Int. J. Renew. Energy Dev. 2024, 13 (5), 995-1004

Contents list available at CBIORE journal website

International Journal of Renewable Energy Development

Journal homepage: https://ijred.cbiore.id

Research Article

Energy efficient design of rural prefabricated buildings based on ANN and NSGA-II

Chaoqin Bai[1*] and Xiaolin Xue[2]

[1]School of Civil Engineering and Architecture, Henan University of Science and Technology, Luoyang, 471000, China

[2]Luoyang Xiaozhaidi Construction Technology Co., Ltd, Luoyang, 471000, Henan, China

Abstract. The growing concern about global climate change and the rapid development of rural areas highlight the need for energy efficient building design. This study aims to establish a multi-objective optimization model based on artificial neural network (ANN) and non-dominated sorting Genetic algorithm II (NSGA-II) to optimize the energy consumption of rural prefabricated buildings. Firstly, ANN and simulation technology are used to build building models and predict building energy consumption. Then, NSGA-II algorithm was used to optimize the energy consumption and material selection of the building, and the best prefabricated building scheme was obtained. The experimental results show that the optimization efficiency of the model is about 95%, which is better than the traditional method. Specifically, compared with the NSGA-II algorithm, the model reduces energy consumption by 16.7%, operating costs by 20.0%, and carbon emissions by 20.0%. When the cost optimization, energy consumption optimization and carbon emission optimization are difficult to balance, the average optimization efficiency of the research design method is about 90% when the cost optimization rate is low, and the other optimization rates are about 85% when the cost optimization rate rises to 50%. When the cost optimization reaches the maximum, the optimization rate remains at about 80%. These results show that the proposed model is robust and efficient. This study provides a comprehensive framework for designing sustainable and energy efficient rural prefabricated buildings that can help reduce energy consumption and environmental impact. It has positive significance in the sustainable development of rural economy and provides a new way of thinking for rural construction.

Keywords: Rural areas; Artificial Neural Network; Non-dominated Sorting Genetic Algorithm II; Prefabricated buildings; Energy optimization.

Received: 24th Feb 2024; Revised: 17th July 2024; Accepted: 15th August 2024; Available online: 29th August 2024

1. Introduction

In recent years, the worsening global climate change and the rapid depletion of natural resources have heightened the global focus on energy conservation and emission reduction (Von Homeyer *et al.* 2021). Among various industries, the building sector accounts for a significant portion of energy consumption, making energy-efficient buildings a crucial and unavoidable topic (Li *et al.* 2022). In rural areas, prefabricated buildings are constructed using a factory-based production approach, followed by assembly and installation in rural regions (Wasim *et al.* 2022). Compared to traditional brick and timber structures, prefabricated buildings offer several energy-saving advantages (Luo *et al.* 2021). Rural prefabricated buildings utilize advanced energy-saving materials and technologies, such as efficient insulation materials like polystyrene boards and rock wool boards for walls and roofs, effectively reducing energy consumption by providing thermal insulation (Awad *et al.* 2022) and (Arjomandnia *et al.* 2023). However, energy-efficient building design in rural areas faces challenges related to varying climate conditions, financial and technological constraints, limitations in construction materials and techniques, building land and spatial constraints, as well as awareness and education levels (Doerr *et al.* 2023) and (Fakhr *et al.* 2023). Additionally, in the energy-efficient design of rural prefabricated buildings, artificial neural networks can be used for building energy consuming simulating, thermal comfort, daylighting, and other performance factors under different design parameters while employing complex nonlinear function approximation and pattern recognition (Hamida *et al.* 2021) and (Hobbie *et al.* 2021). Non-dominated sorting genetic algorithm, as a multi-objective optimization (MOO) algorithm, can be combined with artificial neural networks to significantly reduce the time required for performance evaluation during the rapid optimization process for building performance simulation (Jayakeerti *et al.* 2023) and (Jayashankara *et al.* 2023). In this context, this study considers the practical performance requirements of energy-efficient design, innovatively integrating objectives such as energy consumption, cost, and carbon emissions to comprehensively assess the sustainability of buildings (Khettabi *et al.* 2022). Furthermore, the study creatively considers the coupling effects between envelope structure design and renewable energy system design while also considering independent parameter optimization for different facade orientations to better meet energy-saving needs under different conditions. Ultimately, a MOO model for energy-efficient rural prefabricated buildings is proposed, based on artificial neural networks (ANN) and non-dominated sorting genetic algorithm II (NSGA-II), integrating

* Corresponding author
Email: chaoqinbai@163.com (C.Bai)

https://doi.org/10.61435/ijred.2024.60153
ISSN: 2252-4940/© 2024.The Author(s). Published by CBIORE

building energy consumption simulation. This model assists designers in weighing and selecting among multiple objectives.

The study conducted technical exploration and analysis from four aspects. The first part discussed and summarized the current research on energy conservation in the building sector. The second part focused on researching building energy consumption simulation, ANN, and multi-objective algorithms, including the construction of a MOO model. The third part mainly validated the MOO model through experiments and analyzed the data. The fourth part provided a comprehensive overview of the entire article and reflected and summarized its shortcomings.

2. Related works

The increasing depletion of global non-renewable resources and the enormous energy consumption in the construction industry have led to a further demand for energy-efficient buildings. Constructing efficient and energy-saving construction methods has become an important research area for some scholars. Deng *et al*., (2022) addressing the issue of urban building energy modeling, proposed a city building energy model based on clustering and random forest algorithms, thereby enhancing the control over building energy usage and conservation and emissions reduction. Ali *et al*., (2021) focusing on the analysis of energy consumption and potential energy savings in a particular institution in Malaysia, proposed an energy consumption analysis method based on energy audits, thereby improving the targeted and feasible measures for building energy conservation. Berawi *et al*., (2023) addressing the energy performance, indoor comfort, and life-cycle cost efficiency of office buildings, proposed an intelligent integrated workspace design framework based on IoT technology, thereby enhancing building energy performance and efficiency. Shafie *et al*., (2021) addressing the energy efficiency management issue in university campus buildings, proposed energy and energy efficiency management strategies based on expert interviews and the collection of electronic materials and books, thereby providing sustainable solutions for energy and energy efficiency management in university campus buildings. Mahapatra and Nayyar (2022) addressing the optimization of energy management in residential housing, proposed an impromptu creative building design method based on green building principles, thereby enhancing the efficiency and reliability of residential energy management systems. Ye *et al*., (2021) addressing the impact of energy efficiency measures on medium-sized office building energy consumption in the United States, proposed an optimization strategy for energy efficiency retrofit measures based on sensitivity analysis combined with standard regression coefficients and sensitivity analysis methods, thereby providing decision support for energy-saving retrofitting of medium-sized office buildings. Long R *et al*., addressing issues related to energy-efficient building design, proposed an energy-efficient building design framework based on building information modeling simulation technology combined with artificial intelligence technology, thereby improving energy utilization efficiency in the building design process (Long and Li 2021).

In addition, Amani *et al.,* addressing the issue of improving energy efficiency in residential buildings, proposed a residential building energy efficiency optimization model based on ecological technology analysis software, thereby enhancing the energy utilization efficiency of residential buildings under different environmental and climatic conditions (Amani *et al.* 2022). Zekić-Sušac *et al.,* (2021) focusing on the prediction of energy consumption costs in public buildings, proposed an energy cost prediction model based on ANN, thereby improving the prediction capability in the field of energy management and estimating the surplus generated after reconstruction measures. Al-Habaibeh *et al.,* (2021) addressing the heat performance preservation issue during building retrofit processes, proposed a building heat performance assessment model based on deep learning ANN, thereby enhancing energy-saving effects during building retrofit processes. Nazari *et al*., (2023) addressing the reduction of energy consumption and improving indoor environment quality in commercial buildings, proposed a commercial building energy efficiency improvement model based on NSGA-II, thereby improving the indoor environmental quality while reducing energy consumption in commercial buildings. Li *et al*., (2023) addressing the issues of sustainable development and energy system construction in public buildings, proposed a structure of renewable energy microgrids based on an improved NSGA-II, thereby enhancing the sustainable development and energy utilization efficiency of public buildings.

From the research conducted by scholars from different countries, most of the building energy-saving studies mainly focus on optimizing a single aspect, neglecting the systematic parameter optimization of the entire system composed of the building and its environment. Therefore, the proposed MOO model for energy-saving in rural prefabricated buildings, based on ANN and NSGA-II combined with building energy consumption simulation, exhibits certain innovativeness.

3. Research and design of energy-efficient models for rural prefabricated buildings

Compared to traditional models, a multi-objective optimization model can automatically extract the complex relationships of building energy consumption by learning from a large amount of data, thereby accurately predicting building energy consumption. Additionally, this model can simultaneously consider multiple optimization objectives, such as energy saving, cost reduction, and improved comfort, enabling more comprehensive optimization. Therefore, the design and implementation of the algorithm model are particularly important to ensure continuous optimization. Hence, this section mainly analyzes the fundamental principles of the model and the construction of the system.

3.1 Building energy consumption simulation and artificial neural network

The building system studied in this paper is the rural prefabricated building system. The system focuses on combining advanced building technologies with energy efficient materials and renewable energy technologies. A key element of the system is high-performance insulation materials for walls and roofs, such as polystyrene and rockwool, which significantly improve thermal efficiency. In addition, the system includes solar photovoltaic panels for on-site renewable energy generation, an efficient heating, ventilation and air conditioning (HVAC) system for maintaining an optimal indoor climate, and a smart energy management system for real-time monitoring and control of energy consumption. Together, these features aim to optimize energy use, reduce carbon emissions, and improve the sustainability of rural prefabricated buildings.

Buildings are considered as thermodynamic systems comprising closely connected and interacting indoor and outdoor environments (Mehboob 2021) and (Ma *et al.* 2023). Various factors, such as heat radiation within the rooms and building equipment, can influence the internal environment,

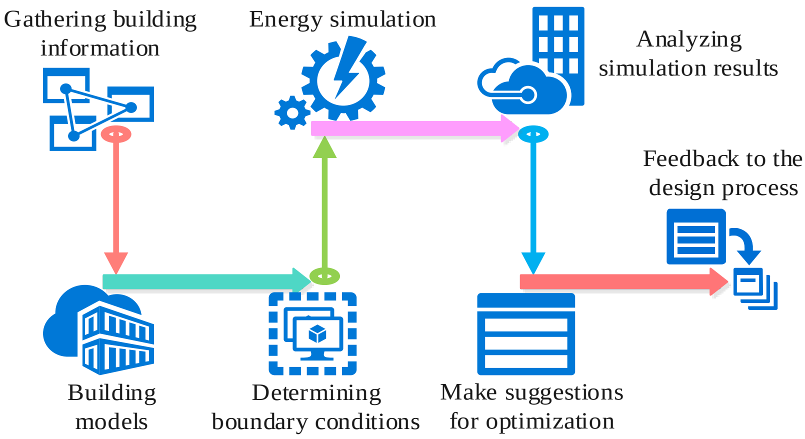


Fig. 1 Flow chart of building energy consumption simulation

while external factors like solar radiation and climatic conditions can affect the thermal conduction and optical properties of the building's structural components (Jin *et al.* 2023). The general process is illustrated in Figure 1.

From Figure 1, building energy consumption simulation converts building information into a computer model. Based on the building model, boundary conditions, and material properties, it calculates internal heat transfer, energy consumption, and other factors, and then analyzes the results for improving the energy efficiency and sustainability of the building (Patil *et al.* 2024). The mathematical expression for building energy consumption calculation is shown in Equation (1) (Saber *et al.* 2021) and (Singh Rajput *et al.* 2023).

$$q_{all} = q_{conv} + q_{CE} + q_{IV} + q_{sys} \tag{1}$$

Equation (1), q_{all} represents the building's energy consuming, q_{conv} represents the convective energy consumption on the building surfaces, q_{CE} represents the convective energy consumption indoors, q_{IV} represents the energy consumption due to airflow infiltration and ventilation, q_{sys} represents the energy consumption of the air conditioning system. The convective energy consumption outdoors and indoors is shown in Equation (2).

$$\begin{cases} q_{conv} = h \times A \times \Delta T \\ q_{CE} = h_{CE} \times A_{CE} \times \Delta T_{CE} \end{cases} \tag{2}$$

In Equation (2), h represents the convective heat transfer coefficient, A represents the surface area for heat conduction, ΔT represents the temperature difference between the object surface and the fluid, h_{CE} represents the convective heat transfer coefficient for indoor loads, A_{CE} represents the surface area affected by indoor loads, and ΔT_{CE} represents the temperature difference between the indoor environment and the load surface. Additionally, the energy consumption due to airflow infiltration and air conditioning is shown in Equation (3).

$$\begin{cases} q_{IV} = m \times Cp \times \Delta T_{IV} \\ q_{sys} = UA \times \Delta T_{sys} \end{cases} \tag{3}$$

In Equation (3), m represents the mass flow rate of the airflow, C_p represents the specific heat capacity of the air, ΔT_{IV} represents the temperature difference between indoor and outdoor airflow UA represents the thermal conductivity coefficient, and ΔT_{sys} represents the temperature difference in the return water of the air conditioning system. Due to the complexity and uncertainty of real buildings, simulations may not accurately capture all factors. By introducing ANN into the simulation, the accuracy and precision of predictions for nonlinear problems can be improved through training with a large amount of data, enabling better prediction of actual building energy consumption (Fan *et al.* 2021). The ANN model is illustrated in Figure 2.

From Figure 2, the ANN model is composed of multiple neurons (or nodes) arranged in a network structure, which contains input, hidden, and output layer. Input from the previous layer is imported and calculated a weighted sum using weights, which is then passed through an activation function to generate an output (Verma *et al.* 2023) and (Vijayan *et al.* 2022). ANN can be used to process various types of data, including

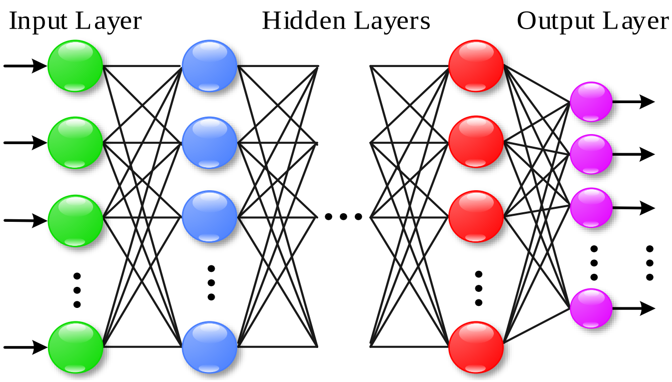


Fig. 2 ANN model structure diagram

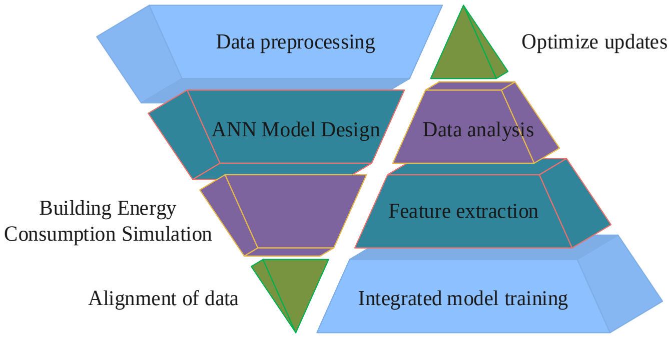


Fig. 3 Flow chart of building energy consumption simulation combined with ANN

structured data and sequential data. The weight calculation is represented by Equation (4).

$$\begin{cases} Z^1 = W^1 \cdot X + b^1 \\ Z^2 = W^2 \cdot A^1 + b^2 \\ A^1 = \sigma(Z^1) \end{cases} \quad (4)$$

σ represents the activation function, Z^1 represents the output of the weights from the input layer to the hidden layer, W^1 represents the weight matrix from the input layer to the hidden layer, X represents the input data vector, b^1 represents the bias vector of the hidden layer, Z^2 represents the output of the weights from the hidden layer to the output layer, W^2 represents the weight matrix from the hidden layer to the output layer, b^2 represents the bias vector of the output layer, and A^1 represents the activation value of the hidden layer. The output is then passed through the weight matrix added with the bias and sequentially through the activation function. After obtaining the predicted result, it is necessary to measure the error between the predicted value and the actual value using a loss function. The loss function is defined by Equation (5).

$$\begin{cases} J = -\frac{1}{m}\sum_{i=1}^{m}\left(Y_i \cdot \log(A_i^2) + (1-Y_i) \cdot \log(1-A_i^2)\right) \\ A^2 = \sigma(Z^2) \end{cases} \quad (5)$$

J represents the loss value, m represents the number of samples, Y_i represents the actual value of the sample, A^2 represents the predicted value from the output layer, and Z^2 represents the input to the output layer. After calculating the error using the loss function, the error needs to be backpropagated. The mathematical expression for backpropagation is shown in Equation (6).

$$\begin{cases} dZ^2 = A^2 - Y \\ dZ^1 = (W^2)^T \cdot dZ^2 \cdot \sigma'(Z^1) \end{cases} \quad (6)$$

In Equation (6), dZ^2 represents the error in the output layer, dZ^1 represents the error in the hidden layers, T represents the transpose operation, and σ' represents the derivative of the activation function. After calculating the error, it is necessary to compute the weight gradients for weight update, as shown in Equation (7).

$$\begin{cases} dW^2 = \frac{1}{m} dZ^2 \cdot (A^1)^T \\ dW^1 = \frac{1}{m} dZ^1 \cdot X^T \end{cases} \quad (7)$$

In Equation (7), dW^2 represents the weight gradient from the hidden to the output layer, dW^1 represents the weight gradient from the input to the hidden layer. The computed errors and weight gradients are then used to update the weights according to Equation (8).

$$\begin{cases} W^1 = W^1 - \alpha \cdot dW^1 \\ W^2 = W^2 - \alpha \cdot dW^2 \end{cases} \quad (8)$$

Equation (8) introduces the learning rate, α. The artificial neural network adjusts the weights gradually during training through the forward and backward propagation processes, controlling the step size of weight updates using the learning rate. This iterative adjustment of weights helps the network approach the true values and achieve the goal of performance prediction. (Verma *et al.* 2023). The general process of combining ANN with building energy consumption simulation is depicted in Figure 3

From Figure 3, the general process involves several steps: preprocessing the collected data, selecting an appropriate ANN architecture, simulating the building energy consumption and inputting relevant parameters, aligning the input data from ANN with the output data from building energy consumption simulation, training ANN using the aligned data as input, extracting feature values from the output of each training iteration to form a feature database, analyzing and evaluating the trained feature data, and periodically updating the model parameters based on the analysis results.

3.2 MOO Model for Rural Prefabricated Buildings

In rural areas, the economic level is relatively low and resources, including land, materials, and energy, are relatively limited. Optimizing the building structure and material selection can reduce material waste, construction and maintenance costs, and energy consumption of buildings (Ve *et al.* 2021) and (Wei *et al.* 2024). The optimization model that combines ANN structure with building energy consumption simulation can only achieve single-objective optimization. Therefore, a MOO model is needed to fully consider the environmental impact of buildings and take corresponding measures in the design process. The overall technical roadmap of the MOO model for rural prefabricated buildings is shown in Figure 4.

From Figure 4, the overall technical roadmap of the MOO model for rural prefabricated buildings consists of three modules: parameter design, research stage, and optimization objectives. The NSGA-II can be used to achieve MOO of the system. and find a set of non-dominated solutions among multiple objectives (Doerr and Qu 2023). The general process of the NSGA-II algorithm is shown in Figure 5.

From Figure 5, the algorithm first randomly generates an initial population. Then, it calculates the fitness value and

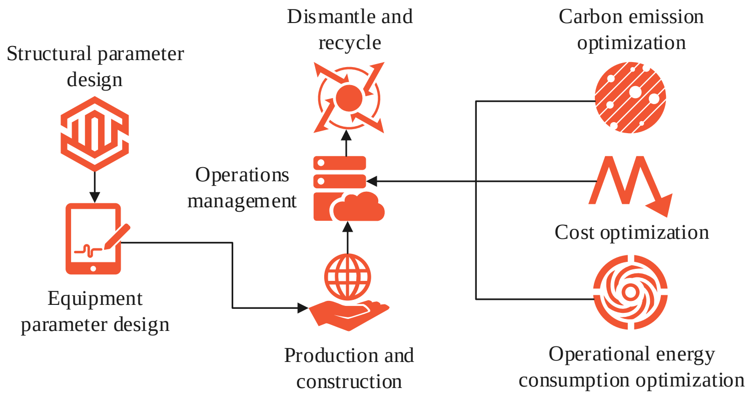


Fig. 4. Technical roadmap of MOO model

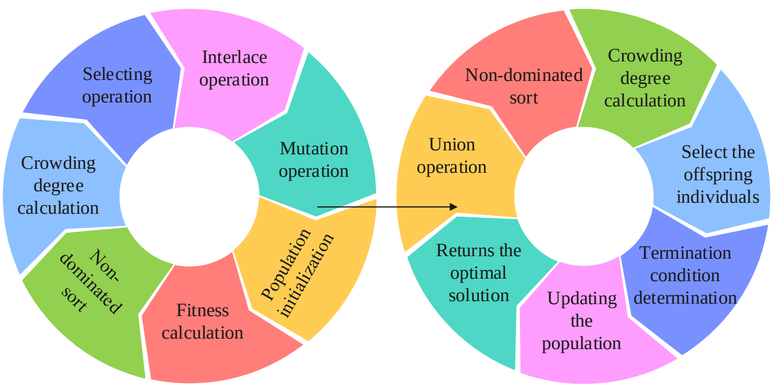


Fig. 5 Flowchart of the NSGA-II algorithm

generates offspring individuals through crossover, mutation, and merging operations to generate a new population. This process is repeated until the termination condition is met, and the population is updated to return the optimal solution. The initialization of the population and the fitness value calculation are mathematically expressed in Equation (9) (Yan *et al.* 2021).

$$\begin{cases} population = [G_1,\ G_2,\ ...,\ G_i] \\ fitness_i = f(G_i) \end{cases} \quad (9)$$

In Equation (9) *population* represents the initial population, G_i represents the gene of an individual, $fitness_i$ represents the fitness value of an individual, and *f(Gi)* represents the fitness function. The formula for the selection operation on the randomly generated initial population is shown in Equation (10).

$$P_i = \frac{fitness_i}{\sum_{j=1}^{N} fitness_j} \quad (10)$$

In Equation (10), P_i represents the probability of an individual being selected, and N represents the total number of individuals in the population. The mathematical expression for the crossover and mutation operations on the selected individuals is shown in Equation (11).

$$X'_{ij} = \left\{ x_{ij}, \text{if } r \le P_c y_{ij}, \text{if } r \le P_m \text{r, otherwise} \right\} \quad (11)$$

In Equation (11), X'_{ij} represents the new individual obtained from crossover and mutation operations on different individuals, x and y represent the parent individuals, r represents a random number, P_c represents the crossover probability, and P_m represents the mutation probability. The new individuals generated until the termination condition is met form a new population, which represents the optimal solutions. The combination of the NSGA-II, ANN structure, and building energy consumption simulation is depicted in Figure 6.

From Figure 6, the overall technical roadmap consists of three parts: dataset generation, construction of artificial neural network, and solution using the NSGA-II MOO algorithm. Firstly, building simulation is performed using the constructed building model to calculate the objective functions and obtain a dataset with building energy consumption, operational costs, carbon emissions, etc. Then, the determined ANN structure is trained using the dataset to obtain prediction models for energy consumption, costs, and carbon emissions. Finally, in the process of MOO based on the NSGA-II algorithm, the ANN prediction models are used for prediction and correction of the data, and the non-dominated sorting is employed to generate a set of multi-objective optimal solutions (Fang *et al.* 2022). When combined with the multi-objective building optimization technique, a cost calculation for production and construction can be derived as shown in Equation (12).

$$IC = IC_0 + \sum_{i}^{n} IC_{Mi} \quad (12)$$

IC_o represents the construction costs of buildings of the same type, and IC_M represents the additional costs. Additionally, the calculation formula for operational costs is shown in Equation (13).

$$OC = \sum_{y=1}^{n} a_y [E_h W_1 + (E_c + E_l + E_w + E_e) W_2 - E_r W_3] + \sum_{z=1}^{n} a_z dw_z \quad (13)$$

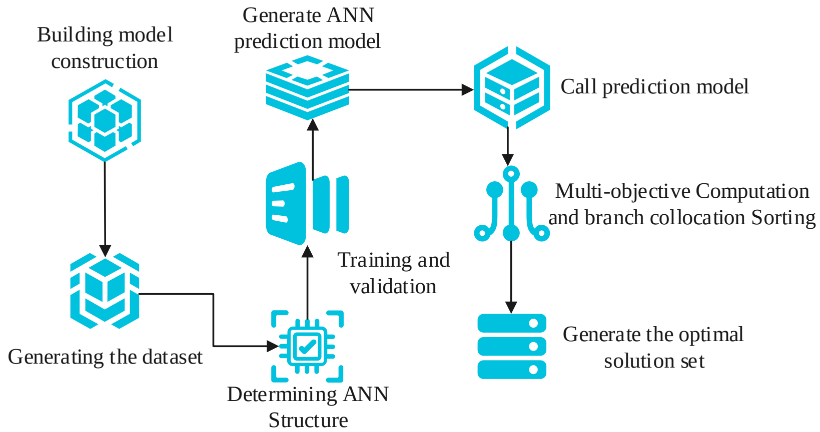


Fig. 6 Algorithm combination technology roadmap

a represents the cost coefficient due to price fluctuations, E_h represents the energy consumption of the heating system, E_c represents the energy consumption of the cooling system, E_l represents the energy consumption of the lighting system, E_w represents the energy consumption of the hot water system, E_e represents the energy consumption of appliances, E_r represents the energy output of rooftop photovoltaic systems, W_h represents the heating energy price, W_2 represents the average energy price, and W_3 represents the price of renewable energy grid connection. Lastly, the cost calculation for the recycling stage is shown in Equation (14).

$$RC = (RC_D + RC_T + RC_C)a_y \quad (14)$$

RC_D represents the dismantling cost, RC_T represents the cost of waste transportation, and RC_C represents the cost of waste treatment. By summing up these various costs, the final cost calculation formula can be obtained. Additionally, the calculation of carbon emissions during the lifecycle is shown in Equation (15).

$$LCCO_2 = C_A + C_B + C_c \quad (15)$$

C_A represents the carbon emissions generated during the production and manufacturing process, C_B represents the continuous carbon emissions generated during operation and management, and C_C represents the carbon emissions generated during the dismantling and recycling process. In summary, the energy consumption optimization of rural prefabricated buildings is a MOO problem that needs to consider multiple objectives, such as energy consumption, comfort, and economy. Building energy consumption simulation provides data, ANN can analyze and predict these data, and NSGA-II can optimize multiple objectives. Therefore, combining ANN, NSGA-II, and building energy consumption simulation for MOO of rural prefabricated buildings can help designers balance between multiple objectives and obtain a set of optimal solutions to achieve energy consumption optimization.

4. Experimental verification and data analysis

For confirming the performance of the MOO Model (MOM) that incorporates ANN, the NSGA-II, and building energy consumption simulation in optimizing energy consuming of rural prefabricated buildings, the MOM model is compared with traditional optimization algorithms including NSGA, Strength Pareto Evolutionary Algorithm (SPEA), Indicator-Based

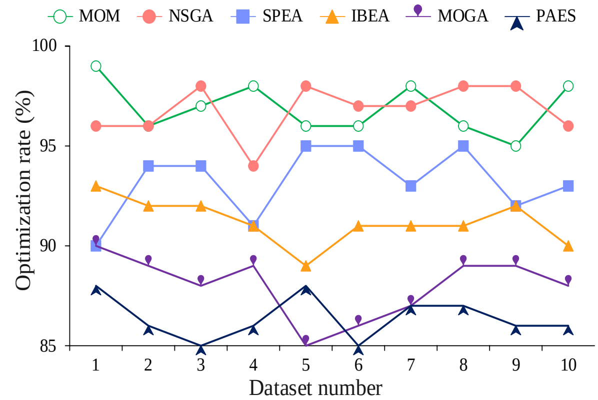


Fig. 7 Comparison of single-storey building optimization

Evolutionary Algorithm (IBEA), Multi-Objective Genetic Algorithm (MOGA), and Pareto Archived Evolution Strategy (PAES) using 10 datasets that include different parameters of rural single-story standard buildings. The results of the parameter optimization comparison are presented in Figure 7.

From Figure 7, MOM achieves approximately 1% improvement over NSGA, about 4% improvement over SPEA, about 7% improvement over IBEA, about 10% improvement over MOGA, and about 11% improvement over PAES. Since rural single-story building designs are relatively simple with fewer parameters, the improvement of MOM compared to NSGA is relatively small, and the overall optimization efficiency

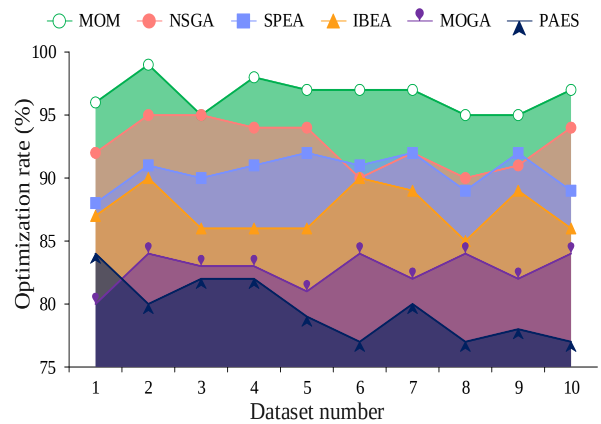


Fig 8. Optimization comparison of special-shaped buildings

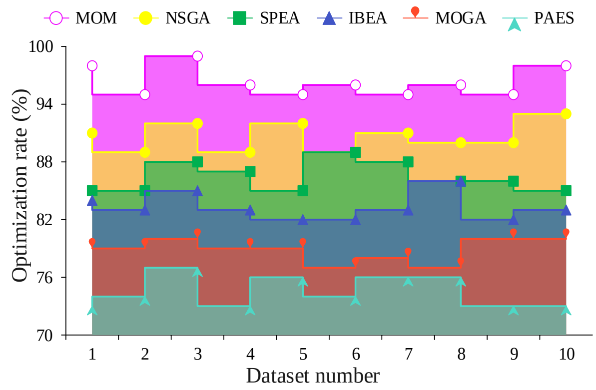


Fig. 9 Comparison of villa building optimization

is similar. However, thanks to the artificial neural network model in MOM, it has gained advantages even with fewer parameters. Further research compares different algorithms in single-story irregular structure building parameters, as shown in Figure 8.

From Figure 8, as parameter structures vary, the optimization efficiency decreases, leading to differences in optimization efficiency among the algorithms. Among them, MOM achieves approximately 4% improvement over NSGA, about 6% improvement over SPEA, about 9% improvement over IBEA, about 13% improvement over MOGA, and about 15% improvement over PAES. As the economic conditions in modern rural areas gradually improve, some rural buildings are evolving into villa-type structures. Further research compares the optimization efficiency of different algorithms in villa-scale buildings, as shown in Figure 9.

From Figure 9, in the optimization efficiency comparison of villa buildings, the MOM model still maintains an average optimization efficiency of over 95%, while the traditional NSGA algorithm's average optimization efficiency decreases to about 88%, SPEA's average optimization efficiency is about 85%, IBEA's average optimization efficiency is about 80%, MOGA's average optimization efficiency is about 78%, and PAES's average optimization efficiency is about 72%. As mentioned earlier, further research refines the optimization objectives to Comprehensive Energy Consumption Optimization (CEO), Integrated Cost Optimization (ICO), and Integrated Carbon Emission Optimization (IEO), and compares the algorithms as shown in Figure 10.

From Figure 10, the MOM model consistently maintains a comprehensive optimization efficiency of over 90% in different category optimization tests. Its optimization efficiency is approximately 7%, 8%, and 5% higher than the SPEA algorithm, and approximately 10%, 15%, and 20% higher than the PAES algorithm.

Figure 9 compares the optimization efficiencies of different algorithms specifically for villa-scale buildings, showing how the MOM algorithm outperforms others like NSGA, SPEA, IBEA, MOGA, and PAES in this context. Figure 10, on the other hand, breaks down the MOM algorithm's performance across three specific optimization objectives: CEO, ICO, and IEO. It highlights the algorithm's ability to balance these distinct goals. In summary, Figure 9 focuses on overall efficiency in villa buildings, while Figure 10 details the MOM algorithm's performance in specific optimization categories. A set of parameters for a 2-story villa is optimized using the MOM algorithm, and the optimization results are shown in Table 1.

From Table 1, the MOM model provides specific optimization strategies for different optimization types. The solutions with the lowest energy consumption and the lowest carbon emissions tend to use three-layer glass windows with low emissivity coatings. All recommended solutions suggest using a 10mm insulation layer and recommend insulation thickness of around 50mm for the suspended floor. Additionally, all recommended solutions have a permeability rate of 0.2, and the installation scale of the photovoltaic system is 8 kW. The experimental data above fully demonstrate that the MOM model can design different optimization solutions based on different objectives (energy consumption, carbon emissions, cost, etc.) to achieve optimal energy efficiency and environmental performance in transparent envelope structures.

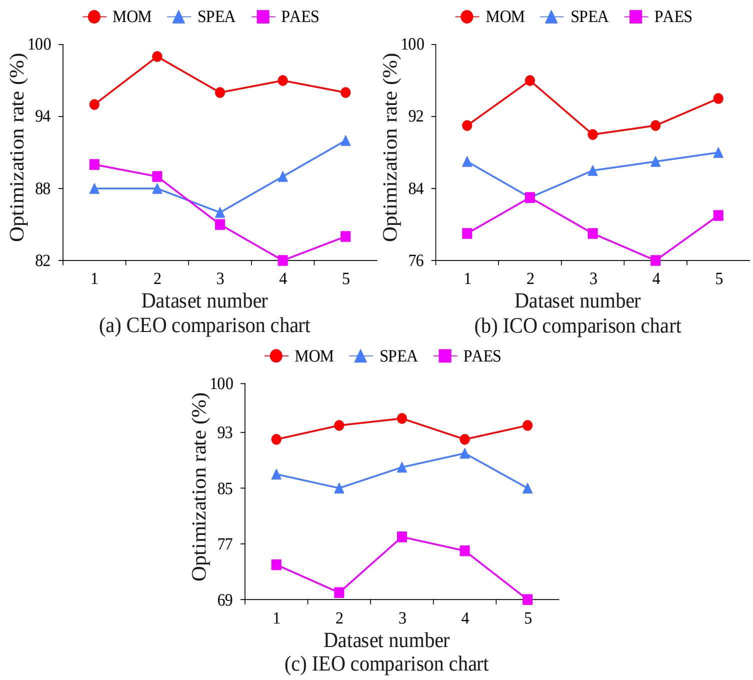
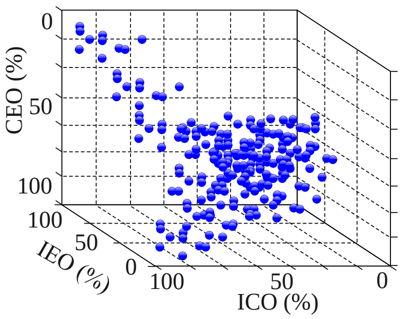


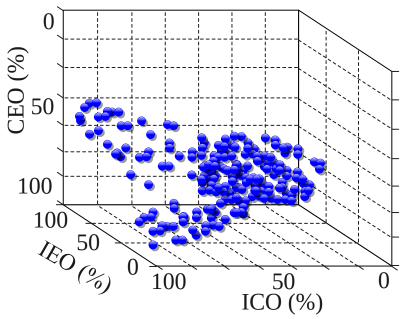
Fig. 10 Comparison of energy consumption, cost and carbon emission optimization

Table 1
Comparison of villa optimization results

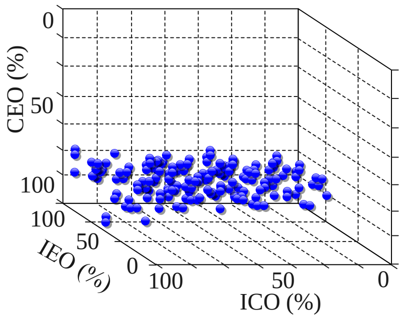
Serial number	Parameter	CEO	ICO	IEO
1	North elevation exterior window type	7	3	8
2	West elevation exterior window type	7	1	6
3	South elevation exterior window type	8	2	7
4	East elevation exterior window type	4	1	5
5	EPS insulation thickness of exterior wall insulation panels (mm	60	90	60
6	Thickness of insulation layer of prefabricated exterior wall panel (mm)	120	140	120
7	Roof insulation board Thickness (mm)	40	10	20
8	Thickness of floor insulation (mm)	10	10	10
9	Thickness of overhead floor insulation (mm)	50	50	45
10	North visor overhang length (cm)	100	40	100
11	West visor overhang length (cm)	100	40	100
12	South visor overhang length (cm)	20	60	100
13	East visor overhang length (cm)	100	100	100
14	Building orientation (°)	0	0	0
15	Air Tightness of Buildings (ACH)	0.2	0.2	0.2
16	Installed capacity of PV system (kw)	8	8	8



(a) Optimal distribution of PAES



(b) Optimal distribution of SPEA



(c) Optimal distribution of MOM

Fig. 11 Comparison of village optimization

Furthermore, as modern rural areas are also transitioning to more dense construction, large-scale villages are starting to emerge. The optimization efficiency of different algorithms for large-scale villages is compared in Figure 11.

From Figure 11, it is evident that it is difficult to balance cost optimization with energy consumption and carbon emission optimization. PAES maintains an average optimization rate of about 80% when the cost optimization rate is low, but as the cost optimization rate increases to 50%, the other optimization rates start to decrease significantly, averaging around 65%. When the cost optimization is at its maximum, the other optimization rates are close to 0%. SPEA maintains an average optimization rate of about 85% when the cost optimization rate is low, and as the cost optimization rate increases to 50%, the other optimization rates decrease to approximately 75%. When the cost optimization is at its maximum, the other optimization rates are around 50%. MOM maintains an average optimization rate of about 90% when the cost optimization rate is low, and as the cost optimization rate increases to 50%, the other optimization rates decrease to approximately 85%. When the cost optimization is at its maximum, the other optimization rates are around 80%. Therefore, it can be concluded that as the cost optimization rate increases, MOM shows a more stable and higher optimization rate compared to SPEA, with an average

Table 2
Optimization results of three kinds of objective functions under two models

Objective function	NSGA-II Efficiency (%)	MOM Efficiency (%)	Improvement (%)
Energy Consumption (kWh/m²)	120	100	16.7
Operational Cost (USD/m2/year)	10	8	20.0
Carbon Emissions (kg CO2/m2/year)	25	20	20.0

improvement of approximately 10%, and an improvement of approximately 8% compared to PAES. The experiments fully demonstrate that MOM has certain advantages and feasibility in optimizing various types of rural buildings and in MOO.

Energy Consumption, Operational Cost, and Carbon Emissions are selected as three different objective functions, and the optimization results of the traditional NSGA-II model and the MOM model proposed in this paper for the three objective functions are shown in Table 2. As can be seen from Table 2, compared with NSGA-II algorithm, MOM algorithm significantly improves the optimization efficiency of all targets. Specifically, the MOM algorithm reduced energy consumption by 16.7%, operating costs by 20.0%, and carbon emissions by 20.0%.

5.Conclusion

For the energy optimization problem of rural prefabricated buildings, a MOO Model was proposed, combining ANN and NSGA-II, and building energy consumption simulation. Experimental comparisons and data analysis were conducted for optimizing various types of building performance and MOO. The experimental results show that in the case of ordinary single-story rural prefabricated buildings, MOM achieves approximately 1% improvement over NSGA, about 4% improvement over SPEA, about 7% improvement over IBEA, about 10% improvement over MOGA, and about 11% improvement over PAES. In the case of multi-story rural buildings, MOM achieves approximately 4% improvement over NSGA, about 6% improvement over SPEA, about 9% improvement over IBEA, about 13% improvement over MOGA, and about 15% improvement over PAES. In the optimization efficiency comparison of villa buildings, MOM still maintains an average optimization efficiency of over 95%, while NSGA's average optimization efficiency decreases to about 88%, SPEA's average optimization efficiency is about 85%, IBEA's average optimization efficiency is about 80%, MOGA's average optimization efficiency is about 78%, and PAES's average optimization efficiency is about 72%. In the scenario where cost optimization and energy consumption and carbon emission optimization are difficult to balance, MOM maintains an average optimization efficiency of about 90% when the cost optimization rate is low, and as the cost optimization rate increases to 50%, the other optimization rates are around 85%. When the cost optimization is at its maximum, the optimization rates remain around 80%. The experiments demonstrate that MOM has certain advantages in optimizing different types of rural prefabricated buildings and in MOO. However, it should be noted that the computational resources required for the fusion model are relatively large, leading to higher resource consumption. Further exploration is needed to optimize the performance and energy consumption of the model itself.

Reference

Al-Habaibeh A, Sen A, Chilton J. (2021). Evaluation tool for the thermal performance of retrofitted buildings using an integrated approach of deep learning artificial neural networks and infrared thermography. *Energy and Built Environment*, 2(4), 345-365. https://doi.org/10.1016/j.enbenv.2020.06.004 .

Ali S B M, Hasanuzzaman M, Rahim N A, Mamun M A A, Obaidellah U H. (2021). Analysis of energy consumption and potential energy savings of an institutional building in Malaysia. *Alexandria Engineering Journal*, 60(1), 805-820. https://doi.org/10.1016/j.aej.2020.10.010 .

Awad M, Abouhawwash M, Agiza H N. (2022). On NSGA-II and NSGA-III in portfolio management. *Intelligent Automation & Soft Computing*, 32(3), 1893-1904. https://doi.org/10.32604/iasc.2022.023510 .

Amani N, Sabamehr A, Palmero Iglesias L M. (2022) Review on energy efficiency using the ecotect simulation software for residential building sector. *Iranian (Iranica) Journal of Energy & Environment*, 13(3): 284-294. https://doi.org/10.5829/ijee.2022.13.03.08 .

Arjomandnia R, Ilbeigi M, Kazemidemneh M, Hashemi A N. (2023). Renovating buildings by modelling energy–CO2 emissions using particle swarm optimization and artificial neural network (case study: Iran). *Indoor and Built Environment*, 32(8), 1621-1637. https://doi.org/10.1177/1420326x231151244 .

Berawi M A, Kim A A, Naomi F, Basten V, Miraj P, Medal L A, Sari M. (2023). Designing a smart integrated workspace to improve building energy efficiency: an Indonesian case study. *International Journal of Construction Management*, 23(3), 410-422. https://doi.org/10.1080/15623599.2021.1882747 .

Deng Z, Chen Y, Yang J, Chen Z. (2022). Archetype identification and urban building energy modeling for city-scale buildings based on GIS datasets//Building Simulation. Beijing: *Tsinghua University Press*, 15(9), 1547-1559. https://doi.org/10.1007/s12273-021-0878-4 .

Doerr B, Qu Z. (2023). Runtime analysis for the NSGA-II: Provable speed-ups from crossover. *Proceedings of the AAAI Conference on Artificial Intelligence*. 37(10), 12399-12407. https://doi.org/10.1609/aaai.v37i10.26461 .

Doerr B, Qu Z. (2023). A first runtime analysis of the NSGA-II on a multimodal problem. *IEEE Transactions on Evolutionary Computation*, 27(5), 1288-1297. https://doi.org/10.1109/TEVC.2023.3250552 .

Fakhr B V, Mahdavinejad M, Rahbar M, Dabaj B. (2023). Design Optimization of the Skylight for Daylighting and Energy Performance Using NSGA-II. *Journal of Daylighting*, 10(1), 72-86. https://doi.org/10.15627/jd.2023.6 .

Fan F L, Xiong J, Li M, Wang G. (2021). On interpretability of artificial neural networks: A survey. *IEEE Transactions on Radiation and Plasma Medical Sciences*, 5(6), 741-760. https://doi.org/10.1109/trpms.2021.3066428 .

Fang Y, Luo B, Zhao T, Fang, Y., Luo, B., Zhao, T., He, D., Jiang, B., & Liu, Q. (2022). ST-SIGMA:Spatio-temporal semantics and interaction graph aggregation for multi-agent perception and trajectory forecasting. *CAAI Transactions on Intelligence Technology*, 7(4):744-757. https://doi.org/10.1049/cit2.12145 .

Hamida A, Alsudairi A, Alshaibani K, Alshamrani O. (2021). Environmental impacts cost assessment model of residential building using an artificial neural network. *Engineering, Construction and Architectural Management*, 28(10), 3190-3215. https://doi.org/10.1108/ecam-06-2020-0450 .

Hobbie J G, Gandomi A H, Rahimi I. (2021). A comparison of constraint handling techniques on NSGA-II. *Archives of Computational Methods in Engineering*, 28(5), 3475-3490. https://doi.org/0.1007/s11831-020-09525-y .

Jayakeerti M, Nakkeeran G, Aravindh M D, Krishnaraj L. (2023). Predicting an energy use intensity and cost of residential energy-efficient buildings using various parameters: ANN analysis. Asian *Journal of Civil Engineering*, 24(8), 3345-3361. https://doi.org/10.1007/s42107-023-00717-y .

Jayashankara M, Shah P, Sharma A, Chanak P, Singh S K. (2023). A novel approach for short-term energy forecasting in smart buildings. *IEEE Sensors Journal*, 23(5), 5307-5314. https://doi.org/10.1109/jsen.2023.3237876 .

Jin Z, Zheng Y, Zhang Y. (2023). A novel method for building air conditioning energy saving potential pre-estimation based on thermodynamic perfection index for space cooling. *Journal of Asian Architecture and Building Engineering,* 22(4), 2348-2364. https://doi.org/10.1080/13467581.2022.2109645 .

Khettabi I, Benyoucef L, Amine Boutiche M. (2022). Sustainable multi-objective process planning in reconfigurable manufacturing environment: adapted new dynamic NSGA-II vs New NSGA-III. *International Journal of Production Research*, 60(20), 6329-6349. https://doi.org/10.1080/00207543.2022.2044537 .

Li J, Zhang C, Zhao Y, Qiu W, Chen Q, Zhang X. (2022). Federated learning-based short-term building energy consumption prediction method for solving the data silos problem. *Building Simulation. Beijing: Tsinghua University Press,* 15(6), 1145-1159. https://doi.org/10.1007/s12273-021-0871-y .

Li S, Zhou H, Xu G. (2023). Research on Optimal Configuration of Landscape Storage in Public Buildings Based on Improved NSGA-II. *Sustainability*, 15(2), 14-60. https://doi.org/10.3390/su15021460 .

Long R, Li Y. (2021). Research on energy-efficiency building design based on bim and artificial intelligence//IOP Conference Series: Earth and Environmental Science. *IOP Publishing*, 825(1), 003-012. https://doi.org/10.1088/1755-1315/825/1/012003 .

Luo T, Xue X, Tan Y, Wang Y, Zhang, Y. (2021). Exploring a body of knowledge for promoting the sustainable transition to prefabricated construction. *Engineering, Construction and Architectural Management,* 28(9), 2637-2666. https://doi.org/10.1108/ecam-03-2020-0154 .

Mahapatra B, Nayyar A. (2022). Home energy management system (HEMS): Concept, architecture, infrastructure, challenges and energy management schemes. *Energy Systems*, 13(3), 643-669. https://doi.org/10.1007/s12667-019-00364-w .

Mehboob K B. (2021). Development of energy saving technique for setback time using artificial neural network. *Australian Journal of Mechanical Engineering,* 19(3), 276-290. https://doi.org/10.1080/14484846.2019.1605685 .

Ma H, Zhang Y, Sun S, Liu T, Shan A. (2023). A comprehensive survey on NSGA-II for multi-objective optimization and applications. *Artificial Intelligence Review*, 56(12), 15217-15270. https://doi.org/10.1007/s10462-023-10526-z .

Nazari S, Sajadi B, Sheikhansari I. (2023). Optimisation of commercial buildings envelope to reduce energy consumption and improve indoor environmental quality (IEQ) using NSGA-II algorithm. *International Journal of Ambient Energy,* 44(1), 918-928. https://doi.org/10.1080/01430750.2022.2157482 .

Patil S R, Sinha M K, Deshmukh M A, Thenmozhi S, Sujatha A. (2024). Predicting and forecasting building energy performance using RSM and ANN. *Asian Journal of Civil Engineering*, 25(1), 159-165. https://doi.org/10.1007/s42107-023-00765-4 .

Saber A. (2021). Effects of window-to-wall ratio on energy consumption: application of numerical and ANN approaches. *Soft Computing in Civil Engineering,* 5(4), 41-56. https://doi.org/10.22115/SCCE.2021.281977.1299 .

Shafie S M, Nu'man A H, Yusuf N. (2021). Strategy in energy efficiency management: University Campus. *International Journal of Energy Economics and Policy,* 11(5), 310-313. https://doi.org/0.32479/ijeep.11265 .

Singh Rajput T, Thomas A. (2023). Optimizing passive design strategies for energy efficient buildings using hybrid artificial neural network (ANN) and multi-objective evolutionary algorithm through a case study approach. *International Journal of Construction Management,* 23(13), 2320-2332. https://doi.org/0.1080/15623599.2022.2056409 .

Verma A, Prakash S, Kumar A. (2023). A comparative analysis of data-driven based optimization models for energy-efficient buildings. *IETE Journal of Research*, 69(2), 796-812. https://doi.org/10.1080/03772063.2020.1838347 .

Verma A, Prakash S, Kumar A. (2023). AI-based building management and information system with multi-agent topology for an energy-efficient building: towards occupants comfort. *IETE Journal of Research,* 69(2), 1033-1044. https://doi.org/10.1080/03772063.2020.1847701 .

Vijayan D S, Sivasuriyan A, Patchamuthu P, Jayaseelan R. (2022). Thermal performance of energy-efficient buildings for sustainable development. *Environmental Science and Pollution Research*, 29(34), 51130-51142. https://doi.org/10.1007/s11356-021-17602-3 .

Von Homeyer I, Oberthür S, Jordan A J. (2021). EU climate and energy governance in times of crisis: Towards a new agenda. *Journal of European Public Policy,* 28(7), 959-979. https://doi.org/10.1080/13501763.2021.1918221 .

VE S, Shin C, Cho Y. (2021). Efficient energy consumption prediction model for a data analytic-enabled industry building in a smart city. *Building Research & Information*, 49(1), 127-143. https://doi.org/10.1080/09613218.2020.1809983 .

Wei H, Jiao Y, Wang Z, Wang W, Zhang T. (2024). Optimal retrofitting scenarios of multi-objective energy-efficient historic building under different national goals integrating energy simulation, reduced order modelling and NSGA-II algorithm. Building Simulation. *Tsinghua University Press*, 17(6), 933-954. https://doi.org/10.1007/s12273-024-1122-9 .

Wasim M, Vaz Serra P, Ngo T D. (2022). Design for manufacturing and assembly for sustainable, quick and cost-effective prefabricated construction–a review. *International Journal of Construction Management,* 22(15), 3014-3022. https://doi.org/10.1080/15623599.2020.1837720 .

Yan B, Hao F, Meng X. (2021). When artificial intelligence meets building energy efficiency, a review focusing on zero energy building. *Artificial Intelligence Review*, 54(3), 2193-2220. https://doi.org/10.1007/s10462-020-09902-w .

Ye Y, Hinkelman K, Lou Y, Zuo W, Wang G, Zhang J. (2021). Evaluating the energy impact potential of energy efficiency measures for retrofit applications: A case study with US medium office buildings. Building simulation. *Tsinghua University Press*, 14(5),1377-1393. https://doi.org/10.1007/s12273-021-0765-z .

Zekić-Sušac M, Has A, Knežević M. (2021). Predicting energy cost of public buildings by artificial neural networks, CART, and random forest. *Neurocomputing,* 439(1), 223-233. https://doi.org/10.1016/j.neucom.2020.01.124 .