# Study on the Energy Consumption and Response Potential of Building Energy Cells Considering Urban Microclimatic Effects

Juanshi Li<sup>1</sup>, Yi Tang<sup>1\*</sup>, Shan Gao<sup>1</sup>, Xiao Han<sup>2</sup>

1 School of Electrical Engineering, Southeast University, Nanjing 210096, China

2 School of Electric Power Engineering, Nanjing Institute of Technology, Nanjing 211167, China (Corresponding Author: tangyi@seu.edu.cn)

#### ABSTRACT

With the rapid increase in building energy consumption during the urbanization process, the analysis of building energy consumption and response potential needs to consider the impact of urban microclimate. This paper explores the factors and pathways influencing the energy consumption of Building Energy Cells under urban microclimatic conditions and constructs a model of Building Energy Cells affected by urban microclimate, aiming to reveal how these microclimatic conditions affect the energy use behavior and response potential of Building Energy Cells. This study provides a scientific basis for urban planners and architects, promotes a deeper understanding of building energy consumption under urban microclimatic conditions, and offers new perspectives and methods for achieving sustainable use of building energy.

**Keywords:** Microclimate, Building Energy Cells, Energy Consumption Analysis, Demand Response Potential

#### 1. INTRODUCTION

In the context of rapidly progressing urbanization and climatic changes, buildings as fundamental components of urban infrastructure are increasingly confronting challenges related to energy consumption, which have become critical for environmental sustainability. In recent years, micrometeorology has emerged as an interdisciplinary field of study that offers fresh perspectives and methodologies by extensively examining the impacts of microclimatic conditions on building energy use. This paper aims to analyze the concept of micrometeorology and its key determinants, and further explores how microclimatic conditions influence building energy consumption and the potential for demand response.

Microclimate refers to the meteorological conditions within a small, defined area that directly impact human living environments and building energy consumption <sup>[1]</sup>.

Typically, this scope is confined to a few meters to several hundred meters above ground level, encompassing the distribution and variations of meteorological elements such as temperature, humidity, wind speed and etc. on a small scale <sup>[2]</sup>. The influence of microclimatic variations on building energy consumption is primarily manifested in the regulation of the thermal environment inside and outside buildings, primarily in two aspects: in the first place, by affecting the thermal exchange processes surrounding the buildings, altering their heating, cooling, and ventilation demands; in the second place, via impacting the comfort and behaviors of the building occupants, which indirectly affects the building's energy usage patterns.

An analysis of key factors reveals that the impact of microclimatic conditions on building energy consumption is influenced by a multitude of factors. First and foremost, the microclimatic conditions surrounding a building, such as the intensity of sunlight exposure, wind speed and direction, and the ambient temperature and humidity, directly affect the building's thermal load and cooling requirements. In addition, the characteristics of the building itself, including the materials used, color, surface properties, and the architecture's form and layout, also impact the effectiveness of microclimatic conditions on energy consumption. On the other hand, urban layout and topography alter microclimatic characteristics, thereby influencing building energy consumption<sup>[3]</sup>.

Urban microclimate and building energy simulation tools predominantly model individual buildings in isolation, such as e-Quest, EnergyPlus, ESP-r (Environmental Systems Performance Research) and TRNSYS (Transient System Simulation Tool). However, several Urban Building Energy Models (UBEM) are capable of assessing entire districts, such as IES VE (Integrated Environmental Solutions -Virtual Environment), CityBEM (City Building Energy Model), Eco-Tect, GreenBuilding Studio, and CityBES (City



### Fig. 1 Composition of Building Cell Elements Under the Influence of Urban Microclimates

Building, Energy, and Sustainability). Other tools like CitySim and UMI (Urban Modeling Interface) also contribute to this area. Among these, EnergyPlus is noted in scholarly articles as the most extensively utilized building energy simulation software <sup>[2, 4]</sup>

An in-depth exploration into the interconnections between microclimatic conditions and building energy demands can offer empirical support for urban planning and architectural strategies, thus promoting an increase in energy efficiency and a decrease in energy usage within buildings. With the aggravation of global climate change, the optimization of microclimatic conditions surrounding buildings becomes critically essential. Such measures are imperative not only for mitigating energy consumption but also for fostering sustainable urban development.

# 2. ANALYSIS OF THE IMPACT FACTORS ON BUILDING CELL ENERGY CONSUMPTION CONSIDERING MICROCLIMATIC CONDITIONS

As the pace of urbanization accelerates, it becomes increasingly vital to understand how microclimatic variations affect the energy usage of buildings, a key component in fostering sustainable and energyconservative urban environments. The microclimate within urban settings is predominantly shaped by several interdependent factors: the phenomena of urban heat islands, the architectural configuration of the urban scape, diversity and types of cloud cover, ground surface reflectivity, the extent of vegetal cover, the specific meteorological conditions prevalent, and the intensity of atmospheric contaminants. These variables are systematically tracked via designated microclimatic indicators including, but not limited to, ambient temperature, relative humidity, barometric pressure, solar irradiance, aerodynamic wind speed, hyetometry, and particulate accumulation levels <sup>[5]</sup>. These metrics critically influence the thermal milieu within which urban buildings operate and their respective patterns of energy consumption, subsequently influencing the buildings' energy efficiency metrics and the thermal comfort levels experienced by their inhabitants. Figs.1-2 below explicate the fundamental mechanisms through which microclimates influence the energy consumption frameworks of Building Energy Cells.

2.1 Impact of Temperature on Energy Consumption of Building Energy Cells

Temperature is one of the primary microclimatic factors affecting building energy consumption. In summer, high temperatures increase the demand for cooling within buildings, consequently raising the energy consumption of air conditioning systems. Similarly, in winter, low temperatures increase the demand for heating, thereby increasing the thermal load. Additionally, the urban layout and the physical structure of buildings significantly influence the surrounding air temperature, with the urban heat island effect being a typical phenomenon <sup>[6, 7]</sup>. Urban design and planning, building density, the height and width of buildings, and the building envelope can directly impact the local microclimate, which in turn affects the heating and cooling loads of individual buildings.

In terms of annual total energy demand, urban buildings vary significantly compared to rural buildings. The sensible heat cooling demand increases by 10% to 36%, while the heating demand decreases by 9% to 30%. The latent heat cooling demand varies, decreasing by 12% or increasing by up to 17%. Consequently, the overall change in annual total energy consumption (cooling + heating) is relatively small, ranging from -2% to +7% <sup>[8]</sup>. This data underscores the critical influence of temperature and urban microclimatic conditions on building energy efficiency, emphasizing the need for climate-conscious urban design and architecture to optimize energy use while maintaining comfort levels within urban settings.

# 2.2 Impact of Humidity on Energy Consumption of Building Energy Cells

Beyond the well-known urban heat island effect, the variation in humidity between urban and rural settings significantly influences building energy consumption, particularly through its effects on the latent heat load impacting cooling requirements. Variations in humidity impact thermal comfort as well as



Fig. 2 Microclimatic and Building Cell Influence Pathways

cooling loads within buildings. In high humidity conditions, air conditioning systems expend additional energy on dehumidification, thereby increasing the cooling demand. Urban green spaces, including street corner parks and expansive wetland parks, critically regulate urban relative humidity through the transpiration of plants. These areas are instrumental in mitigating urban heat environments and positively influencing air quality, which collectively contribute to a reduced thermal load on surrounding buildings<sup>[9]</sup>.

# 2.3 Impact of Wind Speed on Energy Consumption of Building Energy Cells

An increase in wind speed can lower indoor temperatures by enhancing natural ventilation, thus reducing the dependency on air conditioning systems and decreasing energy consumption. Nevertheless, the influence of wind speed varies significantly across different urban layouts and architectural designs. Research indicates that the configuration of urban blocks, as well as the spacing and height of buildings, profoundly affect the patterns of wind flow, subsequently impacting the thermal environment and the energy efficiency <sup>[10-12]</sup>. Furthermore, an increase in wind speed enhances moisture evaporation, which modifies the moisture conditions of the ground and vegetation, further influencing the energy consumption of buildings.

# 2.4 Impact of Irradiance on Energy Consumption of Building Energy Cells

Solar radiation is a pivotal factor affecting building energy needs, especially regarding the requirements for lighting and heating<sup>[13]</sup>. The orientation of a building, the dimensions of its windows, and the installation of shading devices all determine the impact of solar radiation on the indoor environment<sup>[14]</sup>. Excessive solar radiation can increase indoor temperatures, necessitating additional cooling. The strategic use of shading devices and variable-opacity glass can effectively regulate both light and heat entering a building, optimizing the balance between lighting requirements and energy consumption. This paper utilizes an energy balance model to evaluate the exchange of energy between buildings and their environment, encompassing heat conduction, convection, and radiation processes. Solar radiation, a critical component of this energy input, is analyzed through the model to assess the influence of various design alternatives on building thermal efficiency, thereby optimizing the design of lighting and heating systems <sup>[15, 16]</sup>.

# 2.5 Impact of Air Quality on Energy Consumption in Building Energy Cells

The influence of air quality on building energy consumption manifests in two primary aspects: firstly, the maintenance of indoor air quality (IAQ) and the operational efficiency of Heating, Ventilation, and Air Conditioning (HVAC) systems; secondly, the impact on the efficiency of photovoltaic (PV) power generation.

To preserve optimal levels of IAQ, buildings typically employ HVAC systems designed to filter air, facilitate fresh air exchange, and control humidity. Airborne pollutants, such as PM2.5 (fine particulate matter), CO2, and volatile organic compounds (VOCs), necessitate robust HVAC filtration and ventilation strategies. This process entails significant energy expenditure, particularly when extensive amounts of external fresh air are needed to dilute indoor pollutants, thereby markedly increasing overall energy consumption. Poor external air quality exacerbates the situation by requiring more frequent replacement of air filters and extended operation of fans and air handling units, which in turn elevates energy usage <sup>[17]</sup>. Additionally, reducing the intake of fresh air as a measure to decrease energy use adversely affects IAQ, particularly under conditions of severe external pollution.

Air quality also critically impacts the efficiency of photovoltaic (PV) systems, especially in areas afflicted by substantial air pollution. Pollutants such as particulate matter (PM2.5 and PM10), sulfur dioxide (SO2), nitrogen oxides (NOx), and ozone (O3) reduce the intensity and purity of sunlight, thereby impairing the capacity of PV panels to absorb solar energy effectively. Moreover, specific pollutants like SO2 and NOx may react with atmospheric moisture to form acidic compounds under humid conditions, which can corrode the protective coatings and surface materials of PV panels. This corrosive action can significantly detract from the long-term efficiency and performance of PV systems <sup>[18]</sup>.

The complex interplay between air quality and energy consumption necessitates comprehensive urban and architectural solutions that optimize HVAC system efficiency and safeguard PV panel functionality while counteracting the detrimental effects of air pollution. Such integrated strategies not only enhance building energy efficiency but also contribute to broader environmental sustainability and public health objectives.

### 3. MODELING BUILDING ENERGY CONSUMPTION AFFECTED BY MICROCLIMATE

### 3.1 Building Cell Power Prediction Model

### A) Building Cell Photovoltaic Power Generation Model

To construct a Building Cell photovoltaic power generation model influenced by microclimate, we first introduce the traditional photovoltaic power output model, which mainly considers the effects of solar irradiance and ambient temperature on photovoltaic output. The real-time power prediction model for traditional photovoltaic generation is as follows:

$$P_{\rm PV}(t) = \frac{U_{\rm a}(t)}{U_{\rm PV-SIC}} \cdot P_{\rm PV-N} \cdot \left[1 + \alpha_{\rm PV-T} \cdot \frac{|T_{\rm a}(t) - T_{\rm PV-SIC}|}{T_{\rm PV-SIC}}\right]$$

where  $P_{\rm PV}(t)$  represents the output power of traditional photovoltaic generation at time t, in kW;  $U_{\rm a}(t)$ represents the solar irradiance at time t, which  $U_{\rm PV-SIC}$  is the standard condition solar irradiance indicator, in W/m<sup>2</sup>;  $P_{\rm PV-N}$  is the rated output power of the photovoltaic, in kW;  $\mathcal{A}_{\text{PV-T}}$  is the temperature coefficient of the photovoltaic panel, generally taken as -0.4%;  $T_{a}(t)$ and  $T_{\text{PV-STC}}$  represent the external temperature at time t and the standard external temperature for photovoltaic generation, both in °C.

The photovoltaic power prediction model is a complex model that needs to consider multiple meteorological factors. This paper analyzes the effects of temperature, humidity, irradiance, wind speed, and dust accumulation on the traditional photovoltaic output model, and proposes key parameter modifications. The building cell photovoltaic power prediction model influenced by microclimate is outlined below:

$$P_{\text{PV}}^{(\text{mc})}(t) = k_{\text{PV-U}}^{(\text{mc})}(t) \cdot k_{\text{PV-T}}^{(\text{mc})}(t) \cdot P_{\text{PV-N}}^{(\text{mc})}(t)$$

where  $P_{PV}^{(mr)}(t)$  indicates the output power of the photovoltaic panel at time t after microclimate factor correction, in kW.  $k_{PVU}^{(mr)}(t)$  is the coefficient combining actual solar irradiance at time t with standard condition irradiance after correction.  $k_{PVT}^{(mr)}(t)$  combines the actual temperature effect at time t with the standard condition temperature effect after correction.  $P_{PVN}^{(mr)}(t)$  is the PV's rated output considering the impact of dust accumulation at time t, in kW. The specific calculation method influenced by microclimate involves:

$$\begin{aligned} k_{\text{PV-U}}^{(\text{nc})}(t) &= \alpha_{\text{PV-U}} \cdot \frac{U_a(t)}{U_{\text{PV-SIC}}^{(\text{nc})}} \\ k_{\text{PV-T}}^{(\text{nc})}(t) &= 1 + \alpha_{\text{PV-T}} \cdot \frac{|T_a(t) - T_{\text{PV-SIC}}^{(\text{nc})}|}{T_{\text{PV-SIC}}^{(\text{nc})}} \\ P_{\text{PV-N}}^{(\text{nc})}(t) &= \frac{D_a(t)}{D_{\text{PV-SIC}}^{(\text{nc})}} \cdot P_{\text{PV-N}} \end{aligned}$$

where  $a_{PVU}$  is the solar irradiance microclimate correction factor;  $U_{PVSIC}^{(mc)}$  is the corrected standard condition solar irradiance indicator;  $a_{PVU}$  is the temperature microclimate correction factor;  $T_{PVSIC}^{(mc)}$  is the corrected standard condition external temperature indicator;  $D_a(t)$  and  $D_{PVSIC}^{(mc)}$  represent the actual and microclimate-corrected standard condition dust accumulation levels at time t, both in g/m<sup>2</sup>. *B* ) *Building Cell HVAC Energy Use Model* 

To construct a Building Cell HVAC energy model affected by microclimate, we first propose a traditional HVAC power output prediction model, which only considers the external temperature's impact on HVAC output and targets the impact of environmental factors on human energy use behavior, focusing solely on the temperature index. The quantified model for traditional HVAC energy behavior affected by temperature is as follows:

$$L_{\text{HVAC}}(t) = \beta_{\text{HVACL}} \cdot \frac{1}{\sqrt{(T_{a}(t-1) - T_{\text{HVACSIC}})}}$$

where  $L_{\text{HVAC}}(t)$  represents the quantified coefficient for traditional HVAC energy behavior affected by temperature;  $\beta_{\text{HVACL}}$  is the temperature impact index under standard HVAC conditions;  $T_{\text{HVACSTC}}$  is the average temperature under standard HVAC conditions, in °C. Mapping the quantification coefficient to the air conditioning power prediction model, the formula is as follows:

$$P_{\text{HVAC}}(t) = \frac{1}{\mathcal{O}_{\text{HVACP}}} \cdot \left[ T_{\text{ain}}(t-1) + L_{\text{HVAC}}(t) \cdot \left( T_{\text{a}}(t) - T_{\text{ain}}(t) \right) \right]$$

where  $P_{\text{HVAC}}(t)$  represents the predicted HVAC power at time t, in kW;  $\mathcal{Q}_{\text{HVACP}}$  is the heat exchange coefficient relating HVAC output power to heat, in °C/kW.  $T_{\text{ain}}(t)$  and  $T_{\text{ain}}(t-1)$  are the measured external and indoor temperatures at time t and (t-1), respectively, both in °C.

The HVAC prediction model is complex, requiring consideration of multidimensional meteorological factors. This paper, while considering the impact of microclimate on HVAC output power, analyzes the effects of temperature, humidity, and atmospheric pressure, and proposes key parameter modification methods. The Building Cell HVAC output power prediction model influenced by microclimate is presented below:

$$P_{\text{HVAC}}^{(\text{mc})}(t) = k_{\text{HVAC-}\alpha}^{(\text{mc})}(t) \cdot T_{\text{HVACL}}^{(\text{mc})}(t)$$

where  $P_{\text{HVAC}}^{(\text{mc})}(t)$  is the HVAC output power at time t corrected for microclimate factors, in kW;  $k_{\text{HVAC}\alpha}^{(\text{mc})}(t)$  is the combined correction coefficient for the HVAC efficiency heat exchange coefficient affected by microclimate at time t;  $T_{\text{HVACL}}^{(\text{mc})}(t)$  is the corrected coefficient for the indoor-outdoor temperature difference at time t considering microclimate impact. The specific calculation methods influenced by microclimate include:

$$\begin{cases} k_{\text{HVAC-}\alpha}^{(\text{nc})}(t) = \alpha_{\text{HVACU}}(t) \cdot \frac{1}{\alpha_{\text{HVACP}}} \\ T_{\text{HVACL}}^{(\text{nc})}(t) = T_{\text{ain}}(t-1) + I_{\text{HVAC}}^{(\text{nc})}(t) \cdot \left(T_{\text{a}}(t) - T_{\text{ain}}(t)\right) \\ I_{\text{HVAC}}^{(\text{nc})}(t) = \alpha_{\text{HVACL}}(t) \cdot \beta_{\text{HVACL}} \cdot \frac{1}{\sqrt{(T_{\text{a}}(t-1) - T_{\text{HVACSIC}})}} \end{cases} \end{cases}$$

where  $a_{\text{HVACU}}(t)$  is for HVAC efficiency heat exchange microclimate correction factor;  $L_{\text{HVAC}}^{(\text{nc})}(t)$  is for the microclimate-corrected HVAC energy behavior temperature impact quantification coefficient;  $a_{\text{HVACL}}(t)$  is for the temperature impact microclimate correction factor for HVAC energy behavior.

C) Building Cell Electric Vehicle Charging Model

To construct a Building Cell electric vehicle charging model influenced by microclimates, we initially propose traditional electric vehicle (EV) charging capacity prediction models and charging probability distribution models. These models primarily consider the impact of urban microclimates on EV charging efficiency, usage behaviors of electric vehicles, and users' willingness to charge. The traditional electric vehicle charging capacity prediction model and the charging probability distribution models are as follows:

$$\begin{cases} SOC_{EV}(t) = SOC_{EV}(0) - \sum_{i=1}^{n_{EV}(t)} \left( \frac{\alpha_{EV} \cdot J_{EV,i}}{Q_{EVSOH}} \right) \\ P_{EV}(t) = P_{EVSTC} \cdot f_{EV}(x_{EV}) \\ f_{EV}(x_{EV}) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{\frac{(x_{EV} - \mu)^2}{2\sigma^2}} \\ \frac{\lambda^{x_{EV}} \cdot e^{-\lambda}}{x_{EV}!} \end{cases} \end{cases}$$

where  $SOC_{\rm EV}(t)$  and  $SOC_{\rm EV}(0)$  represent the electric vehicle (EV) battery capacities at time t and at the start of charging, respectively;  $\alpha_{\rm EV}$  is the electricity consumption per kilometer, measured in kWh/km;  $J_{\rm EV,i}$  is the distance traveled during the width i trip segment, measured in kilometers;  $Q_{\rm EVSOH}$  is the base capacity of the EV's power battery;  $n_{\rm EV}(t)$  is the number of trips made by the electric vehicle from the end of charging to time t;  $P_{\rm EV}(t)$  is the predicted EV charging power at time t, measured in kW;  $P_{\rm EVSTC}$  represents the standard charging power in the traditional model, measured in kW;  $f_{\rm EV}(x_{\rm EV})$  is the EV charging probability distribution function, which includes Gaussian and Poisson distribution patterns.

The electric vehicle (EV) charging power prediction model is a complex model that requires consideration of multidimensional meteorological factors. This paper specifically analyzes the impact of urban microclimatic factors such as temperature and rainfall on the traditional electric vehicle model and the methods for key parameter modification. The Building Cell electric vehicle charging capacity prediction model and charging probability distribution model influenced by microclimates are outlined below:

$$\begin{cases} SOC_{EV}^{(mr)}(t) = SOC_{EV}(0) - \sum_{i=1}^{n_{EV}(t)} \left( \frac{\alpha_{EV-\alpha} \cdot \alpha_{EV} \cdot J_{EV,i}}{Q_{EVSOH}^{(mr)}} \right) \\ P_{EV}^{(mr)}(t) = \alpha_{EVP} \cdot P_{EVSIC} \cdot f_{EV}(x_{EV}) \end{cases}$$
  
Where  $SOC_{EV}^{(mr)}(t)$  is the electric vehicle (EV

Where  $SCC_{EV}(t)$  is the electric vehicle (EV) battery capacity at time t after microclimate corrections;  $\mathcal{Q}_{EV,\alpha}$  is the microclimate-adjusted electricity consumption coefficient per kilometer for the electric vehicle;  $\mathcal{Q}_{EVSCH}^{(m)}$ is the microclimate-adjusted base capacity of the electric vehicle's power battery;  $\mathcal{P}_{EV}^{(m)}(t)$  is the predicted EV charging power at time t after considering microclimate effects, measured in kW;  $\mathcal{Q}_{EVP}$  is the microclimate correction coefficient for the EV charging power.

# 3.2 Model for Demand Response Potential of Building Energy Cells

In assessing the demand response potential of Building Energy Cells, it is imperative to first accurately calculate their energy consumption. Section 3.1 of this document has established predictive models for the power outputs of photovoltaics, HVAC systems, and electric vehicle charging stations, all of which are influenced by urban microclimates. Building upon this foundational work, this section introduces a predictive model for the energy consumption of Building Energy Cells that is also influenced by urban microclimates. This model incorporates several critical factors, including the physical characteristics of the buildings, their usage patterns, external climatic conditions, and the efficiency of their energy systems.

The demand response potential of Building Energy Cells refers to the capability of buildings to adjust their original electrical usage patterns in response to electrical grid demands. This potential encompasses the ability of Building Energy Cells to participate in demand response (DR) programs, which involves both increasing and decreasing their load as required. Considering the dynamic temporal characteristics of DR, this paper proposes an analytical model for assessing the demand response potential of Building Energy Cells as follows:  $P_{PC}^{(nc)}(t) = P_{PV}^{(nc)}(t) + P_{PV}^{(nc)}(t)$ 

$$C_{\rm BC}^{\rm (nc)}(t) = \int_{0}^{t} \left[ P_{\rm BC}^{\rm (nc)}(t) - P_{\rm BCBASE}^{\rm (nc)}(t) \right] dt$$

where  $P_{\rm BC}^{(\rm nc)}(t)$  is the predicted power output of the Building Cell under the influence of urban microclimates,



Fig. 3 Photovoltaic Power Generation Curves Under the Influence of Urban Microclimates

measured in kW;  $C_{\rm BC}^{\rm (nc)}(t)$  is the predicted demand response potential of the Building Cell at time t, measured in kWh.

### 4. CASE STUDIES

This study aims to analyze the impact of urban microclimates on building energy consumption and demand response. To comprehensively assess this impact, we have established four different scenarios, each corresponding to varying climatic conditions and architectural parameter configurations. These four scenarios include: 1) Conventional energy consumption under standard climatic conditions; 2) Increased energy consumption under extreme high temperature conditions; 3) The impact of enhanced building insulation on energy consumption; 4) The effect of reducing energy consumption through sustainable building strategies such as green roofs.

Fig.3 presents the photovoltaic power generation curves over the course of a day for four different scenarios. The x-axis represents the time of day from 00:00 to 24:00, the left y-axis indicates the photovoltaic power output (measured in kW), and the right y-axis displays the cumulative photovoltaic power generated (measured in kWh).

All four scenarios experience a rapid increase in photovoltaic (PV) power generation shortly after sunrise, reaching a peak around noon. As solar intensity diminishes, the power generation gradually declines until sunset. The generation curves for PV Case 1 and PV Case 2 are very similar, indicating that the architectural or microclimatic conditions in these two scenarios are alike. PV Case 3 and PV Case 4 exhibit different trends during most of the day, and notably, PV Case 4 shows slightly lower power generation in the afternoon to evening period, which may suggest that the scenario



Fig. 4 Electric Vehicle Charging Curves Under the Influence of Urban Microclimates



*Fig. 5 Outdoor Temperature and Power of HVAC Curves Under the Influence of Urban Microclimates* 

represented by PV Case 4 encounters lower solar radiation during these hours.

Fig.4 illustrates the charging behavior of electric vehicles (EVs) at different times of the day, specifically under the influence of varying urban microclimatic conditions throughout the hours. During the early morning to morning period (approximately from 0:00 to 8:00 AM), the charging levels for all scenarios are relatively low. From morning to afternoon (approximately from 9:00 AM to 5:00 PM), there is a gradual increase in charging demand.

EV Case 3 consistently exhibits significantly higher charging volumes across almost all time periods compared to the other two scenarios, indicating that the frequency of electric vehicle use in this scenario is more susceptible to microclimatic influences. The peak charging times occur around noon and early evening for EV Case 1, suggesting that these periods either see more vehicles returning to charging stations or represent preferred charging times for electric vehicle users.



Potential Curves Under the Influence of Urban Microclimates

Fig.5 displays the relationship between indoor temperatures and HVAC energy consumption in Building Energy Cells over the course of a day, influenced by different urban microclimatic factors. The left y-axis represents indoor temperatures, the right y-axis shows HVAC energy consumption, and the x-axis represents time from 0:00 to 24:00 hours.

Regarding temperature trends, the three microclimate scenarios exhibit different daily temperature profiles: HVAC Case 1 consistently shows the highest temperatures, while HVAC Case 3 maintains the lowest. In terms of HVAC energy consumption, Case 2 displays relatively stable energy use throughout the day.

Fig.6 provides curves of Building Cell energy consumption and demand response potential over the course of a day under different urban microclimatic impacts. The shaded areas represent the overall demand response potential capacity of the Building Energy Cells.

Energy consumption and demand response potential curves are closely linked; particularly during daytime and around noon when energy and HVAC loads peak due to increased indoor cooling requirements from rising outdoor temperatures. BC Case 1 consistently shows the highest energy consumption among the scenarios, suggesting that the buildings or regions this case represents are subject to more extreme climatic conditions. Conversely, BC Case 3 exhibits the lowest energy consumption and demand response potential, indicating a potentially milder microclimate.

While the energy consumption trends are relatively similar across cases, the levels of demand response potential vary. Optimizing buildings for microclimatic impacts, HVAC Case 3 reflects cooler microclimatic conditions, leading to lower indoor temperatures and reduced demand response potential, whereas HVAC Case 1 indicates higher energy consumption and greater demand response potential.

# 5. CONCLUSIONS

This paper explores the factors and pathways influencing the energy consumption of Building Energy Cells considering urban microclimates and constructs a model of Building Energy Cells influenced by urban microclimates. The results not only demonstrate the direct impact of microclimatic variations on building energy consumption but also provide the potential for energy consumption demand response under various climate-adaptive building strategies. It reveals the most effective architectural strategies and technologies to optimize energy consumption and address potential challenges posed by future climate changes.

# REFERENCE

[1] Vahmani P, Luo X, Jones A, Hong T. Anthropogenic heating of the urban environment: An investigation of feedback dynamics between urban micro-climate and decomposed anthropogenic heating from buildings. Building and Environment. 2022;213:108841.

[2] Sezer N, Yoonus H, Zhan D, et al. Urban microclimate and building energy models: A review of the latest progress in coupling strategies. Renew Sustain Energy Rev 2023;184:113577. ISSN 1364-0321.

[3] Jie P, Su M, Gao N, et al. Impact of urban wind environment on urban building energy: A review of mechanisms and modeling. Build Environ 2023;245:110947. ISSN 0360-1323.

[4] Liu S, Ti Y, Kwok C, Ren C, et al. Investigating the impact of urban microclimate on building thermal performance: A case study of dense urban areas in Hong Kong. Sustain Cities Soc 2023;94:104509. ISSN 2210-6707.

[5] Wang C, Ferrando M, Causone F, et al. Data acquisition for urban building energy modeling: a review. Build Environ 2022;217:109056.

[6] Oke TR, Mills G, Christen A, et al. Urban climates. Cambridge University Press; 2017.

[7] Meng F, Zhang L, Ren G, et al. Impacts of UHI on variations in cooling loads in buildings during heatwaves: a case study of Beijing and Tianjin, China. Energy 2023;273:127189.

[8] Yang X, Yao L, Peng LLH, et al. Impacts of urban air temperature and humidity on building cooling and heating energy demand in 15 cities of eastern China. Energy 2024;288:129887. ISSN 0360-5442.

[9] Shah A, Garg A, Mishra V, et al. Quantifying the local cooling effects of urban green spaces: Evidence from Bengaluru, India. Landsc Urban Plan 2021;209.

[10] Vurro G, Carlucci S. Contrasting the features and functionalities of urban microclimate simulation tools. Energy Build 2024;311:114042. ISSN 0378-7788.

[11] Kianmehr A, Lim TC, Paasonen P, et al. Quantifying interactive cooling effects of morphological parameters and vegetation-related landscape features during an extreme heat event. Climate 2022;10:481497.

[12] Liu J, She X, Wang J. Comprehensive optimization of urban building cluster morphology based on microclimate: A two-level optimization approach. Sustain Cities Soc 2024;100:105005. ISSN 2210-6707.

[13] Liao Z, Liu Z, Wu Q, et al. Solar energy full-spectrum perfect absorption and efficient photo-thermal generation. Chin Phys B 2021;30:084206.

[14] Shen C, Zheng K, Ruan C, et al. Operation strategy and energy-saving of the solar lighting/heating system through spectral splitting. Energy Built Environ 2023;4(3). ISSN 2666-1233.

[15] Ciancio V, Falasca S, Golasi I, et al. Influence of input climatic data on simulations of annual energy needs of a building: EnergyPlus and WRF modeling for a case study in Rome (Italy). Energies 2018;11:2835.

[16] Meng C, Huang C, Dou J, et al. Key parameters in urban surface radiation budget and energy balance modeling. Urban Clim 2021;39:100940. ISSN 2212-0955. [17] Naqvi S, Kar K, Bhattacharya S, et al. Air quality and comfort constrained energy efficient operation of multizone buildings. Build Environ 2023;244:110716. ISSN 0360-1323.

[18] Song Z, Liu J, Yang H. Air pollution and soiling implications for solar photovoltaic power generation: A comprehensive review. Appl Energy 2021;298:117247. ISSN 0306-2619.