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CityEL: A web-based platform to support city-scale building energy efficiency based on AutoBPS

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ABSTRACT

Urban building retrofitting is a critical approach for energy conservation and carbon reduction, and proper quantification tools could help lower the cost for large-scale urban renewal. This paper introduces City Energy Lab (CityEL), a web-based platform that supports city-scale building energy efficiency. Compared to existing Urban Building Energy Modeling (UBEM) tools, which often focus on aggregated regional results, CityEL not only facilitates rapid UBEM but also focuses on analyzing multiple neighborhood scales, particularly for the renovation of old residential neighborhoods. CityEL uses AutoBPS as its core engine to establish benchmark and energy retrofit models and utilizes Geographic Information System (GIS) tools to enable rapid modeling, multi-neighborhood benchmarking, and comprehensive retrofit scenario evaluation. By streamlining energy benchmarking, retrofit scenario development, and economic viability analysis, CityEL provides a comprehensive framework for scalable, cost-effective urban renewal decisions. To illustrate its capabilities, CityEL was applied in a case study of Shanghai's Huangpu District, where the platform modelled 7934 buildings across 304 neighborhoods, 245 neighborhoods were identified as economically viable for retrofitting, reducing electricity consumption to 786.4 GWh and gas consumption to 303.2 GWh, respectively. These findings highlight CityEL's role in streamlining multi-scale decision-making and advancing methodological frameworks for sustainable urban energy management.

1. Introduction

The world is currently experiencing rapid urbanization. About 75 % of the primary energy worldwide is consumed in cities, which also account for over 70 % of global greenhouse gas emissions (Hu et al., 2022). Achieving energy-saving and emission-reducing targets requires awareness of urban structures and the sensible renovation of old residential neighborhood (Liu et al., 2020; Yang et al., 2023). Residential building renovations are often carried out on a neighborhood basis in China. China plans to renovate over 50,000 old urban residential neighborhoods in 2024 to support urban renewal projects, and proper methods could help policymakers to effectively guide these renovations (Zhou et al., 2024).

Urban building energy modeling (UBEM) is the method of computational simulation and analysis of the performance of urban buildings, which could mainly be divided into top-down and bottom-up approaches (Reinhart & Cerezo Davila, 2016). The top-down paradigm is a strategy that begins at a macro-level perspective and progressively refines to a micro-level. It emphasized the link between macroeconomic variables and energy consumption; nevertheless, it lacked a complete study of technological options and spatiotemporal characteristics (Ang et al., 2020). In contrast, the bottom-up paradigm begins with the characteristics of individual buildings, models their physical conditions, and then aggregates these elements to the urban level (Pan et al., 2023). The primary applications of UBEM include individual behavior research (Ferrando et al., 2020), energy consumption analysis (Mansó et al., 2023; Yuan et al., 2023), and the optimization schemes development (Talebi et al., 2016). Bottom-up UBEM provides a quantitative perspective to calculate the overall energy consumption, renovation costs, and post-renovation outputs, thus guiding urban building design

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and energy policy formulation (Ang et al., 2020). The accuracy of UBEM was also validated (Bass et al., 2022). Despite the advantages of UBEM in providing high-precision solutions for specific problems, it requires extensive data, computational resources (Ali et al., 2021) and complex processes.

Many studies attempted to automate the complex processes of UBEM and construct a series of UBEM tools (Ferrando et al., 2020). In the early stages, most UBEM tools operated locally, the Urban Modeling Interface (UMI) (Kandelan et al., 2024) functions as a plug-in for the Rhinoceros 3D, allowing 3D building models to be exported to EnergyPlus models. URBANopt (Charan et al., 2021) is an open-source simulation platform for analyzing the energy performance of low-energy districts, high-performance buildings, and energy systems in urban areas with customizable modules for flexible use; Combined Energy Simulation And Retrofitting (CESAR) (Wang et al., 2018) calculates current building energy demand and projects future scenarios to evaluate energy strategies and sustainability targets in Swiss districts; City Energy Analyst (CEA) (Cevallos-Sierra et al., 2024) was a Python-based tool with an intuitive graphical interface, simplifying building heating and cooling load analysis for neighborhood energy planning. TEASER (Remmen et al., 2018) was another Python-based application that aims to integrate UBEM and urban system energy modeling, enhancingthe representation of the urban building environment more detailed and promoting a comprehensive understanding of city-scale energy systems. Recently, Hunan University developed Automated Building Performance Simulation (AutoBPS) (Deng et al., 2023), which uses Geographic JavaScript Object Notation (GeoJSON) as input and EnergyPlus as the calculation engine, providing comprehensive urban building energy consumption simulation for residential and commercial buildings. AutoBPS supported diverse energy analyses, including prototype building generation (Yang et al., 2024), rapid urban building energy modeling (Deng et al., 2022; Song et al., 2024), analysis of various energy-saving measures (including demand response (Peng et al., 2023), renovation (Ji et al., 2023), rooftop photovoltaics (Ren et al., 2024)).

UBEM tools is suggested to adopt a clear step-by-step interface to attract more professional users, and focus on specific input-output data to enhance reliability and simulation efficiency (Salvalai et al., 2024). Some UBEM tools use or complement the modeling process with web-based platforms to enhance the tool usability. Most UBEM tools require complex setup and software installation, and UBEM involves managing large data sets that are challenging to visualize effectively (Hong et al., 2020). Web-based platforms provide a solution to these challenges. CityBES (Hong et al., 2024) was an early web platform for simulating the energy performance of large structures, supporting energy benchmarking, urban planning, retrofit analysis, building management, photovoltaic (PV) potential assessment, and urban microclimate visualization. CEA also transitioned to a web tool, using data from OpenStreetMap and modeling with established physical models. Massachusetts Institute of Technology developed ubem.io (Ang et al., 2022) with UMI as its core engine to reduce the UBEM cost. It categorized UBEM engineers into three groups: city representatives, urban planners or GIS managers, and building consultants or energy modelers and created three representative functional modules. Recently, Sebin Choi and Sungmin Yoon (Choi & Yoon, 2024) used GPT-4o to develop GPT-UBEM, a top-down urban building energy modeling tool that integrates diverse data sources to optimize energy predictions and provide insights for low-carbon urban planning, with case studies in South Korea demonstrating its potential and limitations

Retrofit analysis of existing buildings was a key function of the UBEM tools, as selecting appropriate energy conservation measures (ECMs) was essential for crucial for achieving energy savings and carbon reduction (Fahlstedt et al., 2022), especially in developed cities with a large stock of existing buildings. Compared to commercial buildings, residential buildings receive greater attention for retrofitting (Ohene et al., 2022), with objectives primarily focused on improving comfort, reducing energy consumption, lowering renovation costs, and decreasing carbon emissions. Earlier retrofitting researches mainly focused on the level of a single building (Huang et al., 2020). Recently, large-scale retrofitting becomes increasingly popular because it includes energy sharing, peak shaving, trade-offs across multiple buildings, and a broader formulation of energy and sustainability goals and policies (Bjelland et al., 2024).

At the scale of a neighborhood, Vahid-Ghavidel et al. (2024) proposed an optimization framework using the umi to integrate urban building energy modeling with renewable energy planning, highlighting in a Chicago neighborhood study that solar PV and energy storage systems are crucial for achieving CO_2 reductions and cost-effectively balancing energy demands in low-carbon neighborhood development. Mansó Borràs et al. (Mansó Borràs et al., 2023) developed the UBEM of energy communities using CEA. They concluded that, compared to individual residences, energy communities could provide greater photovoltaic power self-sufficiency. Munguba et al. (Munguba et al., 2024) analyzed building complexes in Recife, Brazil. They concluded that integrating building modeling, economic analysis, and optimization better adjusts photovoltaic system scale and reduces overall energy consumption than implementing individual ECMs. At the scale of the city, Ali et al. (Ali et al., 2020) utilized a data-driven approach to develop the UBEM for Ireland. After comparing the efficiency and outcomes of various ECMs, they identified 16 effective measures and provided retrofit recommendations for different types of residential buildings. Chen et al. (Chen, Hong & Piette, 2017) conducted ECM analyses for buildings in San Francisco, but these renovations primarily targeted large offices and small retail. Existing research indicated that community-based transformation was the optimal scale for transformation. Zhang et al. (Zhang et al., 2023) studied the impact of ECMs on carbon emissions at the building, community, and regional levels. Annual cost at the community scale was reduced by 27.3 % compared to individual buildings, and community-scale strategies reduced costs by 1.9 % compared to the city scale.

The concept of "neighborhood" varies between international and Chinese contexts. Internationally, neighborhoods are generally considered loosely regulated residential areas where individual homeowners have the autonomy to update their properties, typically consisting of single-family homes. In contrast, in China, neighborhoods refer to gated residential complexes, often comprising apartment buildings with shared management (Liu et al., 2021). Residents have no control over community-wide renovations or maintenance, which is handled by property management companies and local government authorities. Policymakers need to balance cost-effectiveness and energy-saving outcomes under limited economic conditions, but selecting the optimal residential communities is a challenge. Residential communities may contain mixed-use buildings and structures built in different periods (Conticelli et al., 2024), leading to varied building parameters (Liu et al., 2022). Consequently, their energy-saving potential and appropriate retrofitting measures differ.

Comparative analysis of multiple neighborhoods aids urban policymakers in decision-making and supports the analysis of neighborhoods-level energy retrofits and the establishment of nearly zero-energy neighborhoods. Natanian et al. (Natanian et al., 2024) also indicate that UBEM tools require further integration for the design and analysis of nearly zero-energy neighborhoods and positive-energy neighborhood. Existing UBEM research and tools processed uploaded buildings as a single entity for input and output. However, the roofs of high-rise residential buildings are not owned by individual residents but are managed by the neighborhoods in most conditions in China. Additionally, analyzing shared energy storage in neighborhoods is necessary due to the mismatch between photovoltaic peak generation and peak electricity demand (Walker & Kwon, 2021). Therefore, current methods that aggregated results for the whole city or neighborhood lacked comparative analysis for multiple neighborhoods.

This paper introduces CityEL, a web-based tool that uses AutoBPS as its core engine to quickly establish city-level EnergyPlus building models, which can address the challenges of rapidly aggregating energy consumption data from multiple neighborhoods, and identifying the most suitable communities for retrofitting CityEL integrates multiple rapid UBEM analysis tools, including retrofit, photovoltaic and energy storage assessments, and incorporates a GIS system to quickly aggregate results from multiple neighborhoods and conduct a series of analyses. In addition to performing the basic functions of existing UBEM tools, CityEL provides comprehensive results for multi-neighborhood analyses. Policymakers could swiftly select and compare various energy-saving retrofit measures and strategies across multiple neighborhoods in a city.

2. Methodology

This paper used CityEL to complete the process depicted in Fig. 1. Firstly, the user prepared the necessary building data and the area data to be analyzed as required and uploaded them to CityEL. Then, relevant project and retrofit settings were configured. CityEL then analyzed and combined the uploaded data on the back-end, selected suitable prototypes, and generated building footprint files in JSON format for AutoBPS, which could build EnergyPlus models automatically with GeoJSON and JSON as input. Subsequently, the back-end used the AutoBPS-Geo module to generate the uploaded building EnergyPlus models and ran them in multiple threads to obtain results. Following this, the back-end modules of CityEL were called to conduct spatial analysis on regional models aggregated from multiple areas. This process produced three outcomes: individual building models, the total results for all input buildings, and the neighborhood-level results based on user-uploaded areas.

2.1. Introduction to CityEL

CityEL is a project with a frontend-backend separation architecture. The front-end, developed in TypeScript, utilizes ReactJS as its framework, with Cesium for 3D visualization. To better integrate with AutoBPS, the back-end was developed using Ruby and Ruby on Rails as the framework, with MySQL serving as the database.

The overall interface of CityEL is shown in Fig. 2. The main component of the interface is a 3D building visualization using Cesium. The modules are divided as follows: PART 1. User Info, managing user login and projects; PART 2. Processing Steps, representing the current modeling steps. CityEL divides the modeling process into five steps: Step 1, "Data," includes data upload and preprocessing; Step 2, "Model," includes running and viewing the baseline model; Step 3, "Retrofit," includes setting up and modeling energy retrofit scenarios; Step 4, "UBEM Results," includes the results of the entire model; and Step 5, "Aggregated Results," includes the aggregated results for multiple areas based on user-uploaded boundaries.

For the PART 3. Buildings and PART 4. Boundaries consist of user-uploaded data, allowing users to click and interact to display PART 5, which is Entity Detailed Information. This part contains various selectable information: "param" for basic building information, "baseline" and "retrofit" for the energy consumption results of the baseline and retrofit models, "hourly" for selecting and displaying energy consumption curves for any time within the 8760 h of a year, and "download" for downloading the corresponding data. PART 6. Analysis Tools include various selectable and usable tools, with different tools available at each processing step, such as coloring parameters and displaying them in PART 7. Colorbar. PART 8, the GIS Info Bar includes information on the current location.

CityEL uses AutoBPS to convert GeoJSON data into EnergyPlus models and provides additional features. In pre-processing, it standardizes key fields like building type and adjusts inputs to match AutoBPS's format. In post-processing, CityEL extends beyond individual building calculations by generating city-level prototypes and aggregating simulation results, which AutoBPS alone cannot do. CityEL uses geographic analysis module for energy consumption aggregation based

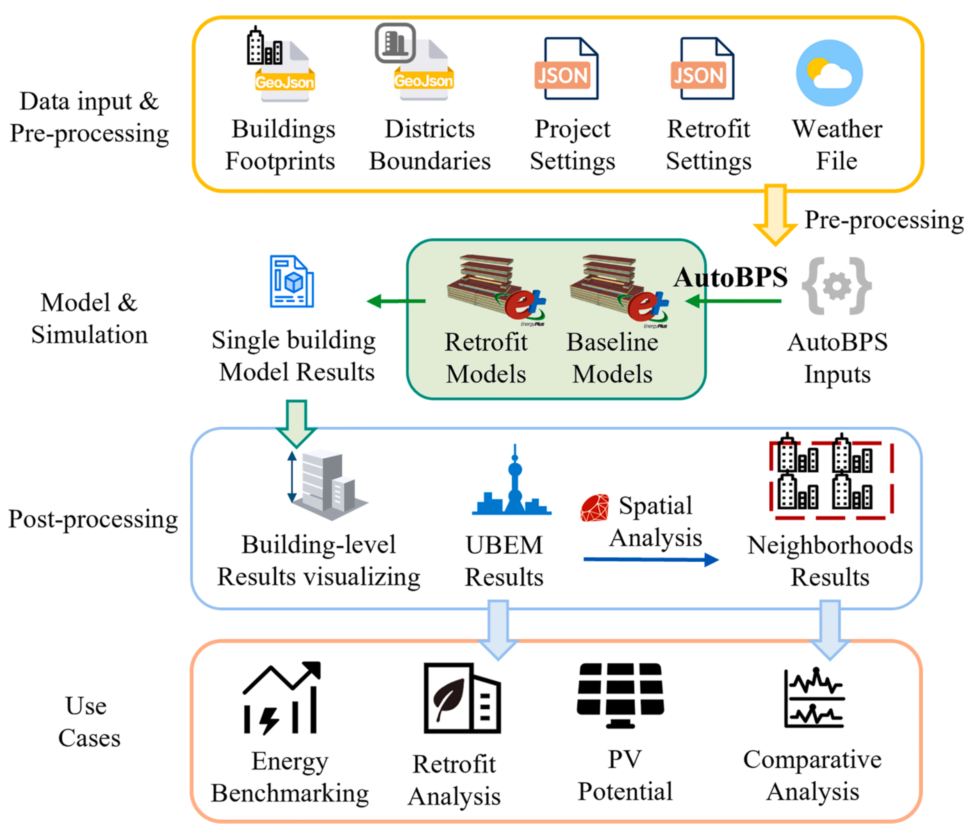

Fig. 1. The framework of the research.

Fig. 2. The overall interface of CityEL.

on user-defined areas, meeting urban renewal needs by summarizing energy performance across multiple neighborhoods. It also helps configure energy storage in residential areas to manage excess energy from distributed PV systems.

2.2. Input data and preprocessing

CityEL currently only accepts input files in GeoJSON formats, a widely used format for encoding geographic data structures using JavaScript Object Notation (JSON). A GeoJSON must include geographic features, geometries, and properties.

CityEL is a flexible tool that can be used in many regions and cities, with only basic building data requirements. Below are some possible sources and references for obtaining the necessary data. Cities with established urban databases, such as New York, can easily generate results using existing datasets. For areas and cities with comprehensive OpenStreetMap coverage, OpenStreetMap can be used to access suitable data (Atwal et al., 2022). In areas where data is provided by open mapping providers, the corresponding map services or a combination of multiple data sources can be utilized to acquire the required information (Song et al., 2024). For areas without access to the above sources, very high resolution satellite imagery can be used to gather the needed information (Wang et al., 2025).

After uploading, CityEL verifies if the uploaded files meet basic requirements: compliance with the GeoJSON standard, no overlapping building footprints, and the properties of these buildings must also contain the building height/stories, built year and building type to match appropriate prototype buildings. If the data meet GeoJSON requirements, CityEL proceeds with GIS processing, assigning parameters like width, length, aspect ratio, area, and perimeter. With building age and type, AutoBPS assigns building physical parameters (including the wall U-value, window-to-wall ratio, and window performance, ect.) automatically with the specific building prototype and standards. Since the building types uploaded by users may be self-named, users can select building types and templates compatible with AutoBPS to preprocess the required building types.

Currently, CityEL supports 22 building types from ASHRAE 90.1, 16 building types from DOE, and 22 building types developed by AutoBPS for urban buildings in China. AutoBPS adjusts local prototype building parameters according to Chinese standards based on city location: Residential and non-residential buildings are divided into three groups. Residential buildings follow JGJ 134–2001 and JGJ 134–2010 standards: before 2001, 2002–2009, and after 2010. Commercial buildings follow GB 50,189–2005 and GB 50,189–2015 standards: before 2005, 2005–2015, and after 2015. For mixed-use buildings, relevant parts are referenced according to respective regulations. Specific building types are shown in Table 1. Each building type corresponds to three prototype templates, with different parameters for each building year. Generally, older buildings have poorer thermal performance and energy efficiency of air conditioning systems.

Boundaries uploads does not require any properties. Neighborhoods boundaries can be obtained from OpenStreetMap or local mapslike Google Maps, Baidu Maps, Amap. Users can also manually delineate boundaries in software like QGIS or ArcGIS. This flexibility allows users to aggregate results for any area or number of areas as desired, including overlapping regions if needed.

2.3. Introduction to the case study area

Shanghai is one of the most developed cities in China, with a permanent population of 24.8 million, Shanghai located in eastern China, along the west coast of the Pacific Ocean. Shanghai has a humid subtropical climate, with four distinct seasons. Summers are hot and humid, often exceeding 35 °C, while winters are mild but sometimes chilly. Huangpu District, as shown in Fig. 3, is a central area of Shanghai and one of its earliest developed districts, featuring many older buildings in need of renovation. This paper chose the Huangpu District of Shanghai,

Table 1
The prototypes supported by CityEL.

ASHRAE 90.1	AutoBPS	DOE
Small Office	Small Hotel-stores	Warehouse
Small Hotel	Small Hotel	Small Office
Small Data Center	Shopping mall	Small Hotel
Secondary School	Retail Standalone	Secondary School
Retail Strip mall	Restaurant	Retail Strip mall
Retail Standalone	Primary School	Retail Standalone
Quick Service Restaurant	Office-shopping mall	QuickServiceRestaurant
Primary School	Mid-rise Apartment-stores	Primary School
Outpatient	Mid-rise Apartment	Outpatient
Mid-rise Apartment	Medium Office	Mid-rise Apartment
Medium Office Detailed	Low-rise Apartment-stores	Medium Office
Medium Office	Low-rise Apartment	Large Office
Large Office Detailed	Large Office-stores	Large Hotel
Large Office	Large Office	Hospital
Large Hotel	Large Hotel	High-rise Apartment
Large Data Center	Hotel-mall	Full-Service Restaurant
Laboratory	Hotel-office-mall	
Hospital	Hotel-office	
High-rise Apartment	Hotel-residential	
Full-service Restaurant	High-rise Apartment-stores	
Warehouse	High-rise Apartment	
Super Market	Hospital	

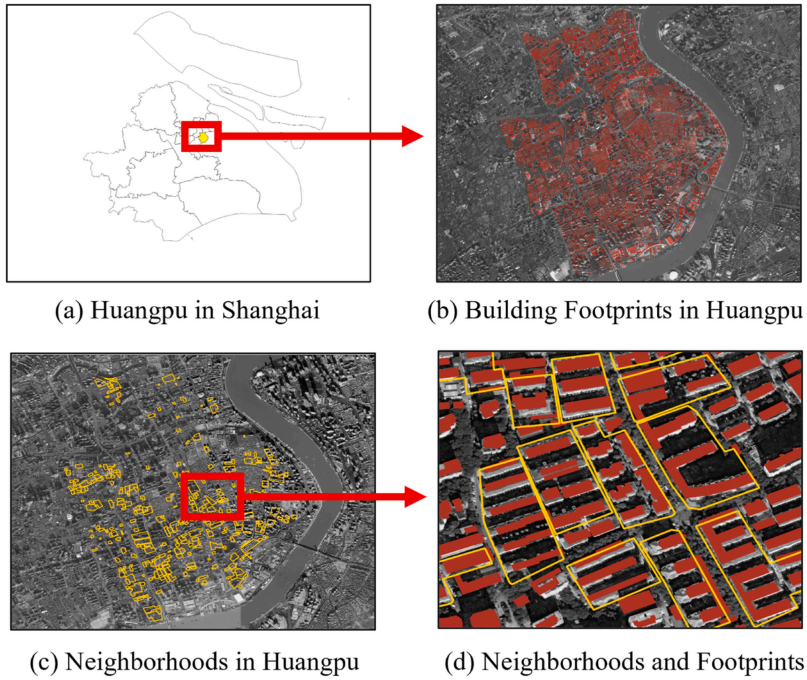

Fig. 3. Introduction to Huangpu District.

China, as a case study for rapid UBEM modeling and analysis to demonstrate how CityEL operates within the UBEM workflow.

This analysis included 12,578 building footprints with properties, including building ID, number of floors, building type, and construction era. Shanghai's building input data was derived from a multi-source data fusion; detailed methods and data are available in this work (Song et al., 2024). The building type results for the Huangpu District were manually calibrated to ensure accuracy. Similar data for other

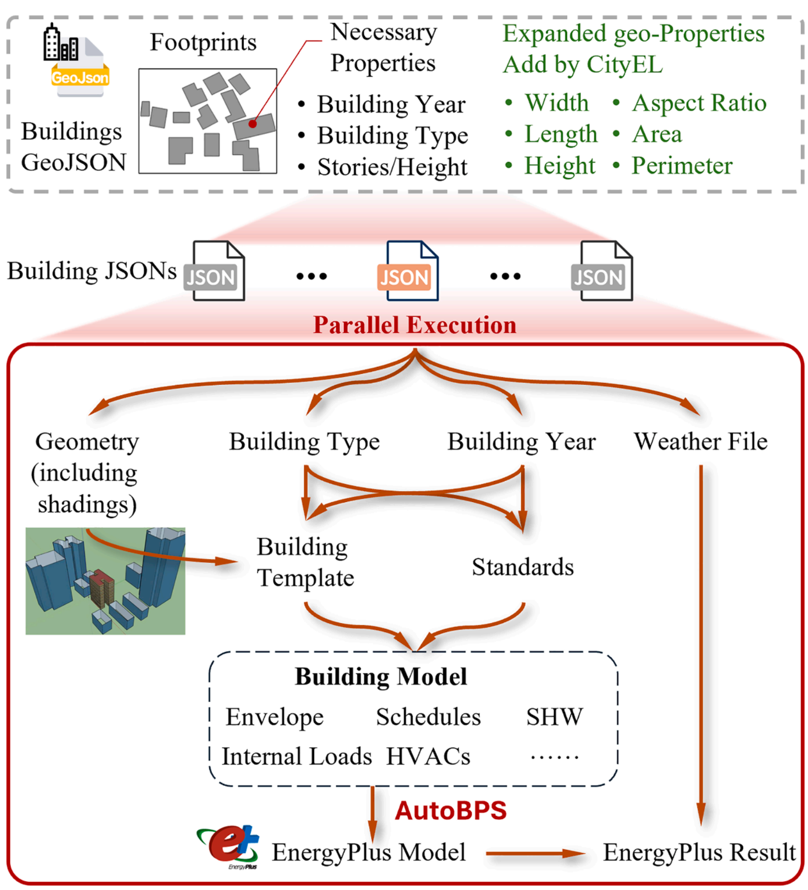

Fig. 4. Urban building energy model generation framework.

cities can be obtained using the same method.

Fig. 3(c) shows the neighborhoods in Huangpu, Huangpu District is predominantly composed of residential areas. Additionally, a significant portion of these residential areas consists of aging or older housing units. In this study, a total of 304 neighborhoods were considered for analysis.

2.4. Urban building energy model generation

The establishment of prototype buildings relies on the AutoBPS module AutoBPS-geo, as shown in Fig. 4. The input GeoJSON file contains building footprints and necessary properties, and then CityEL adds more geometric properties using geographic analysis module and decomposes these buildings into individual building JSON files containing geometry, type, construction year, and the appropriate climate file. Building geometry includes length, width, and number of floors. CityEL assigns the climate file based on the geographic location to the nearest epw file. Building type and construction year determine the prototype used. Each building runs the same process in parallel, and the results are merged on the back-end to enhance modeling and processing speed.

Current energy retrofit strategies for old residential neighborhoods in China mainly focus on roofs, walls, window overhangs, windows (e.g., replacing glass, adding energy-efficient coatings), energy-efficient air conditioners, and adding rooftop photovoltaics. In this case study, building parameters are set according to the mandatory national standards in Shanghai and China. The specific parameters are referred to in Table 2.

2.5. Retrofitted building energy model generation

The original AutoBPS-retrofit was further enhanced to support more energy retrofit strategies during the development of CityEL. The current AutoBPS-retrofit energy model establishment process is shown in Fig. 5. The generated files include building geometric parameters (length, width, floors, height) and building prototypes (determined by building age and type). AutoBPS adjusts the geometric dimensions of the prototype buildings with AutoBPS-Param module (Xi et al., 2023) to create a baseline model. This model, combined with the ECM list, generates the retrofitted building model. Subsequently, running the economic analysis module provides results, including baseline results, retrofitted results, energy savings, retrofit cost, and retrofit returns.

Table 2
The baseline parameters of the prototype buildings in this case study.

Parameters	Residential part			Commercial part		
	Pre-2001	2002–2009	Post-2010	Pre-2005	2006–2014	Post-2015
Exterior wall U-value(W/(m^2·K))	1.96	1	0.8	2	1	0.6
Roof U-value (W/(m^2·K))	1.66	0.8	0.5	1.5	0.7	0.4
Window U-value (W/(m^2·K))	6.6	3.2	2.8	6.4	3	2.6
Window SHGC	0.85	0.48	0.34	0.69	0.43	0.35
Lighting power density (W/m^2)	7	7	6	15	11	9
Equipment power density (W/m^2)	4.3	4.3	4.3	20	20	15
Occupancy (person/m^2)	0.05	0.05	0.05	0.125	0.125	0.125
Cooling/heating setpoints (°C)	26/18	26/18	26/18	26/20	26/20	26/20
Cooling/heating COP	2.2/1	2.3/1.9	2.9/2.2	4.2	5.1	5.6

For the renovation of walls and roofs, adding external insulation layers is the primary method, with options for different materials and thicknesses. The selection of insulation type, thickness, and thermal conductivity can significantly affect the thermal performance of the building envelope. Users can choose the default Expanded Polystyrene Insulation Board (EPS) as the material by simply setting the thickness or creating new materials and thicknesses as EnergyPlus options. Alternative insulation types, like mineral wool or rigid foam, allow users to balance cost, performance, and environmental impact. Insulation type, thickness, and thermal conductivity significantly affect building envelope performance. For example, the R-value of EPS varies with thickness, influencing heat loss reduction through walls and roofs.

For lighting adjustments, the primary modification is using high-efficiency LEDs to reduce lighting power density, and The use of LEDs also reduces cooling loads by minimizing waste heat. Window glass adjustments involve replacing them with Low-E windows, which may affect parameters such as U-factor, Solar Heat Gain Coefficient (SHGC), and Visible Transmittance (VT). Users need to be aware that SHGC and U-value are not independent of each other, and CityEL will check for their consistency. Replacing windows with Low-E glass reduces heat gains in summer and heat losses in winter, which directly impacts cooling and heating demands. For improvements to the cooling system, the focus is on the efficiency enhancement of the chiller and mini-split heat pump. For residential buildings, high-efficiency mini-split air conditioners and heat pumps are recommended to enhance energy performance. Variable-speed compressors can further improve efficiency. For commercial buildings, advanced air-cooled or water-cooled chillers are suggested for larger cooling loads. Higher COP systems, variable-speed compressors, and advanced heat exchangers can increase efficiency, with options depending on specific building needs. Each measure's impact on COP is assessed to enhance overall cooling performance and reliability.

The retrofit of building overhangs involves identifying windows with exterior boundary conditions in EnergyPlus and automatically adding overhangs to them, and the users can select the depth and angle of the overhangs. Adding overhangs to windows helps improve shading, reduce cooling demands in summer, and enhance energy efficiency. The energy consumption changes due to overhangs depend on the region; in low-latitude areas, overhangs can significantly save energy, in low-latitude areas, overhangs significantly reduce cooling loads, while in higher latitudes, they allow more winter sunlight.

The photovoltaic module uses the Equivalent One-Diode model in EnergyPlus. In the current CityEL, the supported parameters are mainly listed in Table 3. Users can adjust these parameters to set the specific characteristics of the photovoltaics. As shown in Fig. 7, the modeling of photovoltaics places a photovoltaic panel at the center of the building and estimates its power generation potential using a covered roof area percentage of 60 %.

After completing the energy simulations, CityEL supports users in conducting economic analysis and allows them to input the retrofit cost per unit. The retrofit costs for glass, walls, and roofs are calculated per square meter, while window shades and the Coefficient of Performance (COP) improvements are calculated per unit. These specific retrofit units are automatically retrieved from the EnergyPlus model and multiplied by the input prices.

The specific retrofit parameters in the case study were primarily based on two mandatory national standards in China: the Technical Standard for Nearly Zero Energy Buildings (GB/T51350–2019) and the Standard for Lighting Design of Buildings (GB 50,034–2024), as summarized in Table 4. The material prices used are sourced from a construction material pricing website in China. Users can also input their prices for their input materials. The total cost, including the material, labor, and other expenses, can be calculated using Eq. (1):

$$C = C_m + C_L + C_O \tag{1}$$

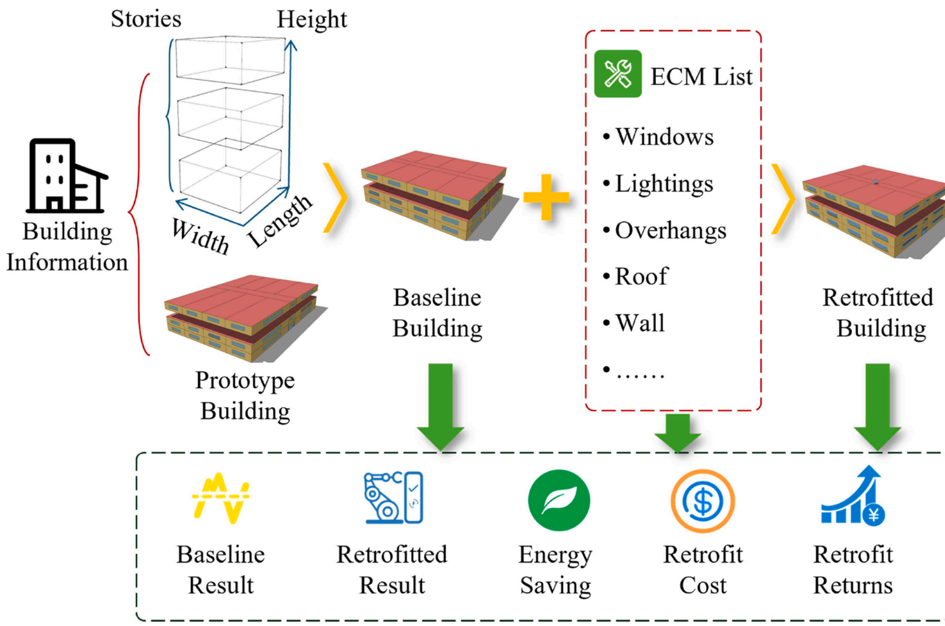

Fig. 5. The generation of retrofitted building model by enhanced AutoBPS-retrofit.

Table 3
The supported parameters for photovoltaic retrofit.

Description	Typical Value Range
PV cell type	Crystalline Silicon, Amorphous Silicon
Number of cells in a PV module	36–72
Current at maximum power	5–10 A
Voltage at maximum power	20–40 V
Short circuit current	6–12 A
Open circuit voltage	20–60 V
PV module area	0.5–2 m^2
Tilt angle from horizontal	0–90°
Orientation	North, East, South, West
Covered roof area percentage	1 %–100 %

Where C_m is the price of materials as shown in, C_m is the labor cost, and C_m represents the other costs, Based on the investigation by He et al., in mainland Chinese cities, the ratio between labor cost and material cost is 20 % and 60 %, respectively. Users can also customize these parameters in CityEL.

For rooftop photovoltaic settings, commonly available photovoltaic modules are used in the case study, with prices and parameters referenced from the Chinese photovoltaic website: *guangfu.bjx.com.cn*. The tilt angle of the photovoltaics is set according to the latitude of Shanghai to achieve optimal photovoltaic generation efficiency. The government subsidy amounts are derived from the "*Huangpu District Energy Conservation and Emission Reduction Special Fund Management Measures*," with specific parameters referenced from Table 5.

2.6. Aggregate method

The aggregation process of the neighborhoods is as shown in Fig. 6, after the front-end uploads the neighborhoods GeoJSON, it is split into multiple neighborhoods for parallel processing. Then, the geographic analysis module identifies buildings within each neighborhood, defined as those with at least 80 % of their area falling within the neighborhoods. The EnergyPlus results of these buildings are classified as the

Table 4
The ECMs materials used in the case study.

Construction	Year built	Indicator	Baseline	Retrofit	Measure	Specific Material	Price (CNY)	Price (USD)
Exterior wall	Pre-2001	U value W/(m^2·K)	1.96	0.36	Adding EPS layers	80 mm	42.07/m^2	6.00/m^2
	2001–2010		1	0.39		60 mm	34.15/m^2	4.87/m^2
	2010-After		0.8	0.39		50 mm	30.19/m^2	4.30/m^2
Roof	Pre-2001	Thickness (mm)	1.66	0.29	Adding EPS layers	90 mm	46.03/m^2	6.56/m^2
	2001–2010		0.8	0.34		65 mm	36.13/m^2	5.15/m^2
	2010-After		0.5	0.34		35 mm	24.25/m^2	3.45/m^2
Window	Pre-2001	U value W/(m^2·K)	6.6	1.6	Replacing existing windows with Low-e glazing	5 + 12Ar+ 5Low-*e* + 12Ar+5low-e	139/m^2	19.8/m^2
	2001–2010		3.2	1.6				
	2010-After		2.8	1.6				
	Pre-2001	SHGC W/(m^2·K)	0.85	0.287				
	2001–2010		0.48	0.287				
	2010-After		0.34	0.287				
External shading	Pre-2001	Depth m	0	0.5	Adding 90° overhang to windows facing south		500/each	71.3/ each
	2001–2010		0	0.5				
	2010-After		0	0.5				
Air conditioner	Pre-2001	Cooling/Heating COP	2.2/1	3.2/2.4	Change to high-efficiency air condition		3000/ each	430/each
	2001–2010		2.3/1.9					
	2010-After		2.9/2.2					

Table 5
The PV settings of the case study.

Parameter Description	Selected parameter
PV cell type	Crystalline Silicon
Number of cells in a PV module	60
Current at maximum power	7.5 A
Voltage at maximum power	30 V
Short circuit current	8.3 A
Open circuit voltage	36.4 V
PV module area	0.89 m^2
Tilt angle from horizontal	31.2°
Orientation	South
Price per unit	3.4 CNY/W
Government subsidy	1.8 CNY/W
Covered roof area percentage	60 %

target building results, and CityEL aggregates these results into the neighborhoods results.

Baseline and retrofitted results include total, sub-metered, and hourly results. Total results provide an overview of total electricity consumption, including heating, cooling, interior lighting, interior equipment, and fans, along with the total usage. Sub-metered results break down the electricity consumption by category and summarize equipment for chillers, boilers, pumps, and cooling towers. Hourly results provide hourly data for 8760 h, including outdoor temperature, humidity ratio, relative humidity, wind speed, etc. It also includes electricity-related data on electricity load center-produced energy, cooling electricity usage, facility electricity usage, plant electricity usage, etc.

Each retrofitted building has an economic result, including changes in energy consumption before and after the retrofit, the cost of the energy retrofit, savings in electricity bills (calculated by multiplying energy savings by the cost of electricity), payback period, ect.

2.7. Neighborhood battery storage module

Aggregated power suppliers enable real-time price response. The EnergyPlus battery storage module is designed for standalone buildings, which is uncommon in China, where the whole neighborhood is managed as a unit. CityEL cloned the EnergyPlus Battery Storage module on the back-end but only uses its simple model, namely the constrained bucket with energy losses model. The generator load request ($P_{\text{load-request}}$) is compared to the generator production ($P_{\text{gen-supply}}$) as shown in Eq. (2):

$$\begin{cases} P_{\text{stor-charge}} = P_{\text{gen-supply}} - P_{\text{load-request}} & P_{\text{load-request}} < P_{\text{gen-supply}} \\ P_{\text{stor-draw}} = P_{\text{load-request}} - P_{\text{gen-supply}} & P_{\text{load-request}} > P_{\text{gen-supply}} \end{cases} \tag{2}$$

The new state of charge ($Q^{t+\Delta t}_{\text{stor}}$) is updated as Eq. (3):

$$\begin{cases} Q^{t+\Delta t}_{\text{stor}} = Q^{t}_{\text{stor}} + P_{\text{stor-charge}} \cdot \eta_{\text{charge}} \cdot \Delta t & \text{charging} \\ Q^{t+\Delta t}_{\text{stor}} = Q^{t}_{\text{stor}} - \dfrac{P_{\text{stor-draw}} \cdot \Delta t}{\eta_{\text{draw}}} & \text{discharging} \end{cases} \tag{3}$$

Where Δt is the length of the system time step in hours.

2.8. Key performance indicators definition

To clarify the impact of building retrofits on energy consumption and economic performance, several Key Performance Indicators (KPIs) are defined. The Energy Saving Percentage (ESP) is calculated by comparing the Energy Use Intensity (EUI) of baseline and retrofit models. The calculation for ESP is as follows in Eq. (4):

$$\text{ESP} = \frac{\text{EUI}_{\text{baseline}} - \text{EUI}_{\text{retrofit}}}{\text{EUI}_{\text{baseline}}} \times 100\% \tag{4}$$

The PayBack Period (PBP) refers to the time required to recover the initial investment as shown in Eq. (5)

$$\text{PBP} = \frac{\text{InitialInvestment}}{\text{AnnualCashInflow}} \tag{5}$$

Net Present Value (NPV) represents the difference between the present value of cash inflows and outflows over a period of time, used to assess the profitability of an investment. The NPV calculation is as shown in Eq. (6):

$$\text{NPV} = \sum_{t=0}^{n} \frac{R_t}{(1+r)^t} \tag{6}$$

Where$R_t$is the net cash inflow at the time t,$r$is the discount rate, and $n$is the remaining life of the building. In China, the life span of residential buildings is usually 50 years. The remaining life span of residential buildings built before 2001, 2001–2010, and built after 2010 is assumed to be 20 years, 30 years, and 40 years.

The Investment Value Index (IVI) is defined as Eq. (7) to show the relationship between energy savings and investment. This index allows users to sort and filter neighborhoods based on any interesting criteria.

$$\text{IVI} = \left(\frac{\text{ESP}}{\text{TotalInvestment}}\right) \times 10^7 \tag{7}$$

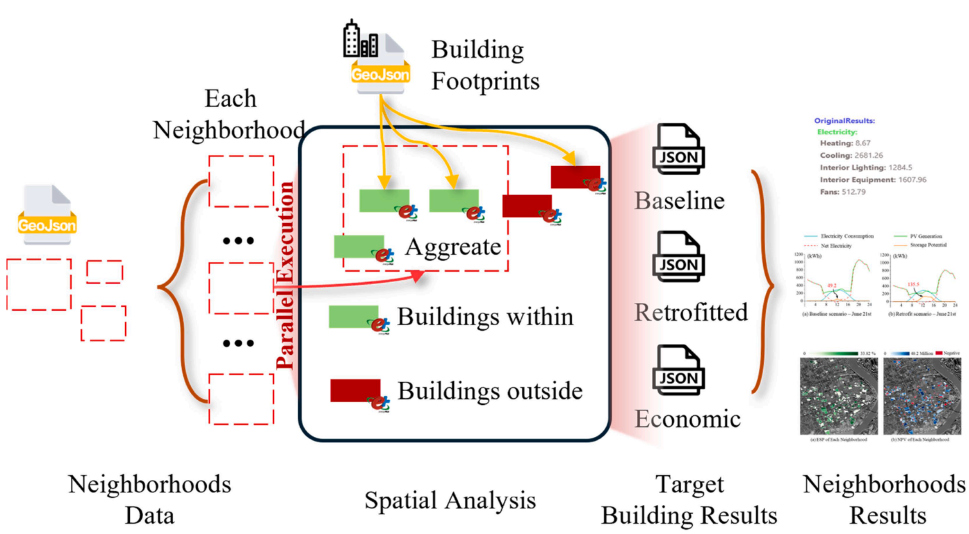

Fig. 6. The aggregate method in CityEL.

3. Results

3.1. The enhanced AutoBPS retrofit model results

This work enhanced the quick modeling of building energy retrofits in the AutoBPS. The energy retrofits were conducted on 66 building types (22 categories, three building years). The specific retrofit measures can be referred to in Table 4. An example of the retrofitted models is shown in Fig. 7. Visible retrofits include photovoltaic panels and window overhangs.

The Energy Saving Percentage (ESP) and the NPV results of the retrofitted buildings can be seen in Fig. 8. The size of the squares represents the ESP—the larger the square, the more effective the retrofit. The color of the squares indicates the NPV—the darker the color, the better the economic return. The red squares indicate that the building type has no profit.

Fig. 8 shows that nearly all buildings achieve some energy savings after retrofits. However, the energy-saving potential varies significantly depending on the building's age and function. Generally, older buildings have greater energy-saving potential. This is primarily due to aging envelope and the use of outdated HVAC systems in older buildings, which were often constructed under less strict building energy performance standards. These factors contribute to poor thermal performance, including insulation, windows, and lighting systems. As building energy saving technology has advanced, newer buildings follow stricter energy standards, which include HVAC upgrades, better insulation, and LED lighting, giving older buildings more potential for energy savings. For example, medium-sized office buildings constructed before 2005 offer the highest retrofitting potential, achieving energy savings of up to 46.5 %. In contrast, newer buildings, such as restaurants built after 2015, were designed according to modern energy efficiency standards and thus have limited room for improvement, with energy-saving potential as low as 0.15 %.

In addition to building envelope parameters, the building type and operational patterns play a critical role in determining the effectiveness of retrofits. Medium and large office buildings typically have stable and predictable energy consumption patterns throughout working hours, making them more suitable for retrofits aimed at improving HVAC systems and reducing energy use during peak demand periods. On the other hand, buildings such as restaurants or low-rise apartments exhibit more volatile or lower energy use, which limits the potential impact of energy-saving measures. For instance, restaurants' energy consumption often fluctuates based on customer demand, and their limited operating hours reduce the overall effectiveness of energy efficiency upgrades.

Although most building types can achieve energy savings with retrofit, not all retrofits are economically viable. Fig. 8 shows that certain building types, including low-rise apartment shops, low-rise apartments, elementary schools, restaurants, and standalone retail stores, as well as newer high-rise apartments, high-rise apartment shops, and office malls, did not yield positive returns on investment. These buildings typically have lower overall energy consumption, and even after retrofitting, the absolute energy savings may not be sufficient to offset the high upfront costs of retrofits, such as materials, labor, and installation. For example, schools and low-rise residential buildings, while benefiting from improved insulation or HVAC systems, often generate limited financial returns due to their relatively low baseline energy consumption. As a result, the NPV for these buildings remains negative, as indicated by the red blocks in Fig. 8.

Furthermore, the economic feasibility of retrofitting is strongly influenced by the operational conditions and energy intensity of the buildings. Buildings with higher baseline energy consumption, such as older office buildings or hotels, are more likely to achieve positive returns on investment, as their energy savings are sufficient to offset the initial retrofit costs. In contrast, newer buildings, particularly those already equipped with efficient energy systems, offer limited opportunities for further savings, reducing the economic attractiveness of retrofits.

3.2. Results for the whole district

UBEM establishment involves two main paradigms. The first paradigm collects geometric data for various buildings types to create prototype buildings, calculate building areas, and perform multiplications. The second paradigm calculates results for individual buildings and then summarizes them. CityEL provides analytical support for both paradigms. For the method using prototype buildings, CityEL offers the geometric statistical analysis, the result as shown in Table 6 (see also Fig. 16), which provides statistical geometry data for each building type, including average length, width, and number of floors, as well as the corresponding area and distribution, which could support the method of summarizing using prototype buildings. CityEL can directly generate the corresponding prototype buildings, and the related data can be downloaded for further processing.

This case study used the individual building calculation paradigm, which takes the shading between buildings into account and allows more specific energy-saving modifications for each building. CityEL utilized AutoBPS to create and run 15,868 EnergyPlus models for 7934 buildings (baseline and deep retrofit models for each building) on a 12th Gen Intel(R) Core(TM) i9–12900H @ 2.5 GHz processor, using 12 cores in parallel, with an NVIDIA T600 Laptop GPU. The simulations took 22 h and 3 min in total, averaging about 2 min per model, and the

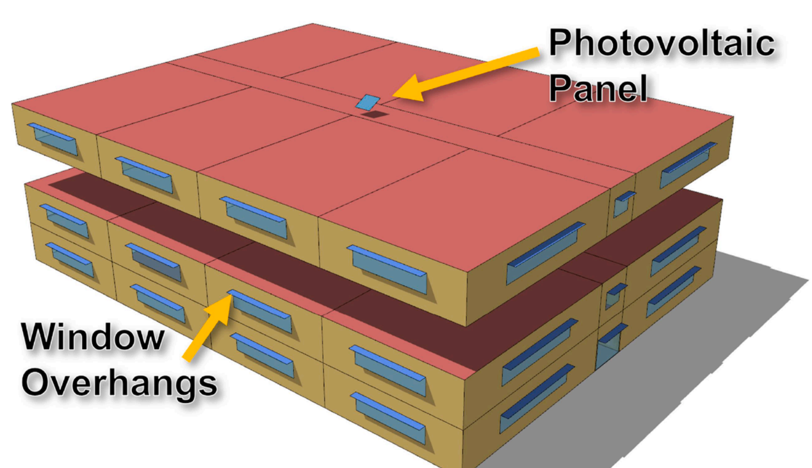

Fig. 7. A retrofitted mid-rise apartment EnergyPlus model.

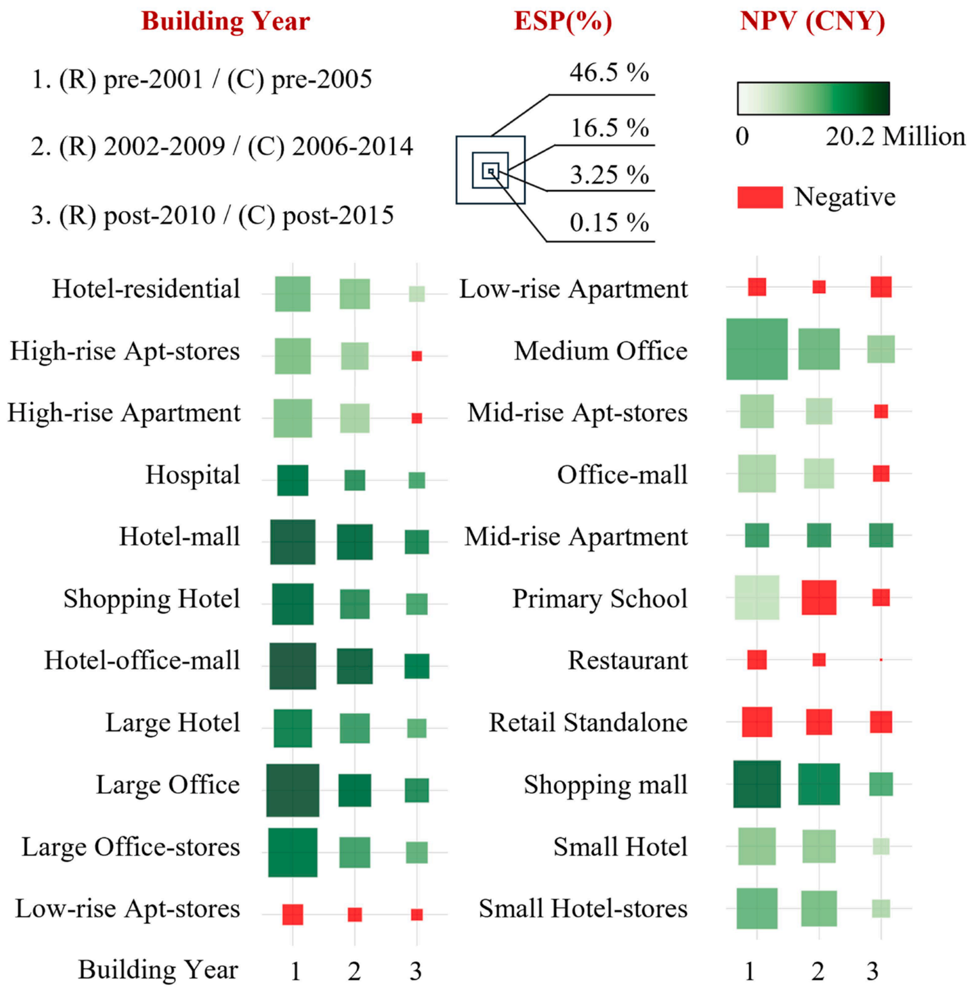

Fig. 8. The ESP and the NPV results for retrofitted buildings.

Table 6
The geometry distribution of building types.

Building Type	Geometry			Building Area with year (hm^2)		
	Avg. Width	Avg. Length	Avg. Story	Before 2005	2005–2015	After 2015
Hotel-residential	19.61	41.42	6.42	3.28	57.80	6.32
High-rise Apartment-stores	21.31	31.82	15.26	3.63	98.51	13.52
High-rise Apartment	19.75	35.04	13.97	243.44	852.84	171.19
Hospital	17.42	28.51	5.92	4.99	47.57	1.79
Hotel-mall	19.02	30.80	7.75	28.75	94.66	21.22
Hotel-office	17.89	27.09	10.00	2.64	4.97	0
Large Hotel	33.18	49.31	11.62	16.52	67.80	5.41
Large Office	27.66	42.07	17.62	69.70	67.75	11.23
Large Office-stores	20.68	34.58	8.48	162.13	355.60	56.06
Low-rise Apartment-stores	12.67	32.29	2.62	1.17	0.78	0.54
Low-rise Apartment	14.70	26.46	2.09	37.02	148.19	91.31
Medium Office	28.08	41.64	8.20	34.96	41.95	4.01
Mid-rise Apartment-stores	12.35	26.97	4.36	0.24	1.61	0.10
Mid-rise Apartment	16.67	34.88	4.11	16.44	246.54	38.99
Primary School	18.03	30.31	4.17	3.31	80.42	8.35
Retail Standalone	27.91	42.78	5.74	4.82	28.71	0.29
Shopping mall	18.63	31.72	4.16	22.22	123.56	53.69
Small Hotel	20.77	37.09	11.94	0.00	12.44	2.51
Others	20.55	36.68	4.88	29.60	47.69	53.43

computation time for each model varied depending on the building type. CityEL provides statistical analysis for the results of this paradigm, categorizing energy consumption of different building types by electricity and natural gas as shown in Fig. 9 (see also Fig. 17).

Fig. 9 indicates that, in Huangpu District, large office stores have the highest proportion of electricity consumption, followed by high-rise residential buildings. This result is consistent with Huangpu District's role as the commercial center of Shanghai.

In this case study, the Energy Use Intensity (EUI) of each building varied due to the geometric differences. Fig. 10 illustrates the EUI

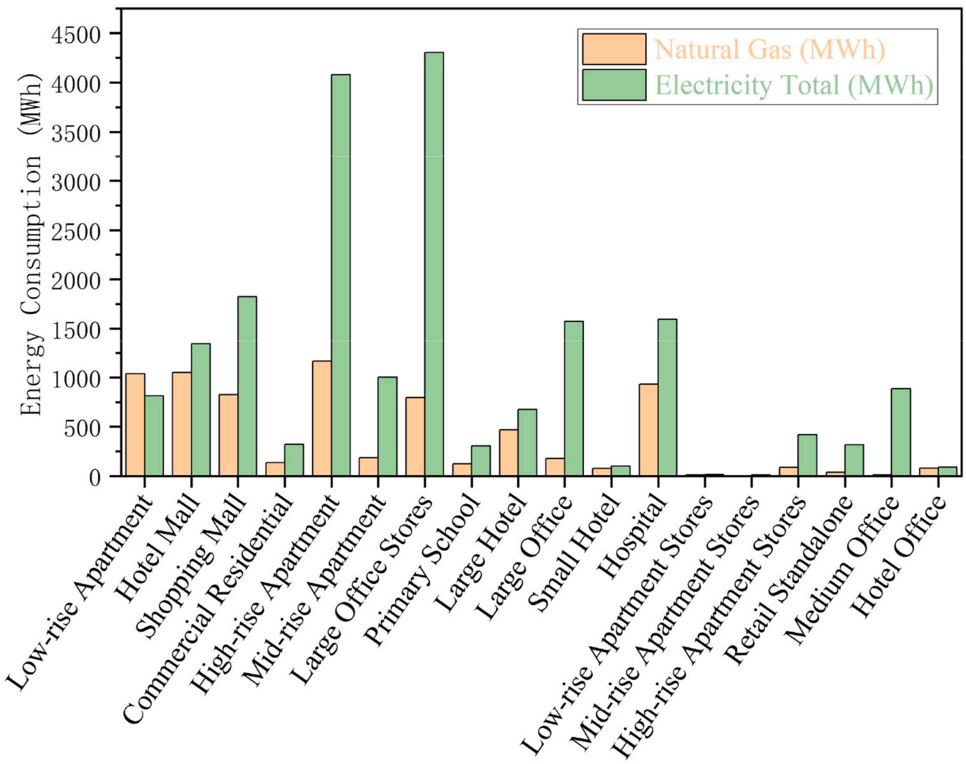

Fig. 9. Total energy consumption of different building types.

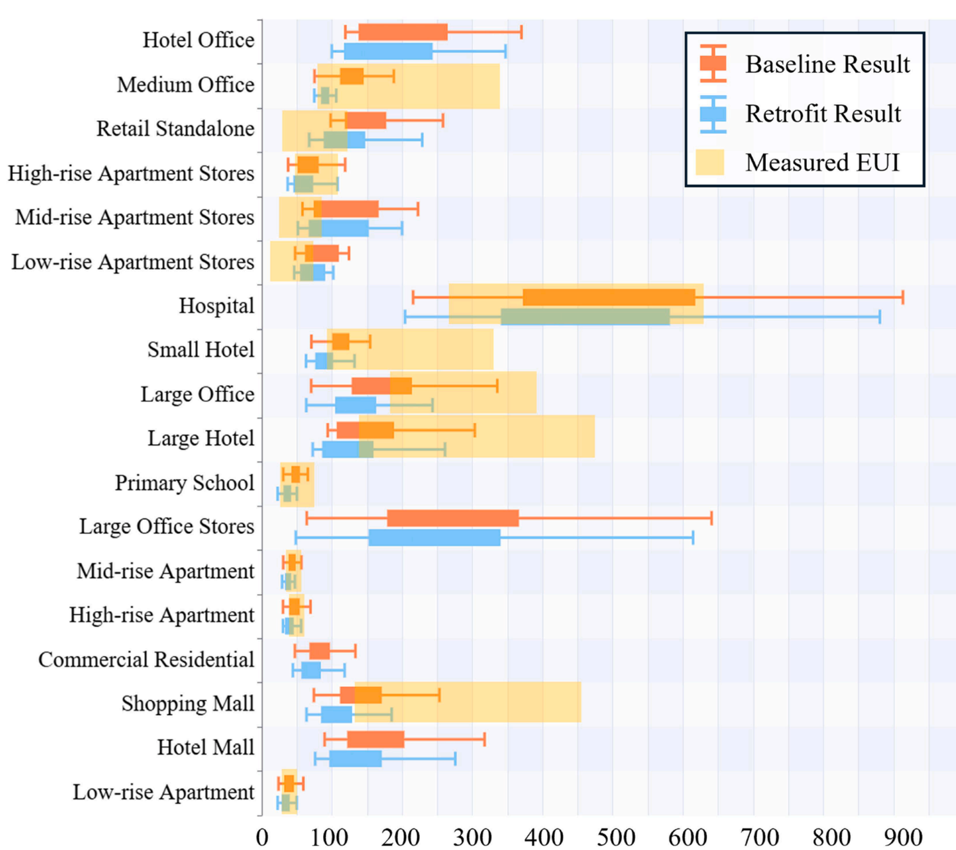

Fig. 10. The distribution of the building EUI.

distribution of these buildings (see also Fig. 18). All types of buildings experienced a reduction in EUI after energy retrofits with varying degrees. Medium office buildings demonstrated the most significant energy savings. Fig. 10 also includes some reference EUI data from measured building data in research papers and government reports from Shanghai (Shanghai Municipal Commission of Housing & Urban-Rural Development, 2024). However, for some composite buildings, there is still a lack of relevant reference literature to provide measurement ranges. It can be observed that the majority of prototype buildings fall within the reference range.

As shown in Fig. 11, The baseline annual electricity consumption of buildings in Huangpu District was approximately 864.13 GWh, and natural gas consumption was 318.14 GWh. If all energy-saving measures, collectively referred to as a Deep Retrofit, were implemented, the deep retrofitted electricity consumption was 721.34 GWh, and the natural gas consumption was 297.29 GWh, this represents an electricity saving of 16.5 % and a natural gas saving of 6.5 %. For primary energy conversion, the primary energy conversion factor for electricity is 2.5, and for natural gas is 1.1. The primary energy savings for electricity is 356.975 GWh, and for natural gas is 22.935 GWh. The combined primary energy savings amount to 379.91 GWh, leading to an overall primary energy saving rate of approximately 15.1 %. If PV systems are included, Huangpu District could generate an additional 113.9 GWh of electricity, increasing the overall primary energy saving rate to 26.48 %. For neighborhoods where only economically feasible energy-saving measures are considered, the saving rate is 8 %, which can rise to 19 % when combined with PV systems.

If only neighborhoods with a positive economic benefit (NPV > 0) are considered for energy-saving renovations, as shown in Fig. 13, 245 out of 304 neighborhoods are worth renovating. After renovation, electricity consumption would be 786.4 GWh and gas consumption would be 303.2 GWh, resulting in energy savings of 8.9 % and 4.7 %, respectively. And the total energy retrofit cost for Huangpu District is approximately 1.27 billion CNY, equivalent to 178.6 million USD. As a reference, Huangpu District's expenditure on old neighborhoods renovations in 2021 was about 0.13 billion CNY.

Understanding the peak and off-peak electricity consumption of the city is important, especially regarding the interaction between energy use and PV generation, to minimize waste and avoid the duck curve. CityEL provides the hourly result analysis: Fig. 12 displays the hourly results of UBEM, which can be selected between baseline and retrofit scenarios, with the default retrofit scenario corresponding to the conditions in Table 4. Fig. 12 shows that PV generation significantly reduces urban energy consumption, and CityEL identifies the times when rooftop PV generation exceeds urban energy consumption, with a surplus of 3689.56 GWh, providing a reference for energy storage configuration (see also Fig. 19).

3.3. Results for the individual buildings

Individual buildings received less attention in previous UBEM tools because they were not the primary focus of UBEM. However, checking data for individual buildings helps reduce significant errors. CityEL conducts statistics and analyses for each building to enhance error detection. Besides providing detailed information checks for buildings when clicked as shown in Figs. 20 and 21. This function allows users to quickly identify potential issues with any building.

3.4. Results for the Neighborhoods

The summary of results for each neighborhood is shown in Fig. 13. CityEL clearly identifies which neighborhoods have the highest energy retrofit potential and calculates the return on energy retrofitting for these neighborhoods. As seen in Fig. 13a, almost all neighborhoods in the Huangpu District have some energy retrofit potential, with the highest reaching 33.82 %. These neighborhoods are relatively concentrated and located in earlier developed areas. Fig. 13b shows that although some neighborhoods have energy retrofit returns as high as 40.2 million CNY, equivalent to 5.65 million USD, there are still some neighborhoods that do not have economic feasibility for energy

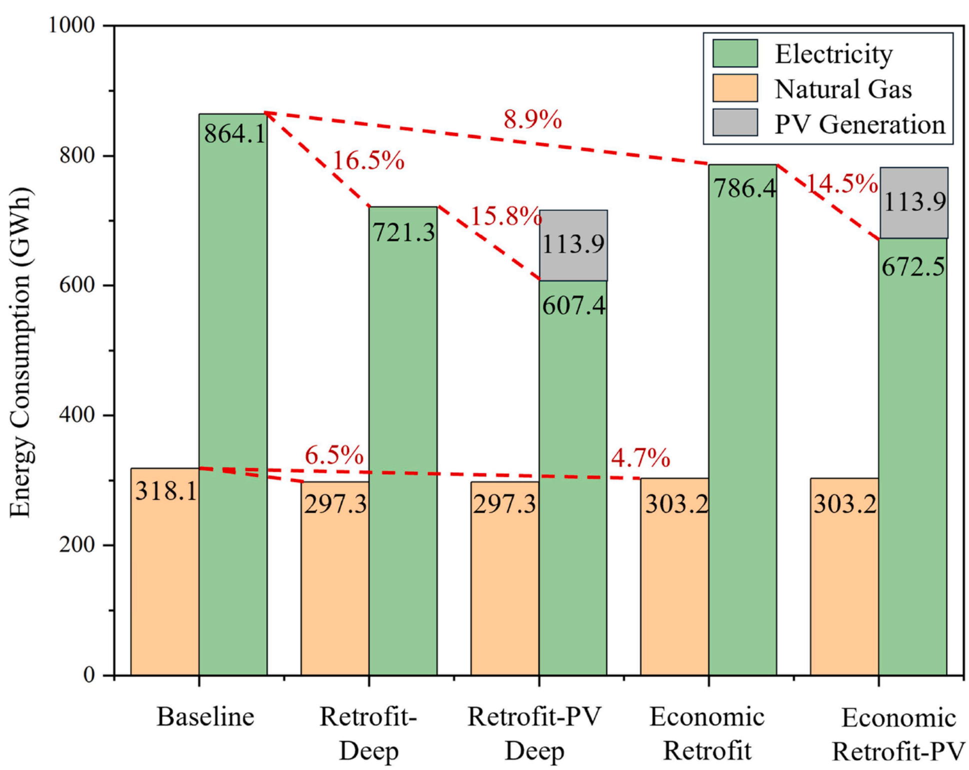

Fig. 11. Total annual energy consumption for different scenarios in Huangpu District.

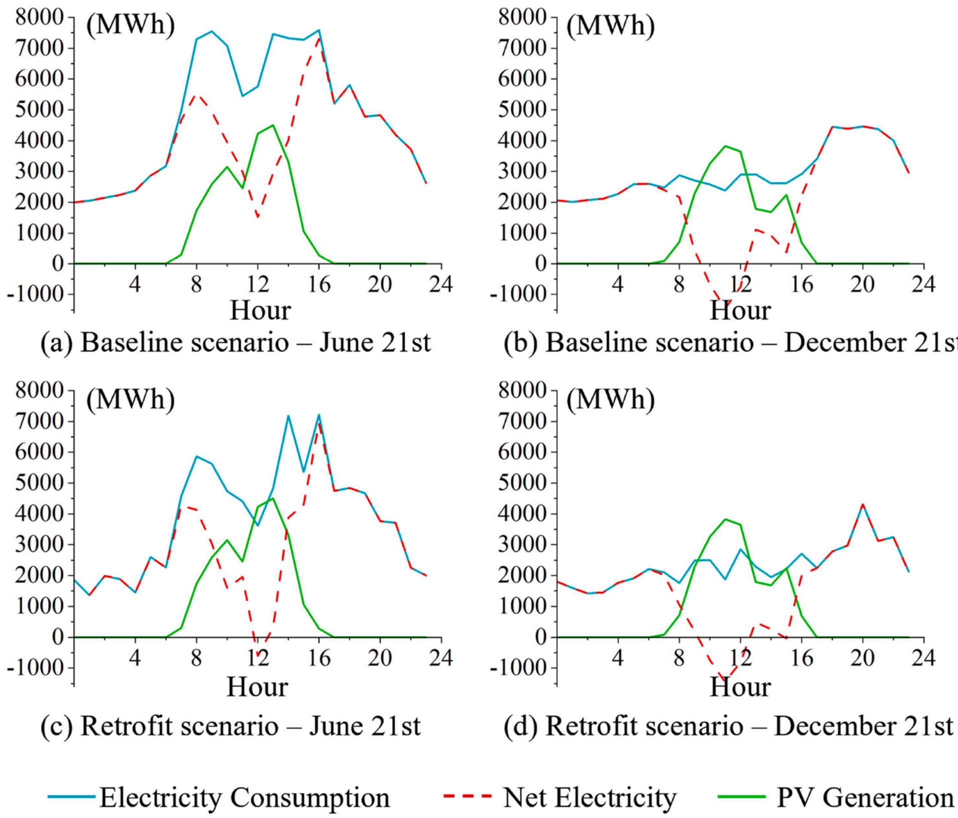

Fig. 12. Hourly energy demand for summer solstice and winter solstice of Huangpu district.

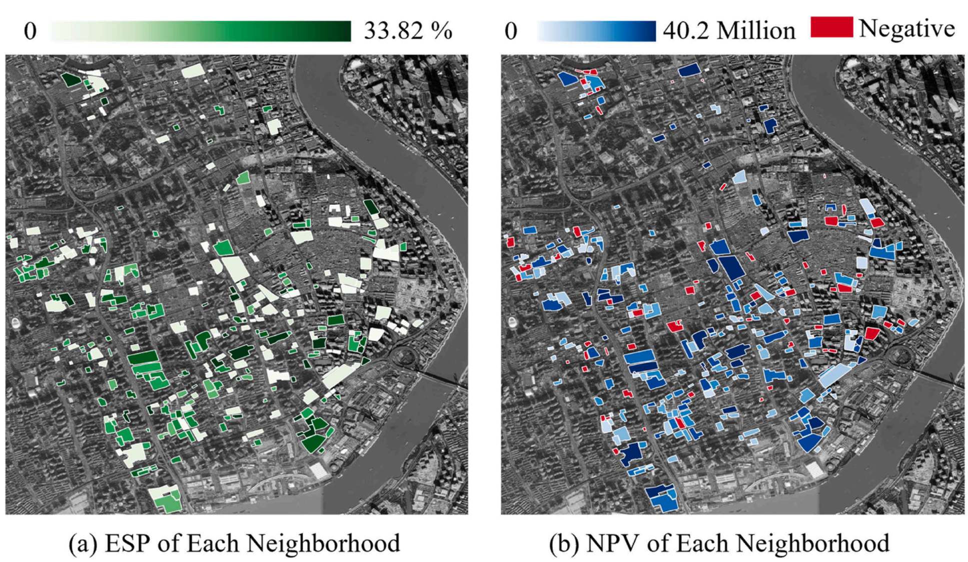

Fig. 13. Energy savings potential and economic analysis across neighborhoods.

retrofitting.

The method for checking the results of the neighborhood is similar to that for individual buildings. Taking an ESP top-ranked neighborhood "B00152EBDF" as an example, this neighborhood consists of mixed building types: two low-rise residential buildings, two high-rise residential buildings, and a hotel-mall. As shown in Fig. 14, the energy consumption curve on the summer solstice day indicates that this neighborhood experiences peak electricity usage at night (due to cooling). Daytime energy consumption is lower (as occupants go to work or school). However, the neighborhood maintains a certain level of daytime energy consumption, which is characteristic of the hotel-malls. CityEL captures the energy usage distribution over time for the entire neighborhood. It could be observed that energy-saving retrofits had an impact comparing Fig. 14(a) and (b). Although the energy usage distribution over time remains unchanged (since CityEL did not change the occupant behavior schedule), the overall energy consumption changed, the peak demand has decreased from 1063.44 kWh to 813.93 kWh, and the total energy consumption has also reduced, which alters the relationship between energy consumption, PV generation, and energy storage. In the baseline scenario, PV generation is almost fully

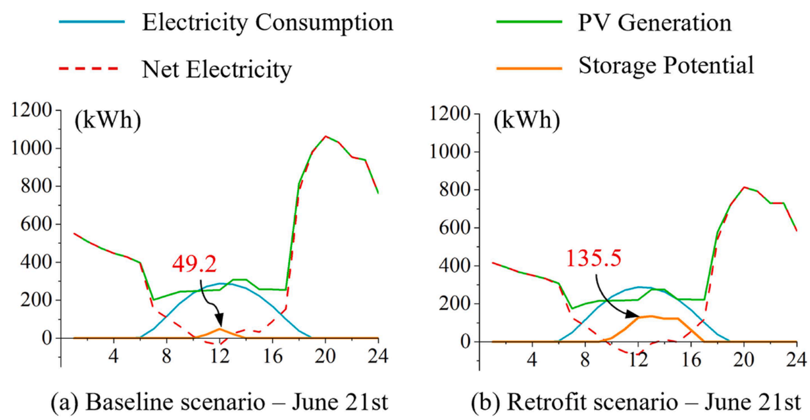

Fig. 14. Hourly result of a neighborhood for baseline and retrofit scenario.

consumed, and only 50 kWh of storage is needed to store all available PV generation. In the retrofit scenario, setting up 150 kWh of energy storage helps enhance overall neighborhood energy savings. This feature of CityEL assists users in determining the appropriate storage configuration for the neighborhood as shown in Fig. 25.

3.5. Advanced analysis for the neighborhoods

CityEL could conduct advanced analyses of each building and community to help determine the optimal energy retrofit strategies. This step generates EnergyPlus models for each energy retrofit measure. Then, it computes the results, which are computationally intensive and cannot be applied to the entire building cluster at once. Instead, after identifying the neighborhood with the highest retrofit potential, users confirm the execution.

This study conducted an advanced analysis of various energy retrofit measures within the B00152EBDF neighborhood, which included mixed building types: two low-rise residential buildings, two high-rise residential buildings, and a hotel-mall. The energy-saving effects and investments analyzed are shown in the Fig. 15.

For this B00152EBDF neighborhood, the most effective measures for energy savings are air conditioning and wall retrofits. Given the building types, air conditioning upgrades are crucial for improving cooling and heating efficiency, especially for residential buildings that previously relied on inefficient units, cooling is the primary concern in Shanghai, and natural gas is mainly used for hot water, so modifications to windows and shading have minimal impact on hot water usage. Wall retrofits are also effective for reducing heat gain in summer and enhancing winter insulation, benefiting all residential types. For the hotel-mall complex, roof insulation and HVAC system upgrades provide the greatest benefits. From the perspective of investment return on energy retrofits, air conditioning offers the highest returns in the B00152EBDF neighborhood because it directly enhances cooling and heating efficiency, leading to quick, significant energy savings. Roof and wall retrofits require higher initial costs and longer payback periods, but they are still beneficial. Therefore, for this neighborhood, the recommended retrofits are air conditioning, roof, and wall improvements.

4. Discussion

Existing UBEM studies often focus on overall results, with less emphasis to individual building results and neighborhoods summaries. This paper introduces CityEL, a new UBEM tool that enables quick access to energy consumption results for individual buildings within the UBEM and regional summaries. These features make CityEL a valuable tool for analyzing energy-saving renovations at the neighborhood level. In this paper, a suitable neighborhood for energy-saving renovations was selected and analyzed among 304 neighborhoods in Huangpu District, Shanghai. The optimal energy-saving measures were identified.

CityEL offers extensive scalability. A related review (Kamel, 2022) indicates that UBEM studies can involve from tens to hundreds of thousands of buildings. CityEL's aggregation method creates multiple

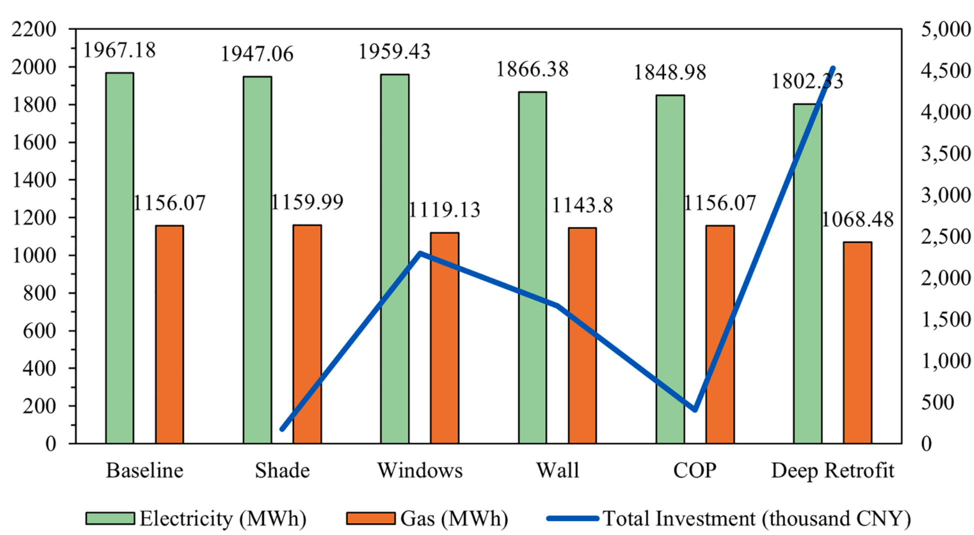

Fig. 15. The energy-saving effects of various measures within the neighborhood.

small UBEMs within a larger study area, allowing for comparisons between them. In this case study, residential neighborhoods were used as an example, but in practical applications, the area division is user-defined. It can also quickly analyze several large neighborhoods of a city or perform grid analysis. Additionally, CityEL uses AutoBPS as its engine, which is continuously evolving, with all future AutoBPS functionalities integrated into CityEL.

Compared to similar web-based UBEM tools, CityEL's features are distinct. While CEA (Cevallos-Sierra, Pinto Gonçalves & Santos Silva, 2024) uses its own engine, CityEL employs the more widely recognized EnergyPlus as its calculation engine. EnergyPlus is designed for energy consumption calculations of individual buildings, and CityEL enables users to quickly view various results for individual buildings, thereby making its energy consumption calculations more precise. Furthermore, compared to CityBES (Hong et al., 2024), which mainly supports office and commercial buildings, CityEL accommodates a broader range of building types, including those developed by DOE, ASHRAE, and AutoBPS for Chinese buildings. While UBEM.io (Ang et al., 2022) primarily functions as an input file generator and output result analyzer, requiring tools like Rhino and UMI for actual calculations, CityEL is a fully integrated platform for both front-end input and back-end calculations, eliminating the need for additional tools.

CityEL has some limitations and potential development directions. First, CityEL's calculations rely on EnergyPlus, leading to high computational resource consumption. Considering energy-saving renovations (which exponentially increase model generation), using a personal computer as a server to calculate 10,000 buildings might take several days. Therefore, CityEL is currently used only as a local tool and is not yet available online. Second, CityEL still employs simplified strategies for many functions of its models, including photovoltaic and energy storage modules, but CityEL reserved interfaces for these modules, allowing future integration of more advanced algorithms. Third, many retrofit measures in urban renovations, such as installing elevators, require further research for accurate modeling. Fourth, CityEL currently does not support demand response or adjustments based on occupant schedules, which should be incorporated in future studies. Finally, the data required by CityEL needs to be downloaded and organized by users according to specific requirements, which still poses a significant barrier. In future development, efforts will be made to provide simpler methods to guide users in obtaining the necessary data of their city.

5. Conclusions

This paper introduces CityEL, a web-based UBEM tool powered by AutoBPS, proficient in regional aggregation analysis. CityEL facilitates scalable and rapid neighborhood-level energy analyses, offering a practical framework for urban renewal projects, overall, this paper makes the following contributions:

- Development of a scalable platform: CityEL provides capabilities for aggregating and comparing energy retrofit options across multiple neighborhoods, enabling policymakers and planners to evaluate and prioritize renovation strategies efficiently.
- Enhanced retrofit modeling: The existing AutoBPS-retrofit module was enhanced by providing a method for the rapid generation of EnergyPlus models for various retrofit measures, including walls, roofs, shading, lighting upgrades, and HVAC system enhancements.
- Neighborhood-level decision-making support: CityEL supports neighborhood-level decision-making through quickly comparative analysis, as demonstrated in Shanghai's Huangpu District. Modeling 7934 buildings and evaluating 304 neighborhoods, it identified 245 economically viable retrofits, achieving 8.9 % electricity and 4.7 % gas savings, showcasing its efficiency in large-scale data processing and cost-effective planning.
- Policy and planning implications: CityEL provides a reproducible framework for urban energy planning, equipping policymakers with the tools to prioritize retrofitting efforts based on energy and economic outcomes. Its ability to integrate spatial and energy data supports informed, scalable urban renewal strategies.

In conclusion, CityEL integrates AutoBPS with GIS tools to offer an efficient and scalable platform for evaluating urban building energy performance and comparing retrofitting strategies across neighborhoods. By enabling rapid modeling and multi-scenario analysis, CityEL addresses gaps in traditional tools for multi-scale energy assessments and provides significant support for advancing the methodological framework of urban energy management.

Declaration of generative AL and AL-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly and ChatGPT to improve readability and detect spelling/grammar mistakes. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Chengcheng Song: Writing – original draft, Software, Methodology, Conceptualization. **Jingjing Yang:** Writing – review & editing. **Zhiyuan Wang:** Writing – review & editing. **Ruoheng Li:** Writing – review & editing. **Xiufeng Pang:** Writing – review & editing. **Yixing Chen:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. The Screenshots of CityEL

Fig. 16. Screenshot of buildings geometry statics from CityEL.

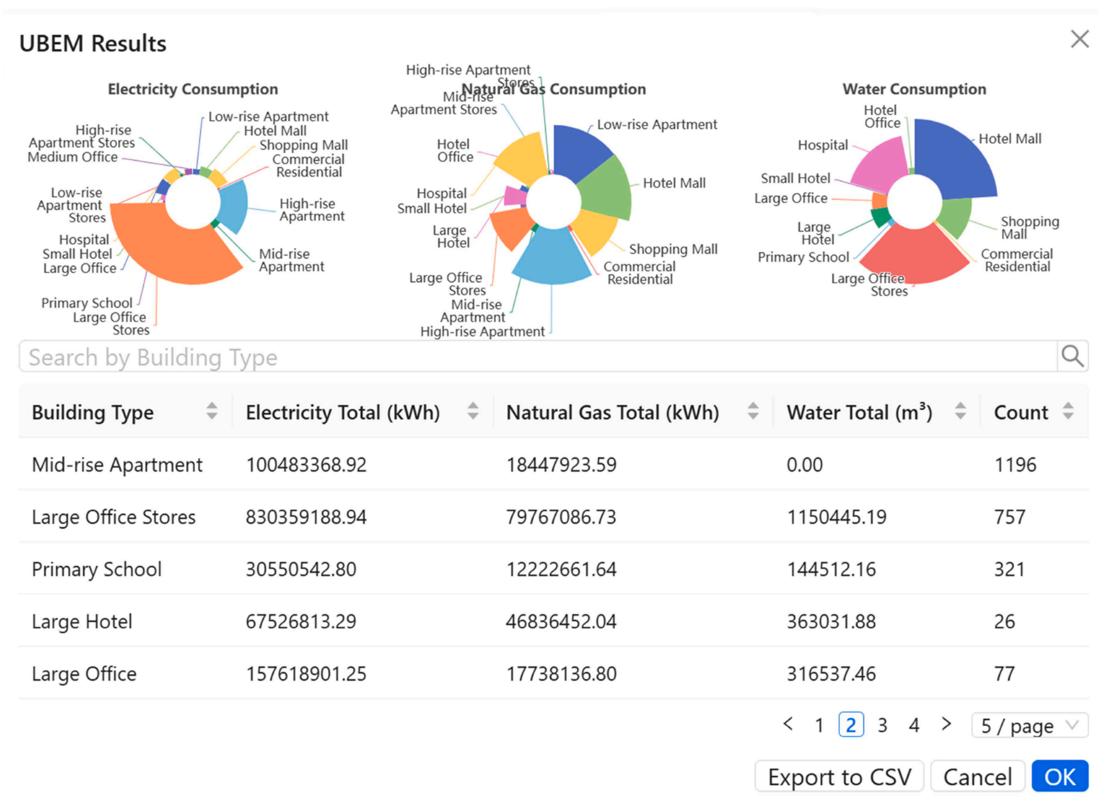


Fig. 17. Screenshot of the baseline UBEM results from CityEL.

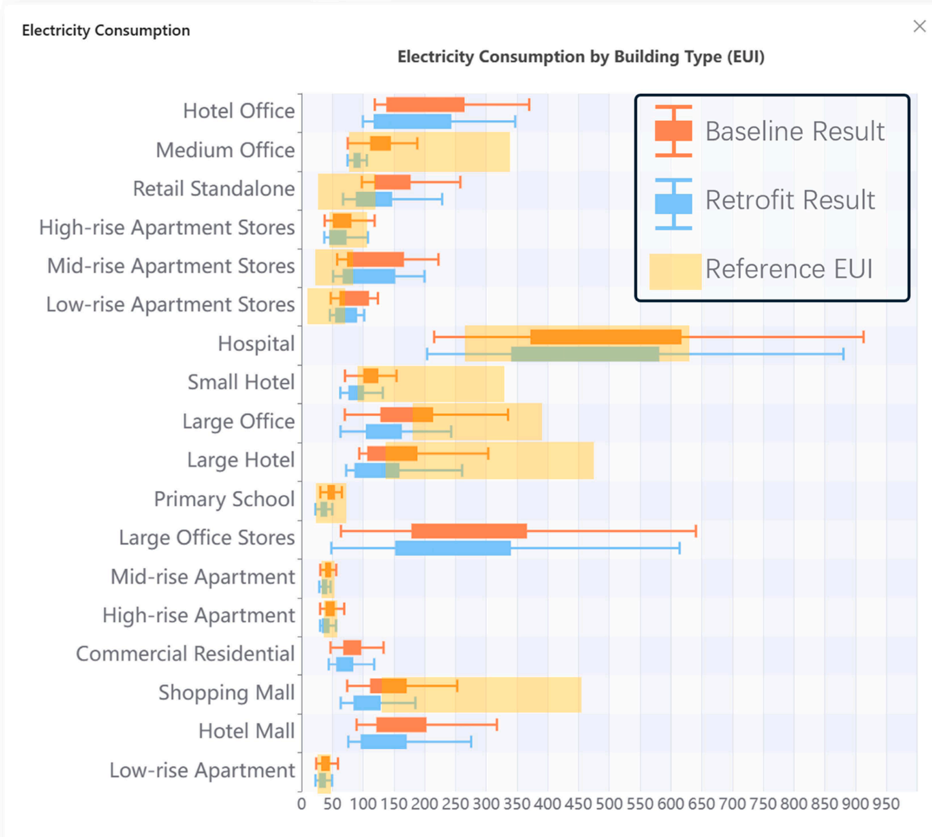
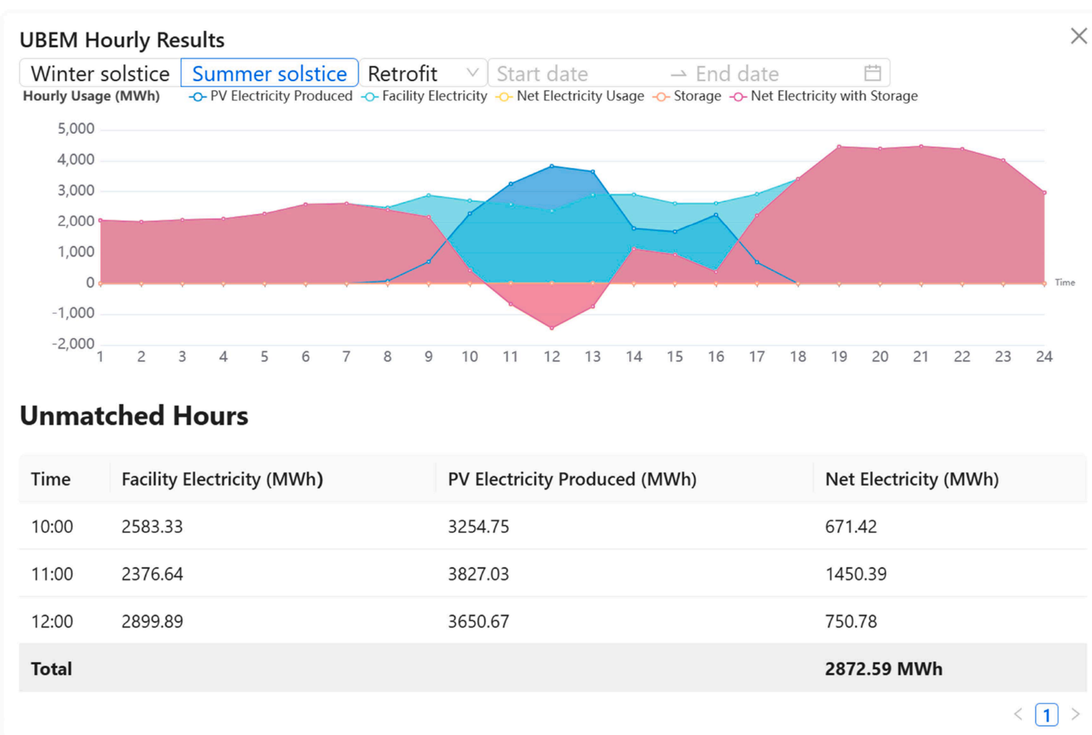


Fig. 18. Screenshot of UBEM EUI Result from CityEL.



Time	Facility Electricity (MWh)	PV Electricity Produced (MWh)	Net Electricity (MWh)
10:00	2583.33	3254.75	671.42
11:00	2376.64	3827.03	1450.39
12:00	2899.89	3650.67	750.78
Total			**2872.59 MWh**

Fig. 19. UBEM hourly result for the baseline scenario.

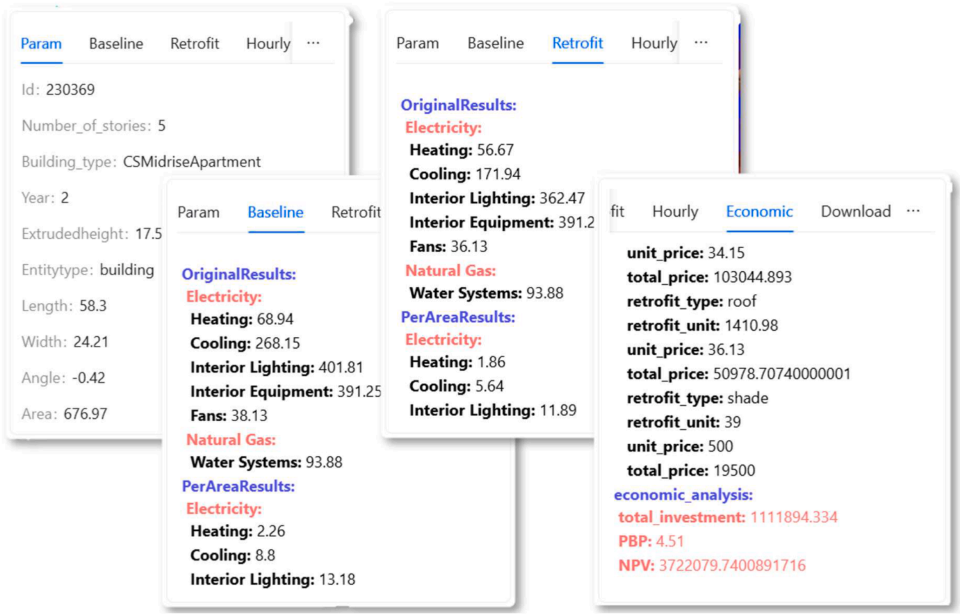


Fig. 20. Detailed information and the results of an individual building.

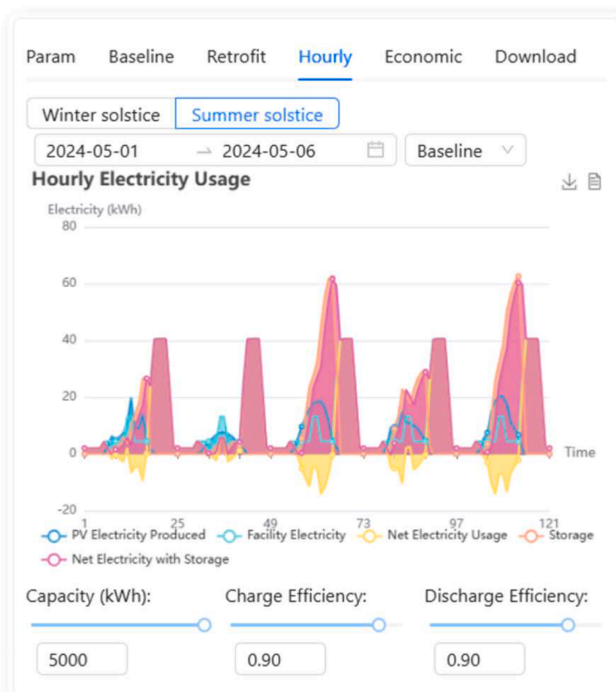
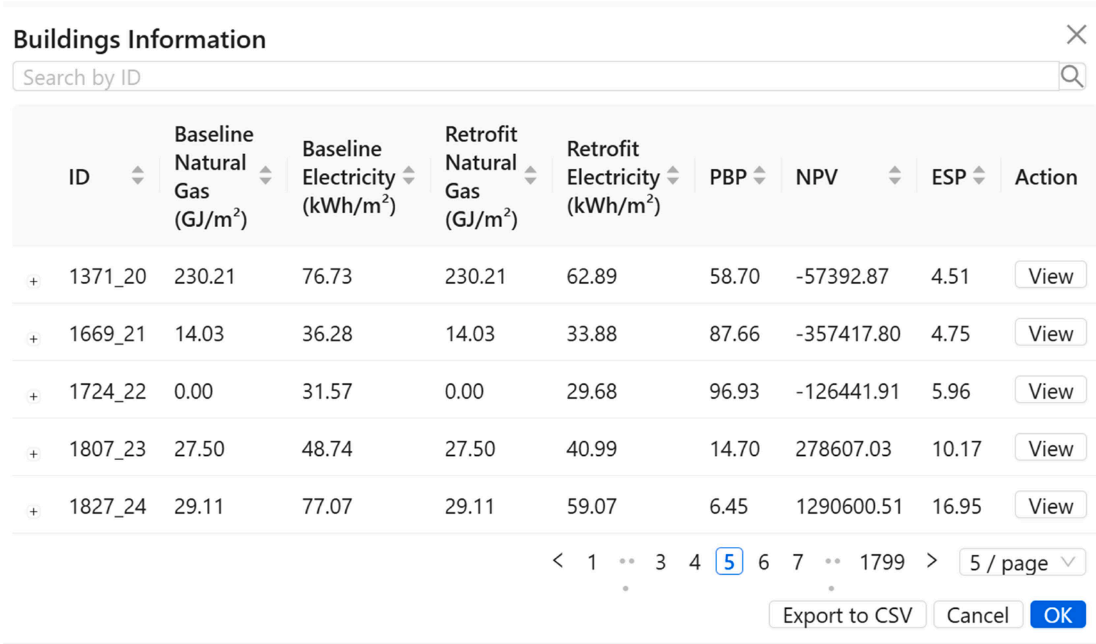


Fig. 21. Hourly result of an individual building.



ID	Baseline Natural Gas (GJ/m²)	Baseline Electricity (kWh/m²)	Retrofit Natural Gas (GJ/m²)	Retrofit Electricity (kWh/m²)	PBP	NPV	ESP	Action
1371_20	230.21	76.73	230.21	62.89	58.70	-57392.87	4.51	View
1669_21	14.03	36.28	14.03	33.88	87.66	-357417.80	4.75	View
1724_22	0.00	31.57	0.00	29.68	96.93	-126441.91	5.96	View
1807_23	27.50	48.74	27.50	40.99	14.70	278607.03	10.17	View
1827_24	29.11	77.07	29.11	59.07	6.45	1290600.51	16.95	View

Fig. 22. Building energy information statics.

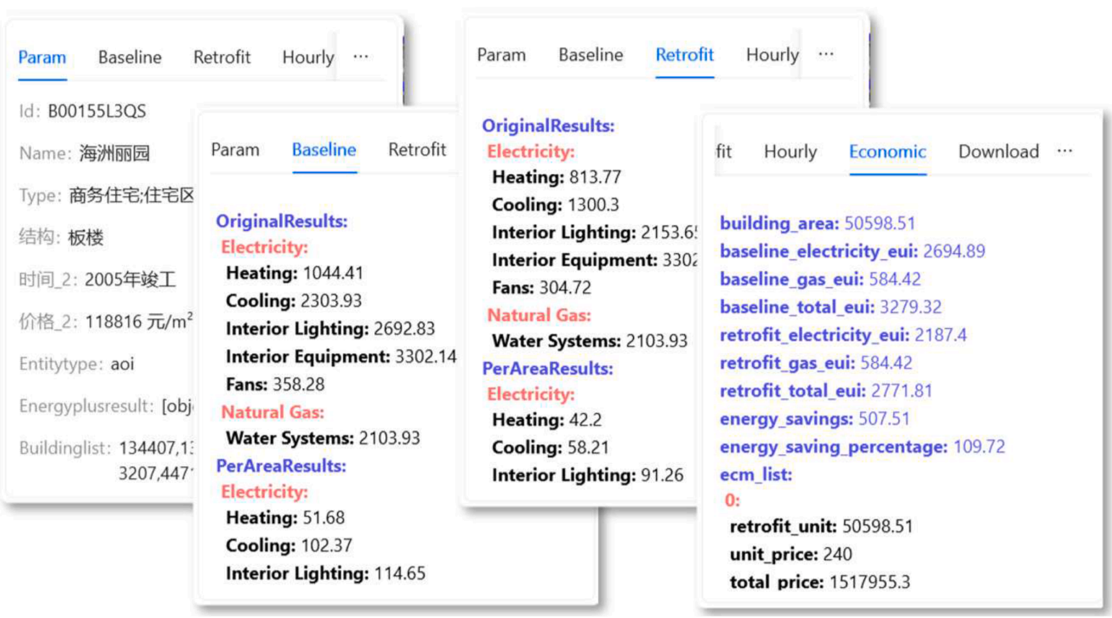
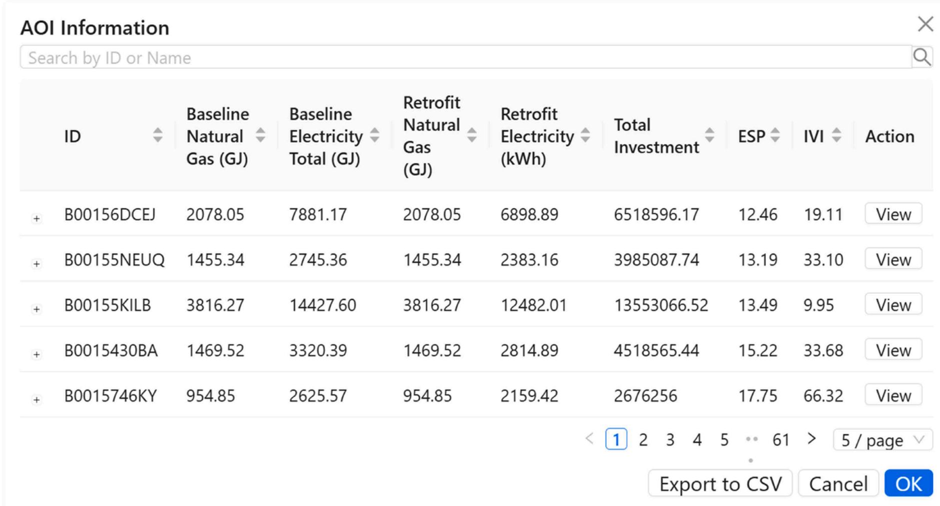


Fig. 23. Detailed information and the results of a Neighborhood.


AOI Information

Search by ID or Name

	ID	Baseline Natural Gas (GJ)	Baseline Electricity Total (GJ)	Retrofit Natural Gas (GJ)	Retrofit Electricity (kWh)	Total Investment	ESP	IVI	Action
+	B00156DCEJ	2078.05	7881.17	2078.05	6898.89	6518596.17	12.46	19.11	View
+	B00155NEUQ	1455.34	2745.36	1455.34	2383.16	3985087.74	13.19	33.10	View
+	B00155KILB	3816.27	14427.60	3816.27	12482.01	13553066.52	13.49	9.95	View
+	B0015430BA	1469.52	3320.39	1469.52	2814.89	4518565.44	15.22	33.68	View
+	B0015746KY	954.85	2625.57	954.85	2159.42	2676256	17.75	66.32	View

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Export to CSV Cancel OK

Fig. 24. Neighborhood energy information statics.

(a) Baseline Hourly Result (b) Retrofit Hourly Result

Fig. 25. Hourly result of a neighborhood for baseline and retrofit scenario.

Data availability

Data will be made available on request.

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