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Zero energy potential analysis of photovoltaic direct-driven air conditioners based on thermal comfort using machine learning methods

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ABSTRACT

Usually the energy matching between building load and PV generation is rigid for photovoltaic direct-driven air conditioners (PVAC). The utilization of thermal comfort can improve the flexibility of building loads to increase the real-time energy matching for PVACs. This study aims to propose a dynamic zero energy evaluation method considering the thermal comfort temperatures for PVAC. The interaction between the flexible building load and rigid PV generation is investigated using different machine learning models with an one-minute time resolution. The indoor temperatures conditioned by PVAC are simulated under actual operations. Indicators such as hourly self-consumption (SC), hourly self-sufficiency (SS), hourly zero energy time (ZET), and real-time zero energy ratio (RZER) are used to evaluate the dynamic energy performance of PVAC in different seasons. With fixed indoor setting temperature selected from standard, the RZER is only 27.87% in summer for hot-summer and cold-winter zone. While taking the thermal comfort temperature into account, the corresponding RZER for PVACs reaches 51.31% with 100% SC of PV generation. Moreover, zero energy points always appear at times of large cooling demand, which can reduce the burden on the utility grid. An optimization for PV capacity is also conducted and is found that an increase of PV capacity helps to raise RZER but results in the excessive energy output. The real-time zero energy evaluation method with indoor comfort taking into account is useful for evaluating the zero-energy potential and designing more flexible PVAC systems.

Keywords: zero energy building, photovoltaic direct-driven air conditioners, machine learning, energy matching

NONMENCLATURE

Abbreviations	
PVAC	Photovoltaic direct-driven air conditioners
ML	Machine learning
COP	Coefficient of performance
ZET	Real-time zero energy time
RZER	Real-time zero energy ratio
SZEP	Storage zero energy probability
SC	Self-consumption
SS	Self-sufficiency
L	Electricity load consumed by air conditioners
P	Electricity generated by PV system
t	time
Q	Building load
T	Temperature
R	Solar irradiance per unit area
Symbols	
a	Air conditioner
i	Indoor
o	Outdoor
c	Cooling
h	Heating

1. INTRODUCTION

Photovoltaic direct-driven air conditioners (PVAC) have the features of a simple structure, good reliability and quick response [1]. PVAC systems are unrivalled in their potential to realize the zero energy goal for buildings [2]. Usually, PV generation is subject to the predetermined PV capacity and the solar radiation, so was not adjusted without energy storage devices. The load is also considered rigid, which is calculated according to a fixed indoor setting temperature [3][4]. According to the current zero energy building standards of China, the building cooling load is often determined by 26℃ [5]. The flexibility of building load and the energy matching degree between the building load and PV generation are limited. With the further application of PV systems in buildings, the focus of zero energy buildings can no longer be just about reducing the building load, but more consideration should be given to improving the energy matching degree between building load and PV generation.

The indoor thermal comfort temperature range is the simplest method to effectively improve the flexibility of the building load and enhance the energy matching degree [6] [7]. Peng et al. found that the comfortable temperature range of a split air conditioner is 23.9-28.3℃ in summer. Compared to the fixed temperature, it can make the rigid energy match between the PV generation and building load become flexible. However, the discussions that the indoor comfort temperature can be a contributor for improving the energy matching between the PV generation and load demands are seldom mentioned [8][9][10]. One reason for the lack of the discussion may be that the simulation software has some difficulties in predicting the actual indoor temperature [11]. Energy simulation software such as EnergyPlus has been shown to simulate building loads with high accuracy [12]. The discussion can be with the aid of machine learning methods. The multivariable linear regression (MLR) [13], support vector machine (SVM), artificial neural networks (ANN), random forest (RF) [14], and extreme gradient boost (XGBoost) [15] are the most common machine learning models.

Except for rigid energy matching of PVAC system, the focus of zero energy buildings also should be given to improving the real-time energy matching degree. With the improved penetration rate of PV systems, increasing the real-time energy matching degree of PVACs is more important for reducing the sudden drops and ramps of the electricity supply on the utility grid [16]. However, zero energy is still a very basic and simple consideration of the total energy balance between the energy generation and supply [17]. This consideration makes the PVAC system will occasionally suffer a shortage of self-sufficiency for the load demands under low irradiation levels [18]. The main evaluation indicators of energy matching are self-consumption (SC), and self-sufficiency (SS). SC is defined as the proportion of the PV generation directly consumed by the PVAC units to the total PV generation. SS is the ratio of electricity consumption provided by the PV system to the total energy consumption [19]. These evaluation indicators for PVAC system are calculated monthly, seasonally, and annually. The energy matching evaluation with a shorter time resolution is not discussed.[19][19][19]

In this study, firstly, we simulated the PV generation and load demand at one-minute time resolution using EnergyPLus. Secondly, different ML models were used to study the relationship between the building load, the outdoor and indoor temperature, and the time-related variables. The actual indoor temperatures as the PVAC system consuming 100% of the PV generation were obtained by the ML model with the highest prediction accuracy. Thirdly, a real-time zero energy potential evaluation method was proposed for PVAC. The real-time zero-energy potential of PVAC systems was investigated in hot-summer and cold-winter zones in summer using several indicators.

2. DESCRIPTION OF MODELS

2.1 Building model

In this study, an office building with dimensions of 20m×15m×8.4m in Shanghai was adopted. The normal working hours are from 8:00 am to 6:00 pm. The indoor temperature ranges from 16℃ to 30℃ which is in line with the temperature range of air conditionings in marked. From the public energy efficient building design standards of China, the heat transfer coefficients of external wall, floor, roof, and windows are 0.6, 0.86, 0.47 and 2.97 (W/m^2K), respectively.

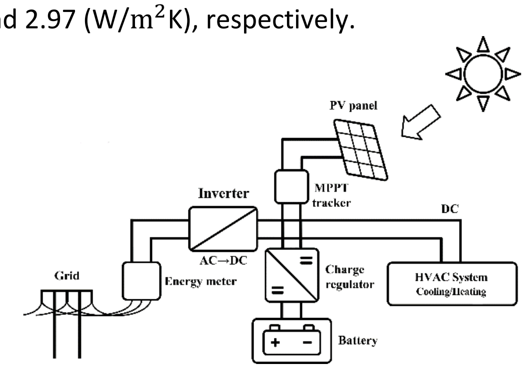

Fig. 1. PVAC system schematic

2.2 *PVAC system model*

In this study, a grid-connected PVAC system was selected. The PVAC system is illustrated in Fig. 1. The air conditioning system works at stepless speed regulation of frequency.

3. METHODOLOGY

3.1 *Machine learning*

The load simulations for EnergyPlus with a one-minute resolution for the indoor temperature ranges were conducted. The simulation results were used as the preliminary work to prepare a sufficiently large database to train the ML models. 70% of the data set for model training and 30% set for model testing. The calculation framework is shown in Fig. 2. Then, different ML models were adopted to predict the actual indoor temperature of the PVAC system. The weather data, including solar irradiance and outdoor temperature, the load demand and time-related variables (hour of the day and month of the year) are selected as the input features. The PV generation was converted to the corresponding building load, and the results were substituted into the ML models to obtain the actual indoor temperatures. The time in which the actual indoor temperature stayed in the range defined to be comfortable for humans is regarded as the real-time zero energy time. Lastly, we defined that the ratio of the real-time zero energy time of PVAC to the total air conditioner operation time as the real-time zero energy probability. The real-time zero energy potential of PVAC system for Shanghai in summer was investigated.

In this study, we compared some popular ML models for predicting indoor temperature of PVAC systems, including Multiple Linear Regression (MLR), Decision Tree Regression (DTR), K Neighbors Regression (KNN), Random Forest Regression (RF), and Extreme Gradient Boosting (XGBoost). The model performances were evaluated by the root means squared error (RMSE), which can show the regression errors of the indoor temperature and help determine the most suitable model.

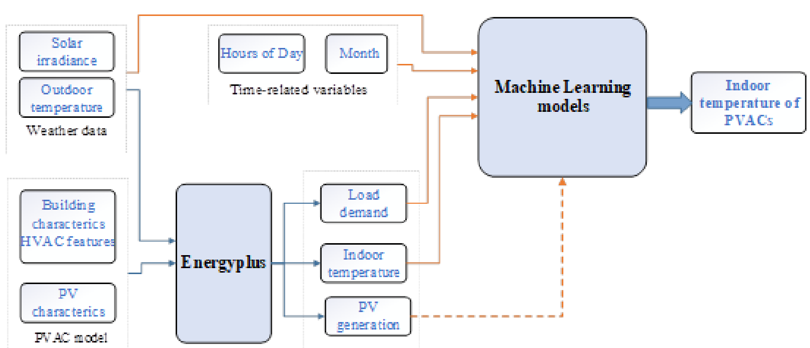

Fig. 2. A calculation framework for the indoor temperature of the PVAC system

3.2 *Real-time zero energy evaluation*

The building loads were simulated in EnergyPlus using an ideal load air system model with a one-minute time resolution. The maximum cooling load of the office building is 106.74 kW. The rated cooling capacity of the air conditioner is 100.5kW. The simulation results accord with the law of building load in Shanghai [20]. The rated COP is 3.99.

The initial PV capacity was determined to make the total PV generation in a summer to meet the total cooling demand. The upper bound for the PV capacity was determined that the total PV generation reaches twice the total energy consumption. Then, we investigated the real-time zero energy potential of PVAC systems by increasing the PV capacity by 10% each time.

Fig. 3 presents the hourly energy matching diagram of a PVAC system on a typical day in Shanghai, in which the profiles of energy generation and energy consumption are illustrated. In Fig. 3, the areas of L and P represent the total electricity consumption of the air conditioners and the total generation of the PV system, respectively. Area A shows the deficit of the air conditioners supply with relation to the demand, which could be provided by a battery or the utility grid. Area B represents the surplus PV generation, which could be stored in a battery or uploaded to the utility grid.

The performance of PVAC systems can be modeled by the following variables: $L(t)$, which is the electricity consumption of the air conditioners per minute, and $P(t)$, which is the electricity generation of the PV system per minute. $M(t)$, which is the PV generation utilized directly by the air conditioners. The formulas are as follows:

$$M(t) = \min\{L(t), P(t)\} \qquad (1)$$

Hourly SS indicates the probability that the PV electricity generation can directly meet the consumption requirements of the air conditioners in an hour. The equation of hourly SS is presented by Eq. (2). The value of hourly SS ranges from 0 to 1. When SS for a certain hour is less than 1, the PV generation cannot fully and timely meet the energy consumption of the air conditioners for that hour. The closer the hourly SS is to 1, the greater the real-time zero-energy probability of the PVAC system in that hour.

$$\text{Hourly SS} = \frac{\int_{t1}^{t1+t} M(t)dt}{\int_{t1}^{t1+t} L(t)dt} \tag{2}$$

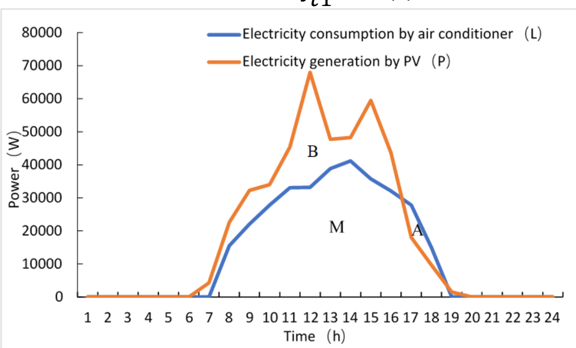

Fig. 3. Hourly energy matching of the PVAC system in Shanghai on June 1st

Hourly ZET is defined as the probability that the indoor temperature of the PVAC system is lower than the highest comfortable temperature for summer or higher than the lowest comfortable temperature for winter in a certain hour. The calculation of hourly ZET is shown in Eq. (3), where t_(Ti) is the time (in minutes) in which the indoor temperature is lower than the highest comfortable temperature in summer during the hour.

$$\text{Hourly ZET} = \frac{\sum t\_(Ti)}{60} \tag{3}$$

RZER is defined as the ratio of real-time zero-energy time to total air conditioner running time. The formula is shown in Eq. (4). The purpose of this indicator is to calculate the real-time zero energy ratio of the PVAC system without any energy storage devices. t_(ss=1) is the time at which SS is equal to 1, and t_a is the total operation time of the air conditioners. t_(ZET=1) is the time at which the indoor temperatures conditioned by the PVAC system are in the thermal comfort zone, tpvac is the total operation time of the PVAC system.

$$\text{RZER} = \frac{\sum t\_(\text{ZET}=1)}{\sum t_{pvac}} = \frac{\sum t\_(\text{hourly ss}\approx 1)}{\sum t_a} \tag{4}$$

4. RESULTS AND DISCUSSION

4.1 Machine learning

Different machine learning models are used to predict the actual indoor temperature of PVAC systems. From Table 1, it is seen that the prediction accuracy of the XGBoost Regressor model is the highest in summer. Therefore, we used the XGBoost regressor model to predict the indoor temperature.

Table 1 RMSE of different ML models

ML models	Summer	
	Train	Test
Linear regression	1.442	1.440
Decision Tree repressor	0.731	0.986
K Neighbors regressor	1.839	1.955
Random Forest regressor	0.737	0.912
XGBoost regressor	0.782	0.867

4.2 Real-time zero energy potential analysis

In summer, we selected 28.3℃ as the upper bound of the thermal comfort zone for the central air conditioning system of the building. With radiation heat transfer terminal, the highest indoor comfort temperature can be 30.7℃[21]. The radiation terminal can further increase the zero-energy potential of PVAC system. We compared the real-time zero-energy potential of PVAC with flexible and fixed (26℃) indoor temperatures under the premise that the total PV generation is equal to the energy consumption of air conditioners. The zero-energy potential of different terminals were investigated. As shown in Fig. 4, the green and dark parts represent the indoor thermal comfort range of the building with radiation heat transfer terminal and convective heat transfer terminal, respectively. The operation points that below the thermal comfort range and 26℃ are regarded as the over-cooling point. The RZER at 26℃ is 27.87% in summer, while the summer RZER for PVAC system with indoor temperatures is 51.31%. Comparing with the fixed indoor temperature (26℃), the real-time zero energy potential of PVAC with indoor comfort temperatures has increased significantly. In this method, the SC of PVAC system is 100%. However, the 100% consumption of PV generation leads to overcooling at some points. The overcooling probability of comfort temperature is 32.78%. The ratio of a fixed temperature is 23.19%. The overcooling proportion of fixed indoor temperature is higher than that of indoor comfort temperature. Because the excess PV generation have no way to utilize by itself in rigid energy matching method.

In Fig. 5, the point at which the hourly ZET of the PVAC system is close to 1 is around noon. The phenomenon indicates that the PV generation can effectively cover the largest cooling load of a day. The PVAC systems can help the buildings reduce the amount of electricity drawn from the utility grid during the peak power consumption period. The application of PVAC system is a win-win choice for buildings and the utility grid.

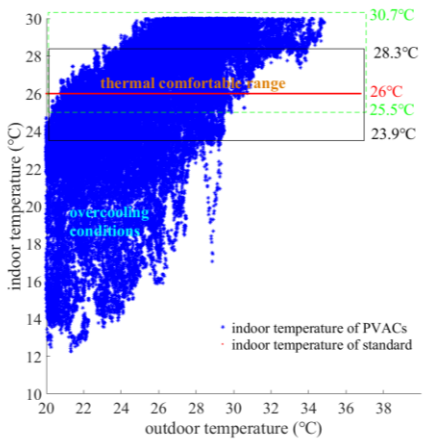

Fig. 4. The fixed and flexible indoor temperatures of PVACs in summer

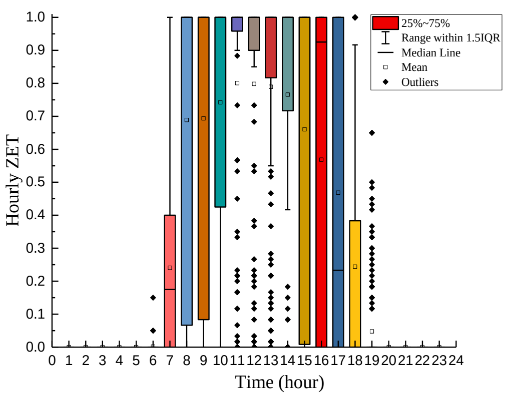

Fig. 5. The hourly zero energy potential of PVACs with indoor temperature.

With the goal of increasing the zero-energy potential, an optimization study on PV capacity was conducted. The zero-energy potential of the PVAC system are calculated under the premise that the total PV generation meets the total energy consumption from 100% to 200%. From Fig. 6, it is shown that the RZER increases steadily with the increase of PV capacity. However, the overcooling rate increases faster with the growth of PV capacity. This means that the increased PV capacity improves the zero-energy potential but at the same time results in more energy wastage.

To further discussion for the effects of PV capacity, we compared the real-time zero-energy potential in July with increased PV capacity. In Fig. 7, the black and red points represent the actual indoor temperature. The green and yellow column represents hourly ZET under different PV capacities of PVAC system. Hourly ZET with 2PV has a significant increase, especially around noon. This indicates that the increased PV capacity is effective in creating a higher zero-energy potential in correct time. The corresponding indoor temperature can also drop from an uncomfortable zone to a comfort zone. Hence, the method can help reduce the amount of electricity drawn from the grid during peak power consumption periods.

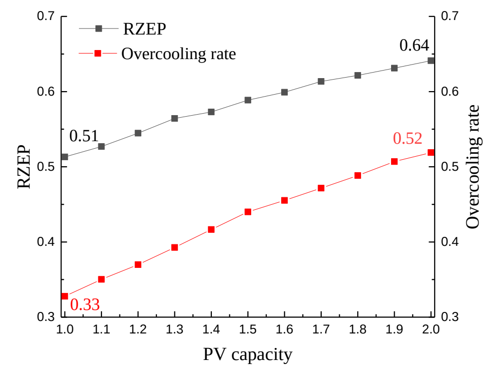

Fig. 6. RZER and overcooling rate for different PV sizes

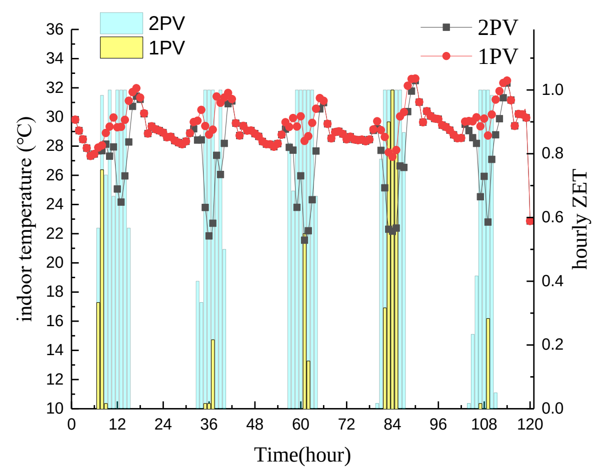

Fig. 7. Comparison of hourly ZET and indoor temperatures for PVACs in a week of July

5. CONCLUSION

The PVAC system is an important contributor to achieve real-time ZEBs. However, strict match between PV generation and building load still appears in existing designs. This paper provided a real-time zero energy potential evaluation method combined with the indoor comfort temperature for PVAC systems. Different ML models were adopted to predict the actual indoor temperature of the PVAC system. The results indicated that the flexibility of the building load effectively increases the real-time zero energy probability and the utilization of PV generation for the PVAC system. The application of PVAC system is a win-win choice for utility grid and users. The key conclusions are as follows:

1. Considering the thermal comfort temperature, the real-time zero energy probability of PVAC system can be increased by 24.44% compared with the fixed indoor temperature in Shanghai. The real-time energy matching degree has been improved significantly by the building load flexibility. The zero energy points often appear more around the larger cooling load points.
2. For the real-time zero energy potential evaluation method with the comfort temperature, the SC of PVAC is always 100%. It is beneficial to design a PVAC with higher utilization of PV generation and minimize the impacts of over sizing in operation.
3. In hot-summer and cold winter zones, the RZER of PVACs with indoor temperatures and increased PV capacity can reach 64% in the summer. The remaining zero energy gap can be overcome by batteries.
4. For predicting the actual indoor temperature of the PVAC system, the XGBoost regressor model has the highest prediction accuracy.

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