Office Energy Consumption Decision Support System Based on Microservices

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Abstract. As global attention to energy conservation and carbon reduction increases, the responsibility of companies in their energy use also grows, requiring them to implement energy-saving measures from various angles. Companies have found that office buildings account for 40% of their total energy consumption, with lighting and HVAC systems making up about 70% of this usage. To address this challenge, this study developed an energy consumption decision support system based on a microservices architecture. This system, leveraging the Internet of Things (IoT) and building automation and control systems, uses multiple sensors and data sources to analyze and identify key factors affecting energy consumption through Structural Equation Modeling (SEM). The decision support system provides users with energy-saving recommendations via a visual platform, aiming to reduce the energy consumption of lighting and HVAC systems in office environments.

Keywords: IoT · Microservices · Energy Saving · Building Automation And Control Systems · Decision Support Systems · Structural Equation Modeling

1 Introduction

This section discusses the background of global climate change and carbon emissions issues, introducing the energy saving and carbon reduction measures Taiwanese companies need to take. It also outlines the design of an energy consumption data analysis platform based on a microservices architecture. The motivations and goals for establishing the platform will also be explained in this section.

1.1 Background

As global climate change and global warming worsen, carbon emissions have become a major concern. The Paris Agreement, passed in 2015, aims to limit global temperature rise and requires countries to set specific emission reduction targets [1]. The 2020 United Nations Framework Convention on Climate Change states that implementing a carbon tax can effectively reduce carbon emissions and slow global warming trends [2].

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"Energy saving and carbon reduction" has become a global goal [3]. In 2023, Taiwan passed the Climate Change Response Act, which mandates the collection of carbon fees from greenhouse gas emission sources and offers preferential rates to companies that meet reduction targets, aiming for net-zero greenhouse gas emissions by 2050 [4]. This policy sets higher environmental standards for local businesses. According to the Taiwan Financial Supervisory Commission's (FSC) sustainable development action plan for listed companies, starting in 2025, qualified listed companies are required to disclose CSR reports and ESG-related information [5]. Companies must demonstrate their energy policies and implement energy saving and carbon reduction measures to comply with government regulations.

1.2 Motivation and Objectives

In this context, local enterprises must actively take measures to reduce energy consumption and carbon emissions. A leading electrical engineering and heavy electrical company in Taiwan understands the importance of energy management and carbon emission control for sustainable development. The company has already implemented several proactive measures and possesses substantial experience and technical expertise. Therefore, the company has decided to establish an energy consumption data analysis platform based on a microservices architecture, building on existing energy-saving measures. The motivation for this platform is to monitor and analyze the energy consumption of office buildings in real-time, identify energy-saving potential, and provide improvement suggestions to achieve energy-saving and carbon reduction goals.

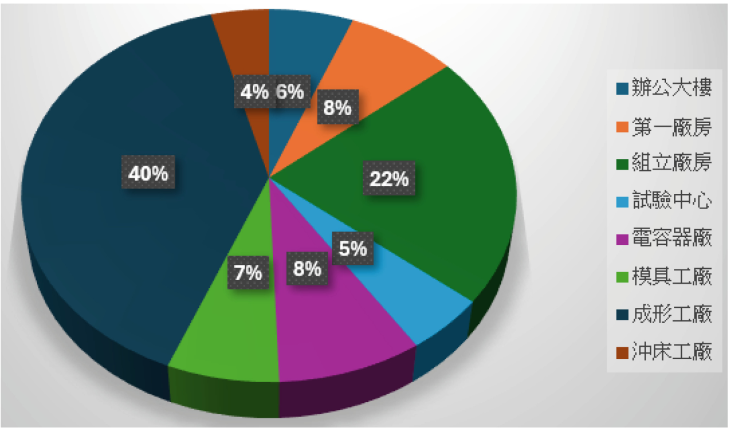

Fig. 1. Pie chart of the building energy consumption.

According to data from the company (Fig. 1), the energy consumption of the company's office buildings accounts for 40% of the total energy consumption of the entire plant area, second only to the first factory, which consumes 22%.

Based on the Energy Audit Annual Report for Non-Productive Industries by the Energy Bureau of the Ministry of Economic Affairs in 2022 [6], the energy consumption of equipment in office buildings in Taiwan ranks as follows: HVAC systems account for 56.73%, and lighting systems account for 12.87%, together making up 69.6%. Therefore, reducing the electricity consumption of HVAC and lighting systems is crucial. This study focuses on these systems and proposes an energy saving Decision Support System based on a microservices architecture.

The system aims to identify key factors affecting energy consumption by real-time monitoring and analyzing various variables, such as indoor and outdoor temperature and humidity, personnel movement, equipment energy consumption, and weather information. The analysis results will be translated into energy-saving recommendations for users. The specific objectives are as follows:

1. **Establish a Data Collection Platform for HVAC and Lighting:** Utilizing a microservices architecture, the system will create processing units paired with various sensors (such as temperature and humidity sensors, light sensors, current sensors, and human presence sensors) to monitor environmental and energy consumption data in the office and external areas in real time. This platform will provide data processing, storage, and analysis.
2. **Develop Energy-saving Decision Support Algorithms Based on SEM:** Using Structural Equation Modeling (SEM) methods, the system will conduct an in-depth analysis of the collected data to identify key factors affecting energy consumption and generate energy-saving recommendations.
3. **Visualize Decision Recommendations:** Utilizing visualization tools, the system will design and implement an intuitive dashboard to display the energy-saving recommendations and related energy consumption data generated by the algorithms. This will help users understand and implement energy-saving measures to achieve energy-saving and carbon reduction goals.

2 Related Work

This chapter introduces related work, including building energy conservation, microservices architecture, decision support systems, and structural equation modeling.

2.1 Building Energy Conservation

Building energy conservation emerged in response to the 1970s energy crisis, leading to the Energy Policy and Conservation Act in the U.S. and standards like the European EN52120 [7, 8]. These standards focus on control functions such as heating, cooling, ventilation, and lighting, highlighting the importance of HVAC and lighting control [9]. Alison Williams et al. [10] conducted a meta-analysis showing that lighting control systems can save 24% to 36% of energy, with potential savings up to 38% when combining strategies. A study by the Pacific Northwest National Laboratory (PNNL) for the U.S. Department of Energy [11] found potential energy savings of 23% to 29% in commercial buildings, with effective measures including VAV terminal box damper flow reductions 、 wider deadbands 、 and demand control ventilation. The three most effective measures are all energy-saving methods for HVAC systems and have energy-saving effects ranging from 7.1% to 16%.

2.2 Decision Support System

A Decision Support System (DSS) is a system architecture designed to provide managers with accurate and intuitive decision recommendations through data management, model management, and dialogue management modules [12]. DSS has significant applications in various fields. In modern agriculture (Agriculture 4.0) [13], DSS helps farmers formulate efficient irrigation plans, improving production and reducing energy waste. In building energy management [14], DSS sets temperature points and uses feedback for energy savings while maintaining occupant comfort, demonstrating its effectiveness in improving efficiency and energy conservation.

2.3 Microservices

Microservices architecture breaks down large software projects into loosely coupled modules, allowing for independent deployment and flexible development using lightweight communication protocols like HTTP and MQTT [15, 16]. This approach is suitable for applications requiring rapid deployment and high scalability. In IoT, microservices facilitate secure and efficient application development and deployment [17]. The microservices framework ensures that each service is lightweight and responsible for specific tasks, enhancing development efficiency, system flexibility, and scalability. It is ideal for developing an energy consumption data analysis platform, enabling precise division of labor and rapid iterative expansion for efficient monitoring and analysis.

2.4 Structural Equation Modeling

Structural Equation Modeling (SEM) is a powerful statistical technique that can simultaneously handle multiple independent and dependent variables, revealing deep relationships among variables in complex systems. SEM's strength lies in its ability to evaluate both measurement models and structural models concurrently, using confirmatory factor analysis and path analysis to test theoretical models robustly [18]. SEM is widely used across various disciplines, including ecology, education, building and IoT. For instance, In ecological research [19], SEM integrates data to model complex interactions within ecosystems. Education researchers [20] use SEM to examine the structural relationships between student satisfaction and performance in online courses during the COVID-19 pandemic. In the field of IoT sensors, SEM is employed for causal analysis of sleep monitoring sensor data [21]. In low-carbon buildings [22], SEM is used to investigate factors affecting office building energy efficiency and identify key intervention pathways. Researchers collected survey data from Nigerian and UK office buildings and used SEM to analyze factor impacts on energy performance.

3 Experimental Design

This chapter first presents the proposed system architecture and then explains the functions of each subsystem based on the system architecture.

3.1 System Architecture

The system architecture of this study is based on a Decision Support System (DSS) and is composed of three subsystems (as shown in Fig. 2):

1. **Database Management Subsystem (DBMS):** The DBMS aims to establish an efficient data collection platform.
2. **Model-Base Management Subsystem (MBMS):** The MBMS is designed to conduct in-depth analysis of the collected data, identify key variables, and generate insights.
3. **Dialog Generation and Management Subsystem (DGMS):** The DGMS aims to generate decision support recommendations for users and provide an easy-to-use visualization interface.

The following sections will explain the three subsystems in detail.

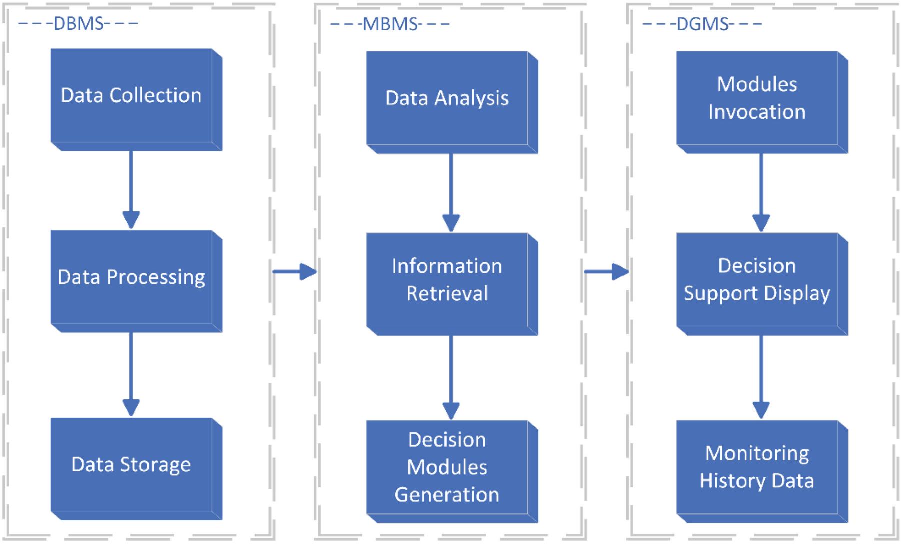

Fig. 2. System Flowchart

3.2 Database Management Subsystem

The Database Management Subsystem (DBMS) is responsible for collecting, processing, and storing data.

In the data collection, various types of data needed for energy-saving analysis and their sources are defined (as shown in Fig. 3). These data sources include IoT sensors and public information. The purpose of collecting this data is to analyze key factors affecting energy consumption and identify potential energy-saving opportunities. The types of data collected include:

Lighting Analysis Data: bulb power, bulb brightness, lighting usage time, number of people indoors.
HVAC Analysis Data: air conditioner power consumption, airflow speed, cooling/heating status, operation time.
Environmental Data: indoor and outdoor temperature, indoor and outdoor humidity, indoor CO2 concentration.

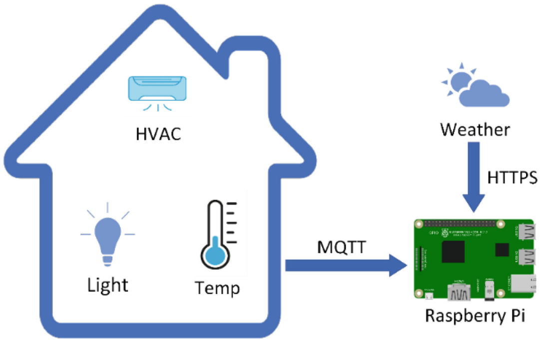

Fig. 3. Data Collection Overview Diagram

After deploying sensors, it is important to consider interference factors (such as transmission interference and sensor errors) before storing the data. Data processing involves two steps: cleaning and standardization. Cleaning ensures data consistency and accuracy by checking for missing values and filling them in, and correcting or removing outliers to ensure data completeness. Standardization converts data from different scales to a common standard to facilitate subsequent analysis, using methods like z-score normalization and min-max normalization. Finally, the preprocessed data is stored in a Database for easy retrieval and further analysis.

3.3 Model-Base Management Subsystem.

The Model-base Management Subsystem (MBMS) is responsible for the in-depth analysis of data to generate decision-support modules. This process includes three main stages: data analysis, information retrieval, and decision modules generation. In the data analysis stage, the system uses statistical analysis tools to analyze the data collected and processed by the DBMS using SEM. This involves the following steps:

Constructing Models and Constructs: Use Exploratory Factor Analysis (EFA) to define the relationships between latent variables and observed variables and to construct models. For example, the latent variable "user_comfort" might be influenced by the observed variables "room1-temperature1," "room1-humidity1," and "room1-co2."
Confirmatory Factor Analysis (CFA): Use CFA to verify the relationships between observed variables and latent variables, known as the measurement model. After confirming these relationships, use path analysis to determine the path coefficients (strength

of influence) between latent variables to see if the hypothesized causal relationships are supported by the data.
Evaluating the Structural Model: Use fit indices (such as CFI, TLI, RMSEA) to assess the model's fit and ensure it adequately explains the data. For example, check if "user_comfort" is significantly influenced by "room1-temperature1," "room1-humidity1," and "room1-co2," and calculate the impact coefficients of these variables on "user_comfort."

After completing the SEM analysis and obtaining results, the purpose of the information retrieval stage is to extract useful information from the analyzed data to support the generation of decision modules. This involves the following steps:

Identifying Key Variables: Check the significance (P-values) and standardized coefficients of path coefficients to identify variables with significant influence. Classify these variables based on the defined latent and observed variables in the model, subdividing them into environmental data, equipment data, and user behavior data. For example, determine that "user_comfort" is influenced by the observed variables "room1-temperature1", "room1-humidity1" and "room1-co2."
Generating Recommendations: Based on the classified observed variables from the previous step, generate specific action recommendations. For example, increasing the air conditioner temperature setting, reducing or stopping cooling but not reducing airflow, can improve "user_comfort" and reduce air conditioner power consumption.

Finally, Based on the recommendations generated in the information retrieval stage, create decision modules that include specific energy-saving measures and strategy details. These modules will contain actionable steps and guidelines for implementing the suggested measures.

3.4 Dialog Generation and Management Subsystem

The Dialog Generation and Management Subsystem (DGMS) is responsible for using the decision modules generated by the Model Management Subsystem (MBMS) to select specific decision tasks and display decision methods to the user. This process includes three main steps: modules invocation, decision support display, and monitoring history data.

In Modules Invocation, based on the previous data analysis and information retrieval results, the system invokes the generated decision recommendations. The system calls these recommendations according to the current energy consumption data and environmental conditions, ensuring the decisions are timely and accurate.

In Decision Support Display, the system presents the invocated decision content to the user in a visual format. Through an intuitive interactive interface, it provides detailed data analysis results and energy-saving recommendations, helping users quickly understand and take action.

In Monitoring History Data, the system continuously displays past data records, allowing users to compare current and historical data. This comparison helps users see the effectiveness of energy-saving measures and provides an objective understanding of the current environmental state.

4 System Implementation

This chapter describes how to establish a data collection platform for HVAC and lighting, develop energy-saving decision support algorithms based on SEM, and create visual decision recommendations. The network topology of the experimental environment is shown in Fig. 4.

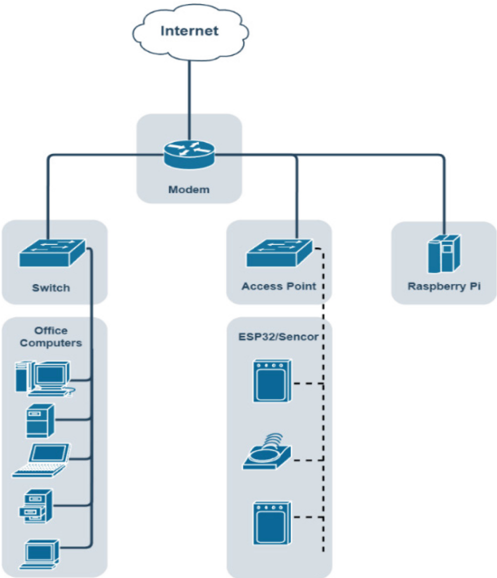

Fig. 4. Experimental Environment Network Topology Diagram

4.1 Establish a Data Collection Platform for HVAC and Lighting

The data collection platform responsible for the collection, transmission, and storage (see Fig. 5). For hardware selection, we used development boards paired with sensors (see Table 1). The ESP32 is used to connect and control the sensors, while the Raspberry Pi 5 serves as the processing unit, responsible for data preprocessing and storage.

In addition to sensor data, we use publicly available weather information from the Central Weather Bureau of the region. This data is divided into observation information and forecast information. Observation information is updated every 30 min, while forecast information is provided for the next three days at 12-h intervals. Both types of information include data on outdoor wind speed, wind direction, temperature, humidity, and atmospheric pressure.

Data transmission is implemented using both wired and wireless methods. Wired connections provide high-speed and stable links for the computing unit, but sensors are often located far from physical network ports. Therefore, ESP32 supports Wi-Fi and

Table 1. Hardware description table

Hardware	Caption	Features
Raspberry Pi 5	Single-board computer	GPIO, RJ45, Higher power
ESP32-C6	Microcontroller development board	Wifi, Bluethooth
DHT22	Temperature and humidity Sencor	Exact, Stable
TSL2561	Light levels (Lux) Sencor	Infrared and visible light
SenseAir S8	CO2 concentration Sencor	NDIR, Exact
ACS712	Electrical Consumption Sencor	Hall Effect, Stable
HC-SR505	Personnel activity Sencor	PIR, Flexible

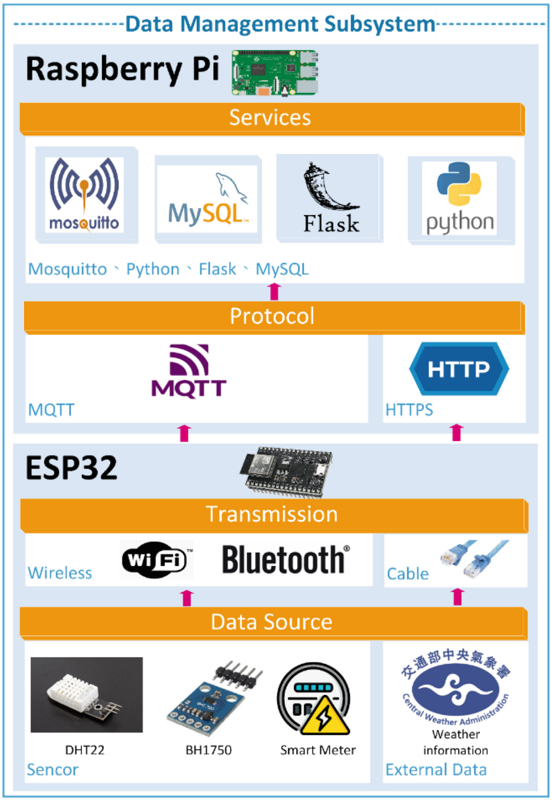

Fig. 5. Data Collection Platform Architecture Diagram

Bluetooth for transmission. Wi-Fi is used for high-bandwidth scenarios, while Bluetooth is used for low-power, battery-operated scenarios. We use the MQTT protocol, a lightweight IoT communication protocol. MQTT supports subscription-based data transmission, ideal for real-time data transfer such as temperature, humidity, and light data. MQTT transmission is implemented using Node-Red deployed on the ESP32. Node-Red is a visual IoT application development tool that uses flow-based programming [23], making it easy to integrate hardware devices, sensors, and APIs. Its visual editing and lightweight characteristics is suitable for the ESP32 with limited computing power.

For services, we use a microservices architecture running on the computing unit (Raspberry Pi). Kubernetes [24], a modern virtualization platform, supports microservices characteristics and requirements such as clustering, containerization, scalability, and self-healing. This platform is used to deploy and maintain the following services: Mosquitto for real-time reception of sensor MQTT data, ensuring data timeliness and reliability; Flask, a lightweight web framework, for sending HTTPS requests to obtain external public data; Python for data cleaning and preprocessing; and MySQL as a relational database for efficient data querying and management, ensuring data security and integrity (Fig. 6).

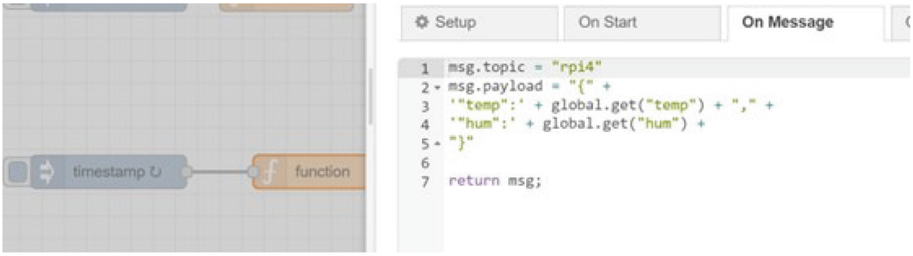

Fig. 6. Using Node-Red to Send Temperature and Humidity Information via MQTT Protocol

4.2 Develop Energy-Saving Decision Support Algorithms Based on SEM

For visualizing the results, we use test data and perform SEM analysis using the Python semopy library. Since the data has been preprocessed during the collection phase, it is clean and ready for analysis. First, we need to construct the model by performing Exploratory Factor Analysis (EFA) on the observed variables. This generates a Scree Plot to determine the appropriate number of factors (Fig. 7). From the Scree Plot, we can see that the eigenvalues of the first three factors are significantly higher than the others, indicating that we should retain these three factors. In Fig. 8, the loadings of each observed variable on different factors clearly show the relationships between variables and factors. Through EFA, we determine the relationships between observed variables and latent variables, which we use to construct the SEM model for further analysis of office energy consumption data and to generate energy-saving recommendations.

In the measurement model, we define the relationships between latent variables and observed variables:

- **Latent Variable 1 (latent_var1):** Composed of bulb power, lighting usage time, and indoor occupancy.

- **Latent Variable 2 (latent_var2):** Composed of air conditioner power consumption, airflow speed, and indoor temperature.
- **Latent Variable 3 (latent_var3):** Composed of outdoor temperature, indoor humidity, outdoor humidity, and indoor CO2 concentration.

In the structural model, we define the causal relationships between latent variables:

- Latent_var1 is influenced by latent_var2 and latent_var3.
- Latent_var2 is influenced by latent_var3.

We then use fit indices such as CFI, TLI, and RMSEA to evaluate the model's fit, ensuring it adequately explains the data.

Finally, we generate decision recommendations:

- To improve latent_var1, increase latent_var2.
- To improve latent_var1, increase latent_var3.
- To improve latent_var2, increase latent_var3.

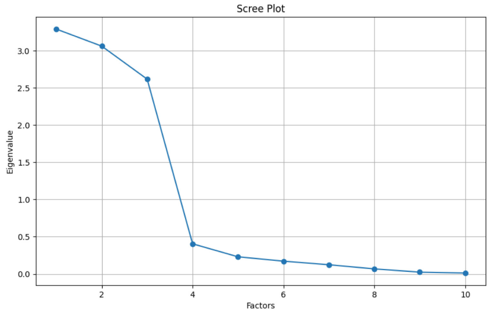

Fig. 7. Scree Plot showing the eigenvalues of factors.

Fig. 8. Loadings of observed variables on factors.

4.3 Visual Decision Recommendations

We should interpret the SEM analysis results into practical actions and present them to users. Grafana can achieve this. It is an open-source data monitoring and interactive dashboard tool capable of anomaly alerting [25]. Grafana allows for the customization of dashboards to display real-time and historical data from various sources. Its extensive expandability enables easy integration with MySQL databases for real-time energy consumption data visualization. Through an intuitive interface, users can clearly view energy consumption data and energy-saving recommendations. We can import the SEM analysis results and energy consumption data into a MySQL database and use Grafana for visualization. The steps are as follows:

1. **Data Import:** Import SEM analysis results and other energy consumption data into the MySQL database.
2. **Configure Grafana:** Connect Grafana to the MySQL database and create custom dashboards.
3. **Visualization:** Use Grafana's chart tools (e.g., line charts, bar charts, pie charts) to display energy consumption data and energy-saving recommendations.

By following these steps, users can view real-time office energy consumption data and take appropriate energy-saving measures based on the recommendations generated by the SEM model (Fig. 9).

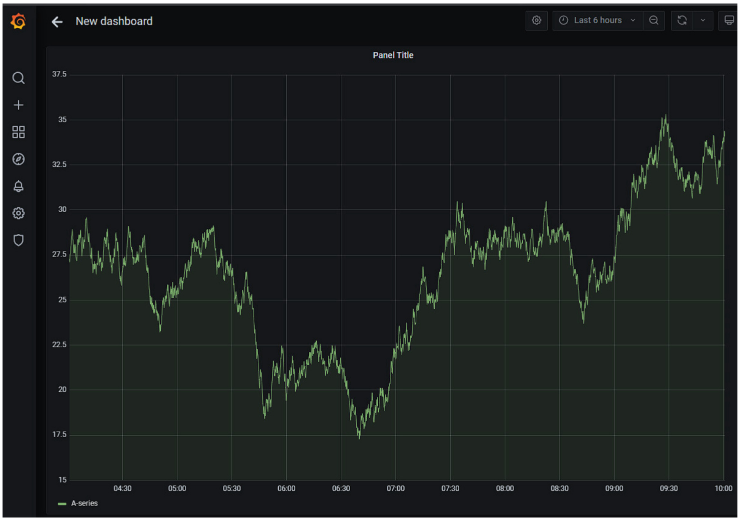

Fig. 9. Grafana displaying MySQL monitoring information in full screen.

5 Discussion

In the process of establishing the data collection platform, we chose ESP32 and Raspberry Pi 5 as our hardware devices. The ESP32, with its built-in Wi-Fi and Bluetooth capabilities, is ideal for connecting and controlling various sensors. The Raspberry Pi 5 serves as the processing unit, responsible for data preprocessing and storage. This hardware combination allows us to deploy sensors flexibly in various environments. Using SEM (Structural Equation Modeling) for data analysis offers significant advantages over linear regression. The primary difference is that SEM can uncover latent variables and reveal hidden concepts within the system, which are crucial for subsequent analysis and system architecture extension. Our system, based on a microservices architecture, is highly scalable, making it easier to add new sensors or computing platforms in the future, thus adapting flexibly to different needs and changes.

However, the system also has some limitations. Firstly, during sensor installation in remote locations, power supply issues can arise. Considering the increasing volume of data, the computing unit may face computational limitations, and in some environments, wiring and power supply challenges increase the complexity of deployment. Secondly, as data analysis is performed on computing units like the Raspberry Pi, increasing data volume may lead to computational power shortages, limiting the system's scalability and real-time processing capability.

To address these limitations, future research can explore several directions. Introducing sensors that use sustainable energy or are low-power can reduce energy demand. Collecting more external data, such as current electricity prices and noise levels, will allow for more precise modeling of user experience and energy costs using SEM. Integrating additional information and algorithms can validate actual energy savings, enhancing system credibility. Combining artificial intelligence can help learn overall energy consumption patterns and provide predictive recommendations, displayed in a graphical interface. To ensure secure data transmission and prevent data leakage and tampering, MQTT should be configured with TLS/SSL encryption. Finally, testing the system in diverse office environments will verify its generality and stability, aiding its adaptation to various needs and expanding its application range.

6 Conclusion

This study successfully designed and implemented an office energy consumption decision support system based on a microservices architecture. By integrating various sensors and data sources, the system achieved real-time monitoring and analysis of office environments and energy consumption. Using Structural Equation Modeling (SEM) for data analysis, it identified key variables affecting energy use and generated specific energy-saving recommendations. The system demonstrated significant advantages in scalability and flexibility, allowing for the easy addition of sensors or computing platforms to adapt to different needs and environments.

In summary, this study highlights the potential of a microservices-based energy decision support system in achieving energy-saving and carbon reduction goals, providing an effective technical solution for sustainable development. With continuous technological advancements and the expansion of application scenarios, the system is expected to play a more significant role in broader fields, contributing to energy management and environmental sustainability.

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