A Case Study for BMPV Systems Optimal Day-Ahead Scheduling and performance evaluation

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Abstract. Optimal scheduling of a distributed energy resources system (DERs) can be beneficial for utilizing renewable energy and relieving the pressures upon the main electric grid. One of the most popular DER systems is the Building mount photovoltaic (BMPV) system. In this paper, a large office building is taken as a case study to develop an optimal day-ahead strategy for the BMPV system considering 24 hours ahead of energy consumption and PV generation uncertainty. This paper mainly includes BMPV system capacity determination, 24 hours ahead of energy usage and PV generation forecasting, and day-ahead optimal strategy development. Firstly, based on collected history energy demands, weather data, and building information, the install capacity of PV is defined by roof area. Furthermore, the battery capacity is constructed by China's latest photovoltaic energy storage capacity standard. Secondly, the ensemble learning model is established using a time-series algorithm and Long Short-term memory (LSTM) to predict day-ahead energy consumption. Moreover, an interval prediction method is used to forecast the PV generation for the next 24 hours. Finally, the accurate energy consumption prediction and PV generation interval are introduced to establish the BMPV system scheduling strategy. The day-ahead optimization scheduling strategy was developed based on Mixed integer linear programming (MILP), targeting minimal economic cost. As a result of the optimization process, the proposed strategy could save 4.8% in economic costs and reduce the peak load of the main grid effectively. Moreover, it can effectively optimize the energy consumption structure of buildings or even distributed energy systems and can provide feasibility to achieve net-zero energy consumption without sacrificing any comfort of occupancy.

1 Introduction

Global environmental and energy concerns have led to rapid growth in mandating the construction of more energy-efficient buildings worldwide [1]. According to statistics[2], the operation of the building sector not only emits more than 2 billion tons of carbon dioxide every year in China but also indirectly leads to 16 to 1.8 billion tons of carbon dioxide emissions in steel materials and other manufacturing sectors. Therefore, it is significant to reduce the carbon dioxide emissions from the building sector to realize low-carbon development.

In recent years, since Zero Energy Building (ZEB) is the ideal form of green building, which can reduce Green House Gas emissions effectively, more and more countries have invested in the construction and research of ZEB [3]. On the one hand, some researchers are committed to continuously improving building envelope performance. For instance, the concept of “passive houses” has been proposed by Germany and has been used widely around the world [4]. On the other hand, introducing renewable energy into buildings and establishing the distributed energy resources system (DERs) has also become a research hotspot. World Alliance For Decentralized Energy (WADE) points out that distributed renewable energy system (DERs) is a kind of energy system with high efficiency, reliability, and better environmental performance, which can absorb multiple types of renewable energy resources [5]. DERs can be a practical solution anywhere thermal energy and power are needed. Liu et al. [6] used the LSTM algorithm to predict solar power generation in DERs. Basu [7] used HOMER software to plan the best economic solar PV capacity incorporation in the DERs. However, the uncertainty of renewable energy may lead to a series of problems. Wind energy, solar energy, and other new energy have random fluctuation, which will become more complex under the interaction between main grid and the distribution system [8]. In addition, the system involves a complex process with multiple time scales, which has strong nonlinearity and uncertainty, resulting in main power grid pressure [9]. Therefore, accurate cooling load prediction and optimal control strategy for managing the charge and discharge of DERS for DERs are two key factors in improving system performance and achieving energy savings [10]. Accurate cooling load prediction and optimal control strategy for managing the charge and discharge of the DERS are two key factors in improving system performance and achieving energy savings.

Accordingly, to absorb renewable energy resources in DERs, relieve the pressure on the main power grid, and improve the operating efficiency of building air conditioning systems. This paper uses data-driven

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technology to construct an optimal dispatching strategy for distributed energy communities based on short-term load prediction for small net-zero residential buildings.

2 Methodology

Due to the improvement of technology level, the DERs model presents different development types, but all of them have the same requirements in improving energy utilization efficiency, reducing environmental pollution, improving the efficiency of load regulation, and realizing the cascade utilization energy.

The total building energy consumption is considerable, and the energy saving potential is huge in China’s hot summer and cold winter regions with a dense population and many residential buildings. However, in this region, the thermal performance of the envelope structure is poor, and the airtight performance is poor, both of which lead to the huge energy consumption of residential heating [11]. Therefore, the development of zero energy buildings in this region is conducive to promoting the development of building energy conservation.

![Fig. 1. The framework structure of the proposed model](image)

The technical route of this paper is shown in Fig. 1. First, we collected a raw dataset from a large-scale shopping mall building. The raw dataset includes basic information from the shopping mall, hourly energy consumption data, hourly weather data, and the economic cost of the PV system. Secondly, we build a PV system according to the roof area of the shopping mall. Then the prediction model of short-time energy consumption is established by the LSTM algorithm. Finally, a day-ahead optimization scheduling model based on MILP was established by linearizing and comprehensively considering a variety of renewable energy and energy storage components and various component constraints and security constraints of power grid operation. The proposed model has the characteristics of discrete and continuous, optimizing the structure of the office building energy consumption, saving energy and resources, reducing greenhouse gas emissions, reducing peak season client demand increase impact has a good effect on the electric network and also on the design of the BMPVs pattern provides a design idea.

3 Case study and Modelling

3.1 Dataset introduction and pre-processing

In this work, the target building is located in Beijing, China. The duration of the data set was collected from January 1st, 2018, to December 31st, 2019. A total of 17,520 sets of data. The range of energy consumption is [0 kWh, 6172 kWh].

To determine the input variables of the energy consumption prediction model, a correlation analysis is carried out. The meteorological parameters and time labels with the greatest correlation with energy consumption are obtained. The correlation analysis results are shown in Fig. 2. To reduce the complexity of the model and improve the calculation speed, only the variables whose correlation absolute value is greater than 0.2 are retained, which are outdoor temperature, atmospheric pressure, and visibility or outdoor air quality for the object city.

3.2 BMPV system modeling

Aiming to decrease energy consumption, enhance the energy efficiency, and reduce electricity and natural gas grid pressure, DERs are designed to cooperate to apply the consumer energy demand. Efficient design and layout between the energy production Sector and the demand side are essential in
the DERs planning in the context of energy Internet. Under the premise of not sacrificing residents' comfort, the system reduces investment as much as possible, maximizes Renewable Energy consumption, and reduces Green House Gas emissions, reflecting the system’s superiority in an all-around way.

In this paper, the BMPV system combined with the battery is taken as the research object; the Flow chart of this system is shown in Fig.3. The energy demand of the shopping mall is supplied via the main grid and PV system. The function of batteries is to ensure the stability of the power grid and maximize the economic benefit at the same time. Especially in this paper, only taking the electricity from the main grid to our system, the electricity can’t feedback to the main grid. According to the area of a target shopping mall, the installation capacity of PV is 200 kW. Battery capacity is 20 kWh according to standard.

![Flow chart of PV/Batter-based DERs](image)

**3.3 Prediction Model**

**3.3.1 Energy consumption prediction**

As a kind of time series, residential building load often has both linear and nonlinear characteristics, which shows periodicity from a macro perspective. However, analyzing more detailed time granularity will show nonlinear fluctuation and randomness. Therefore, LSTM is a powerful technology for time-series prediction. The feature extraction results are used as the input of a node of the LSTM cell, and the LSTM is used for time series modeling to obtain the final prediction result. Compared to previous studies, we developed LSTM for multi-outputs; this structure is beneficial for applying to different forecasting tasks.

**3.4 Multi-objective optimization definition**

**3.4.1 Objective function**

From the residential physical model of the distributed energy system, the residential building system can flow more complex; to achieve the expected economic effect, energy saving, and emission reduction, it is necessary to consider the demand for residential electricity and heat, the technical characteristics of distributed power equipment, seasonal and inherent volatility of solar energy, electricity and other related factors, and specify a reasonable system operation strategy.

The proposed BMPV system are ideographs composed of input, objective function, constraints, and output. The inputs include the present energy system structure, the user’s hourly power, cooling and heating loads, electrical prices, solar irradiance, fuel cells, photovoltaic cells, and other system components’ performance parameters.

Through simulation analysis, the following outputs can be obtained: 1. The annual operating cost of the system satisfying the objective function and constraint conditions; 2. Optimized operation scheme of the DERS; 3. Optimized operation scheme of photovoltaic cells; 4. They optimized the operation scheme of the battery. The relationship between the supply-side and demand-side of DERs is formulated with a coupling matrix as indicated in equations (1) and (2).

**3.4.2 PV generation prediction**

Day-ahead generation of PV is determined by predicting solar radiation based on a data-driven method with uncertainty.

\[
L = \left[ C_1 \quad C_2 \right] \begin{bmatrix} P \\ R \end{bmatrix} - SE \tag{1}
\]

\[
L = C_1 P + C_2 R - SE \tag{2}
\]

Electricity and heating load matrix L equal to coupling matrix C times install generating capacity of P and renewable energy R minus storage SE. S is the storage coupling matrix, and E is stored energy.

**3.4.3 Optimization problem**

As shown in equation (3), the objective of this system is a minimum economic cost, minimum CO2 emission, and minimum grid peak load.

\[
\text{Minimize } \sum_{i=1}^{n} [P_{\text{ele}}(t) \times \text{electricity price} + P_{\text{gas}}(t) \times \text{gas price}] + P_{\text{PV}} + P_{\text{Battery}} \tag{3}
\]

\[
\text{Minimize } \sum_{i=1}^{n} P_{\text{ele}}(t) \times 0.412 + \sum_{i=1}^{n} P_{\text{gas}}(t) \times 0.184 \tag{4}
\]

\[
\text{Minimize } \text{Peak load} \tag{5}
\]

**3.5 parameter determination**

According to the current energy price system in Changsha, the natural gas price is set at 2.5 yuan /m³. According to the latest distributed photovoltaic policies in China, the self-use part of distributed photovoltaic will get a subsidy of 0.42 yuan /kWh.

**Table 1 Economic cost of system components**

| Components       | Initial cost | O&M ratio | Lifetime year |
|------------------|--------------|-----------|---------------|
| PV               | 3500 yuan/kW | 2%        | 20            |
| Battery          | 1000 yuan/kWh| 1%        | 5             |
| Inverter/converter | 700 US$/kW  | 1%        | 10            |
Table 2 Technical parameters of system components

| Items               | value |
|---------------------|-------|
| PV generation efficiency | 18 %  |
| Battery energy storage efficiency | 90 %  |
| Inverter/converter  | 90 %  |

According to the price of non-resident general industrial and commercial buildings in the Beijing urban area, the TOU is set as shown in Fig.5; the peak periods include 10:00-15:00, 18:00-21:00; The flat periods are 7:00-10:00, 15:00-18:00, 22:00-23:00, and the rest periods are valley periods.

Fig.3. TOU of Beijing

4 Results

4.1 Energy Consumption Prediction model evaluation

In Table 3, three evaluation indexes $R^2$, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), were used to evaluate the 24 hours ahead energy consumption prediction model. In general, the smaller these model values, the higher the accuracy of the prediction model. The result shows that the proposed model has great performance for the forecasting task. Based on our target

Table 3 Prediction result evaluation

|                | $R^2$ | CV-RMSE | MAPE  |
|----------------|-------|---------|-------|
| Cooling season |       |         |       |
| Training set   | 0.94  | 6.27%   | 6.45% |
| Testing set    | 0.93  | 7.34%   | 7.03% |
| Heating season |       |         |       |
| Training set   | 0.95  | 5.83%   | 6.21% |
| Testing set    | 0.94  | 6.45%   | 6.98% |

Furthermore, regression analysis of the prediction value and the original dataset is shown in Fig 6. The predicted and true values are horizontal and vertical coordinates to draw the scatter plot. The oblique line is the error line of ±20%, and the points within the two error lines are positive and negative. The closer the point to the diagonal line is, the higher the prediction accuracy is, while the farther the deviation from the diagonal line is, the worse the prediction effect is. As shown in Fig 6, the results show that adding linear time series analysis into the nonlinear neural network model improves prediction accuracy, which shows superiority.

Fig.4. Prediction model regression analysis

\( \text{a) Prediction performance in the cooling season} \)
\( \text{b) Prediction performance in the heating season} \)

4.2 Solar Generation prediction

As shown in Fig.7, this paper achieves the interval prediction of PV generation through the interval prediction of solar irradiation. The blue interval is a 95% confidence interval. The black point is the measured value, and the blue curve is the prediction result.

Fig.5. Prediction result for solar generation

4.3 Electricity balance evaluation

The day-ahead load predicted by the ARIMA-LSTM model is input into the DERs model as electricity demand, and the electricity balance of one day in the cooling season and heating season is obtained as shown in Fig 8, respectively. As shown in Fig 8, in the Cooling season and Heating season, the DERs composed of the battery and the PV system can meet 75% and 21% of the electric power demand of the small zero-energy dwelling, respectively. In this scenario, the annual economic cost of the proposed DERs is $2.23 \times 10^5$ CNY
and CO₂ emission is 2.41×10⁴ kg per year. If the energy demand of this building is completely supplied by the main grid, the cost will be 2.34×10⁴ CNY, and CO₂ emission will be 2.85×10⁴ kg per year, respectively. Accordingly, the approach proposed in this paper can reduce the economic cost by 4.8%, reduce the greenhouse gas carbon dioxide by 15.4%, and reduce the power grid input by 9.28%, which is beneficial to protect the stability of the power grid and maintain the power supply security.

Furthermore, in the cooling season, the main grid only needs to be supplemented at night. During 8:00-19:00, PV and battery cooperation can cover most electricity demand. However, the heating demand set in this paper is all supplied by electricity during the heating season. The main grid still is the major supplier in the case of insufficient PV generation.

![Electricity balance chart](image)

**Fig.6.** Electricity balance of residential building a) Cooling Season electricity balance b) Heating Season electricity balance

### 5 Conclusion

Distributed energy resource (DER) system optimal dispatching is a critical strategy to strengthen the management of the regional energy system. Building mount photovoltaic (BMPV) system is one of the most popular DER systems. This paper developed a framework to provide an optimization strategy for buildings or districts planning to install or have already installed the BMPV system. Based on collected data, the BMPV system is simulated with certainty install capacity of PV and battery at first. Secondly, the day-ahead energy prediction ensemble learning model is established using a time-series algorithm and Long Short-term memory (LSTM). Finally, a day-ahead optimization scheduling strategy was established for the BMPV system based on mixed-integer linear programming (MILP), targeting minimal economic cost. The results show that the proposed BMPV system could save 4.8% in economic costs and reduce the peak load of the main grid effectively. The proposed approach can effectively optimize the energy consumption structure of the building or distributed energy system to achieve net-zero energy without sacrificing customers’ comfort.

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