Design of Smart Building Energy Management System Based on Digital Twin Technology

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Abstract. With the digital transformation of the construction industry, the application of digital twin technology in smart buildings has become a research hotspot. This article explores the application of digital twin technology in energy management of smart buildings, aiming to improve the energy utilization efficiency of buildings through real-time monitoring, data analysis, and optimization strategies. The research covers the basic principles of digital twin technology and its role in energy management. It systematically analyzes the architecture design of digital twin systems, including key modules such as data acquisition, model construction, simulation, and optimization. Through practical cases, this article verifies the application effect of digital twin technology in component models, demonstrating its significant advantages in improving energy management efficiency, reducing energy consumption, and lowering operating costs. The research results indicate that digital twin technology has broad application prospects in energy management of smart buildings, providing important support for the sustainable development of the construction industry. Finally, this article also discusses the limitations of the research and proposes future research directions.

Keywords: Digital twin, smart building, energy management, Internet of Things, real-time data, system optimization

1 Introduction

The rapid development of information technology has significantly transformed modern life, with the Internet serving as a critical infrastructure. The Internet of Things (IoT), an emerging technological concept, has enabled real-time data collection and processing, driving the growth of smart buildings. These buildings integrate various technologies to enhance efficiency and user comfort.

However, traditional energy management methods face significant limitations in managing the increasing complexity of modern smart buildings. These methods often rely on static data and empirical approaches, making them inadequate for real-time monitoring, precise optimization, and predictive analysis. As a result, they struggle to meet the dynamic needs of contemporary energy management.

Digital twin technology addresses these challenges by creating a virtual model that mirrors the physical building, allowing seamless integration between the physical and

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digital worlds. Unlike traditional methods, digital twins enable real-time synchronization, dynamic updates, and predictive capabilities. By leveraging real-time data through IoT, this technology enhances energy management efficiency, reduces consumption, and optimizes building operations[1].

This paper proposes a smart building energy management system based on digital twin technology, detailing its system architecture and key modules. By overcoming the limitations of traditional approaches, this system advances the current knowledge and practice of energy management in smart buildings.

2 Smart Building System and Digital Twin

Smart building is the product of the deep integration of modern information technology and traditional buildings. Through the integration of sensors, Internet of things, automation control, data analysis and artificial intelligence technology, intelligent management and optimization can be achieved. Its application scenarios include energy consumption management, environmental monitoring, equipment maintenance, safety management and user experience improvement[2].

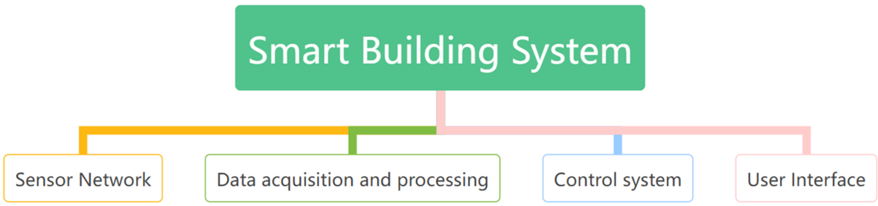

Fig. 1. smart building system architecture

Figure 1 shows the overall architecture of the smart building system, including sensor network, data acquisition and processing, control system and user interface. The sensor network collects building data in real time, such as temperature, humidity, energy consumption, etc., and transmits them to the data processing center through the Internet of things. The control system automatically adjusts the building operation status according to the analysis results, and the user interface provides a convenient operation interface.

As an important means of smart building, digital twin technology realizes the seamless connection between the physical and digital world by creating a virtual model corresponding to the physical building. Its core lies in real-time synchronization and dynamic update. Building data is obtained in real time through sensors and the Internet of things, and reflected in the virtual model to provide the real-time state of the building. Digital twin technology can also prevent problems and optimize management through simulation and prediction of future operation status.

Digital twin technology plays a key role in energy consumption management of smart buildings. The sensor collects energy consumption data in real time and transmits it to the central data processing center through the Internet of things for data cleaning, processing and storage. Big data analysis identifies energy consumption patterns and anomalies, builds a digital twin model, reflects the building operation status in real time, and performs simulation and prediction. Based on the results of model and data analysis, formulate and implement energy consumption optimization strategies, such as regulating HVAC and lighting systems. The user interface provides intuitive energy consumption display and optimization suggestions to assist management decision-making[3-4].

Digital twin technology not only improves the efficiency and accuracy of energy management of smart buildings, but also reduces energy consumption and operating costs, providing support for the sustainable development of buildings.

3 DT based Smart Building System Framework

The smart building energy consumption management system based on digital twin realizes the real-time monitoring, analysis and optimization of building energy consumption by constructing the virtual model of physical building. The system architecture includes data acquisition layer, data processing layer, model layer, application layer and user interface layer, and each layer plays different functions, as shown in Figure 2.

Fig. 2. smart building architecture based on digital twin

3.1 Modeling

Digital space system modeling is the core link of smart building energy consumption management system based on digital twin technology. By constructing virtual building model, real-time monitoring, analysis and optimization of physical building energy consumption can be realized. Modeling methods mainly include physical modeling, data-driven modeling and hybrid modeling.

3.1.1 Physical Modeling.
Physical modeling is based on the structure and physical characteristics of buildings, using engineering principles and mathematical formulas to construct models. Physical modeling methods include thermodynamic models and fluid dynamics models.

Thermodynamic models are used to simulate the heat transfer process of buildings. And fluid dynamics models are used to simulate air flow and pressure distribution inside and outside buildings. Power system models are commonly used to simulate the electricity consumption and distribution of buildings[5].

Field	Formula Name	Formula	Parameter Explanation
Energy Balance	Building Energy Balance Equation	$E_{\text{total}} = E_{\text{input}} - E_{\text{loss}}$	E_{total}: total energy consumption, E_{input}: input energy, E_{loss}: energy loss.
Fluid Dynamics	Navier-Stokes Equation	$\rho\left(\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\mathbf{u}\right) = -\nabla p + \mu \nabla^2 \mathbf{u} + \mathbf{f}$	ρ: fluid density, $\mathbf{u}$: velocity field, p: pressure, μ: dynamic viscosity, $\mathbf{f}$: external force.
Solar Radiation	Solar Radiation Calculation	$I = I_0 \cdot \cos(\theta)$	I: received solar radiation intensity, I_0: incident radiation intensity, θ: angle of incidence.

Fig. 3. Physical modeling process formula

Physical modeling has high accuracy and interpret ability, but usually requires detailed building structure information and a large amount of computational resources (Figure 3).

3.1.2 Data Driven Modeling.

Data driven modeling is based on a large amount of historical data, using machine learning and statistical analysis techniques to construct models. These models are capable of handling complex nonlinear relationships and optimizing and predicting based on data.

Regression analysis is used to establish a relationship model between energy consumption and influencing factors. Common methods include linear regression and logistic regression. Linear regression is used to describe the linear relationship between independent and dependent variables. Logistic regression is used for classification problems, such as predicting whether energy consumption exceeds a certain threshold.

Time series analysis is used to analyze the time series characteristics of energy consumption data for prediction and analysis. Common methods include ARIMA and LSTM. ARIMA (Autoregressive Integral Moving Average Model) is used for modeling time series data. LSTM (Long Short Term Memory Network) is a deep learning model used for processing and predicting time series data[6].

Cluster analysis is used to identify energy consumption patterns and abnormal situations, providing a basis for optimizing strategies. Common clustering algorithms include Kmeans and DBSCAN. Kmeans clustering refers to dividing data points into k clusters and minimizing the distance from each cluster point to the cluster center; DBSCAN (density based clustering algorithm) clusters data points based on their density[7].

Field	Formula Name	Formula	Parameter Explanation
Regression Analysis	Linear Regression	$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + \epsilon$	y: dependent variable, β_0: intercept, $\beta_1, \ldots, \beta_n$: coefficients, $x_1, \ldots, x_n$: independent variables, ϵ: error term.
Classification	Logistic Regression	$\operatorname{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$	p: probability of class membership, β_0: intercept, $\beta_1, \ldots, \beta_n$: coefficients, $x_1, \ldots, x_n$: independent variables.
Time Series Analysis	Autoregressive Integrated Moving Average (ARIMA)	$y_t = c + \phi_1 y_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t$	y_t: value at time t, c: constant, ϕ_1: autoregressive parameter, θ_1: moving average parameter, ϵ_t: error term.

Fig. 4. Data driven modeling formula

Data driven modeling can handle complex nonlinear relationships and large amounts of data, but the accuracy of the model depends on the quality and quantity of the data. Through the above methods, effective analysis and prediction of energy consumption data can be achieved, thereby optimizing the energy management of buildings (Figure 4).

3.1.3 Justification for Methods and Materials Selection.
The selection of modeling methods and materials in this study is based on the specific needs of accurately simulating the energy consumption behavior of smart buildings. Physical modeling, such as thermodynamic and fluid dynamics models, was chosen due to its ability to represent the heat transfer and airflow characteristics within the building, which are critical for optimizing HVAC performance. Data-driven models, including regression analysis and time series analysis, were employed for their effectiveness in handling complex nonlinear relationships and large volumes of historical energy data. These approaches allow the system to predict energy consumption patterns and anomalies with high accuracy, providing a solid foundation for implementing optimization strategies.

Furthermore, the choice of materials, such as temperature sensors and CO2 monitors, ensures real-time and accurate data collection, which is essential for maintaining the synchronization between the physical and digital models. The materials were selected to match the specific operational needs of the building, enabling reliable and efficient monitoring of key environmental variables such as temperature, humidity, and air quality[8].

3.2 Intelligent Computation

In the smart building energy management system based on digital twins, intelligent computing and data analysis are key to achieving energy optimization. By processing and analyzing a large amount of energy consumption data, it is possible to identify energy consumption patterns, predict trends, and develop optimization strategies.

3.2.1 Data Preprocessing.

Data preprocessing is a fundamental step in data analysis, aiming to improve the quality and usability of data.First, handle missing values, outliers and repeated values to ensure the accuracy and integrity of data.Then, normalization processing is performed to make the data within the same scale range for subsequent analysis.Finally, extract representative features to simplify the complexity of the model[9].

3.2.2 Statistic Analysis.

Statistical analysis is used to describe and summarize data, revealing basic characteristics and distribution. By calculating statistical measures such as mean, standard deviation, and median, analyzing the central tendency and dispersion of data, identifying the correlation between variables, and determining the key factors affecting energy consumption. Statistical testing is used to verify significant differences and relationships between data.

3.2.3 Machine Learning.

Machine learning is the core of intelligent computing, aimed at learning patterns from data and building predictive and optimization models. Firstly, using labeled data for energy consumption prediction and classification, commonly used algorithms include linear regression, decision tree, random forest, and support vector machine. Untamed data is used for clustering and pattern recognition, and commonly used algorithms include Kmeans, hierarchical clustering, and principal component analysis. Finally, a multi-layer neural network model is used to handle complex nonlinear relationships and large-scale data[10]. Common network structures include convolutional neural networks and long short-term memory networks.

3.2.4 Time Series.

Time series analysis is aimed at predicting trends and detecting anomalies in energy consumption data based on their temporal characteristics. ARIMA model, autoregressive integral moving average model, used to capture linear relationships in time series; Seasonal decomposition involves breaking down time series into trends, seasonality, and random components to identify periodic patterns in the data; LSTM network, a long short-term memory network, is suitable for processing time series data with long-term dependencies for accurate energy consumption prediction.

3.2.5 Optimization Algorithm.

The optimization algorithm is used to find the best scheme among a large number of possible energy management strategies. Linear programming is to find the optimal solution to the optimization problem under linear constraints. Genetic algorithm is based on the principle of biological evolution, through selection, crossover and mutation operations, to find the global optimal solution. Particle swarm optimization (PSO) can find the optimal solution of multi-objective optimization problem by simulating the foraging behavior of birds[11].

Data analysis and intelligent computing play an important role in the smart building energy consumption management system based on digital twins. Through the methods of data preprocessing, statistical analysis, machine learning, time series analysis and optimization algorithm, the refined management and optimization of building energy consumption can be realized.

3.3 System Optimization

System optimization is the key link of smart building energy consumption management system based on digital twin. Through the continuous optimization of building energy consumption management strategy, the maximization of energy efficiency and the minimization of operation cost can be achieved[12]. System optimization mainly includes model correction, implementation of optimization strategy and closed-loop feedback mechanism.

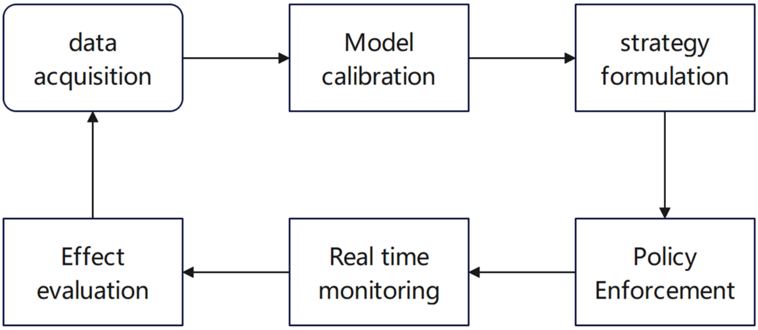

Fig. 5. system optimization and closed loop feedback

Figure 5 shows the optimization and closed-loop feedback mechanism of smart building energy consumption management system based on digital twins. The system forms a closed-loop feedback loop through data collection, model calibration, strategy formulation, strategy implementation, real-time monitoring and effect evaluation, and continuously optimizes and improves the energy consumption management strategy to ensure the efficient operation of the system.

Through model correction, implementation of optimization strategy and closed-loop feedback, not only the accuracy and reliability of the model are improved, but also the continuous optimization and improvement of energy consumption management strategy are realized, ensuring the efficiency and economy of energy utilization.

4 Practical Application

4.1 Experimental Background

This experiment takes a three story office building as the research object, uses EnergyPlus software to build its digital twin model, and optimizes the operation efficiency of HVAC system and lighting system through data-driven technology.

4.2 Experimental Setup

The office building covers an area of 3000 square meters and has three floors. The exterior wall is made of concrete with a thermal conductivity of 1.4 w/m · K. the window is double glazed with a U value of 1.6 w/m² · K. The office building includes 10 offices, 2 meeting rooms and public corridors. The HVAC system consists of a central air conditioner and fan coil units. The lighting system adopts LED lamps with a power of 10w/m².

One temperature sensor is set in each room to monitor the indoor temperature in real time. The temperature simulation data follows a normal distribution, with an average of 23 °C and a standard deviation of 1.5 °C; One humidity sensor is set in the corridor and meeting room on each floor to monitor the humidity level; CO_2 sensors shall be installed in meeting rooms and open office areas[13-14].

4.3 Data Acquisition and Processing

The data is collected every minute and transmitted to the central control system for analysis and processing through the wireless network. The data format is JSON

```
import json
data = {
    "temperature": 22.5,
    "humidity": 47,
    "co2": 420,
    "time": "2024-08-19T12:00:00Z"
}
json_data = json.dumps(data)
# Data transmission to central system
```

Temperature data analysis: time series analysis of temperature data using ARIMA model

Python code implementation:

```
from statsmodels.tsa.arima.model import ARIMA
model = ARIMA(temperature_data, order=(1, 0, 1))
model_fit = model.fit()
forecast = model_fit.forecast(steps=24)
# Predict next 24 hours
```

Humidity and CO2 data analysis: linear regression model is used to analyze the relationship between humidity and CO2 concentration and time

4.4 Optimal Results

Table 1 is the display of optimization results[15-16].

Table 1. Display of optimization results

Optimization Area	Optimization Action	Optimization Result
HVAC System Optimization	Adjusted temperature set point based on predicted temperature data.	Set point reduced from 23°C to 21.5°C, system runtime reduced by 20%.
Lighting System Optimization	Optimized lighting on/off times based on illuminance sensor data.	Reduced lighting intensity by 50% during non-working hours, saving 15% on lighting energy consumption.
Temperature Control	Improved temperature fluctuation range.	Reduced from ±1.5°C to ±0.75°C, average indoor temperature decreased from 23°C to 21.8°C.
Humidity Control	Reduced high humidity periods and maintained humidity levels.	High humidity periods reduced by 45%, humidity levels maintained between 43%-55%.
CO2 Level Control	Reduced CO2 concentration.	CO2 concentration reduced by 18%, time spent above 900ppm reduced by 55%.
Energy Consumption	Reduced energy consumption of HVAC and lighting systems.	HVAC energy consumption reduced by 14%, lighting energy consumption reduced by 16%, total energy consumption reduced by 12%.

5 Conclusion

This paper studies the smart building energy consumption management system based on digital twin technology, introduces the system architecture and the design of each module in detail, and verifies the effectiveness of the system in energy consumption management through a practical case. Research shows that digital twin technology can not only monitor building energy consumption in real time, but also significantly improve energy efficiency and residents' comfort through accurate analysis and optimization. In the specific implementation case, the application of the system in the model has greatly improved the efficiency of energy consumption management, while significantly reducing energy consumption and related operating costs, showing the importance and broad application prospects of digital twin technology in the field of smart building.

However, the current research still has some limitations, especially in the accuracy and reliability of digital twin model. Future research should focus on further optimizing these models and extend their application to other management fields of smart buildings, such as safety management and equipment maintenance. In addition, with the continuous development of the Internet of things and big data technology, the application prospect of digital twin technology will be broader. Through continuous innovation and optimization, digital twin technology is expected to provide more powerful support for the sustainable development of smart buildings.

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