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A novel smart framework for optimal design of green roofs in buildings conforming with energy conservation and thermal comfort

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ABSTRACT

The rise in greenhouse gas emissions in cities and the excessive consumption of fossil energy resources has made the development of green spaces, such as green roofs, an increasingly important focus in urban areas. This study proposes a novel smart energy-comfort system for green roofs in housing estates that utilises integrated machine learning (ML), DesignBuilder (DB) software and Taguchi design computations for optimising green roof design and operation in buildings. The optimisation process maximises energy conservation and thermal comfort of the green roof buildings for effective parameters of green roofs including Leaf Area Index (P1), leaf reflectivity (P2), leaf emissivity (P3), and stomatal resistance (P4). The optimal solutions can result in a 12.8% increase in comfort hours and a 14% reduction in energy consumption compared to the base case. The ML analysis revealed that the adaptive network-based fuzzy inference system is the most appropriate method for predicting Energy-Comfort functions based on effective parameters, with a correlation coefficient greater than 97%. This novel smart framework for the optimal design of green roofs in buildings offers an innovative approach to achieving energy conservation and thermal comfort in urban areas.

1. Introduction

The buildings and construction sector continue to consume increasing amounts of energy, accounting for nearly one-third of total energy consumption and around 15% of direct greenhouse gas (GHG) emissions in recent decades [31]. Hence, energy efficiency in the building industry has become a crucial focus, with passive design parameters playing a significant role in reducing emissions.

Passive techniques have been proposed to reduce energy consumption and GHG emissions, including strategies that use ambient cooling sinks, such as building materials[47]. Passive cooling strategies refer to those that provide thermal comfort without using electricity and include three approaches: (a) protection, (b) modulation of heat gain, and (c) heat dissipation[20]. These strategies not only save energy but also improve occupants' comfort [5]. Heat protection by microclimate is an efficient strategy that can be achieved through in-house greening, such as green roofs, green walls, green balconies, sky gardens, and indoor sky gardens[53]. Other protection strategies control direct radiation penetration by modifying the aperture direction, such as shading devices, or by decreasing transmitted radiation intensity, such as using window glazing[25]. Modulation of heat reduces solar gain by utilising thermal mass and properties of building materials to store or remove heat, for instance, by integrating phase change materials in the envelope. Finally, heat dissipation strategies reject unwanted heat to environmental heat

Abbreviations: AI, Artificial intelligence; GHG, Green House Gases; ANN, Artificial Neural Network; Hl, Heating load; ANFIS, Adaptive Network-Based Fuzzy Inference System; HVAC, Heating, Ventilation, and Air Conditioning; ASHRAE, American Society of Heating, Refrigerating and Air-Conditioning Engineers; INFONAVIT, Institute of the National Housing Fund for Workers; AU-CO, Author by Country; LAI, Leaf Area Index; BPNN, Back-Propagation Neural Networks; ML, Machine Learning; CTF, Contrast Transfer Function; PMV, Predicted Mean Vote; Cl, Cooling Load; RENO, Regularised Numerical Optimization; DB, DesignBuilder; RF, Random Forests; DE, Frequency distribution; RMSE, Root mean Squared Error; Et, Total Energy; SLR, Stepwise Linear Regression; EPW, Energy Plus Weather; S/N, signal-to-noise ratio; FL, Fuzzy Logic; SDG, Sustainable Development Goals; FS, Fuzzy System; UTI, Urban Heat Island; Genfs2, cluster-based generation of FS; SO, Source Outputs; GA, Genetic Algorithm; SVM, Support Vector Machine.

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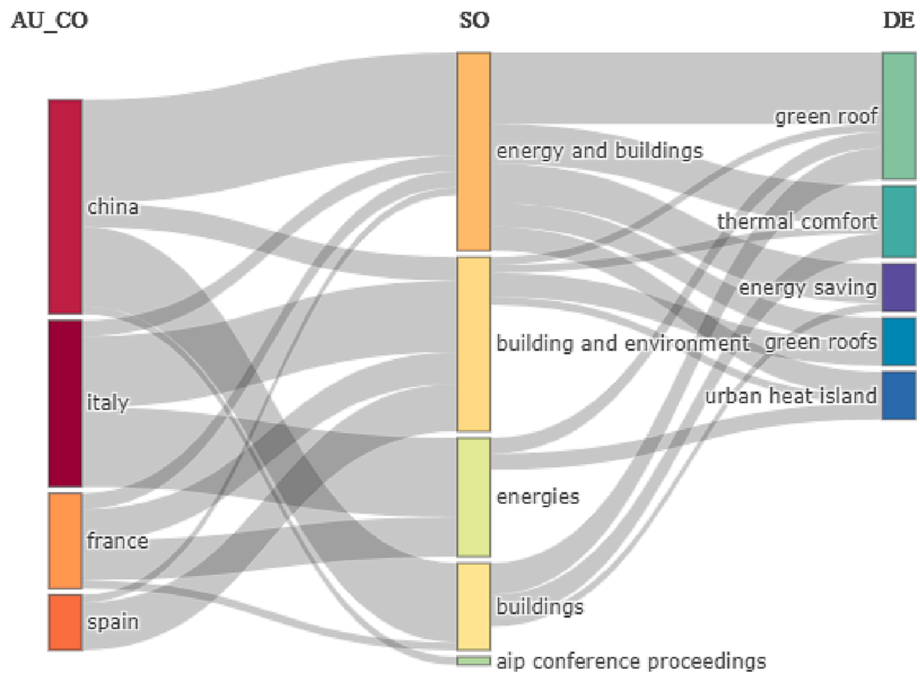

Fig. 1. Sankey diagram for green roof technologies based on Bibliometric toolbox. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

sinks, such as air and water.

The concept of green roofs, also known as living roofs, is an excellent example of a passive strategy that can improve energy efficiency of buildings and ambient air quality[6]. In urban areas, the lack of vegetation significantly contributes to the Urban Heat Island (UTI) effect, which can increase thermal stress and discomfort for occupants[7]. Green roofs can help reduce the impact of UTI by providing various vegetation growth on building envelopes and increasing the greenness index of cities [33]. Additionally, due to their ability to absorb solar radiation, green roofs contribute to the Green City Index, which measures 30 factors related to the performance indicators of cities, including emissions intensity, energy consumption, air quality, and green land use policies[27].

Developing green roof systems can help achieve two of the main Sustainable Development Goals (SDGs): sustainable cities and communities, and climate action (Sustainable development, 2022). Green roofs can contribute to decreasing energy consumption in buildings by reducing temperatures in internal spaces, absorbing CO_2, and reducing carbon emissions. In fact, green roofs can directly capture CO_2 and improve air quality through photosynthesis in leaves, as well as indirectly reduce greenhouse gas (GHG) emissions by decreasing energy demand through reducing building temperature and radiation absorption of surfaces [40]. For example, a study conducted by Seyedabadi et al. [58] found that three types of plants can reduce emissions by directly absorbing 0.14, 2.07, and 0.61 kg/m^2 of CO_2 annually, and indirectly reducing emissions by further amounts of 28.2, 26.5, and 23.4 kg/m^2 per year, respectively, by decreasing energy demand. In addition to reducing carbon emissions, green roofs can also reduce N_2O emissions by around 0.03 kg/m^2 (equal to 298 kg-equivalent of CO_2)[12]The type of vegetation growing on the green roof, based on climatic conditions, is a key parameter with a major impact on the performance of green roofs [58]. The roof envelope can accommodate a wide range of plant forms, depending largely on the depth of the layer and cooling and heating load demands[24,44].

Plants suitable for green roofs share several key characteristics, including Leaf Area Index (LAI), shading capacity, density, emissivity, reflectivity, and moisture transportation rate. Typical green roofs require at least 0.20 m of substrate to support vegetation[14]. Research has shown that these parameters are essential for improving building performance for energy and GHG emissions. For instance, Berardi [7] found that increasing LAI in a green roof can reduce outdoor temperature by up to 0.4 °C during the day, with a more significant temperature reduction at the rooftop level. He et al. [28] confirmed these results through experimental evaluation and showed that green roofs can achieve a reduction of 3.6% and 6.2% in cooling and heating loads, respectively.

Using computing and data-mining technologies allow for better analysis to determine the efficient impact of green roof parameters, which are difficult to solve using traditional numerical and mathematical strategies[30]. For example, Tsang and Jim [64] incorporated Artificial Intelligence (AI) in green roof irrigation efficiency management by integrating Genetic Algorithm (GA), Artificial Neural Network (ANN), and Fuzzy Logic (FL) to reduce irrigation water consumption. Furthermore, the ANN method gains information by comparing simulation data against real data in supervised learning, whereas no labelling is required for unsupervised learning [37]. The FL method is utilised to facilitate the learning process by setting the weights of the neural network during learning, using input–output pairs through a back-propagation algorithm. This method can be applied to predict indoor thermal comfort levels based on various input variables, such as outdoor weather conditions, green roof water content, and indoor air temperature and humidity levels. Lin et al., [42] integrated four Machine Learning (ML) prediction models into a passive house with green roofs and demonstrated energy consumption reduction of up to 34.8%. These ML methods include Stepwise Linear Regression (SLR), Back-Propagation Neural Networks (BPNN), Support Vector Machine (SVM), and Random Forest (RF) models. Additionally, Arab et al., [3] employed CCD-RSM and ANFIS methods to predict and optimise the Coagulation and Flocculation Process (CFP) for the highest removal efficiency of water turbidity.

The literature review conducted in this study by using a Bibliometric toolbox via the R software shows a significant amount of research on green roofs, with a strong focus on energy and comfort. More specifically, based on the input data collected from the Scopus databank, the Sankey diagram shown in Fig. 1 indicates three categories of author by country (AU-CO), source outputs (SO) and frequency distribution (DE).

Table 1
Recent studies related to the impacts of the plant parameters on the performance of green roofs.

Parameter	Climate	Findings	Reference
Thermal behaviour of different species	Mediterranean	Decrease the building energy use for heating by about 11% and the energy for cooling by 19%.	[35]
Irrigation time of 5 species	Semi-warm sub-humid	Aeonium Subplanum need to be irrigated every 9 days.	[16]
LAI and stomatal resistance	Mediterranean	18% reduction in primary energy demand.	[1]
LAI			90
LAI	Humid continental	Reduce total energy demand by 3.7%	[10]
LAI, vegetation coverage ratio, and the substrate thickness	Temperate	High LAI and low stomatal resistance reduce maximum temperature	[52]
Plant reflectance and emittance	Mediterranean	Decrease indoor temperature by 6 °C in the summer, while increasing it by 3 °C in the winter.	[13]

As can be seen in the AU-CO, majority of research works often conducted mainly in four countries (i.e., China, Italy, Spain, and France) while their source outputs (SO) are from journal of energy and buildings, and energies. However, there are still some knowledge gaps, such as the selection of suitable vegetation based on their properties and their impact on human comfort. Additionally, there is a lack of a smart framework to identify the most effective parameters for green roof schemes, despite such frameworks being available for other applications such as biogas energy [59]and bio-recovery in urban waste management[60].

In addition, the performance of green roofs relies heavily on the selection of appropriate vegetation, which is critical in achieving the desired environmental benefits[63]. Recent studies have identified key factors that affect the energy balance and performance of green roofs in different climates, including Leaf Area Index (LAI), Leaf Reflectivity, Leaf Emissivity, and Stomatal Resistance. These factors can be used as parameters in green roof design, with higher LAI values enhancing cooling and reduce runoff, an increased leaf reflectivity, lowering surface temperatures and reducing energy consumption [23]. Leaf emissivity and stomatal resistance also play crucial roles in the water use efficiency and thermal regulation of green roofs [3].

To optimise the performance and environmental benefits of green roofs, it is essential to carefully choose appropriate vegetation and consider key factors during the design phase. Previous studies as summarised in Table 1 gives an overview of recent findings on the factors affecting green roof performance in different climates. However, they have had no focus on identifying the maximum performance of green roofs for the optimum combination of these parameters.

To fill the knowledge gap in previous research, this study will use an AI-based prediction method with machine learning to determine the most effective parameters for plant species used in green roofs taking into account energy savings and comfort improvement in residential buildings specifically in a semi-arid climate where minimising irrigation is crucial. The study will focus on identifying the most sensitive values of the key factors that affect the energy balance and performance of green roofs, including LAI, leaf reflectivity, emissivity, and stomatal resistance. In addition to improving energy efficiency, the study also aims to enhance occupant comfort and increase cooling and heating load savings through the use of novel machine learning computations applied to green roof buildings. By identifying the most critical parameters for optimising energy efficiency in a semi-arid environment, this study will contribute to creating more effective and sustainable green roofs. This can also be valuable for engineers and landscape architects who aim to design effective living roofs that are tailored to specific climate and comfort conditions.

The structure of this study is as follows: the methodology is first presented in the next section including simulation specifications, statistical optimisation methods, and machine learning computations. The case study is then introduced in section 3 and the results of the suggested methodology are then presented in Section 4 followed by conclusions by drawing key findings and remarking notes with recommendations and future works.

2. Methodology

This study proposes a smart framework for the optimal design of green roofs in buildings. The framework consists of three steps, as shown in Fig. 2. In Step 1 (S1), four objective functions related to optimising energy conservation and comfort level in buildings are defined. In Step 2 (S2), the effective parameters of the green roof, including key features of the plants and their allowable bounds taken from literature, are defined. The Taguchi method is used for the design of experiments to evaluate the

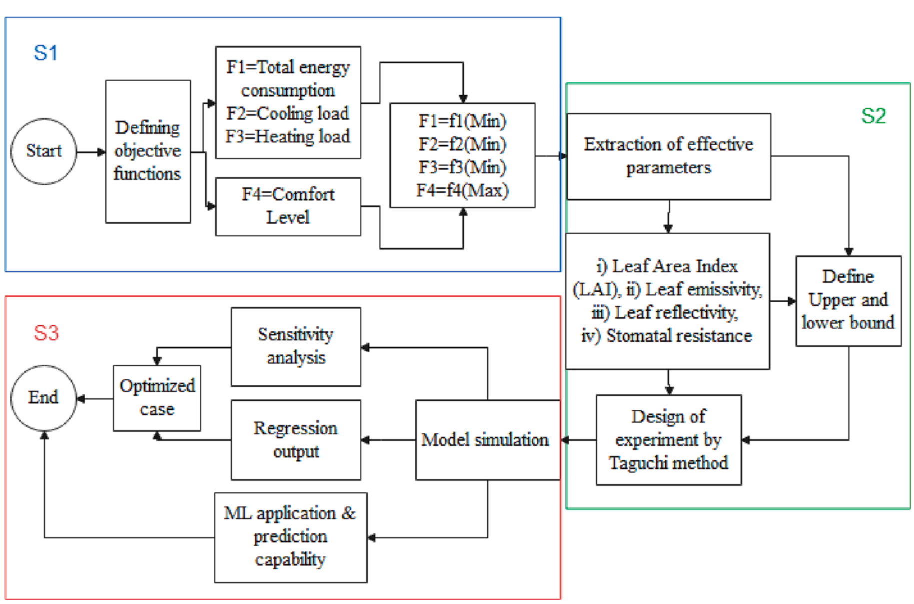

Fig. 2. The flowchart of the methodology in this study.

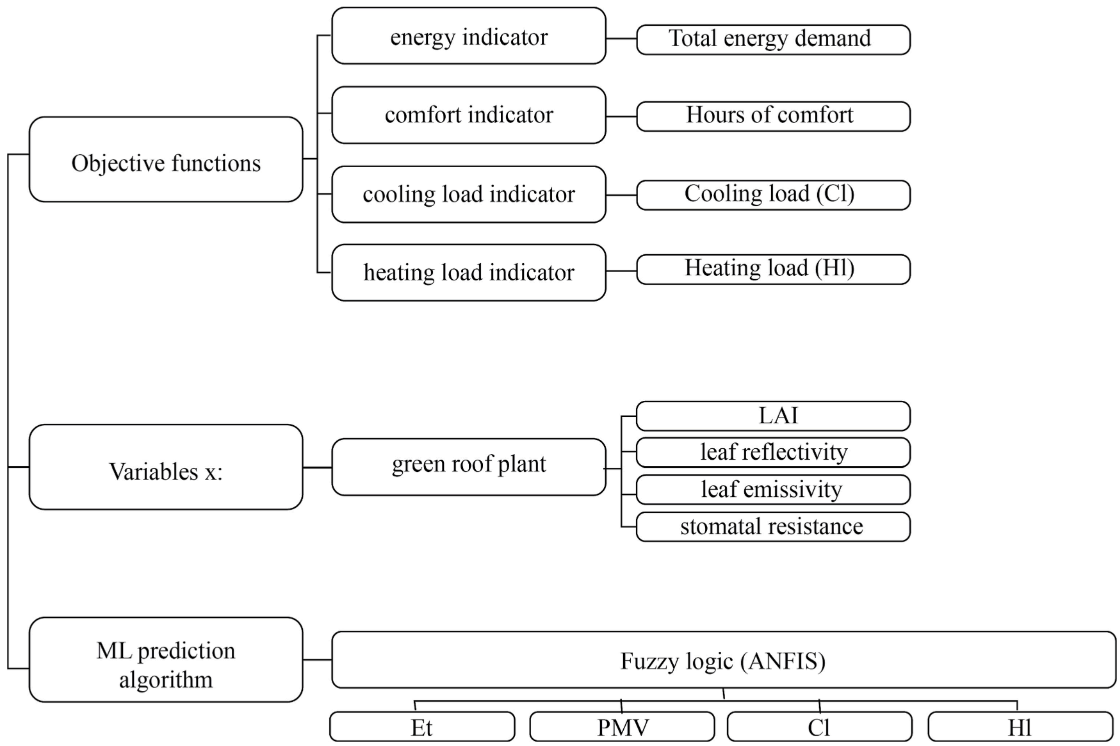

Fig. 3. Main components of the optimisation model for optimal design of green roofs in buildings: objective functions, decision variables and ML prediction model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Typical plants with their LAI index for green roof design.

Plant descriptions	LAI
White flowers, spider lily	3.07
Pink flowers	4.95
Yellow green leaves	3.75
Dark green long blades of leaves/grass	5.82
Tree	1.69

energy performance and calculate the thermal comfort in buildings. The settings for various compositions of the effective parameters are specified using this method. In Step 3 (S3), a simulation model is developed using DesignBuilder (DB) software and predictive machine learning models for the design of the green roof. The DB tool is also used for sensitivity analysis and regression output to obtain the optimal design of green roofs.

In this study, a ML approach using MATLAB was employed for confidence evaluation as a surrogate for the DB tool to develop a predictive model for performance assessment of green roof technologies based on their effective parameters. Specifically, the Sugeno FL method was used to extract the effective parameters, which were then fed into the Adaptive Neuro-Fuzzy Inference System (ANFIS). The Sugeno FL method is a fuzzy if-then rule method that outputs crisp (non-fuzzy) values. On the other hand, ANFIS is a hybrid learning algorithm that combines the decision-making and reasoning capabilities of fuzzy logic with the learning and adaptation capabilities of neural networks. Once the effective parameters are extracted using the Sugeno Fuzzy method, ANFIS can refine the fuzzy rules based on the input–output training data to improve the accuracy and effectiveness of the fuzzy inference system.

The four objective functions defined in step 1 are to minimise the total energy consumption (F_1), cooling load (F_2), heating load (F_3) and maximise comfort level (F_4) when designing a green roof in buildings. Note that the heating load (F_3) is calculated based the zone load within the winter and the cooling load (F_2) is the zone load in the summer in buildings. Hence, these two functions are calculated based on the difference between indoor temperature (T_{in}) and set-point temperature (T_Z) as:

$$Q_{sys} = m_{sys} \times C_{p,air} \times (T_{in} - T_z) \tag{1}$$

where Q_{sys} is the zone demand and m_{sys} is the air flow rate. If the system is active (HVAC), the sign of the zone load is used to determine whether heating or cooling is required. Total energy is then calculated based on the sum of the annual cooling and heating loads as:

$$Q_{tot} = Q_{heating} + Q_{cooling} \tag{2}$$

The comfort level function (F4) is expressed as the total hours of comfort per year in which occupants experience thermal comfort in the building, and is measured in this study using the PMV (Predicted Mean Vote) index suggested by the ASHRAE method [2], which is calculated as:

$$PMV = \left(0.303 \times 10^{-0.036M+0.028}\right) \times (H - L) \tag{3}$$

where PMV is thermal sensation scale in hour based on total energy loss from human (L) derived from their metabolic rate (M), and H is the human internal heat production rate. Hence, the four optimisation functions can be calculated as follows: 1) total energy saving (kWh/m^2), 2) improvement in occupants' comfort level based on PMV index (hours per year), 3) reduction in cooling load (kWh/m^2), and 4) reduction in heating load (kWh/m^2) as presented in Fig. 3.

2.1. Key parameters influencing vegetation in green roofs

This study considers four key features of vegetation for the optimal design of green roofs: Leaf Area Index (LAI), Leaf Reflectivity, Leaf Emissivity, and Stomatal Resistance. The optimal values of these parameters are critical in selecting suitable plant species for green roofs. The upper and lower limits of these parameters are defined based on the literature and used in the optimisation process. LAI is a dimensionless

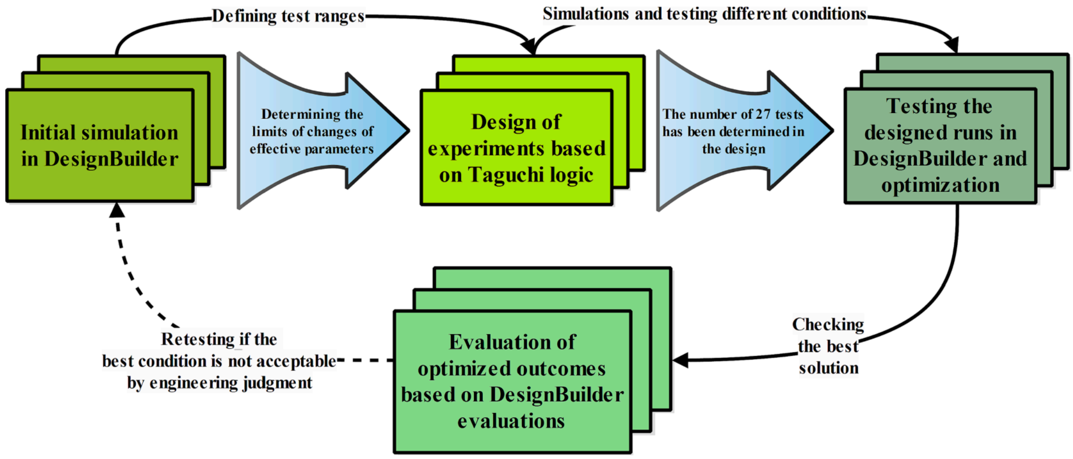

Fig. 4. The structure of optimisation algorithm in this study.

Table 3
Range of effective parameters (low, average and high limits) obtained from the Taguchi method.

Parameters	1	2	3
LAI	1.69	3.75	5.8
Leaf reflectivity	0.1	0.25	0.4
Leaf emissivity	0.8	0.9	1
Stomatal resistance	50	175	300

measure of projected leaf area per unit of soil surface. Table 2 presents the LAI values for five typical plants, ranging from 1.69 for trees to 5.8 for dark green leaves/grass, which are considered for green roof design [66]. Leaf Reflectivity refers to the ability of the plant to reflect incident solar radiation, including the visible spectrum, infrared, and ultraviolet wavelengths, within a range between 0.1 and 0.4[49]. Leaf Emissivity, on the other hand, measures the ability of a leaf surface to emit thermal radiation ranging from 0.8 to 1[26]. Finally, Stomatal Resistance is the resistance to gas exchange (carbon dioxide and water vapor in the air) through stomata, which are small openings on the surface of leaves and stems of plants. Stomatal resistance allows for gas exchange between plants and the atmosphere as an essential process for photosynthesis and water loss regulation through evapotranspiration, ranging between 50 and 300 s/m[55].

In addition to plant selection, substrate moisture is another crucial factor that can greatly impact energy conservation and thermal comfort [50]. Once the plants have been selected, soil moisture sensors can be installed at various depths throughout the green roof to measure the moisture content of the substrate. These sensors can provide real-time data on substrate moisture levels which can inform irrigation schedules and other maintenance practices for the green roof.

2.2. *Optimal design of green roofs*

The selection of an optimisation method for experimental and simulation processes depends on various factors, including simulation run time and the desired level of complexity[34]. In this study, the Taguchi method was deemed appropriate due to its ability to produce logical and efficient answers with a smaller number of tests, simple calculations, and uncomplicated implementation principles [18]. Furthermore, compared to evolutionary or metaheuristic optimisation methods, the Taguchi method requires lower computational costs when the limits of the variables in the optimisation model are known[34]. However, it should be noted that the use of evolutionary optimisation methods, such as genetic algorithms, is generally more suitable when the optimisation model is connected to the simulation or modelling system and data is sent in parallel in each iteration. In many cases, this parallel computation between simulation and optimisation models can be challenging, especially if the simulation models are commercial and non-open-source, as in this study where the DesignBuilder tool was used. Therefore, the use of optimisers that are independent from the simulation system may need to be considered.

Fig. 4 illustrates the process flow of the optimisation algorithm based on the Taguchi method used in this study. The initial step of the process involves determining the bounds of the simulation tests that will be conducted for the case study. Next, the Taguchi model is employed in the Minitab software to design the tests, resulting in 27 tests being recorded and analysed in the DesignBuilder software. After conducting the optimisations using the statistical method provided by the Taguchi model, the optimal mode is assessed in DesignBuilder based on engineering judgment. If the solution is deemed acceptable, it is selected as the best answer and deemed the optimal solution.

2.3. *Taguchi model for design of experiment*

The Taguchi method is being used to optimise the green roof design by identifying the key design parameters and finding the best values for those parameters using statistical methods. This method involves testing different combinations of input parameters and evaluating the corresponding output variables to minimise variation in the parameters. The Taguchi method is preferred in this study due to the multiple experiments required to simulate and evaluate all effective parameters of green roof design in buildings. By using an orthogonal arrays design matrix, the number of compositions of effective parameters is reduced, and the optimum level of each parameter can be found with minimum simulation efforts. Table 3 shows the range of effective parameters for semi-arid climate conditions, which are evaluated within three levels of low, average, and high limits. The Taguchi method has been previously used for assessing building components for energy efficiency [54]and thermal comfort[41], and it is advantageous because it obtains the most information with minimum simulation efforts.

The signal-to-noise ratio (S/N) was used in this study to evaluate the deviation of parameters from the desired values and determine the optimal range. The nominal value was used as the benchmark for achieving energy savings and comfort hours in buildings. A larger S/N ratio indicates a smaller effect of the noise factor. To confirm the optimised range of effective parameters, a verification simulation run was performed through parametric design. The number of compositions for the three levels of the four effective parameters in Table 3 is equal to 81 ($=3^4$), but the Taguchi method was used to reduce this number to 27 compositions of effective parameters based on the standard orthogonal array, as listed in Table A1.

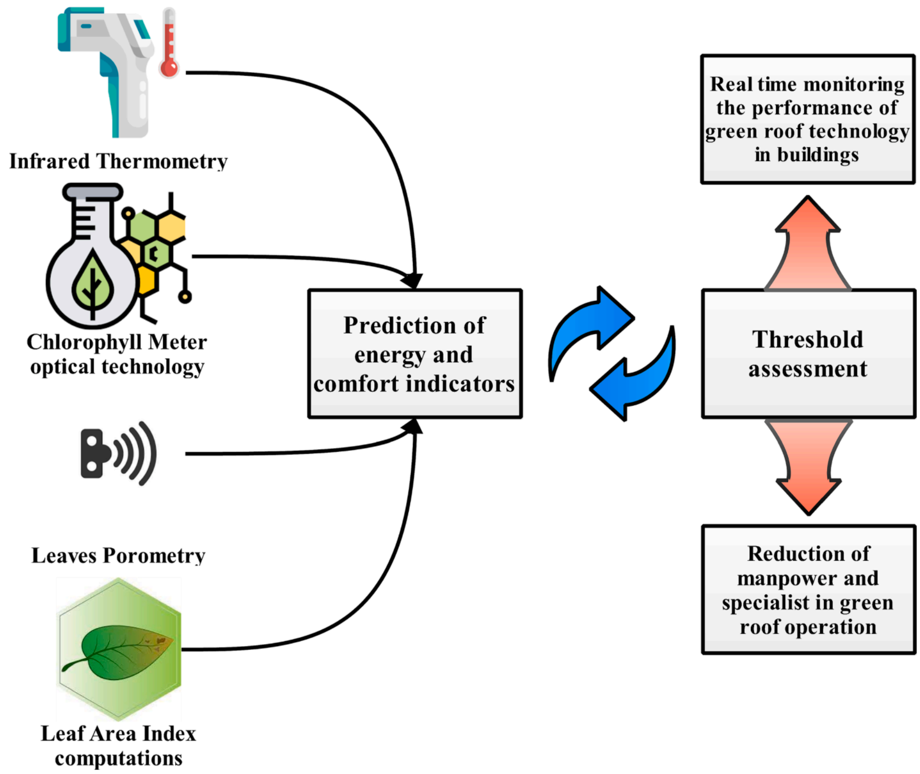

Fig. 5. The structure of AI application in the sensor-based system in this study.

2.4. Model simulation for performance assessment

This study evaluates the energy performance, heating/cooling load, and occupant comfort level of a common Mexican residential building with typical local construction materials using different combinations of effective parameters. To perform this evaluation, we used DesignBuilder V.60.1.19, which is a software tool that incorporates the EnergyPlus engine for building energy modelling, following the ASHRAE standard [2]. To assess the impact of using different vegetation types on green roofs, we employed energy modelling as a reliable method to calculate and compare the effects on energy use and occupant comfort conditions.

In addition, modelling green roofs allows for the analysis of long-wave and short-wave radiation exchange between plants, evaporation, and conduction of soil, as well as convective heat transfer. The energy balance equation for a typical green roof is primarily dominated by solar radiative forces, which are balanced by convection and evaporative heat flux from the plant and soil surfaces.

DesignBuilder's energy balance equation for the plant and soil layers is based on the 'Army Corps of Engineers' vegetation models[38]. The EnergyPlus "Green Roof" module provides designers with the ability to analyse various elements of a green roof, such as leaf area index (LAI), plant height, stomatal conductance (ability to collect moisture), and soil moisture conditions (irrigation). This allows for a comprehensive assessment of the energy and environmental impacts of different types of green roofs.

The simulation model calculates half-hourly temperatures and heat flows for each zone in order to determine the required cooling load to maintain the desired cooling temperature set points. To achieve this, the model employs the Contrast Transfer Function (CTF) module to solve the transient heat conduction equation. The temperature nodes for indoor and outdoor temperatures are used as inputs, while the calculated heat fluxes at external and internal surfaces, which have been tested for high accuracy, are used as the model output[15]. The comfort level is calculated based on ASHRAE [2] and EN16798 (2019) standards using the Fanger model, which consists of a seven-point thermal sensation scale called Predicted Mean Vote (PMV). The analysis takes into account all modes of energy loss for occupants, including convective and radiative losses from the body and clothing surface, as well as heat loss through respiration in steady state with the surroundings. In this study, the comfort range of $|PMV|$ greater than 0.75, as defined by the PMV index for residential buildings [2] (EN16798 2019), is considered the boundary value.

2.5. Machine learning for operation system

This study employs machine learning (ML) as an intelligent tool to estimate the energy functions of the operation system based on the effective parameters of the green roof. It also connects the DesignBuilder simulation, which is based on the design of experiments, with ANFIS method. This enables the estimation of energy parameters without requiring an expert to be present during the simulation.

The four effective parameters of the green roof can be measured in real-time, which enables the development of an automated operation system for green buildings using Artificial Intelligence (AI). The AI-based model developed in this study can eliminate the need for an expert to make or recalibrate a performance assessment model, and it can connect system sensors for detecting effective parameters (i.e., LAI, leaf reflectivity, leaf emissivity, and stomatal resistance) to an automated system for generating outputs and making immediate decisions by the operators or end-users. With the help of low-cost sensors, the operational features of the system can be controlled in a smart manner without the need for additional experimental and simulation practices.

Sensors commonly used to measure these parameters include Infrared Thermometry for leaf emissivity[17], Chlorophyll Meter for leaf reflectivity[19], and Leaves Porometry for measuring stomatal resistance[46]. These sensors have been found to have the highest correlation with the porosity of plants detectable with new Android-based technologies[43]. LAI can be easily calculated based on the ratio of one-

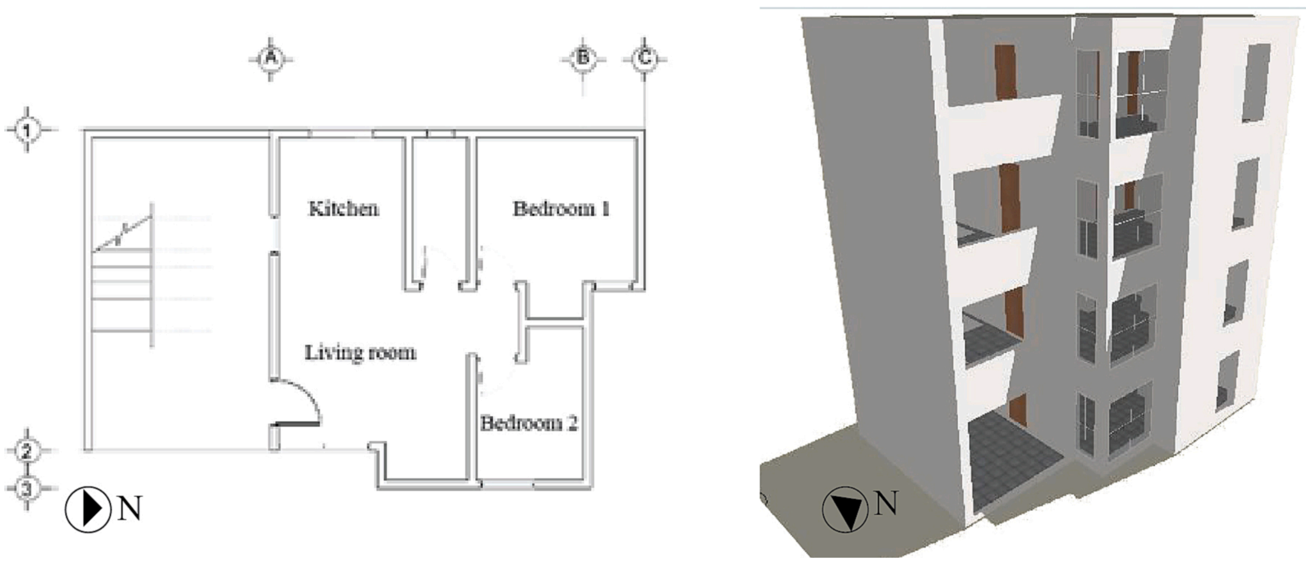

Fig. 6. Typical plan and perspective view of the case study building.

Table 4
Basic specifications of the building case study with their heating and air-conditioning settings.

Characteristics	Description
Orientation	Main façade facing west
Plan shape	Rectangle
Number of floors	4 floors
Floor to floor Height	2.7 *m*
Gross roof area	113 m^2
Window area	10.1 m^2
Type of glass	6 mm single glazed
Solar absorptance	0.5 for wall/0.6 for roof
Occupancy density	4 people
Infiltration	0.5 ACH
System type	Package DX
Thermostat setting	Cooling = 25 °C/Heating = 21 °C
Occupancy schedule (Time of use)	Weekdays (18:00 – 9:00 of following day)Weekend and holidays (00:00 – 24:00)
COP	2.5

sided leaf area to the ground area unit[67]. Fig. 5 presents the structure of the ML model for training, which is based on historical measurements taken from three sensors to estimate energy consumption and thermal comfort in real-time. Additionally, by setting threshold values for these parameters, abnormal measurements can be detected immediately within this structure.

The ANFIS-based predictive model can help in finding the optimal design of effective parameters in green roofs by assessing the nonlinear relationship between the comfort level and the performance of the four objective function indicators. The optimal values of the effective parameters can be obtained by considering the total energy consumption, cooling load, heating load, and comfort level index (PMV). The ANFIS calculator adjusts the function parameters by combining the least-squares method and backpropagation, and it trains the data using both ANNs and FL in a single framework. The fuzzy algorithms (Sugeno) are used to handle vague and imprecise data using the guss2mf function in MATLAB 2020 version. The ANFIS model has a 6-dimensional, multi-layered architecture that can accurately estimate the four objective functions associated with LAI, stomatal resistance, leaf emissivity, and reflectivity. Finally, it is worth noting that in the ANFIS model, percentage of energy saving (Et, CL, and HL) and comfort hours are considered as a target function.

3. Case study

The proposed methodology is illustrated through a case study on a typical residential building block, Popular B3, as depicted in Fig. 6. This building accommodates approximately 23.88% of the total Mexican population and is classified as a middle-income housing unit based on the average annual salary of its buyers with the details given in Table A2. Popular B3 is designed with a rectangular geometry of 6 m × 7 m and a height of 2.7 m for each story, comprising four detached levels as shown in Fig. 6. The building's features, including orientation, plan shape, number of floors, floor to floor height, gross roof area, window area, type of glass, solar absorptance, occupancy density, infiltration, system type, thermostat setting, occupancy schedule, and coefficient of performance, are provided in Table 4.

This building has been classified according to the Housing Registry Organisation (RUV, 2022) alongside other classes of residential buildings. The construction materials used in Popular B3 are based on the recommendations of the Institute of the National Housing Fund for Workers (INFONAVIT) for housing products in Mexico. These materials include a single brick wall with lightweight plaster, a concrete slab roof with plaster on the inner side, and single glazed windows.

The case study is located in Monterrey, the capital city of the Nuevo León state in Mexico. Monterrey has an annual electricity consumption rate of 2.4 TWh (McNeil et al., 2018) and is situated at an altitude of 515 m above sea level. The city has a semi-arid climate categorized as group "B" on the Köppen scale modified by García, falling within the subgroup "BSx" [22]. Monterrey has an average of 3,386 h in a year with a temperature more than 25 °C and the highest temperature on average is 35 °C. Monterrey experiences an average of 3,386 h per year with a temperature above 25 °C, with the highest average temperature being 35 °C. The average annual temperature (1981–2010) is 27.9 °C according to national meteorological information data. However, for simulation in this study, the weather data is based on the Energy Plus Weather (EPW) file, which provides a 25-year interval of average hourly data up to the year 2015. The EPW file indicates a maximum temperature of 35 °C in July and a maximum relative humidity value of 95% in September.

4. Results and discussion

The simulation results are presented in this section using Minitab 2019. The design of green roof is optimised based on heating and cooling loads and then predict and evaluate the comfort level of occupants. To

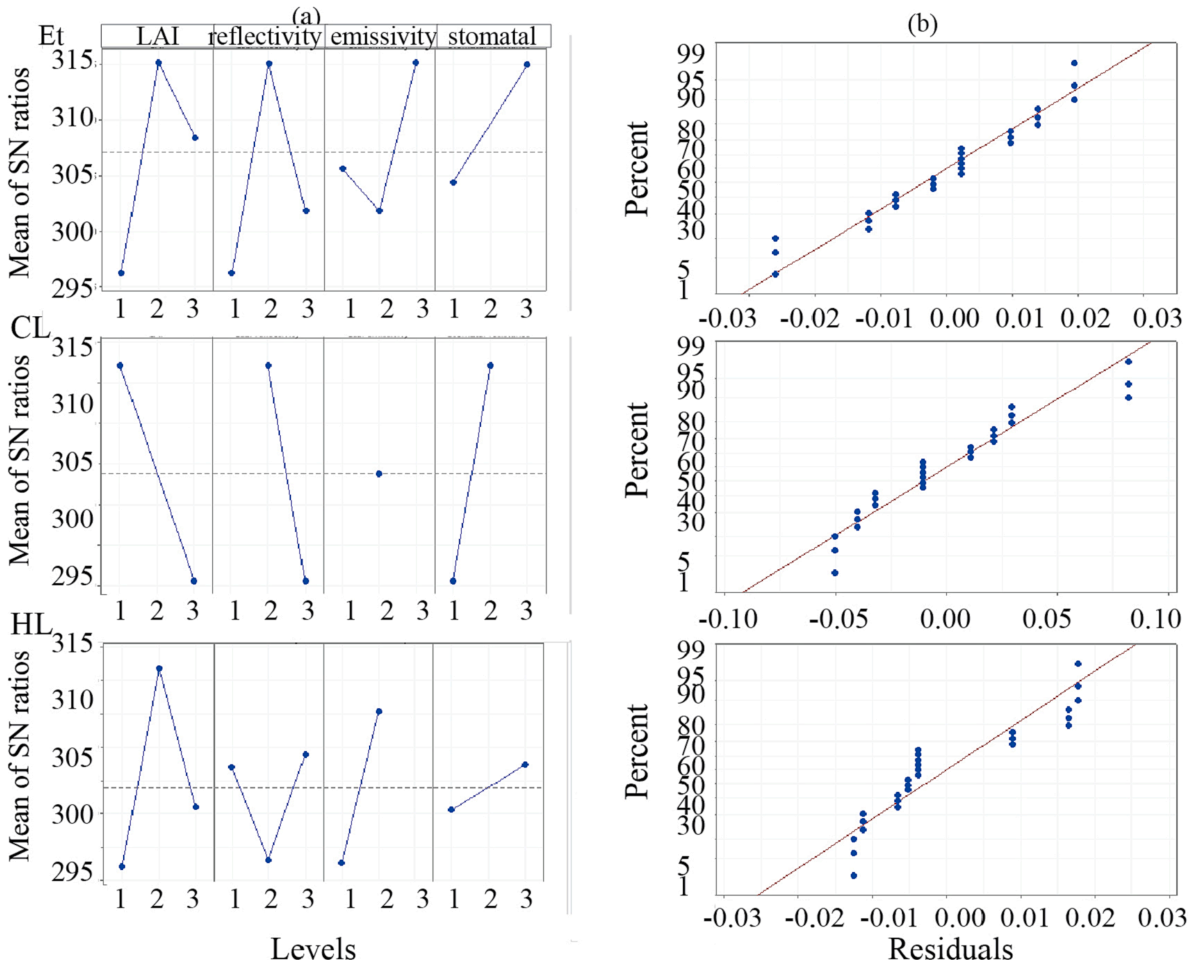

Fig. 7. Total energy reduction, cooling load reduction and heating reduction (kWh/m^2) plots (a) main effects plot for SN ratios (signal to noise ratio (10 × Log10(Y $\overline{Y}^2/s^2$)) | (b) normal probability plot.

Table 5
Optimum level of effective parameters for the best performance of objectives.

Parameter	LAI	Reflectivity	Emissivity	Stomatal resistance
Et	Level (2)	Level (2)	Level (3)	Level (3)
Cl	Level (1)	Level (2)	Level (2)	Level (2)
Hl	Level (2)	Level (3)	Level (2)	Level (3)
PMV	Level (2)	Level (1)	Level (1)	Level (1)

test the predictability of parameters, the most optimum values are reclassified using fuzzy membership functions. The accuracy of the fuzzy prediction model is also evaluated to present the optimum case along with its impacts on energy and comfort factors.

4.1. Optimisation of total energy, cooling and heating loads

The Taguchi design principles as described in section 2.3 were applied using the Minitab software to determine the minimum number of simulations needed to study a specific number of parameters at various levels. Using this approach, the 4 parameters with 3 levels identified in Table 3 were analysed for recommended 27 simulation runs using a L27 orthogonal array, which can provide comprehensive and balanced coverage of all potential factor combinations, enabling a robust analysis of the factors' impacts on the response variable.

Fig. 7a displays the average signal-to-noise ratio (S/N) in relation to total energy, cooling, and heating load indicators. Table 5 shows the optimum level of each effective parameter based on the S/N ratio to achieve the optimal indicators. The best performance of total energy (Et) is achieved when the LAI, reflectivity, emissivity, and stomatal resistance are equal to 3.75, 0.25, 1, and 300, respectively. Also, in cooling load target function, the optimum condition can be seen in LAI = 1.69, reflectivity = 0.25, emissivity = 0.9, and stomatal resistance = 175. Finally, the heat load optimisation can be obtained when LAI, reflectivity, emissivity, and stomatal resistance are equivalent to 3.75, 0.4, 0.9, 300, correspondingly. Significant degree of parameters in each function (E(t), CL, and HL) is determined as per slope of lines in each category. Therefore, in E(t) function, the maximum effects are related to LAI and reflectivity. While, according to CL, the most effects are linked to reflectivity and Stomatal. Whereas HL is affected by emissivity and LAI more than other features.

The normal probability plots for the three performance indicators in Fig. 7b suggest that all indicators, i.e., total energy (Et), heating load (HL), and cooling load (CL), are distributed relatively close to a Gaussian (normal) distribution with only minor deviations from a straight line. Although Et has a better distribution than the other two to the normal distribution function, this also indicates that the approach captures the underlying patterns in the data reasonably well for the Gaussian distribution in modelling the performance indicators. Regression equations to calculate the indicators based on these four variables are expressed as mathematical models presented in Eq. A (1–4). The selection of settings (limits) for effective parameters is based on the maximum saving in Et, CL, HL, and maximum improvement in PMV index as shown in Table 5.

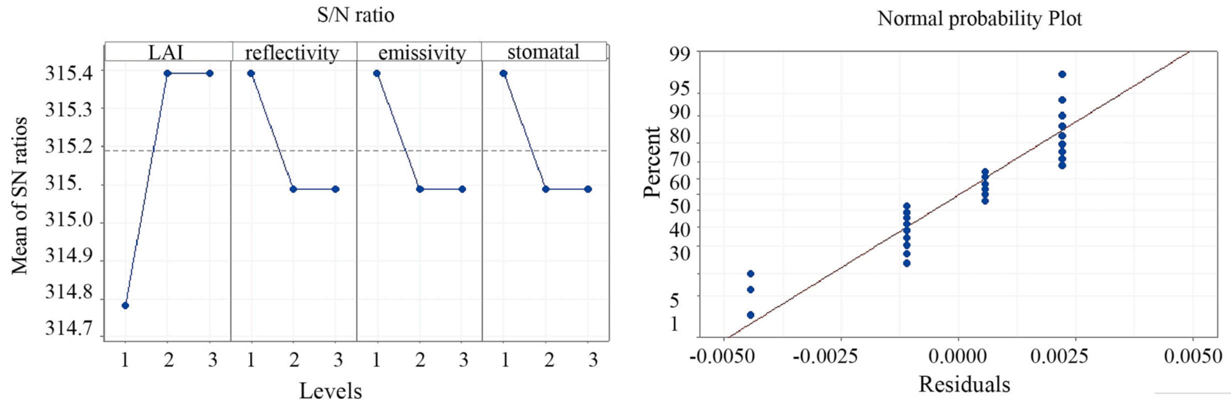

Fig. 8. Comfort improvement with 85% comfort level plots: Main effects plot for SN ratios (signal to noise ratio (10 × Log10(Y $\overline{Y}^2/s^2$); where s is the standard deviation of the noise, and Y is the mean signal), Normal probability plot.

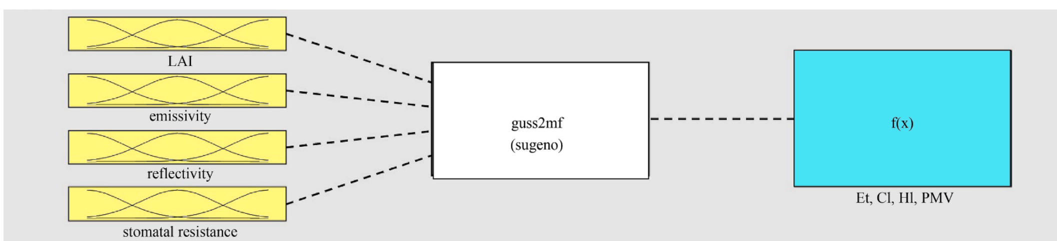

Fig. 9. Fuzzy inference system with three inputs.

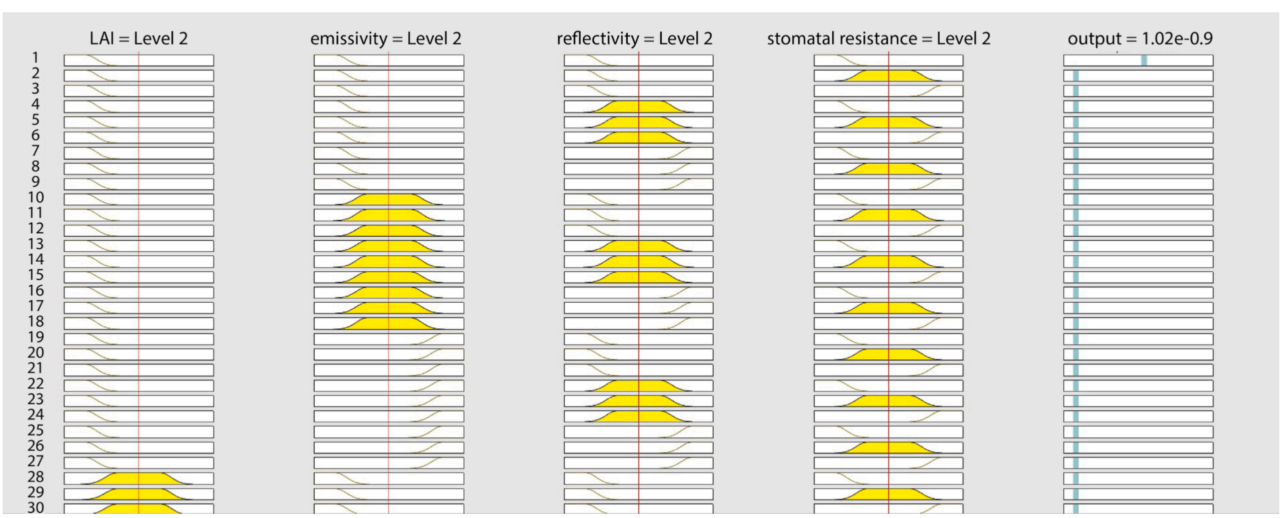

Fig. 10. ANFIS rule structure for Et as a target of this study.

4.2. Optimisation of comfort level

The building's occupants' comfort level was evaluated based on the number of hours in a year, with a range of 8,760 h annually, to measure improvements per hour in the room.

Fig. 8a indicates that LAI has a higher impact than stomatal resistance, leaf reflectivity, and emissivity in improving comfort. However, Fig. 8b shows that predicting the comfort level is more critical compared to other parameters due to its characteristics, such as metabolic rate, radiative and temperature. The outcomes demonstrated that the optimum condition can be provided when LAI = 0.75, reflectivity = 0.1, emissivity = 0.8, and stomatal resistance = 50. As a result, the normal plot is not normally distributed, and the real values are far from the prediction.

4.3. ML prediction

Simulated data with the effective parameters of Et, Cl, Hl, and PMV were used in MATLAB 2020 to train a ML model using Sugeno Fuzzy System (FS). This approach develops a systematic approach to generate fuzzy rules from an input–output dataset of a simulated case, as shown in Fig. 9. There are three commonly used methods for generating the layer clustering process: Regularised Numerical Optimisation (RENO), ANFIS, and the cluster-based generation of FS (genfs2). This study selected ANFIS for all four input variables (i.e., LAI, leaf reflectivity, leaf emissivity, and stomatal resistance) to generate output variables (i.e., comfort hours, total energy, cooling and heating loads).

The model uses two types of ANFIS Membership Functions (MF) –

Table 6
Regression statistics during machine learning computations in this study.

Effective features	R-square	RMSE	Standard error
Et	0.99	3.43E-17	7.04E-18
Cl	0.99	3.10E-1	9.79E-18
Hl	0.97	6.00E-3	6.00E-3
PMV	0.99	6.00E-3	2.26E-5

Gaussian curve and Gaussian combination MF – for each input variable. The hybrid learning algorithm is applied to train the model for 30, 60, 60, and 90 epochs for Et, Cl, Hl, and PMV, respectively. The ANFIS rule structure provides a visual representation of the fuzzy inference rules that have been learned after the training process. This makes it easy to interpret and understand how the input variables are mapped to the output variable. The majority of the rules are "and-rules," indicating that all parts of the rule must be fulfilled cumulatively for the output to be

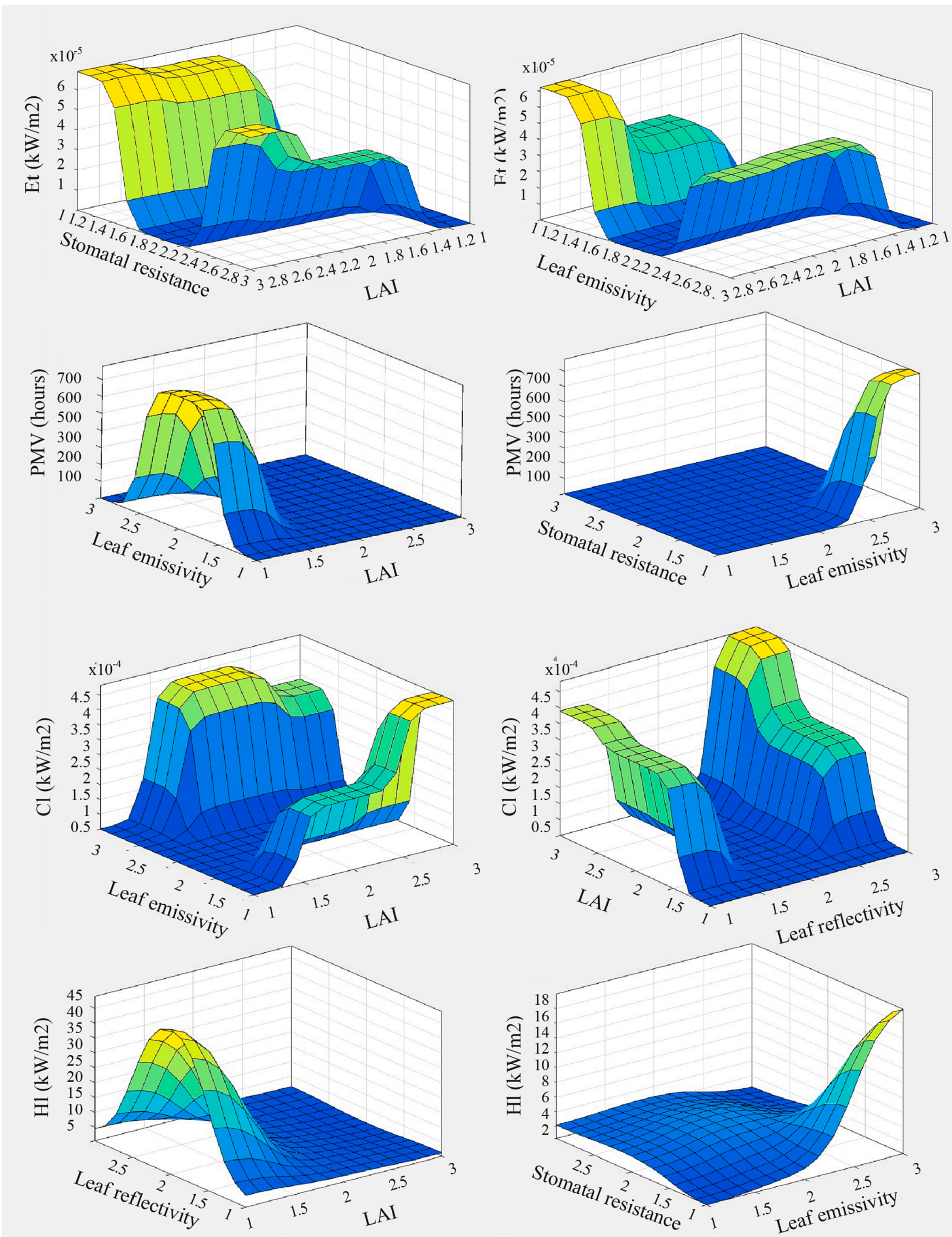

Fig. 11. Predicted ANFIS relationships between combinations of green roof parameters and building performance i.e., comfort (PMV), total energy (Et), cooling load (Cl) and heating load (Hl). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

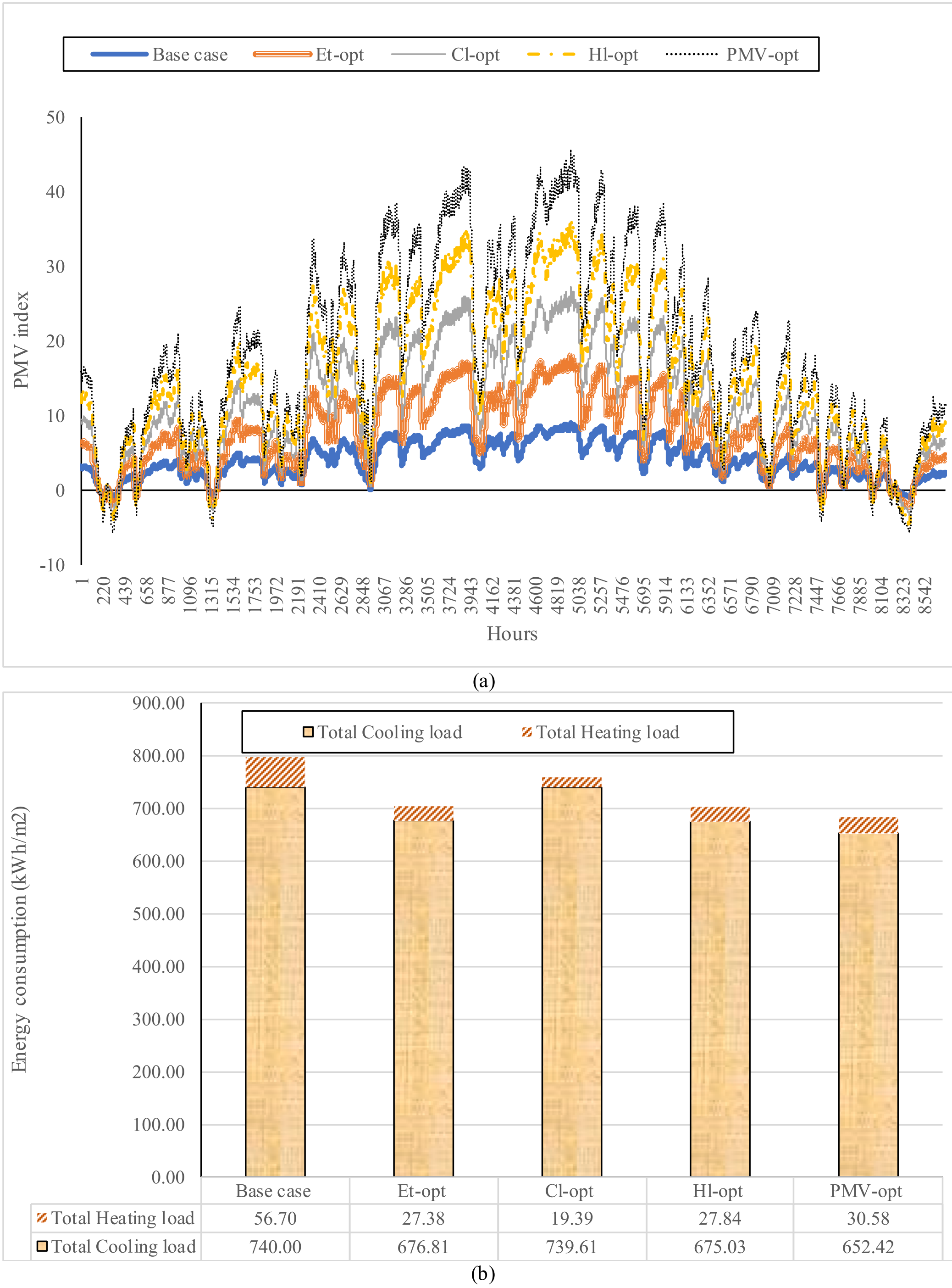

Fig. 12. Comparison analysis of optimised case simulation based on 4 parameters of total energy, cooling load, heating load and comfort level (a) annual comfort hours, (b) proportion of CL to HL compared to total energy.

Table 7
Optimised case simulation outputs based on four different parameters.

Variable	Et-opt	Cl-opt	Hl-opt	PMV-opt
Total energy reduction (kWh/m^2)	92.5	37.7	93.8	113.7
Total hours of comfort	876	781	880	873

accepted. This is a common approach in fuzzy logic systems, ensuring that the output is based on a comprehensive evaluation of all input variables.

Fig. 10 displays the rules for the ML process based on variation

Table 8
Examples of plant species in Mexico with their approximate values [62].

Vegetation	LAI	Leaf reflectivity	Leaf emissivity	Stomatal resistance
Sedum spurium	1.25	0.5	0.77	150
Sempervivum tectorum	0.7	0.4	0.67	190
Opuntia Ficus-indica	2.75	0.6	0.8	115
Echeveria elegans	0.035	0.5	0.8	95

Table A1
The outcome of test design by the Taguchi model.

	LAI	Leaf reflectivity	Leaf emissivity	Stomatal resistance
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	2	2	2
5	1	2	2	2
6	1	2	2	2
7	1	3	3	3
8	1	3	3	3
9	1	3	3	3
10	2	1	2	3
11	2	1	2	3
12	2	1	2	3
13	2	2	3	1
14	2	2	3	1
15	2	2	3	1
16	2	3	1	2
17	2	3	1	2
18	2	3	1	2
19	3	1	3	2
20	3	1	3	2
21	3	1	3	2
22	3	2	1	3
23	3	2	1	3
24	3	2	1	3
25	3	3	2	1
26	3	3	2	1
27	3	3	2	1

Table A2
Residential building classification based on INFONAVIT.

Class	Segment	Minimum VSMM*	Maximum VSMM*	Residence level (%)	Average price
1	Economica	<118	118	2.4	$ 10,500
2.1	Popular B1	118	128	1.53	$ 12,400
2.2	Popular B2	128	158	16.77	$ 14,611
2.3	Popular B3	158	200	23.88	$ 18,047
3	Tradicional	200	350	33.37	$ 26,104
4	Media	350	750	18.95	$ 50,694
5	Residential	750	1500	2.89	$ 100,523

* Times the monthly minimum wage.

changes in target functions, using Et as an example of the four performance indicators. In this case, the rules for Et are used to explain the ANFIS logic in the present model, which is implemented as a smart system instead of relying on expert simulation practices. The rules for ANFIS computation are based on the IF-THEN concept. Specifically, when a variable is changed, a large signal is transferred to the target function, and the variable is classified as an effective parameter (highlighted in yellow). By analysing the changes in the four factors during 27 runs, different rules can be established, with some having higher weights for estimation than others as can be seen in the figure. In simpler terms, the specified rules demonstrate the sensitivity of the target function to the input variables. Some of the records show the effective variables for prediction in the form of highlighted relational functions.

To evaluate the accuracy of the developed ANFIS model in predicting output values, we tested it using both training and testing data. Table 6 compares the statistical indicators by the ANFIS model for the four performance indicators: Et, CL, HL and comfort hours. The Table clearly shows that the output values generated by the ANFIS model fit the measurement data, indicating the good accuracy of the model in its predictions. This suggests that the developed ANFIS model can be a reliable tool for prioritising distribution centres based on multiple criteria. With the application of the smart calculations, green roofs can be operated in buildings without presence of expert persons. However, DB simulations need some expertise in the field of building, mechanics, and architecture for simulations and operations. While, the created

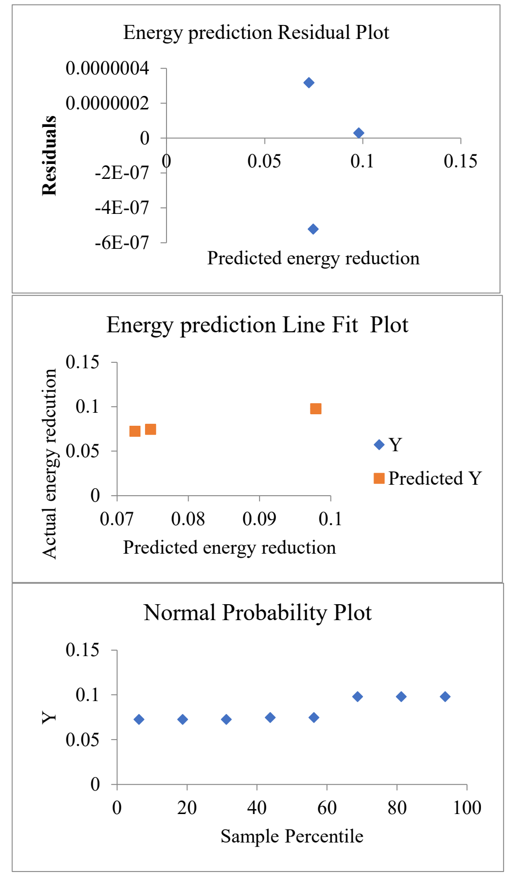

Fig. A1. ANFIS cross validation of energy reduction function model.

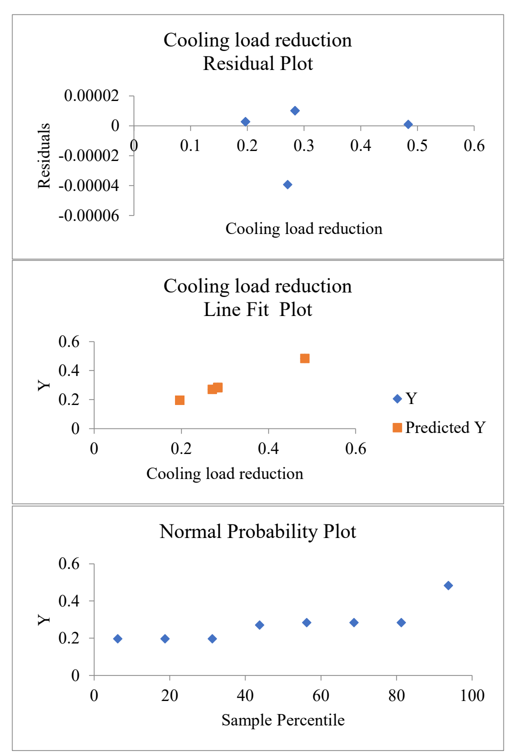

Fig. A2. ANFIS cross validation of cooling load reduction function model.

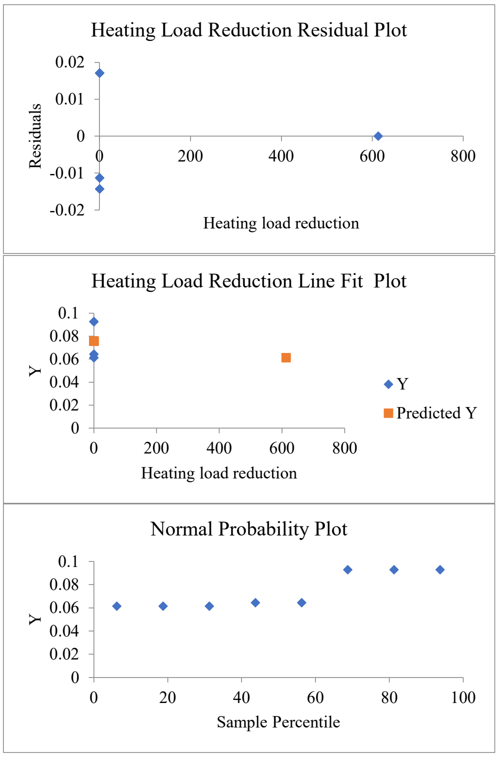

Fig. A3. ANFIS cross validation of heating load reduction function model.

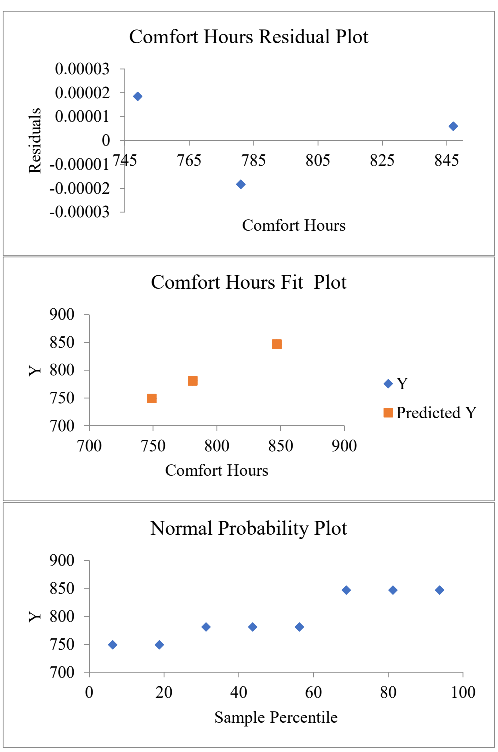

Fig. A4. ANFIS cross validation of comfort hour function model.

smart model is applied for prediction of energy and comfort level in each building as per AI and without consideration to fundamental engineering concepts.

Fig. 11 presents a sensitivity analysis of ANFIS that explores the impact of different combinations of green roof parameters on energy-conform performance indicators. The analysis reveals that the stomatal resistance and leaf emissivity parameters can have a greater impact on the total energy (Et) than LAI. Additionally, the leaf emissivity parameter has a higher impact on the comfort level (PMV) than the stomatal resistance parameter. Furthermore, LAI has a greater impact on the cooling load (CL) than leaf reflectivity and emissivity. However, in terms of heating load (HL), leaf emissivity/reflectivity outperforms other parameters. Therefore, it can be inferred that the LAI parameter has a significant impact on building energy-conform performance in regions where cooling is a dominant factor.

Table 6 presents statistical indicators for the test results of the ANFIS model across four different indicators. The results indicate that the efficiency of the ANFIS model is acceptable for all indicators, demonstrating its potential as a useful tool in smart building systems. However, it is worth noting that the comfort level index in buildings is also influenced by other factors, such as psychological and metabolic rates. Therefore, predicting this complex process can be challenging. However, in this study, the ANFIS model was able to estimate this feature with a high correlation coefficient. Additionally, the validation of the findings was performed using the Root Mean Square Error (RMSE), and the results were below 0.5, indicating the accuracy of the data.

Performance assessment of the ANFIS model was also available in Fig. A1-A4. This was done based on available upper and lower bounds of parameters to train the model using all available data. This subset of data was randomly sampled from the target population to evaluate the model performance on a new representation of the dataset. Note that due to the high computational demands of the available simulation model, significant computing resources are required to generate comprehensive records of data and hence no other data can be introduced and consequently the learning process was important to evaluate its performance.

4.4. Effect of optimised case on energy and comfort

Table 6 outlines the four optimisation solutions based on four performance indicators, namely optimised total energy (scenario Et-opt), optimised cooling load (scenario Cl-opt), optimised heating load (scenario Hl-opt), and optimised comfort (scenario PMV-opt). Fig. 12a presents the simulation results of these scenarios individually. In all cases, there was a higher contribution of cooling load and a significant decrease in heating load compared to the base case. The optimum case was able to reduce energy consumption by up to 11% based on the total energy function.

Table 7 demonstrates that, in terms of the improvement in hours of comfort, the HL-opt scenario outperformed the others. However, when it comes to total energy consumption, the PMV-opt scenario had the highest reduction rate. Overall, both HL-opt and PMV-opt scenarios presented better results based on both energy and comfort. This suggests that the selection of the optimisation scenario should be based on both heating load and comfort improvement. This could be due to the green roof's ability to function as insulation during cold seasons, which has a greater impact on the heating load. The current study found that the base case initially offered 780 h of comfort, which increased to 880 h after the implementation of optimal measures, representing a significant improvement of 12.8%.

After obtaining the optimum value of each parameter, the selection of effective vegetation can be implemented using a localised vegetation library of plants. As an example, Table 8 presents common Mexican plants along with their LAI, leaf reflectivity and emissivity, and stomatal resistance.

The optimal values of the green roof parameters obtained in this study can be compared with local plants used for green roofs in the case study in Mexico to select the best plant types for green roofs. Table 8 presents an example of common Mexican plants with their LAI, leaf reflectivity and emissivity, as well as stomatal resistance. These values can be compared to those optimal ones in Table 3 and 5. For example, the optimal values of LAI with respect to all four performance indicators are between 1.69 and 3.75 where this can be obtained only through Opuntia Ficus-indica through local plant. Thus, other plan type of a green roof can be selected based on the optimal values compared with available local plants.

4.5. Carbon emission impact of optimised case

According to the 2021 National Electric System Emission by Commission of Energy Regulation of Mexico (CRE), GHG emission of electricity is assumed to be 0.423 tCO_2-eq/MWh per annum[47,4]. This study shows green roof application can save around 529 kWh energy annually which is equivalent to a reduction of 223.7 $kgCO_2$ in the optimum scenario according to CRE conversion. This figure can be compared to the study by Borras et al. [9] who found that renovating only the roof in Almeria, a city with a semi-arid steppe climate, resulted in an 8% reduction in energy consumption and 309 kg of CO_2 emissions per year.

Furthermore, the potential of various plant species for reducing CO_2 emissions through photosynthesis can also be considered [29]. For example, Seyedabadi et al. [58] showed that Sedum spurium vegetation can reduce 0.14 kg CO_2/m^2 through photosynthesis. The results of this study indicated that Sedum Spurium vegetation was found to have same values as optimum plant. Therefore, a 113 m^2 living roof consisting of this plant species is expected to reduce 15.82 kg CO_2 annually. This shows that the total CO_2 reduction in this study through combined photosynthesis and energy saving can be a total of up to 239.7 $kgCO_2$ for one house. There are 372,800 registered houses since 2014 that are included in this study [32]. In Nuevo León, a potential of extrapolated annually emission reduction of 89,360 tons CO_2-eq can be envisaged for the total optimised houses. However, the level of greenhouse gas (GHG) emissions in Mexico has risen by 63% between 1990 and 2017[61]. The climate targets set by the government for 2030 (a reduction of 22% below the baseline provided in the Nationally Determined Contribution) and 2050 (a reduction of 50% below 2000 levels) are not aligned with the necessary trajectory to limit global warming to 1.5 °C [65]. This highlights the importance and potential for reducing GHG emissions through the use of living roofs in Mexico and the significance of further research in this area.

4.6. Other impact of green roof application

The vegetation on a green roof causes a lower level of solar radiation absorption than ordinary roofs, leading to a decrease in ambient temperature due to less sensible heat transformation. This decrease in temperature enhances the environment for the performance of solar cells, as they perform better in cooler ambient conditions[57]. However, the selection of plants is critical when it comes to combining them with Photovoltaic panels, as the species need to be adapted to shade[39]. Studies have confirmed that this combination can increase Photovoltaic performance by up to 6% annually [48], resulting in an increase in electricity production.

Irrigation is a critical aspect of green roofs, particularly in arid and semi-arid climates where vegetation requires regular water inputs for survival. However, the impact of irrigation on the energy consumption and performance of the green roofs must be carefully considered. Saraeian et al., [56] found the height, leaf area, abundance, richness and diversity of plans are affected by lowering irrigation frequency for a green roof sown with a mixture of annual plants. Irrigation also provides several benefits to green roofs. For instance, by promoting vegetation growth and health, irrigation can enhance the thermal insulation and shading properties of the roof, thereby reducing cooling and heating loads for the building. Additionally, irrigation can also mitigate the effects of drought and extreme weather conditions, thereby improving the overall resilience and sustainability of green roofs.

Water treatment in buildings can lead to significant reduction in municipal water consumption, up to 46% although the cost of a water recovery system can be high[11]. An alternative option is greywater recycling, which employs a simple and cost-effective decentralised system for toilet flushing[45]. Green roofs in buildings can act as central bio-filters for purifying contaminants due to the presence of vegetation roots, allowing sedimentation and microbial adaptation to occur[51]. The selection of plant species can impact the level of various substances in greywater recovery. For example, a recent study found that using different types of plants resulted in a solid removal rate of 80% and a total nitrogen removal rate of 30%[21].

In addition to stormwater retention, green roofs can also reduce the peak flow rate of runoff, which is beneficial in reducing the risk of flooding. The substrate layer of a green roof acts as a sponge to absorb rainfall, which is gradually released through evapotranspiration and drainage, thus reducing the rate and volume of runoff.

Stormwater runoff generated by seasonal rainfall and snowmelt can cause significant overland flow in urban areas where it cannot be easily absorbed into the ground due to impermeable surfaces such as concrete and hence largely discharged into drainage systems. Green roofs can be a promising Sustainable Drainage Systems (SuDS) solution in urban water management[36].

Evapotranspiration process, as a combination of water transpiration and evaporation, is crucial in green roofs for its impact on heat, water and energy transfer in plants and green roof buildings. More specifically, evapotranspiration can provide a cooling effect on the plant and the building. This is based on transpiring water from the leaves, which absorbs heat energy from the plant, replenishes the plant routes by water from the soil and maintain soil moisture levels and hence cools the plant's surface. This cooling effect can regulate the temperature of plants and consequently green roofs especially during dry periods. In addition, the latent heat of evapotranspiration is a significant source of energy exchange between the surface and the atmosphere in green roof buildings. In order to evaluate this process, beside climatical factors, the characteristics of the vegetation and soil, such as leaf area index (LAI) and water availability at the soil surface, play a significant role[8]. LAI is a crucial vegetation characteristic that impacts heat transfer through the roof. Other factors such as stomatal resistance, plant height, development of vegetation, and transpiration rate of each plant species can also affect the moisture transfer near the surface roots and canopy.

5. Conclusions

This paper conducted an analysis of effective plants for green roofs in semi-arid climate conditions, with the aim of reducing energy consumption and CO_2 absorption. The study utilised a simulation and optimisation model, which considered four variables including LAI, stomatal resistance, emissivity, and reflectivity of leaf, and optimised them based on four performance indicators: total energy, comfort, heating, and cooling load.

The study utilised the Taguchi method for design of experiment model to define upper and lower boundaries based on literature and to test different scenarios in building simulation. The results showed that the optimisation of heating load and PMV outperformed other models, leading to 114 kWh/m^2 annual energy savings.

The study also used MATLAB 2020 to integrate the fuzzy ANFIS model and to find the predictability of the model. The results showed a 99% correlation coefficient for data Et, Cl, Hl, and PMV with 30, 60, 60, and 90 epochs of training, respectively. The study further analysed ANFIS rules and relationship surfaces and found that leaf emissivity had the highest impact on all output parameters.

The finding can provide a reference for plant selection during roof design in semi-arid climates, specifically the LAI of species for residential apartments although future works are recommended for including experimental testing of plants with such characteristics and the use of optimisation methodology applied in other climate conditions to develop a worldwide plant selection guide for landscape architects and designers.

The analyses in this study were based on specific assumptions and conditions. For example, the plant types and their cover in the green roof were chosen based on the climate of a semi-arid region. The study also analysed a building with a particular roof slope and insulation thickness. Therefore, the findings should only be applied to green roofs and buildings with similar features. Furthermore, the simulation only considers a limited time period, and may not accurately reflect the long-term performance of the green roof system. To gain a deeper understanding of the long-term impacts, a life-cycle assessment is recommended. While the results provide potential solutions for designing green roofs, it is important to conduct further analyses for multiple case studies with various types of green roof systems and building features to generalise the approach for energy conservation and thermal comfort levels in green roof buildings.

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.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A

Tables A1 and A2.

$$Total\ energy\ reduction\ \left(kW/m^2\right) = 0.0416 + 0.0412 - -\ LAI - 0.00732\ Leaf\ reflectivity - 0.00500\ Leaf\ emissivity - 0.01606\ Stomatal\ resistance \tag{A1}$$

$$\begin{aligned} Heating\ load\ reduction\ \left(kW/m^2\right) = & -0.01072 + 0.007315\ LAI + 0.001020\ Leaf\ reflectivity + 0.002611\ Leaf\ emissivity \\ & - 0.002370\ Stomatal\ resistance + 0.8136\ Total\ energy\ reduction\ \left(kW/m^2\right) \end{aligned} \tag{A2}$$

$$Cooling\ load\ reduction\ \left(kW/m^2\right) = 0 - -\ 3412 - 0.1136\ LAI + 0.0279\ Leaf\ reflectivity + 0.0082\ Leaf\ emissivity + 0.0527\ Stomatal\ resistance \tag{A3}$$

$$\begin{aligned} Annual\ comfort\ (85\%\ acceptance) = & \ 0.10111 + 0.00333 - -\ LAI - 0.001667\ Leaf\ reflectivity - 0.001667\ Leaf\ emissivity \\ & - 0.001667\ Stomatal\ resistance \end{aligned} \tag{A4}$$

Figs. A1 – A4.

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