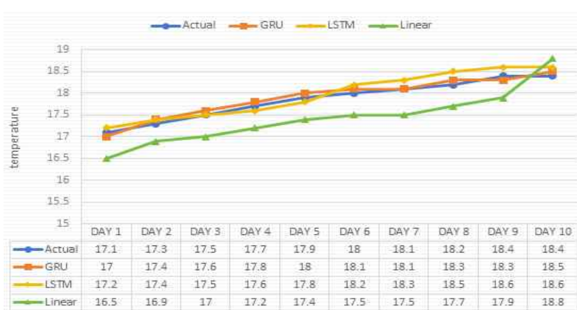

Fig. 6. Line chart of temperature prediction vs. Actual temperature for three models

From Fig. 6, it can be observed that the multi-layer GRU model produces the smallest error between the predicted and actual values, demonstrating its ability to effectively capture trends and fluctuations in temperature changes. The LSTM model comes second, with performance close to that of the GRU but with higher computational complexity and training time. The simple linear regression model shows larger errors, failing to capture the complexity and non-linear relationships in temperature variations.

Despite the strong performance of the GRU model, the dataset used only covers a three-month period, meaning the results may be limited to specific seasonal and climatic conditions. To further enhance the model's applicability, future research should incorporate a full year's dataset and conduct real-time testing in actual smart home environments to verify the model's robustness under various conditions. Additionally, given the security and privacy concerns associated with IoT devices, future system designs should integrate encryption and privacy protection measures to ensure the safe handling of user data.

V. Conclusion

This study proposes an intelligent home temperature control system based on GRU and IoT. The system combines the real-time predictive capabilities of the GRU model with the real-time data collection capabilities of IoT sensors, enabling rapid response to environmental temperature changes and providing a new solution in the field of smart homes. By using time-series prediction techniques to improve temperature control accuracy and efficiency, the system achieves the effect of enhancing living comfort and saving energy. By leveraging the GRU model for learning time-series data, the system can accurately predict future temperature changes. Experimental results show that the GRU model performs exceptionally well in metrics such as MSE, RMSE, and MAE, significantly outperforming traditional linear regression models and LSTM models.

The challenges and limitations encountered in this system are primarily related to the system's performance being highly dependent on the quality and quantity of historical data. If data quality is low or data is scarce, the accuracy of temperature predictions may be affected. If the placement of sensor devices is incorrect, leading to problematic data collection, this could also have a significant impact on temperature predictions. Therefore, to improve prediction accuracy, it is crucial to collect various data from the current environment and user usage habits.

Future research can explore the following directions: For example, introducing more types of data, including local climate and weather forecast data, to further improve prediction accuracy and system responsiveness through multimodal data fusion. Additionally, exploring the integration of the temperature control system with other smart home systems could create a more comprehensive smart home ecosystem, providing users with a more convenient and comfortable living experience.

In conclusion, this study successfully constructed and validated an intelligent home temperature control system based on GRU and IoT. Experimental results indicate that this system has advantages in improving temperature prediction accuracy, reducing energy consumption, and enhancing user comfort. Although some limitations still exist, with future optimization and expansion, this system is expected to become a key technology in the smart home field, laying a solid foundation for the widespread application of smart homes.

References

[1] B. L. R. Stojkoska and K. V Trivodaliev, "A Review of Internet of Things for Smart Home: Challenges and Solutions," *Journal of Cleaner Production*, Vol. 140, pp. 1454-1464, January 2017. https://doi.org/10.1016/j.jclepro.2016.10.006

[2] M. Bor, J. Vidler, and U. Roedig, "LoRa for the Internet of Things," in *Proceedings of the 2016 International Conference on Embedded Wireless Systems and Networks (EWSN '16)*, Graz, Austria, pp. 361-366, February 2016.

[3] M. Goutham, Machine Learning Based User Activity Prediction for Smart Homes, Master's Thesis, The Ohio State University, Columbus, OH, 2020.

[4] R. Dey and F. M. Salem, "Gate-Variants of Gated Recurrent Unit (GRU) Neural Networks," in *Proceedings of 2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)*, Boston: MA, pp. 1597-1600, August 2017. https://doi.org/10.1109/MWSCAS.2017.8053243

[5] S. Sirisumrannukul, T. Intaraumnauy, and N. Piamvilai, "Optimal Control of Cooling Management System for Energy Conservation in Smart Home with Anns-Pso Data Analytics Microservice Platform," *Heliyon*, Vol. 10, No. 6, e26937, March 2024. https://doi.org/10.1016/j.heliyon.2024.e26937

[6] G. Noto La Diega and I. Walden, Contracting for the 'Internet of Things': Looking into the Nest, Queen Mary University of London, London, UK, QMUL School of Law Legal Studies Research Paper, No. 219/2016, February 2016.

[7] K. Zhang, N. Chen, J. Liu, and M. Beer, "A GRU-Based Ensemble Learning Method for Time-Variant Uncertain Structural Response Analysis," *Computer Methods in Applied Mechanics and Engineering*, Vol. 391, 114516, March 2022. https://doi.org/10.1016/j.cma.2021.114516

[8] S. J. Philip, T. J. Luu, and T. Carte, "There's No Place Like Home: Understanding Users' Intentions toward Securing Internet-of-Things (IoT) Smart Home Networks," *Computers in Human Behavior*, Vol. 139, 107551, February 2023. https://doi.org/10.1016/j.chb.2022.107551

[9] S. K. Singh, M. Kumar, S. Tanwar, and J. H. Park, "GRU-Based Digital Twin Framework for Data Allocation and Storage in IoT-Enabled Smart Home Networks," *Future Generation Computer Systems*, Vol. 153, pp. 391-402, April 2024. https://doi.org/10.1016/j.future.2023.12.009

[10] T. Akilan and K. M. Baalamurugan, "Automated Weather Forecasting and Field Monitoring Using GRU-CNN Model along with IoT to Support Precision Agriculture," *Expert Systems with Applications*, Vol. 249, 123468, September 2024. https://doi.org/10.1016/j.eswa.2024.123468

[11] M. Aibin, "The Weather Impact on Efficient Home Heating with Smart Thermostats," in *Proceedings of 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, Edmonton, Canada, pp. 1-4, May 2019. https://doi.org/10.1109/CCECE.2019.8861778

[12] M. O. Turakulovich, "Development and Installation of an Automatic Temperature Control System in Rooms," *International Multidisciplinary Journal for Research & Development*, Vol. 10, No. 12, December 2023.

[13] Y. Jiang, K. A. Ejenakevwe, J. Wang, C. Y. Tang, and L. Song, "Development, Implementation, and Impact Analysis of Model Predictive Control-Based Optimal Precooling Using Smart Home Thermostats," *Energy and Buildings*, Vol. 303, 113790, January 2024. https://doi.org/10.1016/j.enbuild.2023.113790

[14] M. Shin, S. Hwang, B. Kim, S. Seo, and J. Kim, "IoT-Based Intelligent Monitoring System Applying RNN," *Applied Sciences*, Vol. 12, No. 20, 10421, October 2022. https://doi.org/10.3390/app122010421

[15] B. Faniyi and Z. Luo, "A Physics-Based Modelling and Control of Greenhouse System Air Temperature Aided by IoT technology," *Energies*, Vol. 16, No. 6, 2708, March 2022. https://doi.org/10.3390/en16062708

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