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Data-Driven Research on Energy-Efficient Retrofit and Multi-Objective Optimization of Urban Building Clusters

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Abstract. Urban energy-efficient retrofit is an important path to reduce energy consumption and carbon emission. However, balancing environmental and economic benefits and making choices among numerous retrofit packages is challenging for decision-makers. This study proposes a data-driven framework that integrates physical UBEM and machine learning model to evaluate the energy retrofit performance of urban building clusters and assists decision-makers in rapidly selecting the optimal energy-efficient retrofit packages through NSGA-II. The feasibility of the proposed framework is validated using the building clusters of Sipailou campus in Southeast University as a case study and identified 25, 19, and 13 optimal retrofit packages for office, public and education building clusters that minimizes the total energy consumption and carbon emissions while maximizing economic benefits from 343 retrofit packages of each cluster in a 30-year retrofit period.

1 Introduction

Energy shortages and rising global temperatures are challenges worldwide, and the building sector involves nearly 40% and 36% of total energy consumption and CO2 emissions, respectively, for operational energy. Many countries have issued and implemented laws and standards to regulate energy consumption and efficiency in buildings and cities, such as the ANSI/ASHRAE/IES Standard 90.1-2019 in the United States, the Energy Performance of Buildings Directive 2018/844/EU (EPBD) in the European Union, and GB 50189-2015 in China. Reducing energy consumption at the city level is one of the main current challenges Reducing operational energy consumption and greenhouse gas emissions in the building sector is an important task in the implementation of the national "dual-carbon" strategy [1]. As China's urbanization process continues to accelerate and the number of urban buildings in China continues to increase, existing buildings in China have begun to make corresponding modifications based on modern energy-saving and environmental protection concepts in terms of building maintenance structures and heating and air-conditioning system [2]. The scientific evaluation of existing buildings with a large stock of energy-saving modifications to achieve energy saving, aesthetics, economy, and comfort has gradually become a mainstream trend in the field of urban renewal [3]. Wang et al. used the building stock model

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CESAR (Comprehensive Energy Simulation and Retrofit) to develop a sustainable energy transition strategy for buildings in the Swiss region [4]. Allacker et al. adopts the eco-innovation measures to part of the EU building stock and extrapolating the relative impact reduction obtained for the reference buildings to the baseline stock model. The results of the micro-scale analysis are upscaled to the EU housing stock [5]. Deng et al. uses Automated Building Performance Simulation (AutoBPS) for calculating the energy demand of urban buildings and analysing energy retrofits and rooftop photovoltaic (PV) potential [6]. Lin et al. created an Urban Building Energy Model (UBEM) for the mixed modern and historic buildings at a campus in China. The calibrated set of UBEM with the modelled results meeting the 20% error range, were then used to evaluate uncertainties of energy-savings of four building energy retrofit measures[7]. Sun et al. applied and evaluated an automated simulation-based calibration methodology on a commercial building model generated based on real building characteristics for energy simulation calibration by comparing building model results with monthly electricity and natural gas consumption of an actual building [8]. Ye et al. used sensitivity analysis to quantify the energy savings of various energy efficiency measures of an energy retrofit project that provided significant energy savings for a sample prototype mid-sized office building in 15 climatic regions of the United States. Significant energy savings for a sample of prototype midsized office buildings in 15 climate zones across the United States [9]. For planners or urban designers, a regional scale approach to energy retrofit of urban buildings is considered one of the most effective ways to reduce energy use and carbon emissions.

In the field of urban regeneration and in energy-saving efficient building retrofits, most of the studies combine multi-objective optimization with reference buildings in order to select the most efficient energy retrofit measures to implement urban building energy efficiency goals at the neighbourhood scale or to evaluate the value of building energy retrofit measures in terms of urban energy consumption, economic factors, and sustainability goals. For example, Ascione proposed a new Cost Optimization Analysis Framework (CASA) for multi-objective optimization and artificial neural networks to enable a robust evaluation of cost-optimal energy retrofit solutions and applied it to a reference office building located in the south of Italy [10]. Thrampoulidis proposed building envelope and energy system measures for the evaluation of building retrofits required by an Alternative models are effectively used for a wide range of bottom-up retrofit analyses and can contribute to accelerating the adoption of retrofit measures [11]. Ascione used an office building constructed between 1920-1970 in southern Italy to assess the energy consumption and the thermal comfort of the occupants of any member of the building class by using an artificial neural network [12]. With the maturity of computer simulation technologies such as EEDO, TRNSYS, and DOE, the increasing accuracy of energy simulation for residential buildings and domestic equipment, and the rise of machine learning and artificial intelligence technologies have made it possible to predict the future energy consumption of a building [13]. Niemeläet has used simulation-based multi-objective optimization analysis as the main research methodology to Niemelä investigated the energy performance and environmental impacts of a deep retrofit of a typical large, panelized apartment building in a cold climate [14]. Ali et al. used a data-driven approach to optimize energy retrofit solutions for residential structures based on the Berlin Building Inventory Database, resulting in an 86% building energy accuracy [15]. Costa-Carrapiço et al. used a large evidence base to evaluate the energy performance of residential buildings using genetic algorithms to predict the future energy consumption of buildings. large evidence base to assess the potential of Multi-Objective Optimization (MOO) using genetic algorithms to support the development of retrofit strategies and provides an overview of 57 studies [16].

In order to help planners or urban designers make reasonable energy-saving retrofit decisions for urban building clusters at the early stage of design, this study aims to conduct a multi-objective decision-making study on energy-saving retrofit for urban building clusters in the context of urban renewal by using machine learning algorithms, multi-objective optimization and combining with UBEM method, so as to provide planners and architects with a workflow and a guiding framework for the rapid selection of energy-saving retrofit measures in the energy-saving oriented design of low-carbon urban renewal.

2 Methods

2.1 Overview of the methodology

This paper employs a data-driven UBEM approach, combining physical UBEM simulation with machine learning, to assess the energy retrofit performance of existing building clusters. Initially, an ANN is developed to predict the energy performance of a diverse range of retrofit packages. Subsequently, the energy consumption results are amalgamated with environmental and economic impact data to evaluate the environmental and economic performance of the retrofit package. The SNSGA-II algorithm is employed to obtain the Pareto optimal solution. It determines the optimal energy-saving retrofit combination measures, thus assisting decision-makers in formulating the best retrofit plans for urban building clusters. Fig. 1 illustrates the technical framework of this study, which is conducted in three stages.

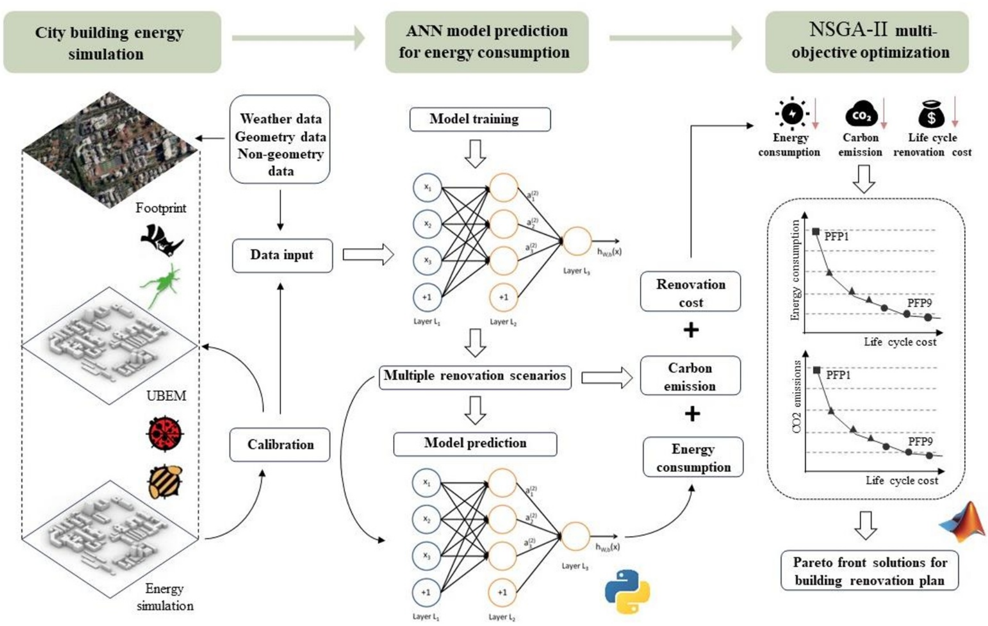

Fig. 1. The framework of data-driven multi-objective optimization of energy retrofit of block-level stock buildings.

2.2 Case study

This study selects the building clusters at Sipailou campus of Southeast University (SEU) in Nanjing as case buildings. Among these buildings, two-thirds are brick-concrete structures, with the remainder being reinforced concrete structures. This study needs to select buildings with real energy consumption data for UBEM calibration and uncertainty analysis. After collecting data of all buildings, screen out buildings that do not have a true record of energy consumption. Finally, 18 buildings were ultimately chosen. Their function types include office, education and public, and all buildings were constructed between the 1920s and 1990s. The current state of the selected buildings is visually depicted in Fig. 2.

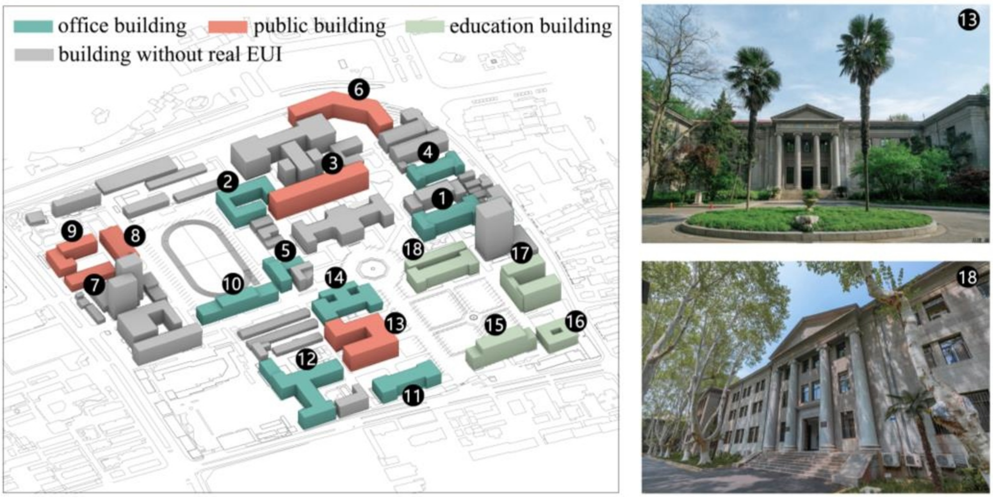

Fig. 2. The layout of selected buildings in case campus.

2.3 UBEM simulation

The workflow of UBEM is shown in Fig. 3. During data preparation and input stage, we imported the weather files for Nanjing and the geometric information of the Sipailou campus buildings into the Rhino platform. Non-geometric data inputs in this study involved parameters derived from on-site surveys, conformity with the "Public Building Energy Efficiency Design Standard GB 50189-2015," and adherence to ASHRAE 90.1 standards for various functional building types. Additionally, a specific allocation for Urban Building Energy Model (UBEM) verification was determined through a trial-and-error process. In consideration of the unique operating hours of campus buildings, this study defines a standardized schedule to differentiate hourly room occupancy rates for semesters, summer and winter holidays, weekdays, and weekends. This approach ensures a comprehensive input range of parameters capable of withstanding Urban Building Energy Model (UBEM) verification. Following parameter input, the building's physical model is constructed using Rhino and Grasshopper, thermal parameters are input via Ladybug and Honeybee, and the data is ultimately uploaded to OpenStudio for energy consumption simulation. All buildings were chosen for calibration, ensuring that the energy consumption simulation results comply with the 20% error requirement. Once the accuracy of the simulation results meets the specified criteria, the data is recorded, contributing to the establishment of a comprehensive energy consumption database for a total of 18 campus buildings.

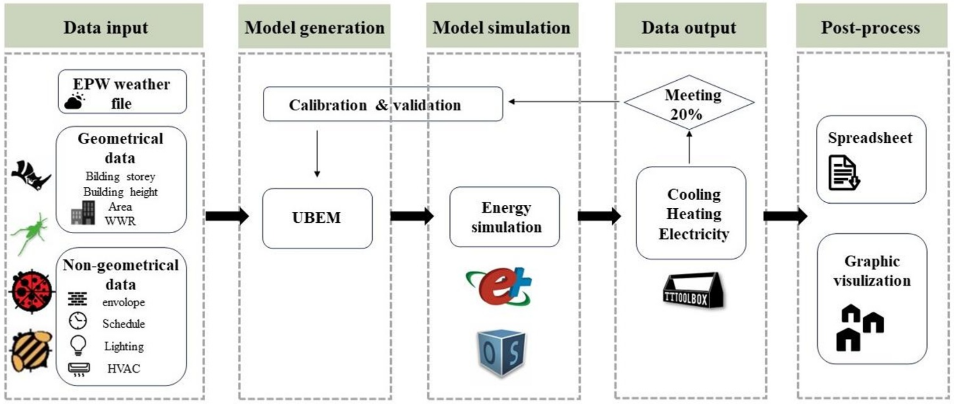

Fig. 3. Workflow of physical UBEM method.

2.4 Building retrofit packages

In the process of implementing energy-saving retrofits for buildings in Sipailou campus, the selection of retrofit packages focuses solely on enhancing the external protective elements of the buildings. Following a thorough screening process, three distinct sets of retrofit packages were devised, addressing the roof, walls, and windows of the buildings, as shown in table 1-3.

Table 1. Measures for exterior roof retrofit.

List	Specification	Parameters
R1	VIP	30mm,K = 0.008(W/㎡.K)
R2	PU	30mm,K = 0.024(W/㎡.K)
R3	SEPS	30mm,K = 0.032(W/㎡.K)
R4	XPS	30mm,K = 0.030(W/㎡.K)
R5	rock wool	30mm,K= 0.044(W/㎡.K)
R6	glass wool	30mm,K= 0.050(W/㎡.K)

Table 2. Measures for exterior wall retrofit.

List	Specification	Parameters
W1	VIP	30mm,K = 0.008(W/㎡.K)
W2	PU	30mm,K = 0.024(W/㎡.K)
W3	SEPS	30mm,K = 0.032(W/㎡.K)
W4	EPS	30mm,K = 0.037(W/㎡.K)
W5	rock wool	30mm,K= 0.044(W/㎡.K)
W6	glass wool	30mm,K= 0.050(W/㎡.K)

Table 3. Measures for exterior window retrofit.

List	Specification	Parameters
G1	6 medium transmissivity heat reflective glass + 12 Air + 6normal glass	U =2.4(W/㎡.K), SHGC=0.2958, VT=0.28
G2	6 low transmissivity heat reflective glass + 12 Air + 6 normal	U =2.3(W/㎡.K), SHGC=0.1566, VT=0.16

	glass	
G3	6 high transmissivity Low-E glass + 12 Air + 6 normal glass	U=1.9(W/㎡.K), SHGC=0.5394, VT=0.72
G4	6 low transmissivity Low-E glass + 12Air + 6 normal glass	U=1.8(W/㎡.K), SHGC=0.2610, VT=0.35
G5	6 high transmissivity Low-E glass + 12 Ar+ 6 normal glass	U =1.5(W/㎡.K), SHGC=0.5394, VT=0.72
G6	6 medium transmissivity Low-E glass + 12 Ar + 6 normal glass	U =1.4(W/㎡.K), SHGC=0.4350, VT=0.62

2.5 ANN energy prediction

Upon acquiring the foundational energy consumption database for the Sipailou campus buildings, this study employed an ANN model for predicting building energy consumption. The objective of artificial neural network is to establish a model capable of predicting unknown situations using a training dataset. During the stages of data collection and preprocessing, 2060 data samples were utilized for the training of the artificial neural network, and preprocessing procedures were applied to the input parameters of the samples. The resulting dataset was partitioned into a training set and a test set, with proportions of 80% and 20%, respectively.

To assess the accuracy of the trained model, it is essential to compare the predicted values with the actual values on the test dataset. This article employs mean absolute percentage error (MAPE), root-mean-square error (RMSE) and coefficient of determination (R^2) as metrics to quantify the accuracy of the trained model, as shown in Eq. 1- 3. Ultimately, the retrofit packages serve as input variables, and the trained neural network model is applied to predict the total energy consumption value for each building post energy-saving retrofit.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i'-y_i)^2}{n}} \quad (1)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i'-y_i|}{y_i} \times 100\,\% \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i'-y_i)^2}{\sum_{i=1}^{n}(\bar{y}_i-y_i)^2} \quad (3)$$

Where y_i' is predicted energy value, y_i is simulated energy value, $\bar{y}_i$ is the average value of simulated energy, n is the number of test data set.

2.6 Multi-objective optimization

The objective functions examined in this study include total building energy consumption, carbon emissions, and building energy-saving retrofit costs. The primary objective is to minimize the values of these functions in order to achieve a balanced decision-making among various stakeholders. The multi-objective optimization problem can be formulated as Eq. 4-5.

$$Min \quad F(X) = \left[F_{energy}(x), F_{carbon}(x), F_{LCC}(x)\right]^t \quad (4)$$

$$s.t. \quad x \in \mathrm{ERM}_i \qquad (5)$$

where $F_{energy}(x)$ is total energy consumption of the block after retrofit; $F_{carbon}(x)$ is the total carbon emission of the block after retrofit; $F_{LCC}(x)$ is the LCC of corresponding retrofit scheme; ERM_i is the i^{th} retrofit scheme.

Energy consumption can be accurately predicted through the application of a machine learning model. The calculation of carbon dioxide emissions adheres to the "Building Carbon Emission Calculation Standard" GB/T51366-2019, while retrofit costs are determined using life cycle cost (LCC).

The total energy consumption of a block is calculated according Eq. 6.

$$F_{energy}(x) = \sum_{i=1}^{n} E_i * t \quad (6)$$

where E_i is the energy consumption of the i^{th} building after retrofit; t is the retrofit life cycle, assuming 30 years; n is the number of retrofitted buildings; d is total energy consumption of the block.

The carbon dioxide emissions resulting from the retrofit of existing buildings primarily originate from the materialization and operation and maintenance stages. The prevailing method for computing these emissions is the emission factor method. Fundamentally, this method involves utilizing a greenhouse gas emissions inventory to examine activity level data and CO2 emission factors for each emission source. The carbon emission factors utilized are derived from China's emission accounts and datasets. Equation (11) is employed for carbon emissions calculation. Additionally, based on the State Grid's average emission coefficient in 2022, the energy consumption coefficient during the operation phase is set at 0.5703 tCO2/MWh. Block carbon emissions are computed by Eq. 7.

$$F_{carbon}(x) = \sum_{i=1}^{n} M_i F_i + \sum_{i=1}^{n} \sum_{i,j} AD_{B_{i,j}} * EF_{B_{i,j}} \qquad (7)$$

where M_i and F_i are the amount of the i^{th} material used and carbon emission factor; $AD_{Bi,j}$ is the j^{th} type of activity data in the retrofitting of the i^{th} building, and $EF_{Bi,j}$ is the corresponding emission factor of the j^{th} type of activity data.

Life Cycle Cost (LCC) has been regarded as a fundamental economic evaluation method for construction investment. Regarding the calculation of energy-saving retrofit costs, this study takes into account both the initial retrofit cost and the operating energy cost. The initial cost of a candidate retrofit solution encompasses material and labour expenses incurred during the acquisition and installation of building retrofit materials. In practical projects, the total cost of retrofit measures typically ranges from 1.5 to 2.0 times the material cost. All cost calculation data are sourced from the "Nanjing Building Materials Market Information Price in September 2023." The initial cost of a candidate retrofit solution can be determined by Eq. 8-10.

$$IC_k = \sum_{i=1}^{n} A_i * c_i + L_k \quad (8)$$

$$\triangle AOC_k = \left(EE_{base} - EE_{retrofit}\right) * EP - MC \qquad (9)$$

$$F_{LCC}(x) = IC_k - \sum_{i=1}^{n} \frac{\triangle AOC_k}{(1+r)^t} \qquad (10)$$

where, IC_k is the initial retrofit cost of the k^{th} candidate retrofit solution; A_i is the quantity of the i^{th} component installed and used during the construction, and c_i is the corresponding unit cost of the i^{th} component; L_k is all labor related cost and general expenses; $\triangle AOC_k$ is the annual operational cost savings of candidate retrofit solution; EE_{base} and $EE_{retrofit}$ are the annual energy consumption before and after retrofit. EP is the local electricity price, the average unit price of electricity for annual electricity consumption in Jiangsu Province is 0.5283 Yuan/kWh. MC is annual maintenance cost. $F_{LCC}(x)$ is the life cycle cost of candidate retrofit solution; CF_i is the cash inflow in each period, and r is the discounted rate (%), takes the value of 4%, which is based on data from the People's Bank of China.

3 Results

3.1 Building energy simulation results

As shown in Fig. 4, for buildings with low annual energy, such as Gym and Old library, the simulation results of energy are mostly more than 20% higher than the actual energy. For buildings with high annual energy, such as Dongli and Zhongxin, their energy simulation results are mostly less than 20% of the actual annual energy. This is due to the significant differences in the area or actual usage frequency of different types of campus buildings, leading to atypical energy consumption characteristics in some buildings. It also reflects that UBEM tends to conform more to the general laws of actual energy. In this study, the parameter assumption that the simulated energy consumption value is within ±20% and closest to the real energy was used as the baseline assumption of UBEM.

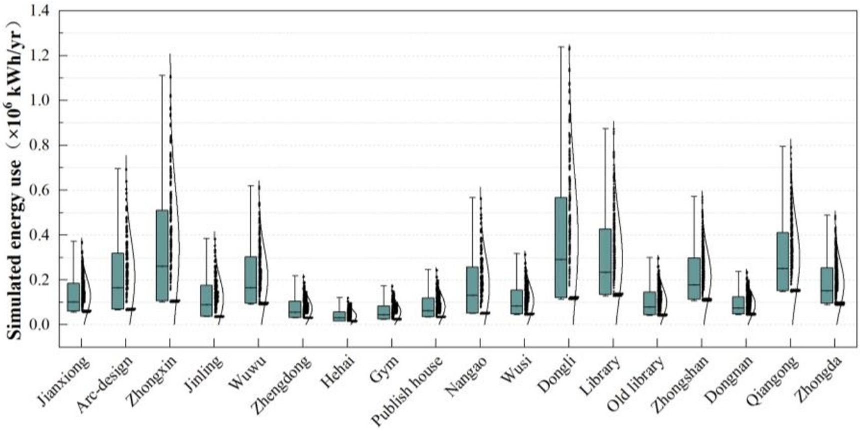

Fig. 4. Simulated energy use by physical UBEM method for individual buildings.

3.2 ANN prediction results

After repeatedly adjusting the parameters of the ANN model, the MAPE, RMSE and R^2 for each trained model are shown in Table 7. The closer R^2 is to 1, the higher the model's prediction accuracy. For all retrofitted buildings' ANN models, the MAPE values are all below 0.032, and the R^2 are between 0.995 and 0.999. The larger values of RMSE are due to the large magnitude of the energy prediction values. These evaluation metrics are sufficient to prove that the trained ANN models possess high accuracy. The trained model parameters are saved, and the parameters for all trained models are shown in Table 8. It should be noted that we trained the ANN model for each building using one set model parameters. The overall best performance predicted by all ANN models under this parameter setting was considered as the suitable model parameters. This is because, in predicting energy consumption for a cluster of buildings at a collective scale, using uniform model parameters for prediction is more efficient. It becomes impractical to individually adjust the model when the number of buildings increases and reaches a regional scale.

Table 7. ANN model performance.

Number	Name	MAPE	RMSE	R^2
1	Jianxiong	0.025	3767.552	0.998
2	Arc-design	0.021	6969.518	0.998

3	Zhongxin	0.020	12319.359	0.998
4	Jinling	0.027	4691.448	0.997
5	Wuwu	0.016	3804.053	0.999
6	Zengdong	0.021	1985.832	0.998
7	Hehai	0.024	1714.552	0.996
8	Gym	0.022	1794.049	0.998
9	Publish house	0.032	3306.065	0.996
10	Nangao	0.023	6135.249	0.998
11	Wusi	0.032	3451.144	0.997
12	Dongli	0.024	13979.535	0.998
13	Library	0.014	5022.19	0.999
14	Old library	0.032	3206.03	0.998
15	Zhongshan	0.015	4589.097	0.998
16	Dongnan	0.031	3455.353	0.995
17	Qiangong	0.015	5479.814	0.999
18	Zhongda	0.017	3731.101	0.999

Linear regression analysis is conducted on the prediction results of all ANN models, as illustrated in Fig. 5. The closer the coefficient of determination R^2 is to 1, the greater the prediction accuracy of the model. It is evident that the R^2 values for all ANN models fall within the range of 0.995-0.999, signifying that the trained ANN model exhibits high prediction accuracy and preserves the trained model parameters.

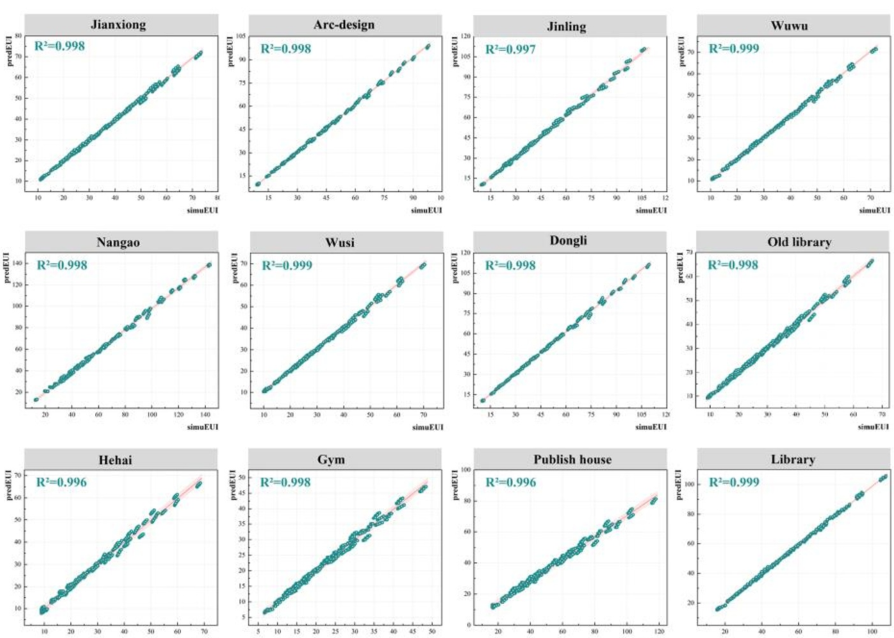

Fig. 5. Prediction performance of part of the ANN models for retrofitted buildings.

3.3 Retrofit performance of all buildings

The analysis of energy consumption results, energy-saving potential, building carbon emissions, and full life cycle costs for all buildings adopting energy-saving retrofit plans is presented in Fig. 6. Following energy-saving retrofit measures, the energy-saving potential for all buildings ranges from -80% to 80%, with the majority falling between 30% and 70%. Notably, the Architectural Design Institute, Jinling Institute, Nanjing Institute of Technology, Power Building, and Center Building exhibit significantly improved energy-saving potential. However, after the implementation of energy-saving retrofit packages, the energy consumption of the old library, gymnasium, and Southeast Campus increased. This discrepancy arises because the post-retrofit building energy consumption is predicted based on the energy consumption patterns simulated by UBEM, rather than the actual building energy consumption patterns. In instances where the simulated energy consumption exceeds the real energy consumption, certain buildings achieve a certain level of energy savings after adopting the energy-saving retrofit package but still do not surpass their actual energy consumption values.

Following energy-saving retrofits for all buildings, the gymnasium demonstrates the lowest carbon emissions. Total carbon emissions over the 30 years post-retrofit range from 714.93t to 940.21t. Conversely, the library exhibits the highest carbon emissions, with total emissions over the 30 years post-retrofit ranging from 5798.24 t to 7545.09 t.

Regarding life cycle costs (LCC), the power building features the lowest LCC, ranging from -8.15 to -5.50 x10^6 Yuan. On the other hand, the library has the highest LCC, ranging from 0.68 to 2.97 x10^6 Yuan. It is noteworthy that the negative LCC values indicate a decrease in equipment operating expenses for the building post-retrofit compared to the original state, thus bringing benefits to the building. Most buildings exhibit a negative LCC 30 years after implementing energy-saving retrofit measures, and there exists a positive correlation between LCC and the annual energy consumption savings of the building.

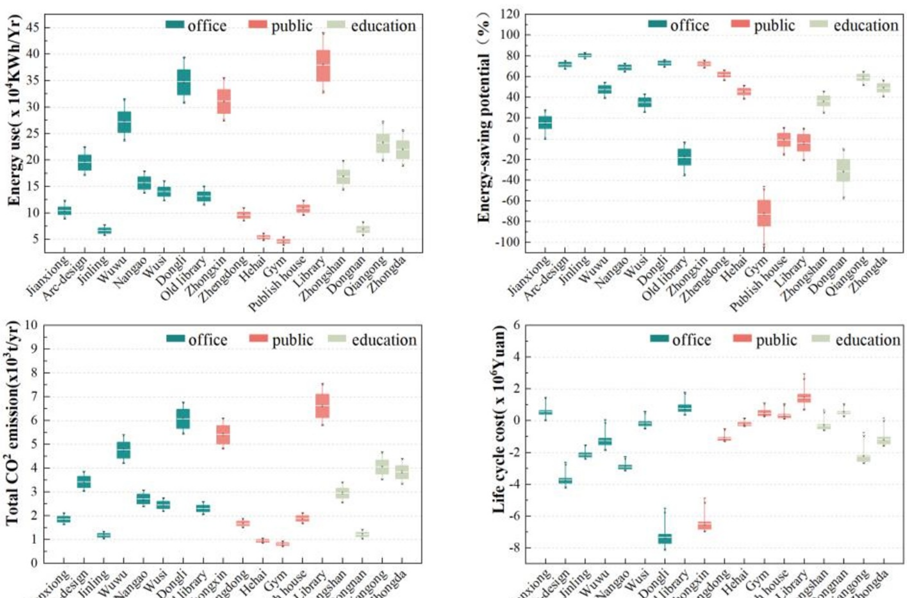

Fig. 6. Energy consumption analysis, energy saving potential analysis, carbon emission analysis and LCC analysis of all buildings after energy saving retrofit.

3.4 Results of NSGA-II optimization

In this case, the energy retrofitting packages described in section 2.4 are combined to form 343 energy retrofitting packages, and when retrofitting different functional building clusters, one of the 343 retrofitting packages is randomly selected. Since each building has different baseline conditions, the energy consumption, carbon emissions and LCC vary after adopting different retrofitting packages. NSGA-II is used for multi-objective optimization of building retrofit decision-making after sdopting different retrofit combination measures. The Pareto solutions obtained after multi-objective optimization of energy retrofitting packages for office buildings, public buildings and educational buildings within the block are shown in Fig. 7. For the retrofitting of office buildings, there are a total of 25 pareto frontier solutions. For the retrofitting of public buildings, there are a total of 19 pareto frontier solutions. For the retrofitting of educational buildings, there are a total of 13 pareto frontier solutions. After TOPSIS ranking, the top-ranked optimal retrofitting solution for all building types is identified as solution ERM-192. In this scenario, the specific retrofitting measures include: the roof selects measure R2, the wall selects measure W3, and the window selects measure G6. Statistical analysis of the Pareto solutions for different types of retrofitting buildings reveals that selecting specific retrofitting measures for walls (W3, W6), roofs (R4, R1), and windows (G6, G4, or no change) makes it easier to achieve the objectives of minimizing total energy consumption, carbon emissions, and LCC for the energy retrofitting packages.

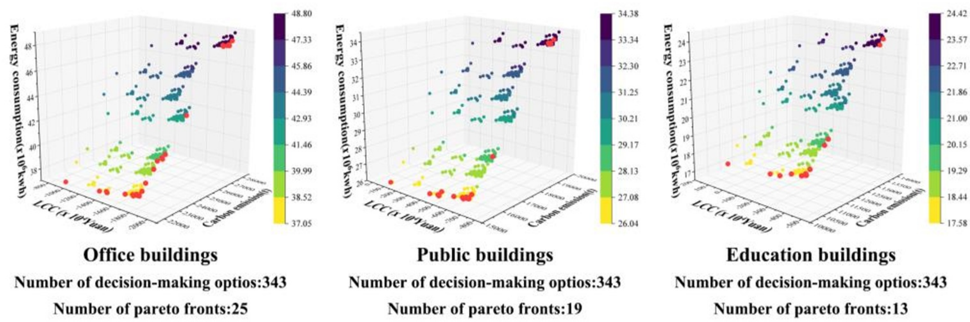

Fig. 7. Pareto fronts of complexes with all functions after retrofitting.

4 Discussion

The study presents a data-driven framework that integrates machine learning, multi-objective optimization, and multi-criteria decision-making techniques to assess the energy-saving retrofit performance of existing buildings in a neighbourhood and formulate optimal retrofit plans. Initially, an Artificial Neural Network (ANN) is developed to forecast the energy performance across a diverse array of retrofit packages. Subsequently, the genetic algorithm NSGA-II is utilized to identify the Pareto optimal solution. The energy consumption results are then amalgamated with environmental and economic impact data to evaluate the overall environmental and economic performance of the retrofit package. The innovation of this research lies in:

First, a hybrid simulation and data-driven urban energy consumption modelling method was employed. Building upon this approach, the energy-saving potential of various energy-saving retrofit measures within the context of low-carbon cities and urban renewal was swiftly assessed, establishing a relatively mature workflow. Historically, urban energy consumption modelling relying solely on physical simulation has been predominantly time-consuming and labour-intensive. However, due to the challenge of comprehensively obtaining domestic data, modelling approaches that exclusively utilize data-driven methods encounter issues with insufficient early data. This study integrates the urban energy consumption modelling method of physical simulation with the machine learning-based urban energy consumption modelling method. It utilizes the urban energy consumption data outputted by physical simulation as the input for the machine learning model, thereby addressing the limitations of a purely data-driven urban modelling method. Concerning data acquisition challenges, the ANN artificial neural network and genetic algorithm are concurrently employed to predict urban energy consumption, achieving a commendable balance between model prediction speed and accuracy. This approach offers a novel avenue for swiftly assessing and predicting urban energy consumption at the block scale.

What's more, the study presents a decision-making framework for designers or planners aimed at achieving a balance among multiple goals and the interests and needs of various stakeholders when undertaking large-scale building energy-saving retrofits. In the realm of energy-saving urban design or block-scale building retrofit, designers or planners encounter a plethora of available building energy-saving technology strategies during the program design phase. It is often challenging to determine the optimal combination of energy-saving technology measures that not only align with national policy requirements and regulatory standards but also satisfy economic and sustainability criteria. This study equips designers or planners with a methodological framework to swiftly decide on a combination of building energy-saving retrofit plans. This approach enhances the current scenario where architects or planners are typically limited to qualitatively selecting building retrofit measures and post-evaluating the energy-saving benefits model. It enables architects or planners to synchronize energy-saving benefits with target decisions in the early stages of the project.

However, it is important to acknowledge that this study has certain limitations. Future research could delve into additional retrofit measures (e.g., other types of insulation, smart lighting, and the utilization of renewable energy sources such as photovoltaic panels) to offer a more comprehensive understanding of the impact of various modification measures on buildings in different climate zones.

5 Conclusion

Energy-saving retrofits for existing buildings in neighbourhood play a crucial role in mitigating building energy consumption and reducing greenhouse gas emissions. This study introduces a data-driven approach to urban energy-saving retrofit, integrating machine learning and multi-objective optimization techniques for assessing the energy-saving retrofit performance of existing buildings in the neighbourhood. This approach assists planners and designers in formulating optimal energy-saving retrofit plans.

Initially, an artificial neural network (ANN) was developed to predict the energy consumption performance across a diverse range of retrofit packages. Subsequently, the genetic algorithm NSGA-II was employed to ascertain the Pareto optimal solution. The energy consumption results were then merged with environmental and economic impact data to assess the environmental and economic performance of the retrofit package. The proposed framework underwent validation using an existing dataset from building complexes at the Sipailou Campus of Southeast University in Nanjing. The trained ANN model demonstrated an overall average prediction performance for energy consumption, with R2 values ranging between 0.995-0.999, affirming the model's high prediction accuracy. The NSGA-II algorithm was employed to obtain Pareto solutions identified 25, 19, and 13 optimal retrofit packages for office, public and education building clusters that minimizes the total energy consumption and carbon emissions while maximizing economic benefits from 343 retrofit packages of each cluster in a 30-year retrofit period. And ERM-192 emerges as the best energy-saving retrofit package. Case studies confirmed that the proposed framework effectively predicts the energy consumption of various energy-saving retrofit plans,

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facilitating planners and designers in selecting optimal energy-saving retrofit plans for existing building clusters.

References

1. H. Tianzhen, J. Langevin, and K. Sun, Build. Simul. 871 (2018)
2. G. Liu, X. Li, Y. Tan, and G. Zhang, Energy Policy **139**, 111356 (2020)
3. R. Jagarajan, M. N. Abdullah Mohd Asmoni, A. H. Mohammed, M. N. Jaafar, J. Lee Yim Mei, and M. Baba, Renew. Sustain. Energy Rev. **67**, 1360 (2017)
4. D. Wang, J. Landolt, G. Mavromatidis, K. Orehounig, and J. Carmeliet, Energy Build. **169**, 9 (2018)
5. K. Allacker, V. Castellani, G. Baldinelli, F. Bianchi, C. Baldassarri, and S. Sala, Int. J. Life Cycle Assess. **24**, 989 (2019)
6. Z. Deng, Y. Chen, J. Yang, and F. Causone, Energy Build. **282**, 112794 (2023)
7. Z. Lin, T. Hong, X. Xu, J. Chen, and W. Wang, Sustain. Cities Soc. **95**, 104602 (2023)
8. K. Sun, T. Hong, J. Kim, and B. Hooper, Build. Simul. **15**, 1385 (2022)
9. Y. Ye, K. Hinkelman, Y. Lou, W. Zuo, G. Wang, and J. Zhang, Build. Simul. **14**, 1377 (2021)
10. F. Ascione, N. Bianco, C. De Stasio, G. M. Mauro, and G. P. Vanoli, Energy Build. **146**, 200 (2017)
11. E. Thrampoulidis, G. Mavromatidis, A. Lucchi, and K. Orehounig, Appl. Energy **281**, (2021)
12. F. Ascione, N. Bianco, C. De Stasio, G. M. Mauro, and G. P. Vanoli, Energy **118**, 999 (2017)
13. A. Nutkiewicz, Z. Yang, and R. K. Jain, Appl. Energy **225**, 1176 (2018)
14. T. Niemelä, R. Kosonen, and J. Jokisalo, Sustain. Cities Soc. **32**, 9 (2017)
15. U. Ali, M. H. Shamsi, M. Bohacek, C. Hoare, K. Purcell, E. Mangina, and J. O'Donnell, Appl. Energy **267**, 114861 (2020)
16. I. Costa-Carrapiço, R. Raslan, and J. N. González, Energy Build. **210**, (2020)