Research on Supply and Demand Forecasting and Energy-Saving Scheduling in Smart Canteens

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https://doi.org/10.70695/IAAI202602A3

Abstract

This paper presents an integrated solution for a smart canteen in a large industrial park, encompassing supply and demand forecasting, meal preparation and procurement, and energy-saving scheduling. Based on operational and energy consumption data from the past four years (2018-2021), a two-tiered demand forecasting model (daily/hourly) was developed. Furthermore, under time-of-use pricing and peak-limit restrictions, coordinated improvements were implemented to kitchen and HVAC equipment. Results show that in the 2025 test dataset, the MAPE value of the random forest forecasting model was 3.31%, a 68.1% reduction compared to the empirical lag method. Regarding meal preparation, the leftover rate decreased from 9.05% to 3.36%, resulting in a total annual saving of approximately 9.45×10^{-6} kJ/m³. One ton of food (calculated at 0.35 kg/meal) saved approximately 1.4 million yuan in raw material costs. From an energy consumption perspective, predictive model control reduced annual electricity consumption by 9.0%, electricity costs by 13.2%, average daily peak power by 14.9%, and carbon emissions from electricity by 38.9 tCO2. This research can provide engineering references for public institutions to coordinate "anti-waste" and "energy conservation and carbon reduction".

Keywords Smart Canteen; Demand Forecasting; Meal Preparation Optimization; Energy-Saving Scheduling; Time-of-Use Pricing; Model Predictive Control

1 Introduction

Campus canteens and park canteens have typical characteristics such as "short peak hours, rich variety of dishes, and large fluctuations in demand". If we still prepare food according to experience and manage energy use roughly, there is a high possibility of food waste due to supply and demand mismatch. Moreover, there will be a situation where electricity consumption increases during peak hours. Qian Long et al. analyzed the behavior of college students wasting food when eating in university canteens from the perspective of the difference between the north and the south. They believed that waste is related to supply strategy, dining habits and environmental factors. Therefore, it is not possible to suppress waste in the long term by simply advocating. A feasible mechanism should be created where supply and demand are matched [1]. Kuang Wenbin gave a two-layer model based on sales forecast to predict the sales of university canteen windows. He proved that layered modeling can improve the accuracy of short-term forecasts. However, his research focused on sales itself and did not link energy consumption with operation scheduling decisions [2]. Cao Shuanghua et al. used XGBoost to predict the load of office building envelope in hot summer and cold winter areas, showing that machine learning has a strong adaptability to nonlinear load prediction. However, there are differences in the excitation factors and time-varying constraints between building load and catering supply and demand. Model transfer still needs to reshape the feature system and constraint conditions according to the scenario characteristics [3]. Wu Tong et al. reviewed the research and implementation of commercial building air conditioning system participating in power grid load regulation. They felt that peak shaving and valley filling can be achieved through regulation strategies and improved frameworks. However, most of their objects are single systems. There are still difficulties in cross-subsystem coordination and service quality constraints [4]. Luo Zhengyi et al. defined the flexibility of building demand side and summarized the flexible load and its quantification method. They emphasized that comfort/service and energy saving should be achieved within the quantifiable flexible boundary. However, in complex operating scenarios, the evaluation of flexible availability and scheduling loop still need further engineering implementation [5]. Existing research has provided evidence and suggestions on consumer behavior and the mechanisms of food waste formation. In terms of demand-side flexibility and building load regulation, demand response and model predictive control have become key technical paths for peak shaving and carbon reduction. However, research on canteen scenarios often only focuses on management functions such as "smart settlement and traceability supervision", and lacks a systematic and feasible engineering framework for "coordinated improvement of meal preparation and energy consumption driven by supply and demand forecasting".

Based on this, this paper, following the relevant standards for the creation of smart catering in higher education institutions, takes a smart canteen in a large-scale park as an example and proposes a technical path that unifies supply and demand forecasting and energy-saving scheduling: First, it forms a daily/hourly demand forecasting model that integrates multi-source data; second, it applies the forecasting results to meal preparation and procurement plans to reduce leftover food; third, under time-of-use pricing and peak limits, it implements closed-loop scheduling for adjustable loads such as the kitchen and HVAC systems to achieve the overall goal of "reducing consumption, reducing costs, reducing peak loads, and reducing carbon emissions." This paper emphasizes the data effects and the reusability of the project, while keeping the description of the technology and system within necessary limits.

2 Project Overview

2.1 Scenarios and Scale

The research subject is a smart canteen group in a large park in a certain place. The park includes teaching area, office area and living area. Its daily meal supply is about 11,000 meals. This number fluctuates greatly during the semester and holidays. Figure 1 shows the monthly meal volume and peak load changes [6].

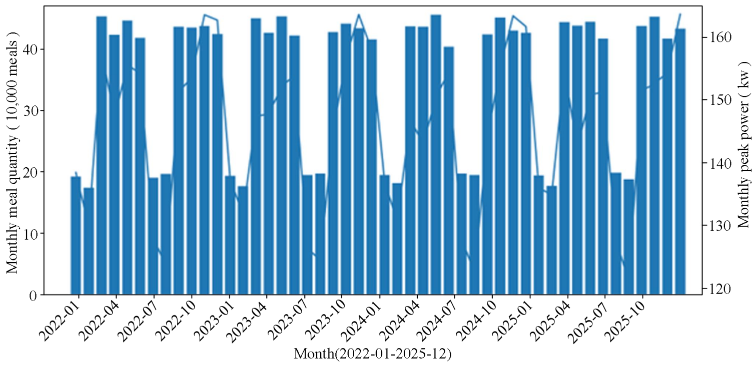

Fig. 1. Changes in monthly dining volume and peak load

The three main peak dining periods occur at breakfast, lunch, and dinner, and a typical weekly hourly demand curve is shown in Figure 2.

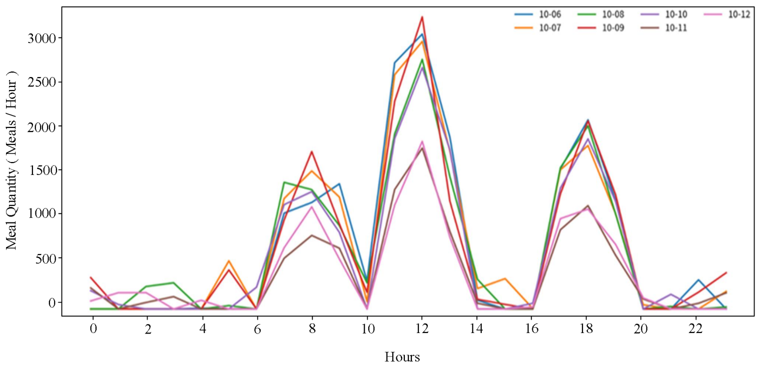

Fig. 2. Typical weekly hourly dining demand curve (October 2025)

From both spatial and temporal perspectives, it can be observed that the demand of each terminal during the semester has a prominent "timetable-driven" characteristic, and the heat distribution of demand during the semester is shown in Figure 3.

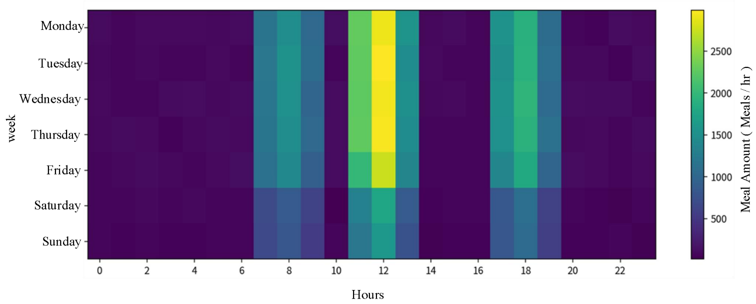

Fig. 3. Heat map of terminal semester dining demand (2025)

2.2 Data Acquisition and Definition

The data sources include three aspects: First, consumer-side data, which involves card swiping/scanning, online reservations, window sales, dish categories, return/packaging markings, etc.; Second, environmental-side data, which relates to weather temperature, rainfall, holidays and school calendars, etc.; Third, energy-side data, which involves sub-meters and water meters, covering refrigeration units, fresh air and exhaust systems, steam ovens/induction cookers/dishwashers, lighting equipment and cold storage, etc. These data are aligned according to the granularity of "day" and "hour" and are thus used as the basis for forecasting and scheduling [7].

2.3 System Architecture

The system has a cyclical architecture of "data access-prediction service-improved scheduling-execution feedback", and its core modules and data flow are shown in Figure 4.

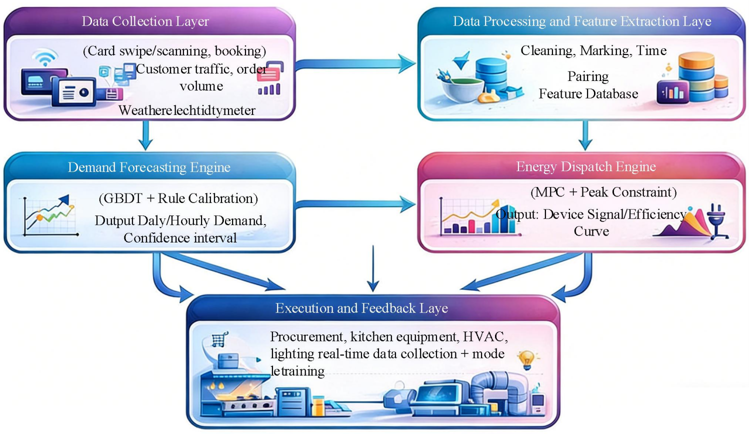

Fig. 4. Architecture of the smart canteen supply and demand forecasting and energy-saving scheduling system

3 Supply and Demand Forecasting and Energy-Saving Scheduling Methods

3.1 Demand Definition and Forecasting Objectives

To balance the needs of meal preparation (calculated on a daily basis) and equipment scheduling (calculated on an hourly basis), this paper defines the demand as d the amount of meals consumed $D_{d,h}$ on a given day per hour h.

$$D_{d,h}=\sum_{i=1}^{n_{d,h}}q_{i,d,h} \tag{1}$$

In formula (1), $D_{d,h}$ represents the number of meals (meals) in hour h of date d, $q_{i,d,h}$ refers to the meal count corresponding to the i-th transaction, which is generally 1, $n_{d,h}$ and is the number of transactions in that hour. Daily demand D_d can be obtained by $D_{d,h}$ performing a summation operation on to 23 $h=0$ [8].

3.2 Demand Forecasting Model and Evaluation Indicators

In the feature layer, a synthetic feature is formed: "Calendar features include weekdays, whether it is a holiday or exam week, meteorological features are related to temperature and rainfall, lag features cover the data of the previous 1 day, the previous 7 days and the previous 14 days, and rolling statistical features focus on the average of the last 7 days". The prediction model mainly relies on random forest regression and will add rule corrections, such as semester transitions, important event dates and the like [9].

To uniformly measure the predictive performance of different models, three metrics can be used: MAE, RMSE, and MAPE.

$$MAE=\frac{1}{N}\sum_{t=1}^{N}\left|y_t-\hat{y}_t\right| \tag{2}$$

In equation (2): MAE is the mean absolute error; N is the number of samples; y_t is t the true value of the i-th sample; $\hat{y}_t$ is t the predicted value of the i-th sample [10].

$$RMSE=\sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_t-\hat{y}_t\right)^2} \tag{3}$$

In equation (3): $RMSE$ represents the root mean square error, and the other symbols are the same as in equation (2).

$$\mathrm{MAPE}=\frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t-\hat{y}_t}{y_t}\right|\times 100\% \tag{4}$$

In equation (4): MAPE is the mean absolute percentage error (%), and the other symbols are the same as in equation (2).

3.3 Energy-Saving Scheduling Model

The canteen's energy consumption includes the base load (cold storage, lighting), kitchen processing load, and HVAC load. To ensure the project's success, the hourly electrical load should $P_{d,h}$ be broken down into three parts :

$$P_{d,h}=P_{d,h}^{base}+P_{d,h}^{kit}+P_{d,h}^{hvac} \tag{5}$$

In equation (5), $P_{d,h}$ represents the total power of hour h during date d (in kilowatts), $P_{d,h}^{base}$ which refers to the basic load, $P_{d,h}^{kit}$ which is the kitchen processing and cleaning load, $P_{d,h}^{hvac}$ and represents the heating, ventilation and air conditioning load [11].

Under the time-of-use pricing mechanism, the daily electricity cost C_d can be expressed as:

$$C_d = \sum_{h=0}^{23} p_h \cdot E_{d,h} \tag{6}$$

In equation (6), p_h represents the electricity price in the h-th hour, in yuan/kWh; $E_{d,h}$ represents the electricity consumption in the h-th hour, in kWh. Within this time range of hours, it can be roughly regarded as the average power $P_{d,h}$.

Taking into account both electricity costs and peak load constraints, the objective function is established as follows:

$$\min J = \alpha \sum_d C_d + \beta \sum_d P_d^{\max} \tag{7}$$

In equation (7), J represents the comprehensive target, α and β are weighting coefficients, $P_d^{\max}$ referring to d the maximum power (in kilowatts) within the specified date.

To ensure equipment safety and comfort, the constraints include:

$$P_{d,h} \le (1-\eta) \cdot P_d^{max,ref} \quad \left(h \in H^{peak}\right) \tag{8}$$

In Equation (8), η represents the peak shaving target ratio, $P_d^{max,ref}$ represents the peak power on the base day, H^{peak} and is the collection of peak periods (such as lunch/dinner and peak electricity price periods). During the project execution, the relevant constraints are met and the cost is reduced by implementing timing and power adjustments on adjustable equipment such as fresh air, exhaust air, pre-cooling/preheating, decontamination and energy storage hot water [12].

Carbon emissions from electricity generation are calculated based on the grid emission factor:

$$CO_2 = EF \cdot \sum_{d,h} E_{d,h} \tag{9}$$

In equation (9), CO_2 represents the carbon dioxide emissions from electricity consumption, expressed in kilograms (kg), and EF refers to the electricity carbon dioxide emission factor, expressed in $kgCO_2$ / kWh ($kgCO_2$ / kWh). represents the hourly electricity consumption, also expressed in kWh (kWh). This paper uses the national average emission factor of 0.5306 $E_{d,h}$ $kgCO_2$ /kWh ($kgCO_2$ / kWh) published by the Ministry of Ecology and Environment and the National Bureau of Statistics in 2023 for calculation.

Figure 5 shows the closed-loop scheduling process for meal preparation and energy saving driven by supply and demand forecasting.

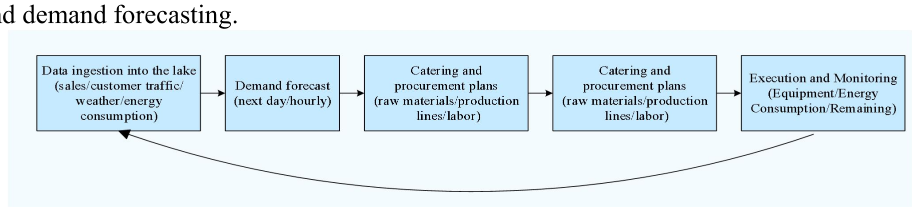

Fig. 5. Closed-loop scheduling process for meal preparation and energy saving driven by supply and demand forecasting

4 Analysis of running results

4.1 Demand Forecasting Effectiveness

The random forest model was trained using data from 2022 to 2024 and tested using data from 2025. In the 2025 test set, its MAE value was 374 meals/day, RMSE value was 505 meals/day, and MAPE value was 3.31%. Compared with the empirical lag method (MAPE=10.37%), the error was reduced by approximately 68.1%. In terms of feature contribution (see Figure 6), the demand in the previous 7 days, whether it is a holiday, and the weekday attribute are very important for prediction.

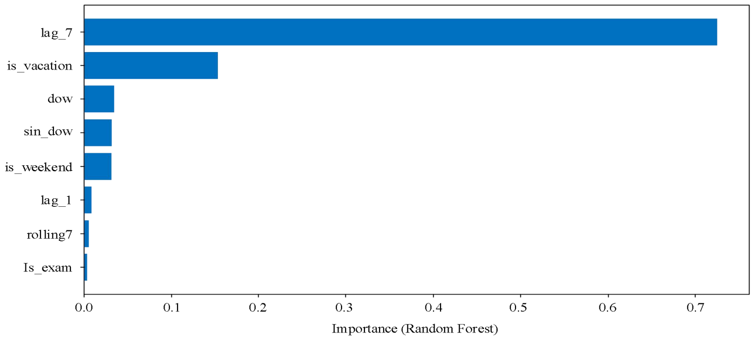

Fig. 6. Contribution of key features in demand forecasting (Top 8)

To verify the rationality of the model selection, the error metrics of Random Forest, Linear Regression, XGBoost, LSTM and other models on the test set were compared, and the results are shown in Figure 7.

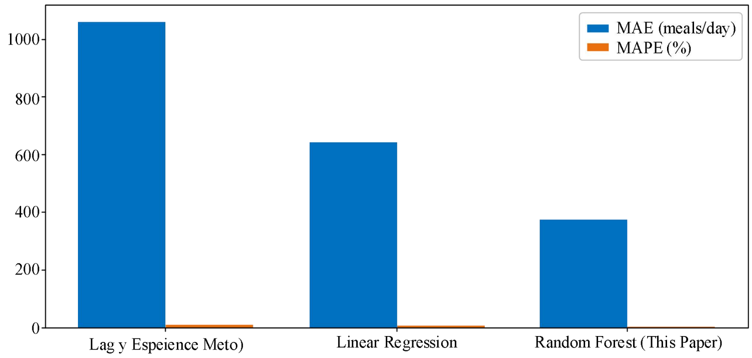

Fig. 7. Comparison of errors of different prediction models (2025 test set)

Further sampling of 14 consecutive days in November 2025 yielded a comparison curve between the prediction and the actual results, as shown in Figure 8. It can be seen that the model has a strong ability to follow the peak times of breakfast/lunch/dinner.

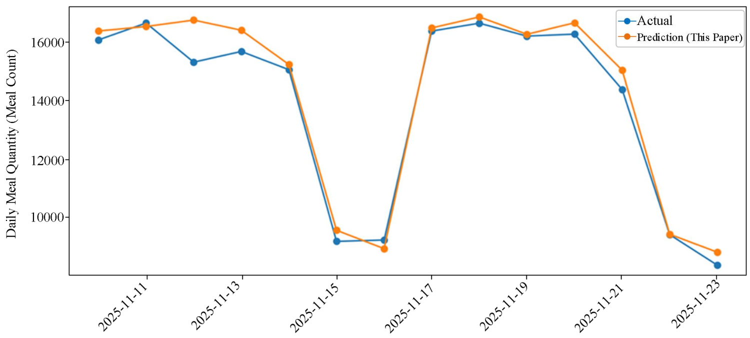

Fig. 8. Comparison of forecast and actual results (November 2025, 14 consecutive days)

Figure 9 shows the error distribution. The residuals are roughly symmetrical. Long-tailed samples mostly appear during the semester transition period and special event days. Through rule correction and manual labeling, the risk can be further reduced.

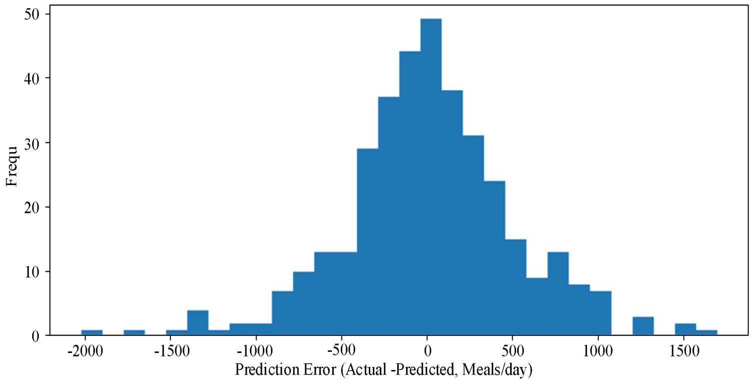

Fig. 9. Prediction error distribution (2025 test set)

4.2 Optimization Effects of Meal Preparation and Procurement

In terms of meal preparation, the baseline strategy (experience-amplified meal preparation) has a leftover rate of 9.05%, while the forecast-driven strategy (predicted value multiplied by 1.03, with the ability to reheat food) has a leftover rate of 3.36%, representing a decrease of 62.9%. By 2025, the number of leftover meals per year will be reduced from 415,023 to 145,089, a reduction of 269,934 meals. If calculated at 0.35 kg per meal, this translates to a reduction of approximately 94.5 tons; and based on a raw material cost of 5.2 yuan per meal, this translates to savings of approximately 1.404 million yuan.

The phenomenon of secondary cooking caused by the low forecast occurred on the 92nd day, accounting for 25.2% of the total annual amount. However, the amount of secondary cooking only accounted for 0.57% of the total number of meals throughout the year. This impact can be mitigated by using "pre-made semi-finished products + flexible scheduling". The comparison of the main relevant indicators is shown in Table 1.

Table 1. Comparison of key indicators for forecasting and meal preparation

index	empirical method	Linear Regression	Random Forest (This article)	Increase
MAPE (%)	10.37	7.67	3.31	↓68.1%
MAE (Meals/Day)	1061	644	374	↓64.7%
Food waste rate (%)	9.05	-	3.36	↓62.9%

4.3 Energy-Saving Dispatching Effect

From an energy consumption perspective, assuming the operation period is until 2025, after the prediction-driven closed-loop scheduling, the annual electricity consumption will be reduced to 740,661 kWh, saving 73,252 kWh compared to before, accounting for 9.0%. The annual electricity cost will also be reduced from 663,101 yuan to 575,564 yuan, saving 87,537 yuan, accounting for 13.2%. The comparison of monthly electricity costs is shown in Figure 10 .

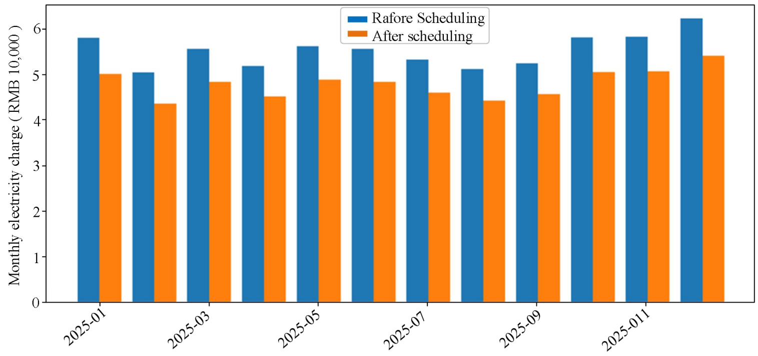

Fig. 10. Comparison of monthly electricity costs in 2025

In terms of peak suppression, the average daily peak power was reduced from 131.6 kW to 112 kW, a decrease of 14.9%. As shown in Figure 11, the electricity consumption per meal decreased from 195.2 Wh/meal to 177.6 Wh/meal. This demonstrates that "on-demand energy supply and time-sharing start-stop" can effectively improve energy efficiency.

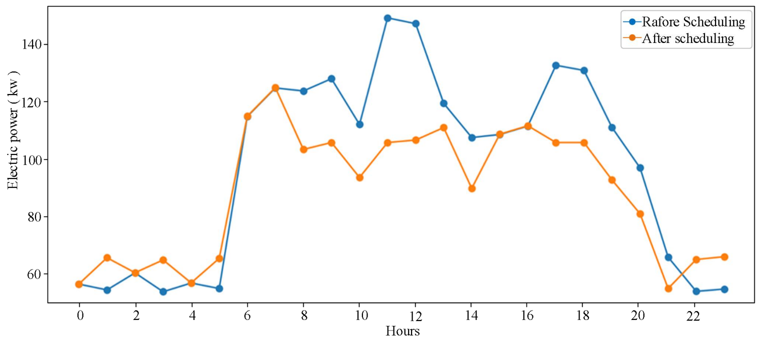

Fig. 11. Comparison of typical daily load curves (October 15, 2025)

Based on the grid emission factor EF = 0.5306 $kgCO_2$ /kWh, the carbon emissions from electricity generation were reduced by approximately 38.9 tCO_2 (see Figure 12).

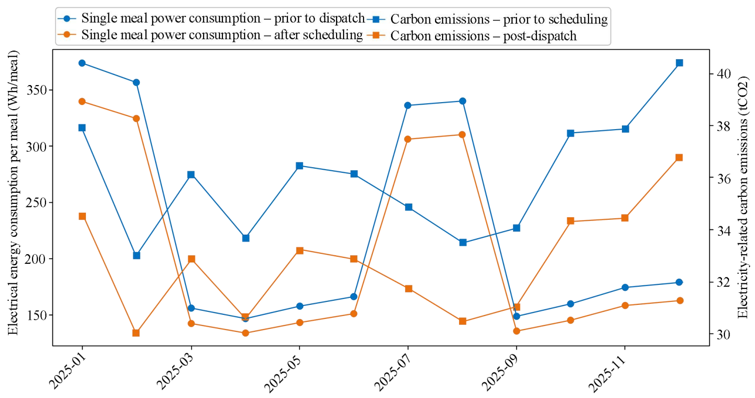

Fig. 12. Electricity consumption per meal and electricity carbon emission trends (2025)

5 Conclusion

(1) An integrated framework of "supply and demand forecasting, meal preparation and procurement, and energy-saving scheduling" for smart canteens was proposed. In engineering, sustainable iteration is achieved through data governance, feature warehouse and closed-loop operation.

(2) In terms of demand forecasting, based on training from 2022 to 2024 and testing in 2025, the random forest model has a MAPE of 3.31%; compared with the empirical lag method (MAPE=10.37%),

the error is reduced by 68.1%; the key influencing factors are concentrated in "demand in the first 7 days, holiday attributes and week structure".

(3) In terms of meal preparation and procurement, the forecast-driven strategy reduced the food waste rate from 9.05% to 3.36%, resulting in a reduction of 269,934 meals (approximately 94.5 tons) of food waste throughout the year, which translates to savings of approximately RMB 1.404 million based on a raw material cost of RMB 5.2 per meal. Meanwhile, the amount of food reheated for the second time accounted for only 0.57% of the total number of meals throughout the year, achieving a balance between "low waste and high availability".

(4) In terms of energy consumption and cost, closed-loop dispatch reduced annual electricity consumption by 9.0%, annual electricity cost by 13.2%, and average daily peak power by 14.9%. The electricity consumption per meal decreased by 9.0% (from 195.2 Wh/meal to 177.6 Wh/meal), which verified the energy-saving potential of "on-demand energy supply + peak constraint".

(5) In terms of emission reduction, based on EF=0.5306 kgCO2/kWh, the carbon emissions from electricity generation will be reduced by approximately 38.9 tCO2 in 2025. Further improvements could be made by introducing features such as status identification of individual equipment, sales forecasting at the dish level, and optimization of uncertainty constraints to enhance robustness under extreme event days and complex dish structures.

Acknowledgement

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

References

1. Qian, L., Li, F., Qian, Z., & Wang, L. (2021). Individual food waste behavior from the perspective of North-South differences: An analysis based on the dining situation of college students in university canteens. Journal of Natural Resources, 36(3), 552-566.
2. Kuang, W. (2021). Sales forecasting of university canteen windows based on a two-layer sales forecasting model [Doctoral dissertation].
3. Cao, S., Guo, H., & Gong, W. (2025). Load prediction of office building envelope in hot summer and cold winter regions based on XGBoost algorithm. Energy Research and Information, 41(2), 90-97.
4. Wu, T., Hui, H., & Zhang, H. (2023). A review of the participation of commercial building air conditioning systems in urban power grid load regulation. China Electric Power, 56(7).
5. Luo, Z., Peng, J., & Cao, J. (2022). Demand-side flexibility of residential buildings: Definition, flexible load and quantification method. Engineering, 16(9), 123-140.
6. China Education Logistics Association. (2025). Standards for the construction of smart catering in higher education institutions.
7. National Development and Reform Commission. (2023, September 27). Measures for electricity demand-side management (2023 edition).
8. Ministry of Ecology and Environment, & National Bureau of Statistics. (2025, December 31). Announcement on the release of 2023 electricity carbon dioxide emission factors.
9. Bai, D., & Li, G. (2024). Exploration of smart green canteens in university logistics projects. China Petroleum & Petrochemical Information, (12).
10. Chen, Z., Luo, W., & Wang, Y. (2022). Performance evaluation analysis of the construction of grassroots responsibility network for food safety. Grain and Oil Food Science and Technology, 30(5), 259-266.
11. Beijing University of Chinese Medicine uses digital intelligence to create a resource-saving smart canteen. (2024, April 10).
12. Science and Technology Daily. (2024, October 31). Smart canteen: Analyzing dining data to optimize food quality.

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智慧食堂供需預測與節能調度研究

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摘要：本文以某大型園區智慧食堂爲研究對象，運用隨機森林模型，構建了涵蓋「供需預測—備餐採購—節能調度」的一體化優化方案。基於2018—2021年的歷史經營與能耗數據，分別建立了日與小時層級的需求預測模型，並在分時電價與峯值約束條件下，對廚房及暖通空調系統用能設備實施協同優化。在備餐環節及能耗方面提出優化路徑，爲公共機構推進「反食品浪費」與「節能降碳」協同治理提供工程參考。

關鍵詞：智慧食堂；需求預測；備餐優化；節能調度；分時電價；模型預測控制

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