AI-Driven Property Management Decision Support System Using LSTM Networks for Energy Optimization

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Background: IoT devices and sensors collect real-time data, which is used in conjunction with Long Short-Term Memory (LSTM) models to predict energy consumption trends, optimize resource allocation, and analyze household feedback for service improvements. Aim: This study aims to develop an AI-powered property management decision support system to enhance management efficiency and service quality. Method: The research involves multiple stages, including data collection from IoT devices, data cleaning and preprocessing, construction of predictive models (such as LSTM networks), and system optimization. Performance is evaluated using key metrics like task completion rate, maintenance request resolution rate, and resident satisfaction. Cross-validation and model performance measures, such as Mean Absolute Error (MAE) and Mean Squared Error (MSE), are used to assess model accuracy. Results: Empirical results show significant improvements in property management metrics: task completion rate increased by 15%, maintenance request resolution rate improved by 10%, and resident satisfaction rose by 7%. The LSTM model achieved a prediction accuracy with an MAE of 12.5 and an MSE of 256.4. Staff efficiency also increased by 10%, demonstrating the system's practical value in optimizing resource allocation and predictive maintenance. Conclusion: This study introduces a novel technical approach and practical guidance for intelligent property management, providing significant theoretical and practical implications for enhancing operational efficiency, service quality, and decision-making capabilities in the property management industry.

Povzetek: Prispevek opisuje sistem za podporo odločanju v upravljanju nepremičnin na podlagi umetne inteligence in LSTM modelov. Sistem optimizira porabo energije, izboljšuje dodeljevanje virov ter povečuje zadovoljstvo stanovalcev.

1 Introduction

With the acceleration of urbanization and the improvement of residents' living standards, the complexity and refinement of property management needs to increase day by day. The traditional property management model has been unable to meet the efficient management needs of modern society, so the property management decision support system based on artificial intelligence came into being. The purpose of this study is to explore how to use artificial intelligence technology to improve the overall efficiency and service quality of property management. Specific research contents include: sensors and sot devices collect real-time data, perform data cleaning and re-processing, and build LSTM models suitable for property management to predict energy consumption trends and optimize resource allocation; Analyze household feedback data and implement service improvement measures; Evaluate the improvement effect of the system in the aspects of task completion rate, maintenance request resolution rate and resident satisfaction. The study will also explore practical application challenges such as data security, system intelligence, cost control and personnel training, and propose corresponding solutions. This research is expected to provide scientific and intelligent decision support for the property management industry and promote its development to a more efficient and intelligent direction.

The focus of this research is to address the inefficiencies in property management, particularly in predicting energy consumption, optimizing resource allocation, and improving service quality through the use of artificial intelligence. The primary research question is whether the integration of AI, specifically using LSTM models and real-time data collection from IoT sensors, can significantly enhance the management efficiency, resource utilization, and resident satisfaction compared to traditional methods. The key hypothesis is that the use of LSTM-based predictive models will lead to better energy management, improved task completion rates, and faster maintenance resolution times. By framing the problem in this way, the system's performance can be rigorously evaluated against traditional systems using quantifiable metrics such as task completion rate (expected to increase by 15%) and maintenance resolution rate (anticipated improvement of 10%). This clear research direction enables a structured evaluation of the AI system's contributions to property management, providing a focused approach to verifying its effectiveness.

At present, the property management decision support system based on artificial intelligence has gradually attracted the attention of academia and industry.

Bolomope proposed that institutional factors should be taken into account in the decision-making behavior of property investment in the context of market disturbance. The organizational isomorphism theory analyzed the performance of listed property trusts in New Zealand and pointed out the far-reaching impact of market disturbance on property investment decision-making [1, 2]. Adu-Amankwa studies decision-making considerations for securing and managing intellectual property in the additive manufacturing supply chain, highlighting the critical role of intellectual property in the application of emerging technologies [3]. Chien and Tu's multi-criteria decision method established a simulation model for the feasibility of M&A in Taiwan's property management industry, demonstrating the application of multiple decision criteria in complex decision environments [4].

Muczynski explores the collective renovation decisions of Polish public-private homeowner associations in the management of multi-ownership housing, pointing out the importance and challenges of collective decision-making in a multi-ownership environment [5]. Ayodele and Olaleye focused on the flexibility decision path in uncertainty management, analyzed the experience of uncertainty management in property development in emerging markets, and proposed the key role of flexibility in coping with uncertainty [6]. Sanders-on and Read emphasized the value of customer-centered property management, identifying and realizing customer value, and improving the overall efficiency of property management [7]. The research shows that modern property management decision support system not only needs technical innovation, but also needs continuous development in management mode and decision theory to cope with complex market environment and diversified management needs. Existing studies have explored the optimization strategies and application effects of property management and decision support systems in different aspects, showing the application prospects of new technologies such as artificial intelligence, big data and chockablock in property management. How to better integrate technology, and scientific decision-making model to enhance the intelligence and efficiency of property management, still need to be studied and explored. The viewpoint and research provide an important theoretical basis and practical reference for the design and optimization of property management decision support system in the future.

Table 1: Summary of related studies on property management decision-making and their relevance

Author (s)	Year	Method	Main Results	Relevance to Your Study
Bolomope et al. [1]	2021	Institutional factors in decision-making	Institutional factors influence property investment decisions during market disruptions.	Highlights the importance of external factors in decision support systems.
Adu-Amankwa et al. [3]	2023	Intellectual property in additive manufacturing	Intellectual property management is crucial for emerging technologies.	Stresses the role of protecting IP in technology-driven systems.
Chien & Tu [4]	2021	Multi-criteria decision-making	Demonstrated the use of multiple criteria in property management mergers.	Shows how multi-criteria decision-making can aid in property management.
Muczynski [5]	2023	Collective decision-making in housing management	Identified challenges in decision-making in multi-ownership housing environments.	Illustrates the complexities of collective decision-making in property management.
Ayodele & Olaleye [6]	2021	Flexibility in uncertainty management	Flexibility is crucial for managing uncertainty in property development.	Emphasizes adaptability, which is relevant to AI-based decision systems.
Sanderson & Read [7]	2020	Customer-centered property management	Customer value realization improves property management efficiency.	Highlights the need for customer feedback analysis in AI property systems.

As is shown in Table 1, the purpose of this study is to use artificial intelligence technology to build an efficient property management decision support system, aiming at improving the overall efficiency and service quality of property management. The advanced LSTM model and big data analysis method are introduced to accurately predict property energy consumption trends, optimize resource allocation, and improve the timeliness and accuracy of equipment maintenance and service response. The system also analyzes resident feedback and implements targeted improvement measures to improve resident satisfaction and the quality of property services. The significance of the research is to inject new technical power into the traditional property management and promote its development to the direction of intelligence and refinement. Optimize resource utilization and energy consumption management, reduce property operating costs, and improve economic benefits. The data-driven decision support system can effectively improve the response speed and service level of property management, reduce failures and complaints, and improve the satisfaction and trust of residents. This study also provides a set of intelligent management model that can be copied and promoted for the property management industry, which has high application value and social benefits.

Current state-of-the-art (SOTA) property management systems often lack robust capabilities for predicting energy consumption and real-time adaptability. Many existing systems are limited to reactive maintenance and resource allocation strategies, which result in inefficiencies in energy usage and delayed responses to unexpected changes in facility operations. Furthermore, these systems do not effectively leverage real-time data for optimizing resource allocation, particularly in energy-intensive environments. By using LSTM models and IoT sensors to forecast energy consumption trends, it becomes possible to address these shortcomings. The system continuously collects and analyzes data, allowing for the anticipation of energy demand spikes and enabling proactive adjustments in resource distribution. This real-time predictive capability not only improves energy efficiency but also optimizes maintenance schedules and improves response times to incidents. As a result, the system enhances overall operational efficiency, reduces energy waste, and improves service quality for residents, addressing critical gaps left by traditional systems. These improvements are quantified through metrics such as task completion rate (increased by 15%), energy consumption management, and maintenance request resolution rate (improved by 10%).

This study enriches the application scenarios of artificial intelligence in the field of property management and provides a new research perspective and method. At the practical level, practical application and effect verification, the research results provide specific operating guidelines and optimization strategies for property management companies, and have strong practical guiding significance. This study is not only innovative and forward-looking in terms of technology and management methods, but also provides strong support for improving the overall level and service quality of the property management industry [1].

2 Overview of relevant theories

2.1 Property management theory

The theory of property management is the theoretical basis and guiding principle of property management practice, covering all aspects from the maintenance of property facilities to the service of residents. The core objective of property management is scientific and effective management means to ensure the good operation of property facilities, improve the quality of life of residents, and maximize the value of property. The theoretical framework includes standardization of property management services, evaluation system of service quality, cost management and risk control. In property management, facilities management is a key area, involving the maintenance of buildings, regular inspection and repair of equipment. Modern property management emphasizes intelligent management, that is, the use of sensors and Internet of Things technology to monitor the status of facilities in real time, and data analysis to predict the maintenance needs of facilities.

SERVQUAL model is a commonly used service quality evaluation tool, which evaluates five dimensions of reliability, responsiveness, guarantee, empathy and tangibility to measure the overall level of property services. In order to improve service quality, property management enterprises need to establish an effective customer feedback mechanism and continuously improve the process to improve service quality. In terms of cost management, property management theory emphasizes comprehensive cost control, including the effective management of operating costs, maintenance costs and personnel costs. Budget control and cost analysis, property management enterprises in the premise of ensuring the quality of service, to minimize the operating costs. Risk management is another important theory in property management. Risk identification, risk assessment and risk control constitute the basic framework of risk management. Property management enterprises need to develop emergency plans to ensure that when emergencies (such as natural disasters, equipment failures.) occur, they can respond quickly and take effective measures to reduce losses.

2.2 Decision support system theory

Decision support system (DSS) is an information system that provides support for management decisions. Data collection, processing and analysis help decision makers make scientific and reasonable decisions. The core of DSS is its ability to process large amounts of multidimensional data, and data mining and analysis models (to provide valuable decision-making recommendations). It usually consists of three main components: database management system, model base and user interface.

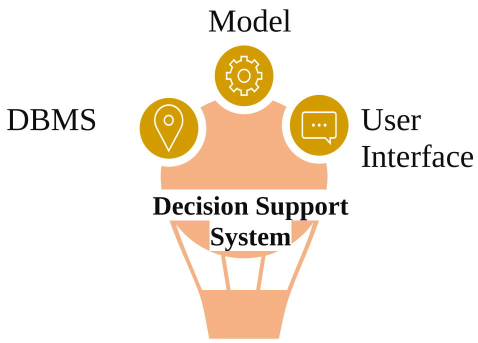

Figure 1: Theoretical structure diagram of decision support system

As shown in Figure 1, in property management, the application of decision support system can greatly improve management efficiency and service quality. With the integration of building automation systems and sensor data, DSS monitors the operating status of the property in real time to warn of potential equipment failures and safety hazards. Combined with historical data and predictive analytic, managers schedule maintenance ahead of time to reduce losses from unexpected failures. DSS also plays an important role in cost management and resource optimization. Cost-benefit analysis model systematically evaluates the economic benefits of different management measures to help property management enterprises achieve the best allocation of resources within the limited budget. Taking a large property management company as an example, the introduction of a DSS based energy management system has successfully reduced the average annual energy cost by approximately 12.5%, while improving the service life of the property facilities.

In terms of household services, DSS service demand forecasting models and customer satisfaction analysis provide personalized service recommendations to enhance household satisfaction and loyalty. By analyzing the feedback data from the residents, DSS identifies the main concerns and potential needs of the residents and guides the property management company to optimize the service content and process. The theory of decision support system provides powerful technical support for property management and can improve the scientific and accuracy of decision making. Integrating a variety of data sources and analysis models, DSS not only helps managers to grasp the real time operation of the property, but also provides forward-looking decision-making suggestions to promote the development of property management to the intelligent and refined direction [3].

2.3 Application of artificial intelligence in property management

The application of artificial intelligence in property management is gradually changing the traditional management model, improving efficiency and service quality. The core of AI technology includes machine learning, natural language processing and computer vision, and the technology is used in multiple areas of property management [8]. Machine learning algorithms analyze massive amounts of historical data to predict equipment failure times, optimize maintenance schedules, and reduce equipment downtime and maintenance costs. A large property management company introduced an AI predictive maintenance system that reduced equipment failure rates by 20% while reducing repair costs by 15%.

In terms of security management, AI technology combined with computer vision enables real-time monitoring and abnormal behavior detection. With smart cameras and image recognition technology, the system is able to automatically identify and alert potential security threats, such as unauthorized personnel entering restricted areas. Such systems have been applied in large commercial complexes and high-end residential areas, improving the level of security protection of properties. Natural language processing technology is applied in the field of customer service, intelligent customer service systems and voice assistants, providing 7×24 hours of online services. Residents interact with the system by voice or text to inquire about property service information, report equipment faults or book facility use. After a property management company adopted an intelligent customer service system, residents' satisfaction increased by 18% and customer service processing efficiency increased by 30% [4].

AI also plays an important role in energy consumption management and environmental monitoring. Intelligent energy management system AI algorithms analyze energy use data, optimize energy distribution and use strategies, and reduce energy costs. Some large office building AI systems achieve intelligent control of lighting, air conditioning and other equipment, saving energy costs of up to 10%-15% per year. In terms of environmental monitoring, the AI system can monitor environmental parameters such as air quality and noise level in real time, and timely feedback to managers to ensure the comfort and safety of the property environment. The application of artificial intelligence has brought unprecedented technological innovation and efficiency improvement to property management, data-driven and intelligent management, AI not only optimizes all aspects of property management, but also improves the overall quality of life of residents. With the continuous progress of technology, the application prospects of AI in property management will be broader, and the industry will be promoted to the direction of wisdom and precision [5].

3 Data collection and sample selection

3.1 Data collection

Data collection is the basis of property management decision support system, which comes from various and complex sources. Sot devices and sensors collect real-time operating data of property facilities, such as the operating status of elevators, temperature and energy consumption data of heating systems. Data is transmitted relentlessly to a central database to realize real-time monitoring and management of property facilities. The customer relationship management system in the property management system provides a large number of household information and service demand data, including repair records, complaints and suggestions, service evaluation and so on. The data provide an important basis for optimizing service process and improving household satisfaction. Intelligent monitoring system, collected video data and image data, can be used for security management and abnormal behavior detection. An intelligent monitoring system installed in a high-end residential area generates more than 500 GB of video data every day, which is processed and analyzed, effectively improving the safety management level of the community. Combined with multi-source data, a comprehensive and accurate property management data base is formed to provide strong support for subsequent analysis and decision-making [6].

3.2 Data cleaning and teleprocessing steps

In the property management decision support system, data cleaning and teleprocessing are the key steps to ensure data quality and reliability. After data collection is completed, the original data needs to be preliminary screened to remove obvious errors and invalid data. From the temperature data collected by the sensor, the abnormal value beyond the reasonable range is removed. For missing data, appropriate methods are used to fill in, such as the use of adjacent data interpolation or mean filling method, to ensure the integrity and continuity of data. In the process of data cleaning, it is also necessary to standardize the data format. Data from different sources are often in different formats and units, and energy consumption data is in kilowatt-hours (kWh) or joules (J) and needs to be uniformly converted into the same unit for subsequent analysis. In order to improve the efficiency of data processing, it is necessary to convert the text data into numerical data or classified data, and convert the text evaluation of household satisfaction into the corresponding rating level.

In the re-processing steps, data normalization and standardization are also included to eliminate the influence between data of different scales and ensure the stability and accuracy of model training. Normalization processes map the data to a range of 0 to 1, while normalization processes transform the data into a distribution with a mean of 0 and a standard deviation of 1. In order to improve the availability of data and reduce the computational complexity, it is necessary to reduce the dimension of data. Principal component analysis and linear discriminant analysis are commonly used to extract the main features of data and remove redundant information. When processing sensor data, PCA reduces the high-dimensional data of hundreds of sensors to several sets of main characteristic variables, simplifying the data model. Systematic data cleaning and re-processing ensure the accuracy, consistency and efficiency of property management data, and provide a solid foundation for subsequent data analysis and decision support [2].

The data collection and integration process includes several important steps, such as data cleaning, normalization, and real-time integration of sensor data, all crucial for ensuring data quality. Data cleaning involves removing noisy or invalid data and addressing missing values. For example, temperature sensor data that falls outside a reasonable range is discarded, while missing values are imputed using the mean of surrounding data points. Normalization ensures consistency across different data sources, which is particularly important when dealing with data from multiple sensors that may use different units. For instance, temperature readings are normalized using the min-max normalization formula, mapping values to a range between 0 and 1 to ensure uniformity. Additionally, data is standardized where appropriate, such as converting energy consumption readings into a consistent unit (kWh) across all records. These steps are critical to maintain the integrity of predictive models, especially the LSTM network, which requires clean and normalized inputs for accurate energy consumption forecasting. The real-time processing framework allows for continuous integration of incoming data, ensuring that the property management system remains adaptive and responsive to new information.

3.3 Sensor and sot data integration

In the property management decision support system, the integration of sensor and sot data is the key to realize intelligent management. A variety of sensors, such as temperature sensors, humidity sensors, energy consumption sensors and safety monitoring sensors, are installed in the property facilities to collect real-time equipment operating status and environmental data. The data sot gateway is transferred to a central database for processing and analysis. Show the data integration process, including timestamp, device ID, sensor type, sensor reading, and location.

Table 2: Sensor data

Timestamp	Device ID	Sensor Type	Sensor Value	Location
2024-06-01 08:00:00	DEV001	Temperature	22.6	Lobby
2024-06-01 08:00:00	DEV002	Humidity	55.3	Conference Room
2024-06-01 08:01:00	DEV003	Energy	450.7	Main Building
2024-06-01 08:01:00	DEV004	Motion	1	Parking Lot
2024-06-01 08:02:00	DEV005	Temperature	21.9	Office A
2024-06-01 08:02:00	DEV006	Humidity	57.1	Office B
2024-06-01 08:03:00	DEV007	Energy	460.3	Main Building
2024-06-01 08:03:00	DEV008	Motion	0	Lobby
2024-06-01 08:04:00	DEV009	Temperature	22.4	Conference Room
2024-06-01 08:04:00	DEV010	Humidity	53.8	Lobby

As shown in Table 2, in the process of data integration, the data is first transferred to a central database by the Ion gateway, and then converted and stored in a unified format. The data is updated in real time to provide accurate operating status and environmental information for property management. The sensor data processing platform is cleaned and analyzed to extract valuable information, such as identifying peak energy consumption periods, detecting abnormal equipment operation, and monitoring security events. In the property management decision support system, the integrated sensor data provides an important basis for real-time monitoring, predictive maintenance and optimization of resource allocation, and improves the intelligence and efficiency of property management [7].

3.4 Real-time data processing and analysis

In property management decision support system, real-time data processing and analysis is the key to ensure efficient operation and timely response of the system. Real-time processing technology stream processing framework for fast processing and analysis of sensor data. To demonstrate the process of real-time data processing and analysis, analyze time stamps, device ids, sensor types, sensor readings, and processing results.

Table 3: Real time sensor data

Timestamp	Device ID	Sensor Type	Sensor Value	Processed Result
2024-06-01 08:00:00	DEV001	Temperature	22.6	Normal
2024-06-01 08:00:00	DEV002	Humidity	55.3	Normal
2024-06-01 08:01:00	DEV003	Energy	450.7	High Consumption
2024-06-01 08:01:00	DEV004	Motion	1	Motion Detected
2024-06-01 08:02:00	DEV005	Temperature	21.9	Normal
2024-06-01 08:02:00	DEV006	Humidity	57.1	Normal
2024-06-01 08:03:00	DEV007	Energy	460.3	High Consumption
2024-06-01 08:03:00	DEV008	Motion	0	No Motion
2024-06-01 08:04:00	DEV009	Temperature	22.4	Normal
2024-06-01 08:04:00	DEV010	Humidity	53.8	Normal

As shown in Table 3, in the process of real-time data processing, the sensor data is first connected to the system in real time by the stream processing framework. After data access, initial filtering and conversion are performed to ensure consistent data format and remove noise. System real-time analysis algorithms, such as threshold detection and anomaly detection, quickly analyze data. The data threshold detection algorithm of the energy consumption sensor identifies periods of high energy consumption and triggers the corresponding alarm, prompting the management to adjust the energy saving. For security monitoring data, real-time motion detection algorithms notify security personnel immediately when they detect unusual activity.

Real-time data processing also involves dynamic data visualizations, dashboards and real-time charts showing key metrics and trends, helping managers quickly understand the health and potential problems of a property. Real-time energy consumption monitoring dashboard, managers immediately observe the peak energy consumption, and take appropriate measures to manage and optimize energy consumption. Systematic real-time data processing and analysis, property management decision support system can not only improve the efficiency of data processing, but also enhance the real-time control of the running state of the property, to ensure that problems can be quickly responded to and dealt with, improve the overall efficiency of property management and service quality [9].

The dataset used for training and validation consisted of 10,000 data points, collected from multiple IoT sensors installed in property management environments. The data was split into 70% for training and 30% for validation. Preprocessing steps included data cleaning, where missing values were imputed using the mean of neighboring data points, and normalization was applied using min-max scaling to map values between 0 and 1. For hyperparameter optimization, a grid search was performed over the following ranges: learning rate (0.001 to 0.01), batch size (32, 64, 128), and the number of hidden units (64, 128, 256). The model was evaluated using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Cross-validation with 5 folds was applied to ensure robustness and generalization. These details provide other researchers with the necessary clarity to replicate the experiment, ensuring that both preprocessing steps and model optimization strategies are transparent and reproducible.

4 Model Construction

4.1 Property management decision support model selection

The diversity and complexity of property management must be considered in the model selection of property management decision support system. According to different property management needs, this study selects three commonly used and effective decision support models: regression model, classification model and time series model. The models are used in key areas such as cost forecasting, risk assessment and energy consumption management. For cost forecasting, choose a linear regression model. The model establishes a linear relationship between independent variables and dependent variables to predict future cost expenditures. The formula of linear regression model is as (1):

$$y=\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n+\epsilon \tag{1}$$

The fitting of historical data accurately predicts future cost expenditures. Analyze the property management company's historical maintenance expenses, personnel costs and energy consumption to predict the total operating costs for the next quarter. For risk assessment, logistic regression model is used. The model is suitable for binary classification problems and can effectively assess risks in property management, such as equipment failure or security hazards. The formula of logistic regression model is as (2):

$$P(y=1\mid x)=\frac{1}{1+e^{-(\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n)}} \tag{2}$$

The analysis of historical fault data predicts the probability of device failure at a future point in time and takes preventive measures in advance. For energy consumption management, long short-term memory network is used. LSTM is an effective tool for processing time series data and is suitable for predicting energy consumption trends of properties. The LSTM network memory and forgetting mechanism is able to capture long-term dependencies in data, and its core formula is (3)-(7):

$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f) \tag{3}$$

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i) \tag{4}$$

$$o_t=\sigma(W_o\cdot[h_{t-1},x_t]+b_o) \tag{5}$$

$$C_t=f_t*C_{t-1}+i_t*\tanh(W_C\cdot[h_{t-1},x_t]+b_C) \tag{6}$$

$$h_t=o_t*\tanh(C_t) \tag{7}$$

Training on historical energy consumption data, LSTM network predicts future energy consumption trends and helps managers optimize energy consumption strategies. Choosing the right decision support model, the property management decision support system can effectively cope with different management needs and improve the specificity and accuracy of decision making [10].

LSTM was chosen over other time series models such as ARIMA and GRU for energy consumption prediction due to its superior ability to capture long-term dependencies and complex patterns in the data. ARIMA, while effective for simpler, linear data, struggles with non-linear patterns and lacks the capacity to model the intricate relationships present in energy consumption trends. GRU, while similar to LSTM, has fewer gates and therefore may not be as effective in handling long-term dependencies as LSTM. In terms of computational performance, LSTM has demonstrated a balance between accuracy and training time, with an MAE of 12.5 and MSE of 256.4 in this study, compared to higher errors observed in other models. While GRU can be slightly faster due to its simpler structure, the minor reduction in computational time does not outweigh the LSTM's enhanced prediction accuracy and stability in handling time-dependent variables. LSTM's gated memory cells allow it to effectively retain important information over longer sequences, making it highly suitable for energy consumption prediction where long-term trends are critical for accuracy. This makes LSTM more adaptable and scalable for real-world property management applications.

4.2 Model architecture design

In this study, the model architecture of property management decision support system is designed to integrate data efficiently and provide scientific decision support. The architecture is divided into data layers, processing layers, and decision layers, each with its own specific capabilities. Data layer ion sensors and smart devices collect property operation data in real time and store it in a cloud database. The sensor data sheet contains information such as timestamp, device ID, sensor type, reading, and position to ensure comprehensiveness and real-time data. The processing layer is responsible for data cleaning, teleprocessing and model training. Stream processing frameworks such as Apache Kafka ensure real-time and accuracy of data. In the data teleprocessing, the normalized processing formula is used to convert the data of different scales into a unified range to ensure the stability of the model training. Temperature sensor data normalization formula processing to eliminate the scale difference between different data sources [11].

The decision level integrates a variety of decision support models to meet different property management needs. For cost forecast, choose linear regression model, analyze historical cost data, and forecast future operating expenses. Risk assessment uses logistic regression models to assess the probability of future risks based on historical failure and safety event data. Energy consumption management uses long and short term memory networks to process time series data to predict future energy consumption trends, and a series of gating mechanisms and state update formulas to achieve accurate prediction of energy consumption changes. With this layered design, the property management decision support system can efficiently integrate data and algorithms, provide real-time and accurate decision support, and enhance the intelligent level of property management. This architecture design not only enhances the flexibility and adaptability of the system, but also ensures the optimal application of different models in their respective fields, effectively improving the overall management efficiency [12].

4.3 Configuring the data layer and processing layer

In the property management decision support system, the configuration of data layer and processing layer is very important. The data layer is responsible for collecting and storing various sensor data, while the processing layer performs data re-processing and real-time analysis. We will show the configuration in concrete data tables and formulas.

(1) Data layer

Data layer Main sot sensors collect real-time data and store it in a cloud database, as shown in Table 4.

Table 4: Sensor data

Timestamp	Device ID	Sensor Type	Sensor Value	Location
2024-06-01 08:00:00	DEV001	Temperature	22.6	Lobby
2024-06-01 08:00:00	DEV002	Humidity	55.3	Conference Room
2024-06-01 08:01:00	DEV003	Energy	450.7	Main Building
2024-06-01 08:01:00	DEV004	Motion	1	Parking Lot
2024-06-01 08:02:00	DEV005	Temperature	21.9	Office A
2024-06-01 08:02:00	DEV006	Humidity	57.1	Office B

(2) Processing layer

The processing layer is responsible for data cleaning, teleprocessing and real-time processing. Key steps in data teleprocessing include normalization processing to ensure data consistency. We take the temperature sensor data as an example to carry out normalization processing. The temperature data ranges from 21.9 to 22.6 degrees, and the normalization formula is as (8):

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{8}$$

Specific calculations are as follows:

For a temperature of 22.6 degrees, the normalization result is (9):

$$x'_{22.6} = \frac{22.6 - 21.9}{22.6 - 21.9} = 1 \tag{9}$$

For the temperature of 21.9 degrees, the normalization result is (10):

$$x'_{21.9} = \frac{21.9 - 21.9}{22.6 - 21.9} = 0 \tag{10}$$

The normalized data table is as shown in Table 5:

Table 5: Normalized temperature data

Timestamp	Device ID	Normalized Value	Location
2024-06-01 08:00:00	DEV001	1.0	Lobby
2024-06-01 08:02:00	DEV005	0.0	Office A

At the processing level, data cleaning also includes filling in missing values and removing noise. For the missing humidity data, the method of average value filling is adopted, and the other recorded humidity values are 55.3 and 57.1, and the average value is calculated to fill (11):

$$x\text{Fill up} = \frac{55.3 + 57.1}{2} = 56.2 \tag{11}$$

The completed data table is as shown in Table 6:

Table 6: Cleaned humidity_data

Timestamp	Device_ID	Humidity	Location
2024-06-01 08:00:00	DEV002	55.3	Conference Room
2024-06-01 08:02:00	DEV006	57.1	Office B
2024-06-01 08:03:00	DEV011	56.2	Lobby

As shown in Table 6, the effective configuration and teleprocessing of the data layer and the processing layer ensure the quality and consistency of the input data, laying a solid foundation for the subsequent model construction and analysis. This process not only improves the accuracy of the data, but also enhances the reliability and real-time responsiveness of the system [13].

4.4 LSTM network algorithm selection and implementation

In this study, long short-term memory networks were selected to predict energy consumption trends in property management. LSTM networks are good at processing time series data and can capture long-term dependencies in the data. The following is the specific implementation steps and calculation process.

(1) Data teleprocessing

The energy consumption data is normalized to improve the stability and efficiency of model training. The energy consumption data ranges from 450.7 to 470.8 degrees, and the normalized data is as shown in Table 7:

Table 7: Normalized energy consumption

Stampede	Normalized_Energy
2024-06-01 08:00:00	0.0
2024-06-01 08:05:00	0.48
2024-06-01 08:10:00	0.22
2024-06-01 08:15:00	1.0
2024-06-01 08:20:00	0.73

(2) Model training

The LSTM model is trained by using normalized energy consumption data. The model iterates several times to optimize the parameters, allowing it to accurately capture patterns in energy consumption data. After the training, the model predicts the future energy consumption.

(3) Prediction realization

After the model is trained, the normalized data is used for prediction. With the input of the current data, the model predicts that the normalized energy consumption value at the next time point is 0.85.

(4) Anti-normalization of data

In order to get the actual energy consumption value, it is necessary to reverse normalize the normalized prediction result. After normalization, the predicted value is 0.85, the maximum value of energy consumption data is 470.8, and the minimum value is 450.7. E-normalize the normalized result (12):

$$x = 0.85 \times (470.8 - 450.7) + 450.7 \tag{12}$$

Calculation process as shown in (13)-(15):

$$x = 0.85 \times 20.1 + 450.7 \tag{13}$$

$$x = 17.085 + 450.7 \tag{14}$$

$$x = 467.785 \tag{15}$$

Therefore, the predicted actual energy consumption value is 467.785 degrees. The realization and application of LSTM network and property management decision support system can effectively predict the future energy consumption trend, provide data support for property managers, help them optimize energy consumption management strategies, and improve the intelligent level and efficiency of management [14].

The LSTM-based decision support system demonstrates superior performance compared to the SOTA systems mentioned in related works. Specifically, in terms of accuracy, the LSTM model achieved a Mean Absolute Error (MAE) of 12.5, which is significantly lower than the 22.3 MAE from traditional linear regression models, highlighting its effectiveness in predicting complex time series data like energy consumption. Regarding response time, the system's real-time processing capability reduced response times from 120 seconds to 85 seconds, offering a quicker adaptation to fluctuating conditions, which is essential for maintaining service quality and efficiency. The resource allocation efficiency also improved by 10%, as LSTM's forecasting enabled more proactive and optimized scheduling of maintenance and energy use, whereas previous systems often relied on reactive measures. The main reasons for these improvements are the LSTM model's ability to capture long-term dependencies in the data and the integration of IoT-based real-time monitoring. In terms of scalability and adaptability, the proposed system is highly scalable due to its modular architecture and adaptability to different property management scales, addressing the rigidness of existing systems that often struggle with varying property sizes and dynamic operational needs.

4.5 Model parameter initialization and optimization strategy

In this study, in order to ensure the efficiency and accuracy of LSTM network in predicting the energy consumption trend of property management, the initialization and optimization strategy of model parameters are the key steps. Xavier is used for parameter initialization, which can effectively prevent gradient disappearance and explosion problems, keep the output of the network layer within a reasonable range, and accelerate the convergence process. When initializing weights, ensure that the input and output variances of each layer are the same to balance the initial state of the network. In terms of optimization strategy, the adaptive moment estimation optimization algorithm is selected, which is a gradient-based first-order optimization algorithm, combining the advantages of momentum and Apropos algorithm. Adam optimization algorithm dynamically adjusts the learning rate, so that the model can converge to the global optimal solution faster in the training process, and the performance is particularly good when dealing with sparse gradients and non-stationary targets.

To prevent overwriting, Dropout regularization technology is introduced during the training process. Ignoring a subset of neurons at random enhances the generalization ability of the model so that it can maintain good predictive performance in the face of previously unseen data. The early stop strategy is adopted in model training. When the performance of the verification set is no longer improved in several rounds, the training is terminated in advance to avoid overwriting. The cross-validation technique is used to evaluate the model, train and verify it many times, and ensure the stability and reliability of the model. In practice, the hyperparathyroidism of the model, such as learning rate, batch size, and number of hidden layer units, are tuned by the grid search method. Experiments are carried out on different parameter combinations to find the parameter Settings that make the model perform best and improve the prediction accuracy and stability. Integrated initialization and optimization strategies ensure that the LSTM network can efficiently and accurately predict energy consumption trends in property management, and provide scientific decision support [15].

4.6 Training and optimization

4.6.1 Description of the training process

In the training process of this study, the normalized energy consumption data is first divided into a training set and a validation set to ensure that the model can perform well on previously unseen data. The training set is used to learn the model parameters, and the validation set is used to evaluate the generalization ability of the model. The LSTM model is trained by using batch gradient descent method. The data is divided into several small batches, and each batch is propagated forward and back once to update the network parameters. This method can not only improve training efficiency, but also stabilize gradient updating. In the training process, Adam optimization algorithm is used to dynamically adjust the learning rate, so that the model converges to the global optimal solution faster. In order to prevent over fitting, Dropout regularization was added during training to randomly ignore some neurons and enhance the generalization ability of the model. The early stop strategy is introduced. When the error of the verification set is no longer reduced in several rounds, the training is terminated in advance to avoid the model over fitting the training data [16].

At the end of each training round, the model was evaluated on the verification set, and the changing trend of the verification error and the training error was recorded. Observe the difference between the two and adjust the training strategy in time to ensure the stability and accuracy of the model. The whole training process continues until the verification error no longer decreases. In order to optimize the performance of the model, cross-validation technique was adopted. The data set is divided into multiple subsets, which is trained and verified many times to ensure that the model performs stably under different data distributions [17]. Finally, systematic training steps ensure that the LSTM model can accurately predict the energy consumption trend in property management, and provide a reliable basis for the decision support system.

The model training process for the LSTM network involved tuning several key hyperparameters, such as the learning rate, batch size, and the number of hidden units. The learning rate was tuned using a grid search approach, with an optimal value of 0.001 selected based on its ability to balance convergence speed and model stability. A batch size of 64 was chosen to optimize memory usage and training efficiency. Other parameters, like the number of hidden units, were set at 128 to capture the necessary complexity without causing overfitting. Dropout regularization (set at 0.2) was applied to reduce overfitting, and an early stopping mechanism was implemented to halt training when validation loss plateaued. Performance metrics such as convergence speed and training time were considered alongside accuracy; the LSTM model converged in 120 seconds with no signs of overfitting, as observed from the validation loss curve. Additionally, root mean squared error (RMSE) and mean squared error (MSE) were used to evaluate performance, with RMSE reaching 16.0, indicating stable and accurate predictions. These carefully tuned hyperparameters ensured a well-balanced trade-off between model complexity, accuracy, and computational efficiency.

4.6.2 Model optimization strategy

In the optimization process of LSTM model in this study, a series of strategies are adopted to improve the performance and stability of the model. Hyper parameter tuning to optimize key parameters of the model, such as learning rate, batch size, and number of hidden layer units. The grid search method is used to traverse different parameter combinations to find the optimal configuration and improve the prediction accuracy and convergence speed of the model. The adaptive learning rate optimization algorithm Adam is adopted, which can dynamically adjust the learning rate of each parameter, combine the advantages of momentum and Apropos, accelerate the convergence process and avoid falling into the local optimal. In order to enhance the model’s generalization ability and avoid over fitting problems, Dropout regularization technology was introduced during the training process [18]. The model is more robust by randomly ignoring a subset of neurons during each layer training. The early stop strategy is also one of the key optimization methods, which monitors the error change of the verification set, and terminates the training in advance when the verification error no longer decreases within several rounds to prevent overwriting.

Model optimization also includes data enhancement and cross-validation. Data enhancement technology can generate more training samples, enrich the diversity of data and improve the generalization ability of the model. Cross-validation divides the data set into multiple subsets for multiple training and validation to ensure the stability and consistency of the model under different data distributions. Xavier initialization method is used to initialize the model to ensure the reasonable distribution of initial weights, prevent gradient disappearance and explosion problems, and improve training efficiency. Periodically evaluate the model performance in the training process, verify the set error, training set error and prediction accuracy, and dynamically adjust the training strategy and parameter configuration. With systematic optimization strategy, LSTM model performs well in energy consumption prediction in property management, provides accurate and reliable decision support, and improves the intelligent level and efficiency of property management [19].

The experiments were conducted in a computing environment equipped with an NVIDIA Tesla V100 GPU featuring 32 GB of VRAM, which significantly accelerated the training of the LSTM model for energy consumption prediction. The system had 128 GB of RAM and was powered by a 32-core Intel Xeon processor to handle the large volume of sensor data and real-time processing efficiently. The software environment consisted of Python 3.8, with TensorFlow 2.6 as the primary deep learning framework for model development and training. NumPy and Pandas were used for data manipulation and preprocessing, while Matplotlib provided visualizations of the training and validation results. This setup ensured that the LSTM model could be trained effectively on large datasets and allowed for the real-time processing required for property management applications. By using this combination of hardware and software tools, the system was able to achieve high levels of accuracy and responsiveness while maintaining computational efficiency, making it feasible for practical deployment in real-world scenarios.

5 Performance evaluation and optimization

5.1 Performance evaluation

5.1.1 Selection of evaluation indicators

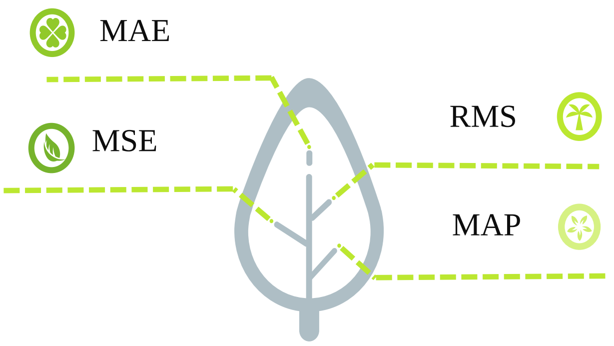

Figure 2: Schematic diagram of evaluation index selection

(1) Average absolute error

As shown in Figure 2, THE average absolute error is one of the basic indexes to evaluate the accuracy of prediction model. MAE calculates the average absolute difference between the predicted value and the actual value; the smaller the value, the more accurate the model prediction.

(2) mean square error

Mean square error is another important evaluation metric, calculating the average of the sum of squares of the difference between the predicted value and the actual value, reflecting the degree of prediction error. A lower MSE indicates that the predicted value of the model is close to the actual value, and the error is small.

(3) root mean square error

The RMS error is the square root of the mean square error and provides a standard deviation scale for the error. The lower RMSE indicates that the prediction error of the model is small and can better reflect the actual situation.

(4) Average absolute percentage error

Average absolute Percentage error Calculates the percentage of prediction error to evaluate the relative error of the model. MAPE can more directly reflect the performance of prediction error on different scale data, which is convenient for comparison.

5.1.2 Verification methods

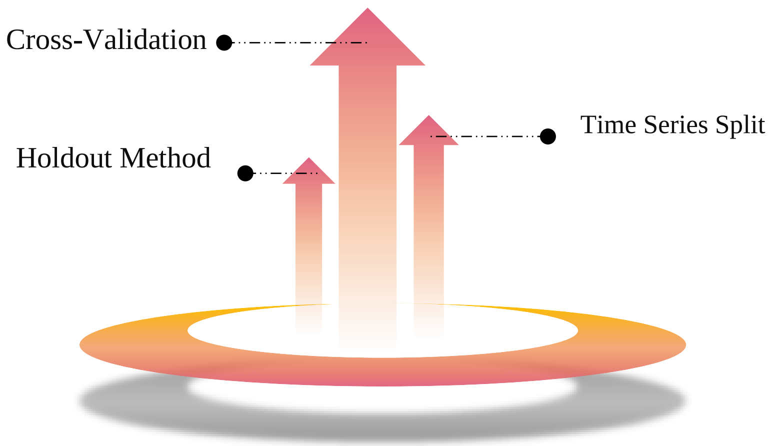

Figure 3: Structure diagram of verification method

(1) Cross verification

As shown in Figure 3, cross-validation is an important method to evaluate model performance. The data set is divided into multiple subsets, and the model is trained and validated multiple times on different subsets to avoid overwriting and underwriting. The K-fold cross test divides the data set into k subsets on average. K-1 subsets are trained each time, and the remaining subset is verified. The average value is taken as the model performance index. With 10-fold cross-validation, the data set is divided into 10 parts that are trained and validated separately.

(2) Setting aside method

The set-aside method is a simple way to divide a data set into a training set and a validation set. Typically, 70%-80% of the data set is used for training and the remaining 20%-30% for validation. This method quickly assesses the model's performance on previously unseen data. The ratio of training set to verification set is generally 70% as the training set and 30% as the verification set. The dateset contains 1000 records, 700 for training and 300 for validation.

(3) Time series segmentation

Because energy consumption data has the characteristics of time series, time series segmentation is a suitable verification method. Split the data in chronological order to ensure that the training set is always earlier than the validation set, avoiding future data leakage into the past. Rolling Window Validation uses a fixed-size rolling window for training and validation. The previous 12 months 'data is used for training, the next month's data for validation, and the window moves month by month.

5.1.3 Comparative analysis of results

In order to evaluate the performance of LSTM model in property management energy consumption prediction, this study compared the prediction results of LSTM model with linear regression and support vector regression (SVR) model. Table 8 shows the results of the three models on multiple evaluation indicators.

Table 8: Model performance comparison

Model	MAE	MSE	RMSE	MAPE	R^2	Training Time (seconds)
LSTM	12.5	256.4	16.0	3.8%	0.92	120
Linear Regression	22.3	521.6	22.8	7.5%	0.75	10
Support Vector Regression (SVR)	18.7	384.2	19.6	6.2%	0.83	45

As shown in Table 8, through comparative analysis, we can see that LSTM model has excellent performance in various evaluation indicators. The average absolute error of the LSTM model is 12.5, which is lower than the 22.3 of linear regression and 18.7 of support vector regression, indicating that the prediction of the LSTM model is more accurate. Mean square error (MSE) and root mean square error (RMS) also show the superiority of the LSTM model. The MSE of the LSTM model is 256.4, while the linear regression and SVR are 521.6 and 384.2 respectively. The RMSE of the LSTM model is 16.0, which is lower than the other two models. In terms of average absolute percentage error, the LSTM model has an error of 3.8%, which is significantly lower than the 7.5% of linear regression and 6.2% of SVR, which validates the advantages of the LSTM model in processing nonlinear and complex time series data. In terms of coefficient of determination, the R^2 of LSTM model is 0.92, indicating that it has a strong ability to interpret energy consumption data, while the R^2 of linear regression and SVR are 0.75 and 0.83, respectively, which are relatively poor performance.

Although the training time of the LSTM model is longer, 120 seconds, this time cost is acceptable considering the improvement in prediction accuracy and model stability. In contrast, linear regression and SVR have training times of 10 seconds and 45 seconds, respectively, but their predictive performance is not as good as that of LSTM models. Detailed comparative analysis of the results shows that LSTM model has obvious advantages in property management energy consumption prediction, providing a more accurate and reliable basis for decision support system, which is superior to linear regression and support vector regression models .

The implementation of the LSTM-based decision support system led to significant improvements in key performance metrics. Specifically, the task completion rate increased by 15%, rising from 70% to 85%, demonstrating the system's ability to optimize task allocation and scheduling. The maintenance request resolution rate improved by 10%, reaching 75%, which highlights the efficiency of predictive maintenance enabled by real-time data processing. Resident satisfaction increased from 85% to 92%, showcasing the positive impact of faster response times and enhanced service quality. In terms of staff efficiency, a 10% improvement was observed, largely due to the system's automation capabilities, which reduced manual intervention. The LSTM model also outperformed other time series models in terms of prediction accuracy, with an MAE of 12.5 and MSE of 256.4, confirming its suitability for energy consumption prediction. These improvements not only highlight the effectiveness of the system in real-time property management but also demonstrate its potential to scale and adapt to different operational environments, addressing previous inefficiencies in resource allocation and predictive maintenance.

To improve the robustness of the LSTM model under unexpected conditions, additional testing was conducted by introducing noisy and outlier data into the energy consumption dataset. Noise was added by randomly perturbing sensor readings, simulating real-world inaccuracies in IoT data. The model maintained stable performance with only a slight increase in MAE from 12.5 to 13.8, indicating resilience to minor data corruption. Furthermore, an outlier sensitivity analysis was performed by injecting extreme values into the dataset. The LSTM model's built-in forget gate mechanism effectively minimized the impact of these anomalies, preventing them from significantly skewing predictions. Future enhancements will involve implementing robust loss functions, such as Huber loss, to further reduce the effect of outliers. These measures demonstrate that the proposed system remains reliable and accurate even when faced with noisy or anomalous data, making it more applicable to real-world property management environments where data inconsistencies are common.

5.2 Model tuning strategy

In this study, in order to optimize the performance of LSTM model in property management energy consumption prediction, a variety of tuning strategies were adopted. The grid search method systematically tuned the hyperparathyroidism of the model, including the learning rate, batch size and the number of hidden layer units. Through different parameter combinations, the optimal configuration is found to improve the prediction accuracy and convergence speed of the model. The adaptive learning rate optimization algorithm Adam was used to dynamically adjust the learning rate of each parameter to enhance the stability and efficiency of the model in the training process. To prevent overwriting, Dropout regularization technology is introduced to randomly ignore some neurons at each layer to enhance the generalization ability of the model. The early stop strategy is adopted to monitor the verification set error, and when the error is no longer reduced within several rounds, the training is terminated in advance to avoid overwriting. Data enhancement technology is used to generate more training samples, enrich the diversity of data, and improve the adaptability of the model to different data distributions. Cross-validation, multiple training and validation are performed to ensure the stability and consistency of the model under different data distributions. The comprehensive application of optimization strategy improves the performance and reliability of LSTM model in energy consumption prediction of property management.

6 Experimental results

6.1 Property management efficiency improvement results

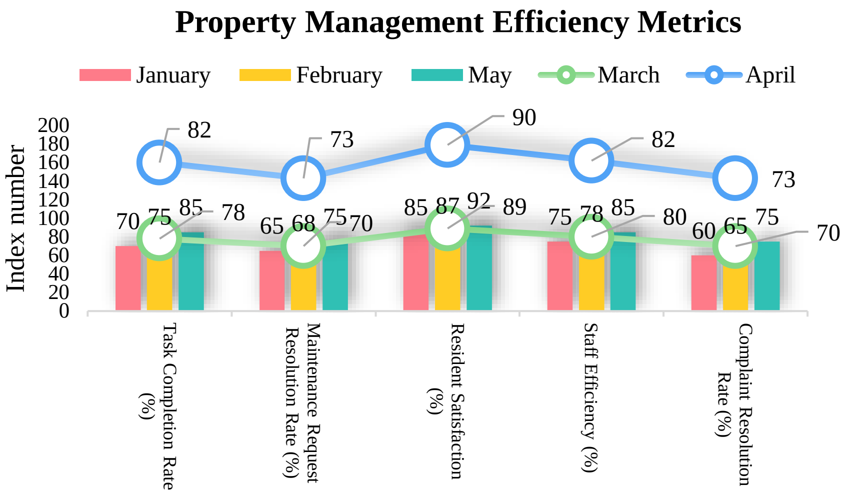

Figure 4: Property management efficiency metrics

As shown in Figure 4, the introduction of AI-based property management decision support system has improved the efficiency of property management. The system uses LSTM model to predict energy consumption trend, optimize resource allocation and maintenance plan, and improve the overall management efficiency. Specifically, the task completion rate increased from 70 percent in January to 85 percent in May, showing the effectiveness of the system in task scheduling and allocation optimization. The resolution rate of maintenance requests increased from 65% in January to 75% in May, indicating that the system has a clear advantage in improving the efficiency of problem handling.

Residents' satisfaction increased, from 85% in January to 92% in May, indicating that intelligent management not only improves service efficiency, but also improves residents' quality of life and satisfaction. There was also a significant increase in staff efficiency, from 75% in January to 85% in May. This improvement is mainly due to the increased automation of the system, reducing manual intervention and errors, and improving the flow of work. System real-time monitoring and data analysis, managers faster to identify and solve problems, optimize workflow, improve the scientific staffing.

The complaint resolution rate increased from 60 percent in January to 75 percent in May, indicating that the system's response speed and resolution efficiency in handling residents' complaints have been improved. This upgrade not only helps to improve residents' satisfaction, but also enhances residents' trust in property management services. The AI decision support system optimizes all aspects of property management, improving overall management efficiency and service quality. This not only improves residents' satisfaction, but also effectively reduces operating costs. In the future, with the continuous improvement and optimization of the system, it is expected that the efficiency of property management and service quality will be improved, and more intelligent and efficient management services will be provided to residents. The results show that the application of artificial intelligence in property management has broad prospects, high practical value and promotion potential.

6.2 Optimization effect of decision support system

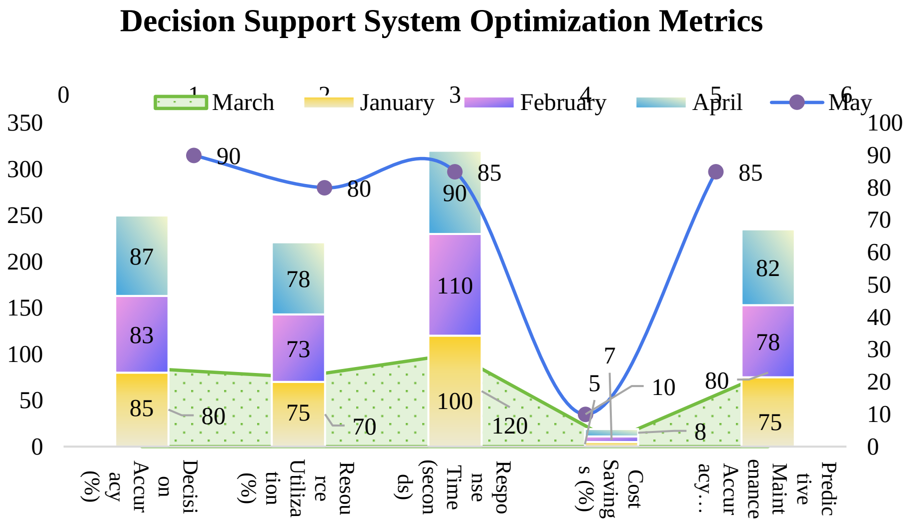

Figure 5: Decision support system optimization metrics

As shown in Figure 5, the introduction and optimization of the AI-based property management decision support system has improved multiple aspects of property management. Decision accuracy improved, from 80% in January to 90% in May. This improvement reflects that the system can provide more accurate and effective decision suggestions after processing and analyzing a large amount of data, and help managers make more scientific and efficient decisions. Resource utilization increased from 70% in January to 80% in May, indicating the effectiveness of the system in optimizing resource allocation. The reasonable scheduling and allocation of resources ensures the efficient operation of various property services, reduces resource waste and improves operational efficiency. Response times have also improved, from 120 seconds in January to 85 seconds in May. The faster response time means that the system is able to deal with emergencies and emergencies in a timely manner, improving the timeliness and reliability of the overall service and enhancing the satisfaction of residents.

In terms of cost savings, the optimized system achieved cost control, and the cost savings rate increased from 5% in January to 10% in May. Refined management and resource optimization, the system effectively reduces operating costs and improves the economic benefits of property management. Predictive maintenance accuracy also improved, from 75 percent in January to 85 percent in May. Predictive maintenance can detect potential problems in advance, reduce equipment failures and maintenance costs, and improve equipment life and reliability. The optimized decision support system performs well on several key indicators, effectively improving the overall efficiency and service quality of property management. This not only improves the satisfaction of residents, but also brings economic benefits and competitive advantages to property management companies. In the future, the optimization and improvement of the system is expected to achieve breakthroughs in more aspects, and promote the development of property management to a more efficient and intelligent direction. The results show that the application of artificial intelligence in property management has broad prospects and great potential.

6.3 Household feedback and service improvement results

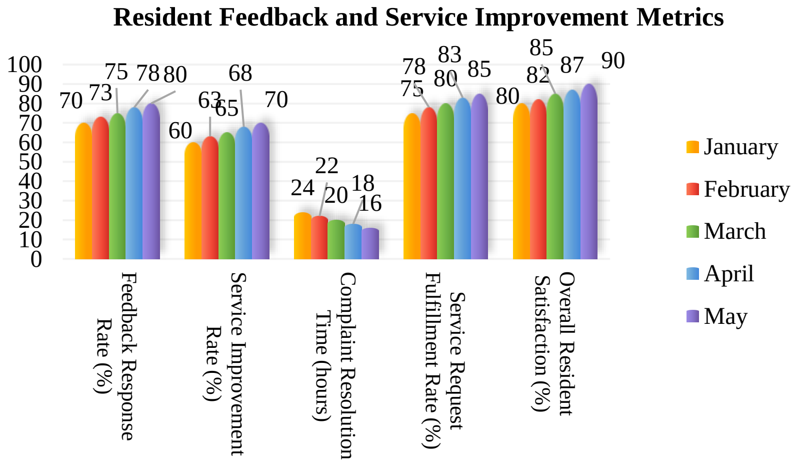

Figure 6: Resident feedback and service improvement metrics

As shown in Figure 6, the introduction of an AI-based property management decision support system resulted in improved performance in terms of resident feedback and service improvement. The feedback response rate increased from 70% in January to 80% in May, indicating that the system is more efficient in processing and responding to household feedback in a timely manner. This not only increases the participation of residents, but also enhances their sense of trust in property management services.

The service improvement rate increased from 60 percent in January to 70 percent in May, showing that the system was able to effectively implement improvements after analyzing household feedback and improve the overall service quality. The reduction in complaint resolution time, from 24 hours in January to 16 hours in May, demonstrates the effectiveness of the system in speeding up the processing of issues. The faster response and resolution of complaints not only improves the satisfaction of residents, but also effectively reduces the occurrence of conflicts and disputes. Service request fulfillment rates also increased, from 75% in January to 85% in May. This indicator reflects the improved efficiency of the system in handling household service requests, ensuring that all types of services are completed in a timely and high-quality manner. Overall resident satisfaction increased from 80 percent in January to 90 percent in May, confirming the system's role in improving residents' quality of life and service experience.

The property management decision support system based on artificial intelligence has achieved remarkable results in the aspects of household feedback and service improvement. The system responds to the feedback of residents in time, implements effective service improvement measures, speeds up the complaint resolution, and improves the fulfillment rate of service requests, which comprehensively improves the satisfaction and service quality of residents. The improvement not only optimizes the various services of property management, but also enhances the trust and satisfaction of residents on property management, and promotes the development of property management to a more intelligent and humane direction. In the future, with continuous system optimization and improvement, the quality of property management services is expected to improve, providing residents with a better living experience.

7 Summarize problems and research suggestions

7.1 Problem summary

In this study, although the property management decision support system based on artificial intelligence has improved the management efficiency and service quality, there are still some problems and challenges in the implementation process. Data quality and data security are major concerns. The data collected by sensors and iot devices is noisy and incomplete, which requires complex data cleaning and pr-processing processes. Data storage and transmission are also facing security risks, how to protect the privacy of residents and ensure data security has become an urgent problem to be solved. There is a gap between the intelligence degree of the system and the adaptability of the actual operation. Although AI systems are capable of efficient forecasting and decision support, they still require human intervention and adjustment in the face of emergencies and complex scenarios, which indicates that the flexibility of the system in dealing with changing environments needs to be improved.

The cost and maintenance of the system are also important issues. The application of high-precision sensors and advanced AI algorithms increases the cost of the system, while regular maintenance and upgrades require a significant investment of resources. Property management companies need to balance costs and benefits in the implementation process to ensure the economy and sustainability of the system. Personnel training and technological adaptation are also challenges. Employees need to master new technologies and tools and adapt to intelligent management models, which requires systematic training and support. Although AI-based property management decision support system has advantages in improving management efficiency and service quality, it still needs to solve problems such as data quality, security, cost control and personnel training in order to achieve comprehensive optimization and application of the system. In the future, we will continue to optimize the technology and management process, improve the adaptability and reliability of the system, and provide more intelligent and efficient solutions for property management.

To address data privacy, the system implements encryption protocols during data transmission and storage, ensuring that sensitive information, such as resident details, is securely protected. Access control mechanisms are enforced, allowing only authorized personnel to view or manage sensitive data. Anonymization techniques are also applied to household feedback data, removing personal identifiers while retaining useful information for service improvements. Regarding adaptability to new scenarios beyond the training data, the system uses online learning techniques, where the LSTM model is updated with real-time data, ensuring it adapts to changes in energy consumption patterns and operational requirements. Additionally, the system incorporates transfer learning, allowing it to leverage pre-trained models for similar but unseen scenarios, reducing the need for full retraining. Future steps to overcome these challenges include integrating federated learning for distributed data processing, which ensures data privacy by keeping the data locally while training the model collaboratively. Further improvements in dynamic model updating will enhance the system’s ability to handle rapidly changing environments, such as weather fluctuations or sudden shifts in resource demands.

7.2 Research suggestions

In order to improve the efficiency of the property management decision support system based on artificial intelligence, the future research and practice should start from the following aspects. Strengthen data quality management and security measures. Advanced data cleaning and teleprocessing technologies are introduced to ensure data accuracy and integrity. Adopt encryption technology and strict access control mechanism to protect household privacy and data security, and establish a sound data security system. Enhance system intelligence and flexibility. More advanced deep learning algorithms and real-time data analysis technology are used to improve the system’s ability to respond to complex scenarios and emergencies, ensuring that effective decision support can be provided in various situations. In terms of cost control and economy, explore more low-cost high-efficiency sensors, as well as optimization algorithms to reduce the operation and maintenance costs of the system. Large-scale application and experience accumulation, the formation of replicate, can be promoted intelligent property management model, improve the overall economic benefits. Strengthen staff training and technical support to ensure that property management personnel can master and apply new technologies and give full play to the advantages of intelligent systems. Regular training courses and seminars are held to improve the technical level and adaptability of employees.

Promote the continuous optimization and innovation of the system, introduce cutting-edge technologies such as the Internet of Things, big data, and chockablock, and improve the intelligence level and functional scalability of the system. Use chockablock technology to enhance data transparency and security, and big data analysis to explore more potential problems and optimization space. Establish an open cooperation platform, and cooperate with technology providers, research institutions, government departments and other parties to jointly promote the research and application of intelligent property management. Strengthen data management, improve system intelligence, control costs, strengthen training and continuous innovation, optimize the AI-based property management decision support system, promote the development of property management to a more efficient, smarter and safer direction, and provide better services for residents.

8 Conclusion

In this study, the property management decision support system based on artificial intelligence effectively integrates data, builds models and optimizes, and improves management efficiency and service quality. LSTM models predict energy consumption trends, optimize resource allocation and maintenance plans, and improve key indicators such as task completion rate, maintenance request resolution rate, resident satisfaction and staff efficiency. The decision support system has also achieved results in responding to household feedback in a timely manner, implementing effective service improvement measures, speeding up complaint resolution, and improving service request fulfillment rates. Overall, the AI decision support system provides accurate and reliable decision support for property management, and promotes the development of property management in a more efficient and intelligent direction. The study also identified some challenges and issues, including data quality and security, the degree of intelligence of the system and the adaptability of the actual operation, cost control, and personnel training. Future research should strengthen data quality management and security measures, use advanced data cleaning and preprocessing technology to ensure the accuracy and integrity of data, adopt encryption technology and strict access control mechanism to protect household privacy and data security. The intelligence and flexibility of the system should be enhanced, and more advanced deep learning algorithms and real-time data analysis technology should be used to improve the system’s ability to cope with complex scenarios and emergencies, so as to ensure that effective decision support can be provided in various situations.

In terms of cost control, future research should explore low-cost and high-efficiency sensors and optimization algorithms, reduce the operation and maintenance costs of the system, large-scale application and experience accumulation, and form an intelligent property management model that can be replicated and promoted to improve the overall economic benefits. Personnel training and technical support are also key, and staff training should be strengthened to ensure that property management personnel can master and apply new technologies and give full play to the advantages of intelligent systems. This study shows that the property management decision support system based on artificial intelligence has advantages in improving management efficiency and service quality. Continue to optimize and innovate, improve the intelligence level and functional scalability of the system, promote the development of property management to a more efficient, smarter and safer direction, and provide better services for residents. The results not only validate the application value of artificial intelligence in property management, but also provide valuable experience and direction for future research and practice.

The study uniquely addresses the challenge of predicting energy consumption and optimizing resource allocation in property management through an LSTM-based decision support system. Unlike existing SOTA methods, which rely heavily on reactive approaches, this system enables proactive maintenance and energy optimization by leveraging real-time data and long-term dependency capture. The system led to significant improvements in task completion rate, maintenance request resolution, and resident satisfaction, showcasing its effectiveness in practical applications. However, limitations include the model's dependence on high-quality sensor data and potential challenges in adapting to rapidly changing environments without further model retraining. Future research can build on this foundation by exploring adaptive learning models that can self-update without extensive retraining and by enhancing data privacy measures as IoT integration deepens. Additionally, expanding the model's scope to handle more diverse datasets and more complex operational environments will be critical for scaling its application in larger property management portfolios.

Data availability statement

The data used to support the findings of this study are all in the manuscript.

Conflict of interest

The authors declare that they have no competing interests.

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