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Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms

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Abstract:

During the last few years, multi-objective optimization processes have become one of the main challenges for energy efficiency in buildings. In this work, a new efficient multi-objective optimization method, based on the Building Performance Optimization (BPO) technique, has been developed to improve the indoor thermal comfort and energy performance of residential buildings, i.e. a Moroccan ground floor + first floor (GFFF) house located in Marrakech region (5th climatic zone according to the Thermal Building Code in Morocco). The most influential design variables have been well explored in order to find the optimal trade-off between these two objectives. Indeed, this technique is based on the integration of Artificial Neural Networks (ANNs), in particular Multilayer Feedforward Neural Networks (MFNN), coupled with the most commonly used metaheuristic algorithms, i.e. Non-dominated Sorting Genetic Algorithm (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-Objective Genetic Algorithm (MOGA), in order to minimize computation time as much as possible. The TRNSYS software was used to establish the various dynamic thermal simulations required to create the database, from which the ANNs were able to set up their learning. The results show that this methodology is being used successfully, leading to different proposed solutions in terms of building envelope design. However, only the solutions using MOPSO are finally retained, as they have shown the greatest desired performance compared to the others. Thus, the thermal needs, particularly those for heating and cooling, have been significantly reduced to 74.52% of the total, while improving the indoor thermal comfort by 4.32% compared to the base design. Finally, we strongly recommend this methodology to the different actors in this field, including designers, engineers, architects, engineering offices, etc., when several objectives need to be contrasted while simultaneously considering several design variables.

Keywords:

Energy efficiency; Passive strategy; Energy performance; Thermal comfort; Multi-criteria decision; Artificial neural networks; Surrogate model; Metaheuristic algorithms.

Nomenclature :

ACH : Air Change Rate in [$\text{v}\cdot\text{hour}^{-1}$]
ADH : Annual weighted average discomfort degree-hours in [$^{\circ}\text{C}\cdot\text{hour}\cdot\text{year}^{-1}$]
ATED : Annual thermal energy demand in [$\text{kWh}\cdot\text{m}^{-2}\cdot\text{year}^{-1}$]
 A_c : Total surface of conditioned zones in [m^2]
 A_l : Automatic learning coefficient [-]
 $A_{m,f}$: Air mass flow coefficient in [$\text{kg}\cdot\text{s}^{-1}\cdot\text{m}^{-1}$]
 B_a : Building azimuth in [$^{\circ}$]
 B_g : Building Geometry [-]
 b_i : ANN Bias [-]
 C : Thermal capacity in [$\text{kJ}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$]
CDD : Cooling Degree-Day in [$^{\circ}\text{C}\cdot\text{day}$]
DH : Discomfort degree-hours in [$^{\circ}\text{C}\cdot\text{hour}\cdot\text{year}^{-1}$]
 E_d : Daily electricity consumption in [$\text{Wh}\cdot\text{day}^{-1}$]
 E_t : Thermal effusivity in [$\text{J}\cdot\text{K}^{-1}\cdot\text{m}^{-2}\cdot\text{s}^{-1/2}$]
 f_{BD} : Value of one of the two objectives for base design [-]
 f_{OD} : Value of one of the two objectives for optimized design [-]
 I : Set of variables [-]
 IN : Number of inputs [-]
 I_P : Improvement potential in [%]
 J : Set of variables' levels [-]
 k : Index of conditioned zones [-]
 l : Equipment number [-]
 n : Total number of conditioned zones [-]
 n_i : Total incoming ANN connections [-]
 n_k : Number of observations [-]
 n_s : Continuous variable coefficient [-]
NS : Number of simulations [-]
 Net_1 : ANN of ATED in [$\text{kWh}\cdot\text{m}^{-2}\cdot\text{year}^{-1}$]
 Net_2 : ANN of ADH in [$^{\circ}\text{C}\cdot\text{hour}\cdot\text{year}^{-1}$]
 N_{num} : Total electrical equipment [-]
 P_t : Linear coefficient of thermal bridges in [$\text{W}\cdot\text{m}^{-1}\cdot\text{K}^{-1}$]
 P_i : Electrical power consumption in [W]
P-type : Wall type [-]
 Q_c : Total heat demand for cooling in [$\text{kWh}\cdot\text{year}^{-1}$]
 Q_h : Total heat demand for heating in [$\text{kWh}\cdot\text{year}^{-1}$]
 R : Correlation coefficient [-]
 R_s : Solar reflectance [-]
 $R_{s,g}$: Annual average horizontal global solar radiation in [$\text{kWh}\cdot\text{m}^{-2}\cdot\text{day}^{-1}$]
 $Scw-n$: Shading coefficient of north-facing windows [-]

Scw-s : Shading coefficient of south-facing windows [-]
 Scw-e : Shading coefficient of east-facing windows [-]
 SHGC : Solar Heat Gain Coefficient [-]
 t_i : Operating time in [heure]
 T_{ps} : Thermal phase shift in [heure]
 $T-s$: Solar transmission [-]
 $T-v$: Visual transmission [-]
 U_f : Transmission coefficient of the frames in $[W.m^2.K^{-1}]$
 U_g : Transmission coefficient of the Glazing in $[W.m^2.K^{-1}]$
 U_M : Transmission coefficient of the external walls in $[W.m^2.K^{-1}]$
 $U_{M,i}$: Transmission coefficient of the internal walls in $[W.m^2.K^{-1}]$
 U_T : Transmission coefficient of the Roof in $[W.m^2.K^{-1}]$
 U_P : Transmission coefficient of the Floor in $[W.m^2.K^{-1}]$
 $w_{i,j}$: ANN Weight [-]
 $W-o$: Window opening factor [%]
 $W-o,c$: Type of window opening control [-]
 $W-sh$: Window shading [-]
 $W-size$: Window size in $[m^2]$ ou $[m]$
 WWR : Windows-to-Wall Ratio [%]
 y : Simulated value
 y' : Predicted value
 Z : Sample set [-]
 $z_{i,j}$: ANN input [-]
 Θ_L : Lowest average monthly temperature in $[^{\circ}C]$
 Θ_H : Highest average monthly temperature in $[^{\circ}C]$
 Φ_i : ANN activation function [-]
 ε : Emissivity [-]
 α_M : Solar radiation absorption coefficient of the exterior walls [-]
 α_T : Solar radiation absorption coefficient of the Roof [-]
 α_t : Thermal Diffusivity in $[m^2.s^{-1}]$
 α_f : Solar radiation absorption coefficient of the frames [-]
 λ : Thermal conductivity in $[W.m^{-1}.K^{-1}]$
 ρ : Density in $[kg.m^{-3}]$
 β : Discrete variable coefficient [-]

Acronyms :

AMEE : Moroccan Agency for Energy Efficiency
 ANN : Artificial Neural Network
 BPO : Building Performance Optimisation
 BPS : Building Performance Simulation
 CSTB : Scientific and Technical Building Center
 DTS : Dynamic Thermal Simulation
 Glz : Glazing
 GFFF : Ground Floor + First Floor

HVAC : Heating, Ventilation and Air-Conditioning
It : Number of iterations
MAE : Mean Absolute Error
MFNN : Multilayer Feedforward Neural Networks
MOPSO : Multi-Objective Particle Swarm Optimization
MOGA : Multi-Objective Genetic Algorithm
MSE : Mean Square Error
MLP : MultiLayer Perceptron
NSGA-II : Non-dominated Sorting Genetic Algorithm
Pop : Population size
POS : Pareto-Optimal Solution
RMSE: Root Mean Square Error
TFEC : Total Final Energy Consumption
VD : Discrete variable
VC : Continuous variable

1. Introduction

Today, the transition to a more sustainable model is necessary to live in a more equitable world and to preserve the planet's natural resources, which will enable human and living beings to benefit from an appropriate quality of life. In Morocco, energy efficiency is a priority action path, aiming to mobilize all operators and stakeholders in favour of limiting global warming and controlling energy demand, in order to achieve energy savings of 12% by 2020 and 15% by 2030 [1]. Indeed, buildings are mainly responsible for energy consumption, energy waste and local and global warming, as well as urban pollution. Therefore, in one way or another, controlling energy demand represents a key factor in minimising CO₂ emissions.

The building sector constitutes a major energy consumer in Morocco, accounting for about 33.6% of the country's total final energy consumption, of which 25.4% for the residential sector and 8.2% for the tertiary sector [2]. Therefore, this sector must undergo a very important mutation since it represents the 2nd highest energy consumer in Morocco. In this respect and in order to initiate the construction of energy-efficient buildings, an energy regulation (RTCM) [3] has been introduced to reduce energy consumption while improving indoor thermal comfort. The passive building strategy depends on different design parameters, through which the various indicators related to energy consumption, thermal comfort, visual comfort, acoustic comfort, environmental impact, economic impact, etc., could be determined. In this regard, building performance optimization (BPO) has a crucial role in promoting sustainability, while at the same time responding strongly to the needs of designers in cases of contrasting objectives that simultaneously consider several design variables [4]. The following lines present, on the same wavelength of this paper, some recent and noteworthy studies on this technique to enhance passive building design.

To address the challenges of multi-objective optimization of building performance using a new meta-model-based approach, Bre et al. [5] presented an efficient method, using the NSGA-II algorithm and artificial neural networks. To optimize glazing design, Zhai et al. [6] proposed a multi-objective optimization method that combines NSGA-II with EnergyPlus software. The method provides architects with rich and valuable information about the effects of parameters on different building design objectives. It can assist designers in achieving an optimal window design solution to minimize the building's energy consumption while improving indoor thermal environment and visual performance. Shi et al. [7] studied the influence of building envelope on the annual energy demand of an underground building using DeST software. The results show that the U-values of the building envelope components have a crucial role in assessing the annual energy demand of the building envelope. Therefore, it is fundamental to optimize them in order to improve the energy performance of the building. Papadopoulos et al. [8] applied the Gradient Boosted Regression Trees (GBRT) as a Machine Learning technique to approximate a Building Performance Simulation (BPS) model and identify, using a GA optimization process, the optimal building design in terms of heating and cooling loads. Yao et al. [9] demonstrated how the use of passive climate-sensitive design solutions can contribute towards improving indoor thermal conditions while reducing energy demand and carbon emissions. Bamdad et al. [10] developed scenario-based optimization to manage the uncertainty of construction parameters, for example, due to internal loads and infiltration rate. A modified version of the ant colony optimization algorithm for mixed variables (ACOMV-M) is proposed and compared to a reference algorithm, showing that ACOMV-M achieves convergence with approximately 50% fewer simulations. Gou et al. [11] proposed a new optimization approach to reduce the energy demand of buildings and maximize the thermal comfort of occupants. The optimization technique has three steps: (1) Definition of objective functions and

decision variables; (2) Definition of the spectrum of variables through a sensitivity analysis; (3) Multi-objective optimization by combining NSGA-II with ANN. Li et al. [12] developed an optimization process based on the interactive use of MATLAB® to improve the energy performance of residential buildings. The single-objective optimization is proposed by comparing three algorithms. However, for multiobjective optimization, four popular algorithms are compared, NSGA-II, MOPSO, MOGA, and Multi-Objective Differential Evolution (MODE). The results indicate that the MODE algorithm provides near-optimal solutions with the best diversity and execution time. In contrast, MOPSO achieves a non-competitive result in this case study. Mostavi et al. [13] developed a new multi-objective optimization model, which is an algorithm based on the harmony search, at the level of the building envelope parameters in order to minimize life cycle cost and greenhouse gas emissions, while ensuring a more satisfactory level of thermal comfort for its occupants. Zhang et al. [14] applied an optimization method, which combines a genetic algorithm with thermal and light simulations, to select optimal values for school building design parameters in order to minimize energy consumption while maximizing thermal and visual comfort. Harmathy et al. [15] proposed a methodology to improve the energy performance of office buildings worldwide. The objective consists in defining appropriate window/wall ratios and window geometry according to visual comfort criteria and electrical energy demand. Delgarm et al. [16] studied a single room model in four major climatic regions in Iran. This study was carried out using Single and Multi-Objective Optimization (MOPSO), combined with the EnergyPlus software, to find optimal solutions for building envelope design. The annual electrical energy demands for cooling, heating and lighting are examined as objective functions. Azari et al. [17] proposed an optimization method, combining MOGA with eQuest software, to explore the optimal building envelope design regarding energy consumption and life cycle contribution to environmental impacts. Brown et al. [18] demonstrated how multi-objective optimization, using NSGA-II, can be applied to geometrically and architecturally important design problems. This allows to obtain diverse and powerful results, which are difficult to generate by other methods. Echenagucia et al. [19] proposed an integrative approach for the early steps of building design to obtain detailed information on energy-efficient envelope configurations. This approach uses genetic algorithms to perform a multi-objective optimization to minimize the energy demand for heating, cooling and lighting of the studied building. Romani et al. [20] developed and validated heating and cooling energy demand meta-models for single-family houses. The results show that this methodology is successfully applied to achieve rapid operational optimization of the building envelope, thus improving the implementation of low-energy buildings. Yu et al. [21] proposed a multi-objective optimization model to determine the optimal or near-optimal design of buildings under given conditions. This model describes the role of combining ANN with NSGA-II in reducing energy demand and thermal discomfort. Yang et al. [22] presented an optimization approach, web-based parallel GA using a high-speed distributed computing environment, to reduce the computational time of complex building energy optimization applications. This approach has been used to optimize the energy consumption of large-scale buildings. The obtained optimization results for a pilot building, showed a significant deduction of the calculation time while obtaining acceptable optimal results.

Finally, the approaches presented in the state of the art above as well as in Table 1 aim to meet the requirements of energy-efficient buildings, either absolutely or partially, through a significant fit between the different design variables. Indeed, some researchers have incorporated artificial intelligence into their approach, while others have not. As for optimization, some have applied it to the building envelope and HVAC set-point temperatures [23]–[25], while others have applied it only to the building envelope. This diversity of approaches leads to a set of

findings related to relevant criteria in this field, such as performance, reliability and calculation time. Although the objective remains the same, i.e., the optimization of the different energy expectations across the building envelope, these findings vary from one approach to another. Thus, some research studies have shown better performance results with a significant degree of reliability, but the calculation time is too high, while others have shown the opposite. This means that the present issue still has shortcomings with regard to the adequacy between the various criteria mentioned above. In other words, a methodology that can lead to an optimal design of the building envelope regarding energy savings, thermal comfort, etc., by ensuring a very high reliability of the calculated performances and a very short calculation time, represents an existing knowledge gap.

For this reason, this article represents a significant contribution that provides a scientific add-value to the existing body of knowledge, since a new and robust method, in terms of performance, reliability and calculation time, is provided to overcome the existing knowledge gap. To this end, a well-defined and detailed plan is presented, which includes 4 steps, the first of which is related to the modeling, the second step defines the optimization problem, the third is dedicated to the development of the ANN model and the last to the selection of the appropriate multi-objective optimization algorithm. As part of this plan, the document is organized as follows, starting with an overview of recent works on this issue, in order to emphasize the usefulness of this contribution in section 2, which will be devoted to the background, by referring to the state of art presented in Table 1. The technical part of the contribution will then be discussed in the other sections, based on the methodology presented in section 2.2, which provides in-depth details on the modeling of the considered systems, then on the optimization and finally on the results.

Table 1. Recent Scientific Literature on Building Performance Optimization (BPO)

Authors	Optimization tools	Simulation tools	Objective functions	Scope	B _g	B _a	U _{M,e}	α _M	U _T	α _T	U _p	Pt	U _{M,i}	P-type	W-size	U _g	SHGC	ε	T-s	R-s	T-v	W-sh	W-o	W-o,c	U _r	a _r	WWR	Air-m,f	ACH
Bre et al. (2020)	NSGA-II	EnergyPlus + Python	Energy demand + Thermal comfort	Residential Buildings		V _D	V _D	V _C	V _D		V _D		V _D		V _C	V _D	V _D	V _D	V _D	V _D	V _D	V _C	V _C					V _C	
Zhai et al. (2019)	NSGA-II	EnergyPlus	Energy demand + Thermal comfort + Visual comfort	Office buildings		V _D										V _D	V _D	V _D	V _D	V _D	V _D						V _C		
Shi et al. (2018)	Sampling	DeST	Energy demand	Office buildings			V _C		V _C																				
Papadopoulos et al. (2018)	Machine learning (Gradient Boosted Regression Trees) + GA	Ecotect	Energy demand	Buildings		V _C	V _C		V _C																		V _C		
Yao et al. (2018)	Unknown	EnergyPlus + Miscrosoft Visual Basic	Energy demand + Thermal comfort	Residential Buildings		V _C	V _D		V _D		V _D											V _C					V _C		V _C
Bamdad et al. (2018)	ACOMV-M + PSOHJ	EnergyPlus + GenOpt	Energy demand	Office buildings			V _C									V _D	V _D				V _D	V _C							
Gou et al. (2018)	ANN + NSGA-II + Monte Carlo method	EnergyPlus + MATLAB® + SIMLAB	Energy demand + Thermal comfort	Residential Buildings		V _C	V _C	V _C	V _C	V _C				V _D		V _C	V _C					V _C	V _C	V _D			V _C	V _C	
Li et al. (2017)	ANN + NSGA-II + MOPSO + MOGA + MODE	TRNSYS + EnergyPlus + DOE-2 + MATLAB® + GenOp	Energy Demand + Life Cycle Cost + CO ₂ Emissions + Thermal Comfort	Residential Buildings		V _C	V _D		V _D		V _D		V _D			V _C			V _C								V _C		
Mostavi et al. (2017)	Harmony search algorithm	EnergyPlus + C++	Life Cycle Cost + Life Cycle Greenhouse Gas Emissions + Thermal Comfort	Office buildings			V _C		V _C		V _C					V _D													
Zhang et al. (2017)	GA (SPEA-2)	Rhinoceros + EnergyPlus + Radiance + Octopus	Energy Demand + Daylighting + Thermal Comfort	School buildings		V _C	V _C		V _C		V _C					V _D	V _D				V _D	V _D					V _C		
Bre et al. (2017)	NSGA-II	EnergyPlus + Python	Energy demand + Thermal comfort	Residential Buildings		V _C	V _D	V _C	V _D		V _D		V _D		V _C	V _D	V _D	V _D	V _D	V _D	V _D	V _C	V _C					V _C	

Table 1. (Continued)

Authors	Optimization tools	Simulation tools	Objective functions	Scope	B _g	B _a	U _{M,e}	a _M	U _T	α _T	U _p	Pt	U _{M,i}	P-type	W-size	U _g	SHGC	ε	T-s	R-s	T-v	W-sh	W-o	W-o,c	U _f	a _f	WWR	Air-m,f	ACH	
Harmathy et al. (2016)	Multi-criterion building envelope optimization	EnergyPlus + Radiance + Autodesk Revit + Open Studio	Energy demand + Visual comfort	Office buildings												V _D	V _D				V _D						V _C			
Bre et al. (2016)	GA + Morris screening method for sensitivity analysis	EnergyPlus • Python	Energy demand + Thermal comfort	Residential Buildings		V _C	V _C	V _C	V _C	V _C	V _C		V _C			V _D	V _D	V _D	V _D	V _D	V _D	V _C	V _C					V _C		
Delgarm et al. (2016)	MOPSO	EnergyPlus + MATLAB® + jEPlus	Energy demand	Office buildings		V _C	V _C	V _D								V _C				V _D		V _D	V _C				V _C			
Delgarm et al. (2016)	NSGA-II	EnergyPlus + MATLAB® + jEPlus	Energy demand	Office buildings		V _C										V _C						V _C					V _C			
Azari et al. (2016)	ANN + MOGA	eQuest	Life Cycle Environmental Impacts	Office buildings			V _C									V _D	V _D	V _D	V _D	V _D	V _D				V _D	V _C				
Brown et al. (2016)	NSGA-II	Archsim + EnergyPlus	Energy demand	High-rise buildings	V _C																									
Echenagucia et al. (2015)	NSGA-II	EnergyPlus + Python	Energy demand	Office buildings												V _D	V _D				V _D									
Romani et al. (2015)	Design of Experiments (D-optimal) + Metamodels	TRNSYS	Energy demand	Residential Buildings			V _C	V _C	V _C	V _C	V _C	V _C				V _D	V _D		V _D	V _D	V _D	V _C						V _C		
Yu et al. (2015)	ANN + NSGA-II	EnergyPlus + MATLAB®	Energy demand + Thermal comfort	Residential Buildings		V _C	V _C									V _C										V _C				
Yang et al. (2014)	NSGA-II	EnergyPlus	Energy demand	Residential Buildings												V _C						V _C							V _C	

2. Background

2.1. Objective and originality

The issue considered in this study concerns the building performance optimization technique (BPO). This is a very complex process involving a large number of potential objective functions and design variables. The objective functions can refer to energy, environmental, economic and/or comfort indicators. The design variables can be related to the building geometry, envelope and energy systems. In this respect, the objective of this study is to discover a new and robust method, in terms of performance, reliability and calculation time, to meet the requirements of energy-efficient buildings. This method consists in finding the optimal building envelope design, considering its opaque and glazed walls, shading devices, thermal bridges and ventilation, in order to minimize the thermal energy demand, in particular that of heating and cooling, as well as the thermal discomfort of the occupants.

According to the existing literature, there are several approaches available to remedy the same issue using different techniques, in terms of methods, simulations, evaluation criteria, etc. In the present study, several criteria have been exposed, mainly that of computation time, which should be minimized as much as possible by introducing artificial neural networks. These could be well learned thanks to a rather small database in terms of the number of samples simulated by TRNSYS software, i.e. 35 samples for about 11 variables. This software remains a very efficient tool regarding a certain number of criteria (see section 3.3), especially accuracy [26], [27], although it has not been used frequently for this kind of case. Indeed, the number of simulations has been in the majority of recent studies, for a number of variables that varies around 11, about 2000. This number is very high in terms of simulation time compared to the proposed path, although this is done automatically, using many DTS software packages, unlike TRNSYS. For this reason, researchers such as Romani et al. [28] and Jeremy Bois [29], for example, have carried out studies in this sense in order to achieve the same desired objective by performing a minimum of simulation, using meta-models based on design of experiments where the DTS tool was TRNSYS. However, for high precision, i.e. the complete quadratic polynomial case, at least 100 simulations are required. In this regard, the approach proposed in this paper represents an original contribution allowing to enrich considerably the current state of scientific research on the concerned issue.

2.2. Methodology

Very low energy buildings do not behave like traditional buildings. A detailed modelling of their behaviour is necessary to optimise their design regarding thermal needs, in particular those of heating and cooling, and indoor thermal comfort. Thus, the use of BPS technique is important in designing highly energy-efficient buildings, both for new buildings as well as for those undergoing major renovations. This technique involves reproducing certain aspects of building performance using a computerized mathematical model created according to fundamental physical principles and good engineering practice. The objective is to quantify the different aspects of building performance that are relevant to their design, construction, operation and control [30].

Currently, one of the main challenges for building performance simulation technology worldwide is the high computational time involved [31]. The approach presented in Fig. 1 is designed to address this challenge, while meeting the requirements of energy-efficient buildings.

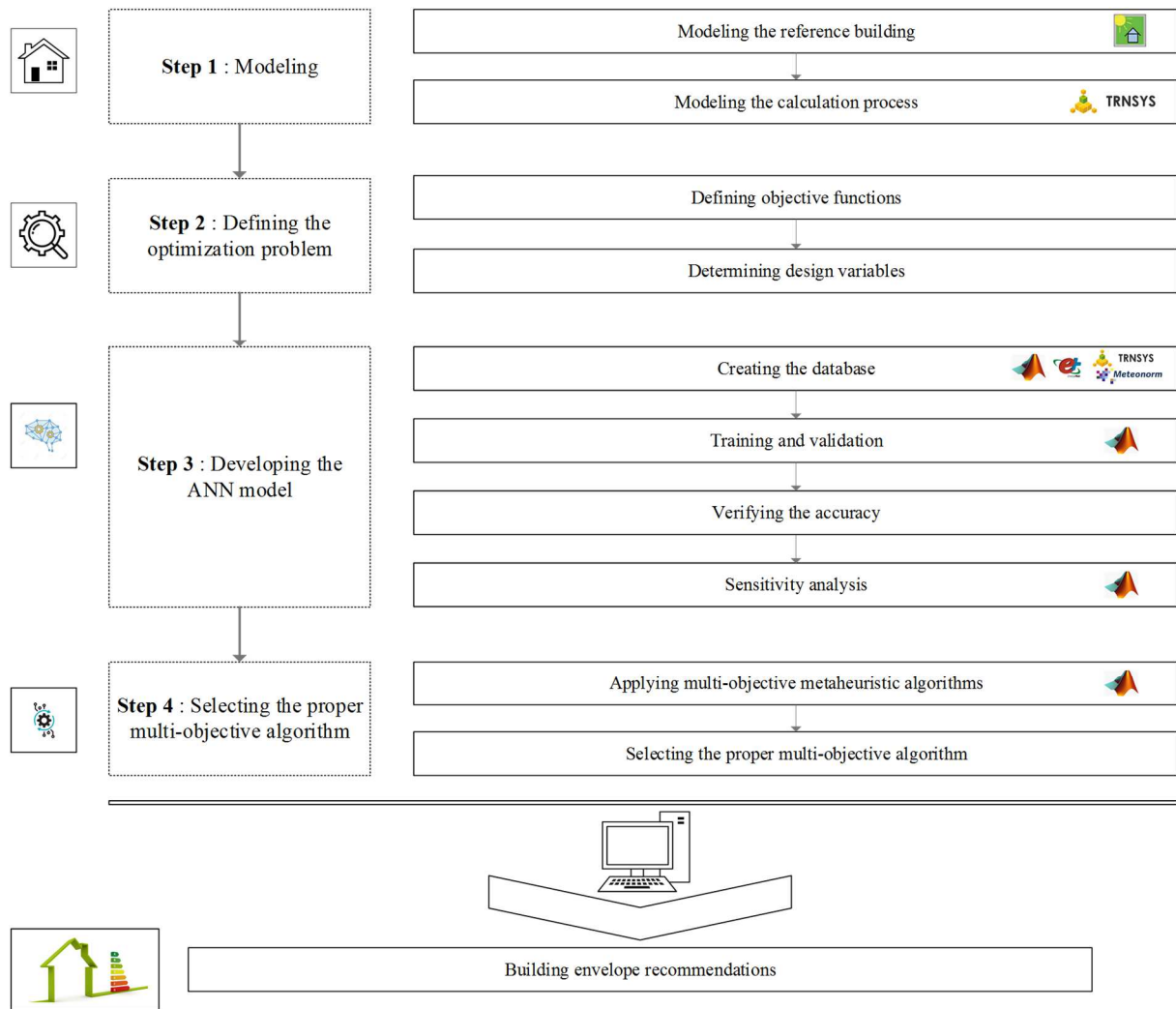


Figure 1. Flowchart of the optimization approach

3. Modeling

3.1. Description of the reference building

The studied building corresponds to a typical GFFF house, often built in Marrakech region of Morocco, with three facades. Fig. 2, Fig. 3 and Fig. 4 show the 3D and 2D architectural plans of the house as well as their designed and modelled dimensions with AutoCAD [32] and SketchUp [33]. Each level has a floor area of 140m² and a height of 3m. The ground floor includes two living rooms, an indwelling, a kitchen and a WC. As for the first floor, it includes two rooms, two dressing, two WC, a parental suite and an indwelling. In addition, each level is occupied by four people (two adults and two children).

It should be noted that other studies related to the evaluation of building performance are carried out on the same building [34]–[37].



Figure 2. Axonometric view of the reference building

3.2. Thermal zoning

The studied building is divided into 13 thermal zones. The two WCs on the first floor are considered as a single zone (11) due to their similar geometries and internal heat gains. As for the stairwell, it is modelled as part of the dwelling since there is no thermal separation. Fig. 3 and Fig. 4 show the thermal zoning of this house.

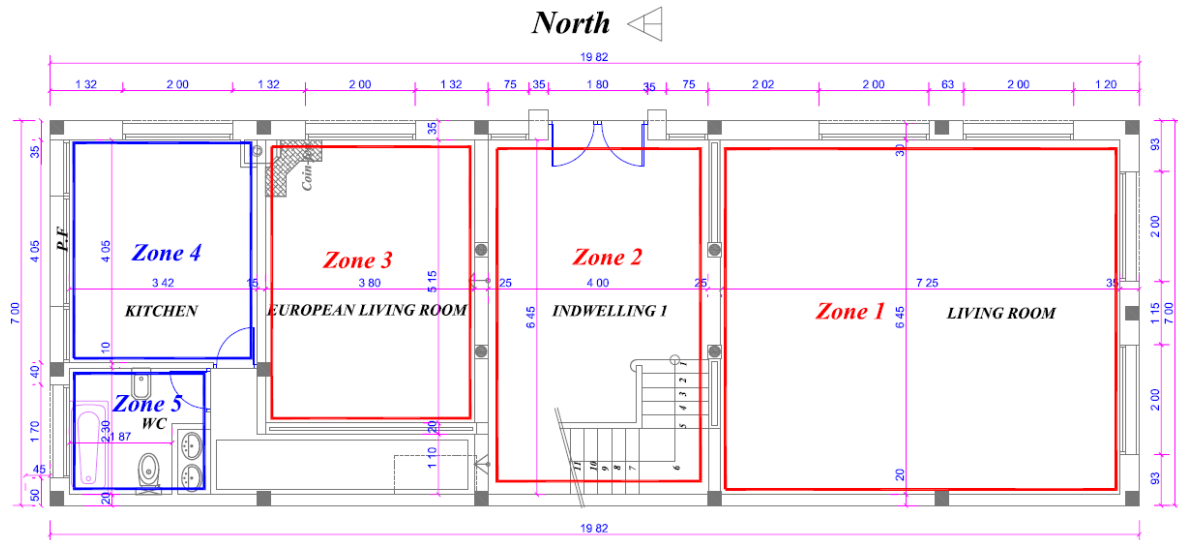


Figure 3. Ground floor 2D plan and thermal zoning.

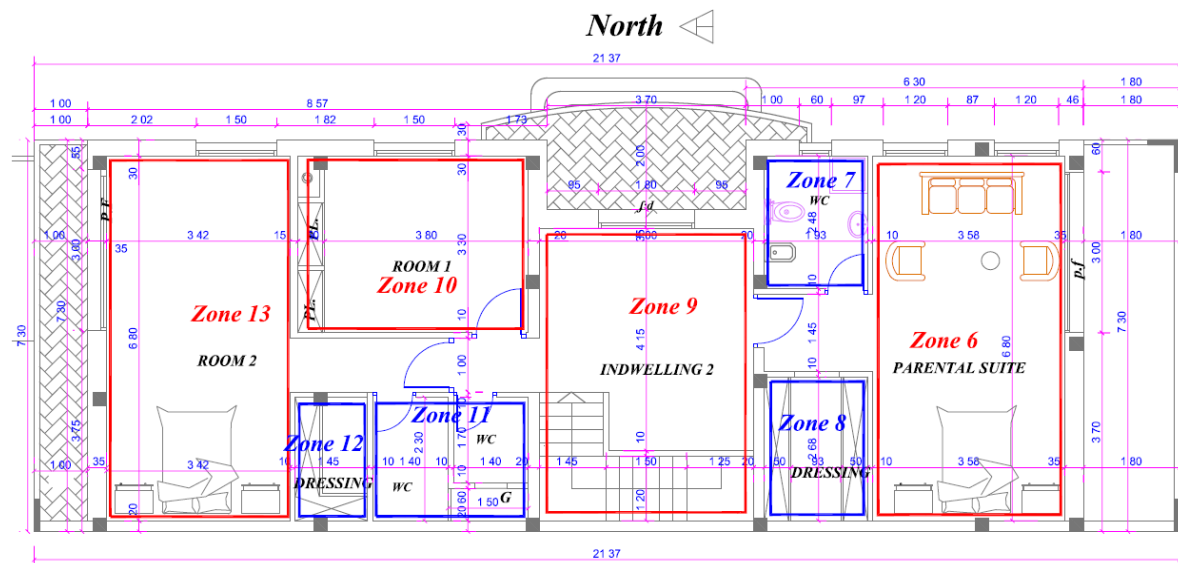


Figure 4. First floor 2D plan and thermal zoning.

3.3. Modelling of the calculation process in TRNSYS environment

Achieving the objective of this study requires the use of a tool that allows the modeling of the reference building, as well as its dynamic thermal simulation. The DTS consists in studying over a defined period of at least a few days, at an hourly time step or less, the thermal behaviour of a building, either of its envelope or of its technical systems. This calculation takes into account all the parameters influencing the energy balance, namely internal and external gains, thermal inertia, transmission through the walls, etc.

In this study, the simulations were performed using TRNSYS software [38], the worldwide reference in the field of dynamic simulation of buildings and systems, combined with the TRNBuild [39] platform. It is a complete simulation package, proposed by the CSTB [40] and recognized by ASHRAE [41], containing several tools, simulation engine programs, a graphic connection with plotters and spreadsheets, etc. It is an integrated and smart tool that can be used from project design to simulation. It offers high accuracy, flexibility and infinite customization, high granularity of reported data and the ability of working with many programs. Thanks to this package, a platform has been designed and developed (see Fig. 1) to calculate the required number of simulations in order to create the database, which constitutes a fundamental element for developing the ANNs models.

Before starting the simulation, it is necessary to provide the characteristics of the studied building, such as geometry, orientation, thermo-physical parameters of the opaque and glazed walls, internal heat gains, air conditioning conditions and meteorological data.

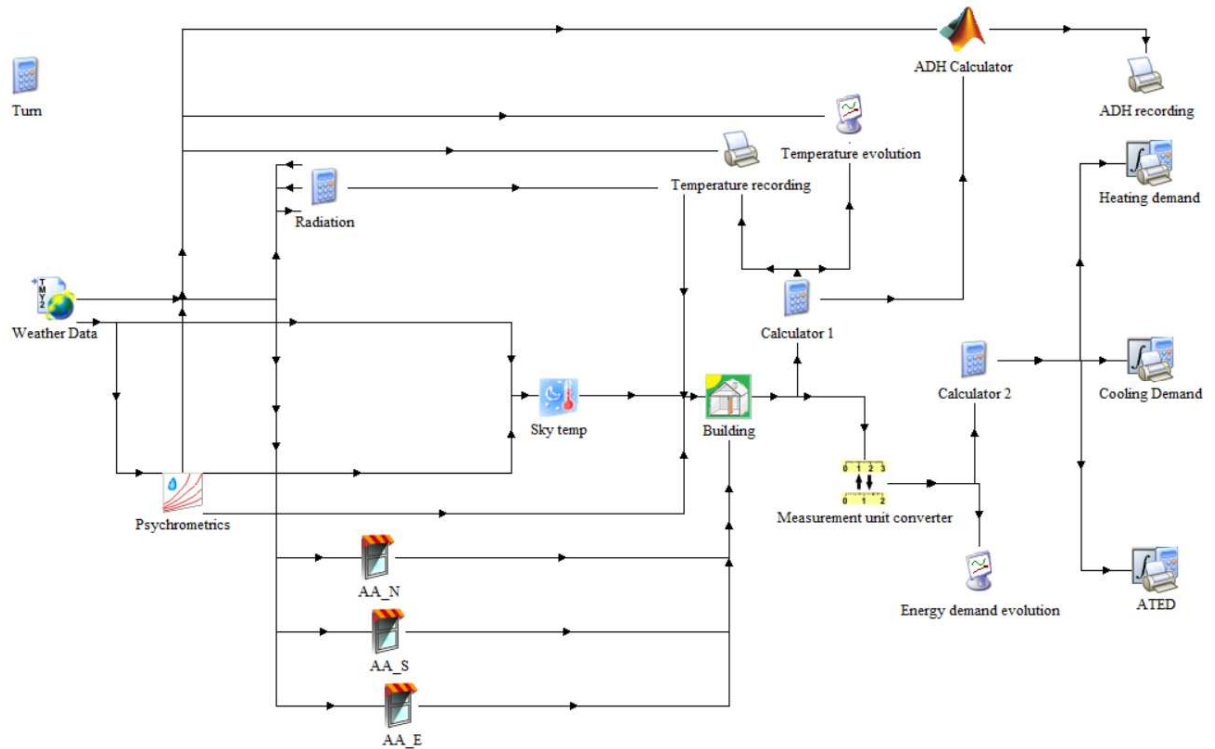


Figure 5. Computation platform in TRNSYS environment

3.3.1. Composition of the building envelope

Table 2 presents the composition of the opaque and glazed walls of the studied building. The collected thermo-physical properties are taken from the BINAYAT perspective library of AMEE [42], according to the technical description of the building envelope composition.

Table 2. Opaque and glazed walls composition and thermos-physical properties.

Construction element	Material	Thickness [cm]	λ	C	ρ	α_t	E_t	T_{ps}
Exterior wall	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
	Raw earth	10.00	1.04	1.00	2350	$4.43.10^{-7}$	1563.33	3.46
	Layer of air	5.00			$R = 0.18 \text{ m}^2\text{K.W}^{-1}$			
	Raw earth	10.00	1.04	1.00	2350	$4.43.10^{-7}$	1563.33	3.46
	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
Roof	Plaster	2.00	0.56	1.00	1350	$4.15.10^{-7}$	869.48	0.71
	Hourdis	20.00	1.32	1.00	1327	$9.91.10^{-7}$	1321.64	4.62
	Concrete	5.00	2.00	1.00	2450	$8.16.10^{-7}$	2213.59	1.27
	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
	Floor tile	1.50	1.30	0.84	2300	$6.73.10^{-7}$	1584.80	0.42
Ground floor	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
	Hourdis	16.00	1.18	1.00	1372	$8.57.10^{-7}$	1270.32	3.98
	Concrete	4.00	2.00	1.00	2450	$8.16.10^{-7}$	2213.59	1.02
	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
Intermediate floor	Plaster	1.50	0.56	1.00	1350	$4.15.10^{-7}$	869.48	0.54
	Hourdis	16.00	1.18	1.00	1372	$8.57.10^{-7}$	1270.32	3.98
	Concrete	4.00	2.00	1.00	2450	$8.16.10^{-7}$	2213.59	1.02
	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
Internal wall	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
	Concrete agglo 6 holes	12.00	0.56	0.83	768	$8.77.10^{-7}$	596.93	2.95
	Ciment	1.50	1.80	1.00	2500	$7.20.10^{-7}$	2121.32	0.41
Glazing	FLOAT_19				$U_g = 5.16 \text{ W.m}^{-2}\text{K}^{-1}$, SHGC = 0.68 and WWR = 24%			

3.3.2. Internal heat gains

Table 3 shows the internal loads of the building [43], which represent a source of heat gain in winter and a charge in summer. In addition, the daily energy consumption can be estimated using the Eq. (1) at 24 kWh.day^{-1} .

$$E_d = \sum_{w=0}^{w=1} P_w t_w \quad l \in N_{\text{num}} = [0,1,...,l] ; N_{\text{num}} \in N \quad (1)$$

Table 3. Internal heat gains

Level	Zone	Designation	Conditioning	Gain type	Number	Daily schedule	Heat gains
Ground floor	1	Living room	Controlled	Lighting		19-22h	5W.m^{-2}
				TV	1	12-14h and 18-20h	100W
				Air conditioning	1	19-22h	120W
				People	4	07-8 h, 12-14 h and 18-20 h (Sitting at rest)	60W.Pers^{-1}
	2	Indwelling 1	Controlled	Lighting		19-22h	5W.m^{-2}
				Air conditioning	1	19-22h	120W
				People	4	07-8 h, 12-14 h and 18-20 h (Sitting at rest)	60W.Pers^{-1}
	3	European living room	Controlled	Lighting		19-22h	5W.m^{-2}
				TV	1	12-14h and 18-20h	100W
				Air conditioning	1	19-22h	120W
				People	4	07-8 h, 12-14 h and 18-20 h (Sitting at rest)	60W.Pers^{-1}
	4	Kitchen	Uncontrolled	Lighting		18-22h	5W.m^{-2}
				Refrigerator	1	24h	300W
				Built-in oven	1	18-19h (One time per week)	2500W
				Washing machine	1	18-19h (Two times per week)	1500W
	5	WC	Uncontrolled	Lighting		18-22h	5W.m^{-2}
First floor	6	Parental suite	Controlled	Lighting		20-22h	5W.m^{-2}
				Laptop	2	20-22h	50W.PC^{-1}
				Air conditioning	1	20-22h	120W
				People	2	20-22h (Rest)	60W.Pers^{-1}
	7	WC	Uncontrolled	Lighting		18-22h	5W.m^{-2}

8	Dressing	Uncontrolled	Lighting		19-22h	5W.m ⁻²
			Lighting		19-22h	5W.m ⁻²
9	Indwelling 2	Controlled	Air conditioning	1	19-22h	120W
			People	4	07–8 h, 12–14 h and 18–20 h (Sitting at rest)	60W.Pers ⁻¹
			Lighting		20-22h	5W.m ⁻²
10	Room 1	Controlled	Laptop	1	20-22h	50W.PC ⁻¹
			Air conditioning	1	20-22h	120W
			People	1	20-22h (Rest)	60W.Pers ⁻¹
11	WC	Uncontrolled	Lighting		18-22h	5W.m ⁻²
12	Dressing	Uncontrolled	Lighting		19-22h	5W.m ⁻²
			Lighting		20-22h	5W.m ⁻²
			Laptop	1	20-22h	50W.PC ⁻¹
13	Room 2	Controlled	Air conditioning	1	20-22h	120W
			People	1	20-22h (Rest)	60W.Pers ⁻¹

3.3.3. Air conditioning conditions

The calculation assumptions for air conditioning taken into account during the simulation are shown in Table 4:

Table 4. Air conditioning conditions

Natural ventilation in all zones [v.h ⁻¹]	Natural ventilation in the kitchen [v.h ⁻¹]	Infiltration [v.h ⁻¹]	Summer setpoint temperature [°C]	Winter setpoint temperature [°C]
1	5	0.1	26	20

3.3.4. Location and meteorological data

The TMY2 file generated using Meteonorm software [44] was used in this case study to describe the climatic characteristics of the studied region, some of which are summarized in Table 5.

Table 5. Location and meteorological data

Location	Latitude	Longitude	Elevation [m]	Θ _H	Θ _L	HDD	CDD	R _{sg}	Classification climatique « Köppen »
Marrakech (Morocco)	31.6°N	-8.0°E	466	28.8 (July)	11.9 (January)	754.24	1041.74	2.087	Bsh (Hot semi-arid climate)

4. Definition of the optimization problem

The increasing energy consumption of buildings in Morocco has attracted the government's attention. Thus, a thermal code has been implemented to apply an energy efficiency approach in the building sector, whether residential or tertiary. This was introduced by the publication of Decree No. 2-13-874 of October 15, 2014 in Official Gazette No. 6306 of November 6, 2014 [45], entitled «Règlement Thermique de Construction au Maroc» (RTCM). This decree approves the general construction code, which defines the energy performance standards for buildings as well as establishing the National Committee for the Energy Efficiency in Buildings. The main objective of the RTCM, which is developed by the AMEE, is to improve the thermal performance of new and existing buildings, while ensuring a better thermal environment for the occupants [3].

The assessment of the building envelope design regarding the energy efficiency plan can be established under various indicators, which can be referred to the energy demand, thermal comfort, visual comfort, acoustic comfort, indoor air quality and the economic and environmental impact, etc. In this study, two evaluation indicators were retained, namely energy demand and occupant thermal comfort, since they account for a very significant degree of impact compared to the others [46]–[48], as well as being the most widely used in the literature presented in Table 1.

4.1. Objective Functions

With the purpose of identifying the interactions between energy consumption and indoor thermal comfort in hot and semi-arid climatic zone of Morocco, the two objective functions, namely the annual thermal energy demand, in particular that of heating and cooling, and the discomfort degree-hours, were simultaneously minimized.

4.1.1. Annual thermal energy demand

The ATED is defined as an indicator, representing the sum of heating and cooling loads over the total conditioned area of the studied building. In this study, the energy demand for artificial lighting, domestic hot water and electronic equipment was not taken into account, as they represent less than 40% of the total energy needs. Therefore, the objective function ATED can be calculated according to Eq. (2) [34]:

$$ATED = \frac{1}{A_c} \times (Q_h + Q_c) \quad (2)$$

4.1.2. Annual weighted average of discomfort degree-hours

The thermal comfort assessment can be carried out using several methods, such as calculating the number of hours during which occupants feel uncomfortable; the ASHRAE adaptive thermal comfort model; the Fanger thermal comfort model and the EN adaptive thermal comfort model. An approach, based on these methods, has been developed by Chegari et al. [35], [36] to assess thermal comfort through the calculation of DH values.

The ADH is defined as an indicator, representing the annual weighted average of the degree-hours, during which the occupant feels uncomfortable, in areas where he/she should feel more comfortable. Therefore, the objective function ADH can be calculated according to Eq. (3):

$$ADH = \frac{1}{n} \sum_{k=1}^n DH_k \quad (3)$$

4.2. Design variables

In Morocco, the RTCM addresses the issue of energy efficiency in buildings through two approaches, the first of which is called perspective and the second, performance. According to the perspective approach, which is related to the building design, certain thermo-physical parameters of the building envelope are well recommended, notably the thermal transmission coefficient of the external walls, roof, windows, the thermal resistance of the floor and the solar factor of the glazing. Thus, this indicates that there are shortcomings in terms of variable design, which constitutes an anomaly for successfully addressing the main issue.

With the objective of optimizing the two objective functions defined above, this study has introduced certain design variables (see Table 6 and Table 7), that present a major interest for architects, engineers and all stakeholders in this field, given that they have a significant impact on these two objective functions. The selection of these design variables was not made randomly, but rather through a whole bibliographical study that brings together recent research work that deconstructs the same problem, while taking into account the anomaly presented in the RTCM.

4.2.1. Opaque walls

The heat flow through the building envelope represents the main heat gain or loss of a building. Therefore, optimizing heat transfer through opaque walls is important for designing high performance buildings. In this respect, U_M , U_T , U_P , α_M , α_T and P_t are selected as design variables. The upper limit of the heat transfer coefficients is defined according to those of the reference building, since this building belongs to the energy-consuming buildings, while the lower limit is defined in accordance with existing best practices. The limits for solar absorption coefficients of opaque wall claddings, particularly those of the exterior walls and roof, are defined according to

the absorption characteristics of existing claddings on the market. Finally, the limits for thermal bridges are defined as follows: lower limit according to the recommendation of the Passivhaus label, while the upper limit is defined according to the reference building situation.

4.2.2. Glass walls

Glass walls generally require special attention, since they represent the weakest part of the building envelope insulation. In this respect, Glz is selected as a design variable consisting of 5 levels, each of which is composed of several parameters, namely U_g , SHGC, T-s, R-s and T-v (see Table 6). The latter is defined as a discrete variable due to the different typologies available on the market (single glazing, double glazing, triple glazing, etc.).

4.2.3. Shading

Shading devices are an effective way to reduce the amount of heat that penetrates the building through light-exposed windows. This is done in order to keep the freshness inside the building. In this respect, Scw-n, Scw-s and Scw-e are selected as design variables related to the ratio of the non-transparent surface of the shading device to the total glazed area. The lower limit indicates that there is no solar shading, while the upper limit indicates that the windows are 100% shaded from solar radiation.

4.2.4. Air change

Air change is one of the major features of the building, especially for its occupants. However, it can become an extremely critical factor, in terms of energy consumption, if it is not well controlled. In this respect, the overall air change rate (ACH) is selected as a design variable for air infiltration and ventilation. The lower limit is defined in accordance with the fact that there is no purely airtight building, while the upper limit is defined according to the reference building situation.

Table 6. External window models considered for x_{11} variable

Designation	Symbol	Thickness [mm]	U_g	SHGC	T-s	R-s	T-v
FLOAT_19	Glz ₁	19	5.160	0.682	0.600	0.070	0.830
Insulating. 2.8	Glz ₂	4/16/4	2.830	0.755	0.693	0.126	0.817
Luxguard SUNGUARD CLEAR PLUS Argon. 2.6	Glz ₃	6/16/4	2.300	0.295	0.214	0.195	0.292
Pilk. 3-ple INFRASTOP Brilliant5025+OPTITHERM S #5	Glz ₄	6/12/4/12/4	0.700	0.222	0.177	0.329	0.436
Insulating. 0.4. Xenon	Glz ₅	4/8/4/8/4	0.400	0.408	0.268	0.231	0.625

Table 7. Different levels of selected design variables

Designation	Symbol	Corresponding variable	Unit	Type	Lower limit	Upper Limit	Step	Level
Transmission coefficient of the exterior walls	U_M	x_1	$W.m^{-2}.K^{-1}$	Continuous	0.1	1.9	0.18	11
Transmission coefficient of the Roof	U_T	x_2	$W.m^{-2}.K^{-1}$	Continuous	0.1	2.5	0.24	11
Transmission coefficient of the Floor	U_p	x_3	$W.m^{-2}.K^{-1}$	Continuous	0.1	2.9	0.28	11
Absorption coefficient of the exterior walls	α_M	x_4	-	Continuous	0.1	0.9	0.08	11
Absorption coefficient of the Roof	α_T	x_5	-	Continuous	0.1	0.9	0.08	11
Linear coefficient of thermal bridges	Pt	x_6	$W.m^{-1}.K^{-1}$	Continuous	0.01	1	0.099	11
Air change per hour	ACH	x_7	$v.h^{-1}$	Continuous	0.1	1.1	0.1	11
Shading coefficient for north-facing windows	Scw-n	x_8	-	Continuous	0	1	0.1	11
Shading coefficient for south-facing windows	Scw-s	x_9	-	Continuous	0	1	0.1	11
Shading coefficient for east-facing windows	Scw-e	x_{10}	-	Continuous	0	1	0.1	11
Glazing	Glc	x_{11}	-	Continuous	Glc ₁	Glc ₅	-	5

5. Development of the ANN model

The introduction of ANNs in energy efficiency improvement approaches for buildings is an important step in achieving the desired performances, as they offer a greater degree of accuracy and timeliness than other conventional methods. Thus, their application in building energy efficiency improvement approaches remains a central idea and a future development for researchers [49], [50].

In this study, the predictions obtained by the ANNs are used to define the envisaged objective functions. Indeed, prediction is a kind of dynamic filtering, in which past values of one or more time series are used to predict future values. This has been used in several research works to predict a possible need in the building sector [51]–[53]. To this end, a database consisting of 35 samples was created, in accordance with the philosophy described in Section 5.1. This represents an important preliminary step for the different ANNs modelling.

5.1. Creation of the database

In this study, the objective functions are defined through the learning of artificial neural networks. Therefore, the availability of a database is indispensable to define them. Indeed, a number of databases have been set up, whose principle and number of simulations differ from a database to another. The objective is to identify the database that has been the subject of a minimum number of simulations while allowing very precise learning. For this reason, a mathematical approach has been well developed according to the envisaged criteria, whose modeling is presented in Eq. (4) and Eq. (5):

$$f_1(X) = \text{ATED}(X) \quad (4)$$

$$f_2(X) = \text{ADH}(X) \quad (5)$$

f_1 and f_2 are defined as functions that represent, in a certain way, the calculation mechanism related to the designed platform in TRNSYS software environment (see Fig. 5), aiming to obtain the ATED and the ADH as a function of $x_{i,j}$ variable (Eq. (6)).

$$X_z = x_{i,j} \quad \forall x_{i,j} \in \mathbb{R}^+ \quad (6)$$

With (Eq. (7)):

$$\begin{cases} i \in I = [1, 2, \dots, 11] \\ j \in J = [1, 2, \dots, 11] \\ z \in Z = [1, 2, \dots, 35] \end{cases} \quad (7)$$

Note ((Eq. 8)):

$$\begin{aligned}
X_1 &= (x_{1,1}, x_{2,1}, x_{3,1}, x_{4,1}, x_{5,1}, x_{6,1}, x_{7,1}, x_{8,1}, x_{9,1}, x_{10,1}, x_{11,1}) \\
X_2 &= (x_{1,2}, x_{2,2}, x_{3,2}, x_{4,2}, x_{5,2}, x_{6,2}, x_{7,2}, x_{8,2}, x_{9,2}, x_{10,2}, x_{11,2}) \\
X_3 &= (x_{1,3}, x_{2,3}, x_{3,3}, x_{4,3}, x_{5,3}, x_{6,3}, x_{7,3}, x_{8,3}, x_{9,3}, x_{10,3}, x_{11,3}) \\
X_4 &= (x_{1,4}, x_{2,4}, x_{3,4}, x_{4,4}, x_{5,4}, x_{6,4}, x_{7,4}, x_{8,4}, x_{9,4}, x_{10,4}, x_{11,4}) \\
\vdots &= \quad \quad \quad \vdots \quad \quad \quad \vdots \quad \quad \quad \vdots \\
\vdots &= \quad \quad \quad \vdots \quad \quad \quad \vdots \quad \quad \quad \vdots \\
X_9 &= (x_{1,9}, x_{2,9}, x_{3,9}, x_{4,9}, x_{5,9}, x_{6,9}, x_{7,9}, x_{8,9}, x_{9,9}, x_{10,9}, x_{11,9}) \\
X_{10} &= (x_{1,10}, x_{2,10}, x_{3,10}, x_{4,10}, x_{5,10}, x_{6,10}, x_{7,10}, x_{8,10}, x_{9,10}, x_{10,10}, x_{11,10}) \\
X_{11} &= (x_{1,11}, x_{2,11}, x_{3,11}, x_{4,11}, x_{5,11}, x_{6,11}, x_{7,11}, x_{8,11}, x_{9,11}, x_{10,11}, x_{11,11}) \\
X_{12} &= (\mathbf{x}_{1,5}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, x_{11,3}) \\
X_{13} &= (\mathbf{x}_{1,7}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, x_{11,3}) \\
X_{14} &= (x_{1,6}, \mathbf{x}_{2,5}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, x_{11,3}) \\
X_{15} &= (x_{1,6}, \mathbf{x}_{2,7}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, x_{11,3}) \\
\vdots &= \quad \quad \quad \vdots \quad \quad \quad \vdots \quad \quad \quad \vdots \\
\vdots &= \quad \quad \quad \vdots \quad \quad \quad \vdots \quad \quad \quad \vdots \\
X_{30} &= (x_{1,6}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, \mathbf{x}_{10,5}, x_{11,3}) \\
X_{31} &= (x_{1,6}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, \mathbf{x}_{10,7}, x_{11,3}) \\
X_{32} &= (x_{1,6}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, \mathbf{x}_{11,1}) \\
X_{33} &= (x_{1,6}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, \mathbf{x}_{11,2}) \\
X_{34} &= (x_{1,6}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, \mathbf{x}_{11,4}) \\
X_{35} &= (x_{1,6}, x_{2,6}, x_{3,6}, x_{4,6}, x_{5,6}, x_{6,6}, x_{7,6}, x_{8,6}, x_{9,6}, x_{10,6}, \mathbf{x}_{11,5})
\end{aligned} \tag{8}$$

The X_z set is a size data matrix (35x11) that characterizes the database designed for automatic learning, of which it contains 35 samples. Indeed, this number of samples was not randomly selected, but rather after several trial-and-error-based evaluation simulations. This database is based on a particular philosophy, as expressed in the following lines:

This philosophy is based on two fundamental principles that are used to achieve high quality learning, the first of which is called level samples, while the second is called weight samples.

- Level samples: this means that in each simulation of a sample, only one level must be taken for all variables.
- Weight samples: this means that in each simulation of a sample, only one variable must be isolated, i.e. its level is different from the other variables whose level, called pivot, is constant. Note that level 6 is the reproduction pivot, since it represents the middle of the levels.

The vectors X_1, X_2, \dots, X_{11} represent the so-called level samples, i.e. in each sample simulation, only one level must be taken for all variables, with the exception of x_{11} since it has 5 levels instead of 11. Thus, the levels of x_{11} are distributed in such a way as to comply with the principle of the others by simulating each one twice, or even three times in the case of X_9, X_{10}, X_{11} vectors.

The vectors $X_{12}, X_{13}, \dots, X_{35}$ represent the so-called weight samples, i.e. in each sample simulation, only one x_i variable must be isolated from the others, whose level varies in this case between the pivot level -1 and +1. The

only exception is x_{11} since it is a discrete variable that has only 5 levels, which does not prevent the addition of its two other levels (X_{32} , X_{35}) in order to improve its weight learning. It should be noted that the X_{34} and X_{35} correspond to the complements coefficient β introduced by discrete variables (Fig. 6).

Finally, the different simulations necessary for creating the database, through which the ANN learning will be carried out, are performed as presented in Eq. (9):

$$\begin{aligned}
 [f_1, f_2](X_1) &= [\text{ATED}, \text{ADH}](X_1) \\
 [f_1, f_2](X_2) &= [\text{ATED}, \text{ADH}](X_2) \\
 \vdots &= \vdots \\
 \vdots &= \vdots \\
 [f_1, f_2](X_{35}) &= [\text{ATED}, \text{ADH}](X_{35})
 \end{aligned} \tag{9}$$

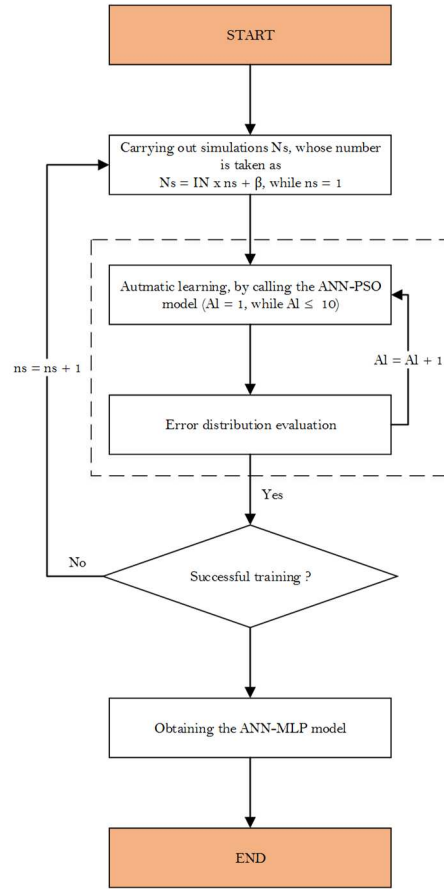


Figure 6. Approval process of the number of simulations adopted for creating the database

5.2. Training and validation of the ANN model

For the purpose of training and validating the artificial neural networks under consideration, the 35 samples were randomly divided into a training set (70%), a validation set (15%) and a test set (15%), as suggested by Shahin et al. [54]. Indeed, the Multilayer Feed Forward Neural Network (MFNN) is used as a type of these ANNs, given that it represents the most recommended type in the literature [55]. MFNNs are computational models composed of many neurons (nodes), which are connected by connective links (weights) and are arranged layer by layer. Thus, the f_i output is calculated mathematically according to Eq. (10):

$$f_i = \phi_i \left(\sum_{j=1}^{n_i} w_{i,j} z_{i,j} + b_i \right) \tag{10}$$

The architecture of both ANNs is shown in Fig. 7, where each ANNs has an input layer that contains 11 neurons corresponding to the 11 optimization variables, then a hidden layer composed of 4 neurons, and finally an output layer, either f_1 or f_2 . The number of neurons in the hidden layer is essential to ensure the performance of the ANN model. An excessive number of hidden neurons will lead to over-fitting, while an insufficient number of hidden neurons will hinder the robustness and reliability of the learning process. In fact, there is no general rule but rather empirical rules. According to the literature, the size of the hidden layer must be either equal to that of the input layer [56], or equal to 75% of it [57], [58] or equal to the square root of the product of the number of neurons in the input and output layer [59]. In this study, the number of hidden neurons was determined using the trial-and-error method based on the mean relative error of the ANN predictions for each output. Thus, the best fit was 4 neurons in the hidden layer for each of the networks, which does not correspond to any of the aforementioned empirical rules (Fig. 7).

The networks were trained using Le-venberg-Marquardt back-propagation algorithm. A sigmoidal function for the hidden layer and a linear function for the output layer were used as transfer functions. This training is not based on the conventional principle, i.e. it stops automatically when the MSE of the validation samples has stabilized, but rather on a special combination with the PSO as suggested by Keshtkarbanaeemoghdam et al. [60]. Indeed, when ANNs start training, specifically when the process reaches the classical MSE, the PSO is invited to find the most MSE-optimized weights ($w_{i,j}$) and biases (b_i) of the neural networks. Then, after a set of well-defined iterations, which are 50 in this case, the coupling process compares each time the two MSEs in order to finally achieve the best training at a very low MSE. Thus, the best performance of the ANN-MLP model is obtained as illustrated in Fig. 8. It should be noted that the implementation of the two ANNs, each one assigned to a single objective function, consists in defining each function separately from the other. Thus, the optimization can be carried out in a suitable way.

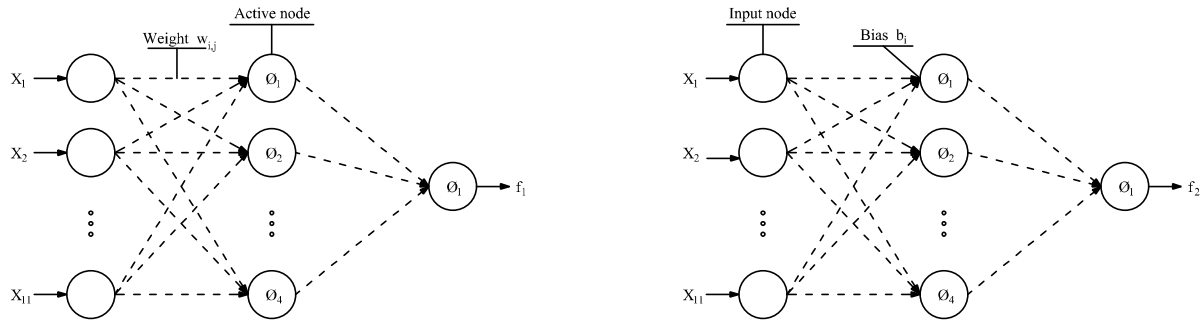


Figure 7. Three-layer feedforward ANN architecture for f_1 and f_2

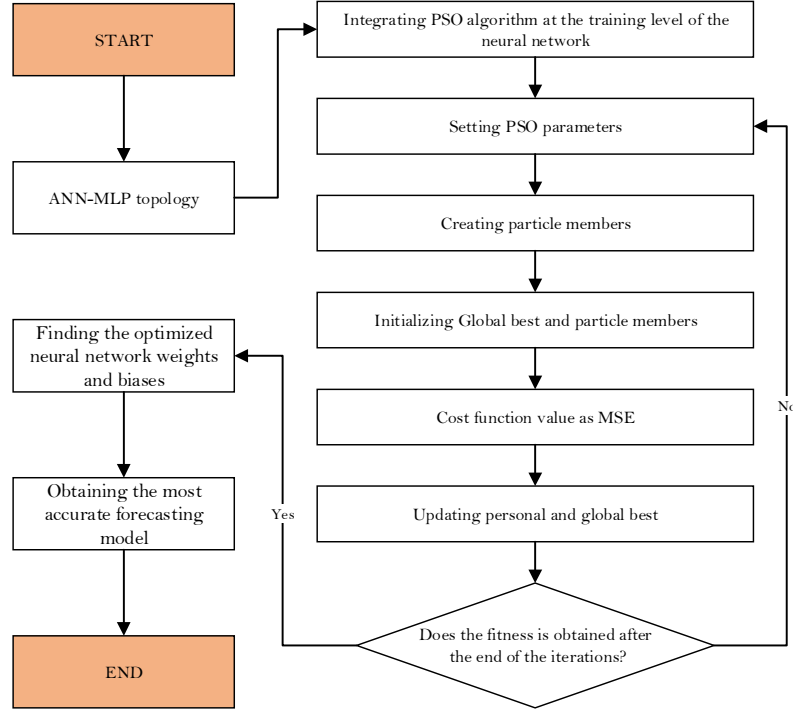


Figure 8. Implementation of the PSO algorithm in neural network training.

5.3. Assessment of the ANN model accuracy

For any approach, leading to build a surrogate model should undergo an accuracy evaluation, in order to have a visibility on its reliability. So, before proceeding to the optimization step, the reliability of the developed ANNs must be evaluated.

The most commonly used error functions to measure the accuracy during the training of ANNs were the mean square error (MSE) and the root mean square error (RMSE). On the other hand, the preferred parameters to quantify the performance of ANN metamodels were RMSE, the coefficient of determination (R_2), and the correlation coefficient (R) [55]. In this paper, the accuracy of the developed surrogate models has been assessed using the most important and frequently used indicators of forecast reliability in the literature, which are RMSE and R . Quite naturally, the root mean square error provides a complete view of the error distribution for any kind of predictive evaluation similar to the present one.

Indeed, the evaluation of ANN-MLP models through these indicators has no rule in terms of reference value since this depends absolutely on the number of observations as many authors have confirmed. In other words, an RMSE that varies around 2 for a prediction evaluation of such an observation size similar to the one presented in this paper seems very satisfactory.

In order to select a surrogate model that has a significant reliability, 10 simulations were established as indicated in Fig. 6, each of which was subject to an RMSE calculation according to Eq. (11).

$$RMSE = \left[n_k^{-1} \sum_{i=1}^{n_k} |y_i - y'_i|^2 \right]^{\frac{1}{2}} \quad (11)$$

Following the establishment of the 10 simulations planned during the development of the database creation algorithm, it turns out that the distribution of errors evolves in a scalable way. However, for each of the performance indicators, namely ATED and ADH, it shows RMSE values below 2.5, which is small enough to

provide a good prediction as illustrated in Fig. 9 and Fig. 10. In this case, the selected ANN-MLP models are those with the smallest RMSE, i.e. RMSE = 1.12 and RMSE = 2.22 for ATED and ADH respectively. This ensures a high predictive reliability since the correlation, measured by the selected models, between ANN predictions and TRNSYS simulations is close to 1, which corresponds to a very high correlation, as shown in Fig. 11 and Fig. 12.

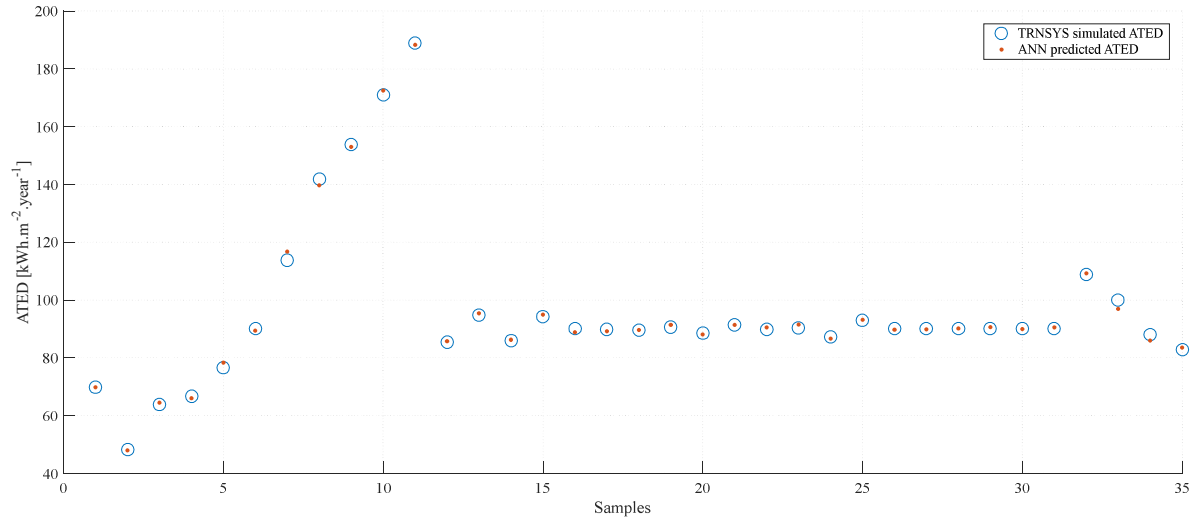


Figure 9. Accuracy of ANN prediction for ATED

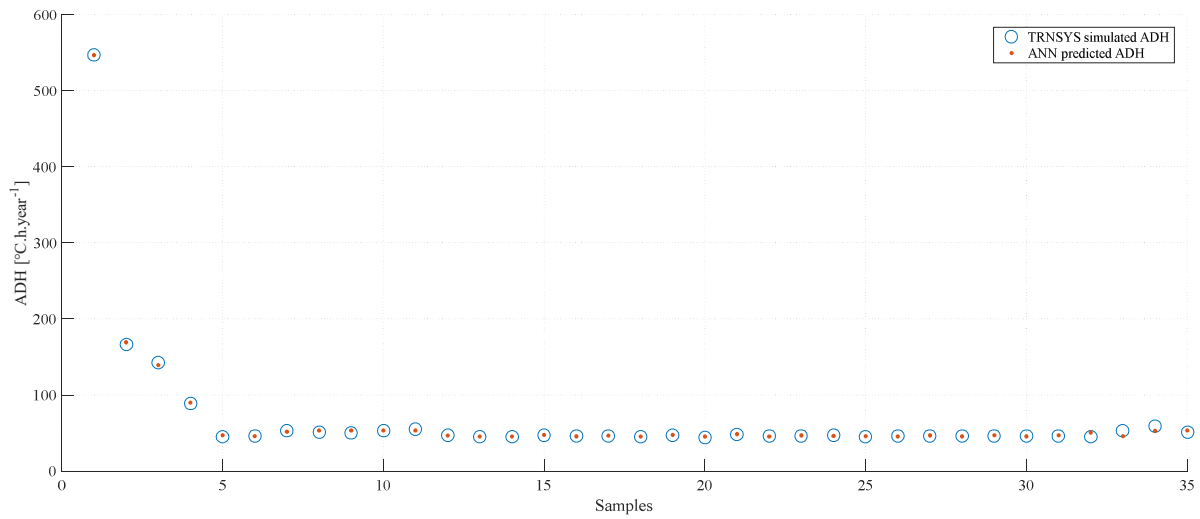


Figure 10. Accuracy of ANN prediction for ADH

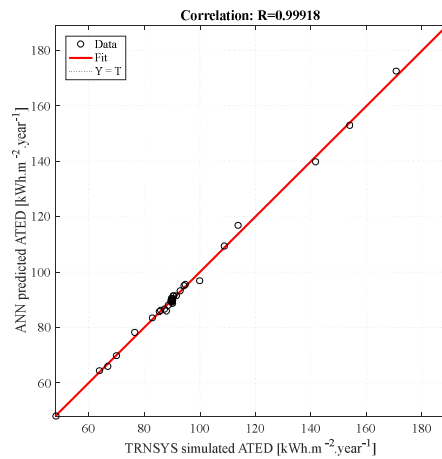


Figure 11. Regression between ANN predictions and TRNSYS simulations for ATED

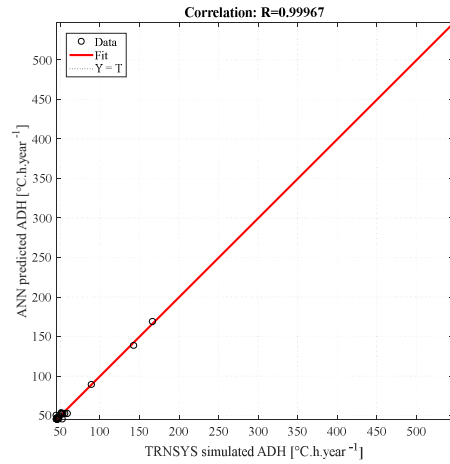


Figure 12. Regression between ANN predictions and TRNSYS simulations for ADH

5.4. Sensibility analysis

In this section, a sensitivity analysis of the learning process was discussed. In particular, the effect of each input parameter on ATED and ADH was examined using the well-known Garson 1991 algorithm [61]. The purpose of using this algorithm is to evaluate the relative importance of each input parameter on the desired output(s). The algorithm procedure is presented in Appendix-A in the Supplementary Data section.

Some researchers such as Calleja Rodríguez et al. [62] and Laine et al. [63] have performed a sensitivity analysis using different metaheuristic methods to determine the most important impact of input parameters on the energy performance of buildings. In this research, the sensitivity analysis of the ANN-PSO model is presented in Fig. 13. This analysis was performed based on the algorithm of Garson as suggested by Keshtkarbanaeemoghadam et al. [60]. The results show that the different input parameters have an important impact on ATED and ADH, which is already expected from the choice of envelope design parameters. Thus, the three parameters that have a greater impact on ATED compared to the others are the Transmission coefficient of the exterior walls with 18.77%, the Transmission coefficient of the Roof with 11.80% and the air change per hour with 10.13%. On the other hand, for ADH, the air change per hour ranks first with 11.99%, then the transmission coefficient of the floor with 11.25% and the glazing with 10.97%.

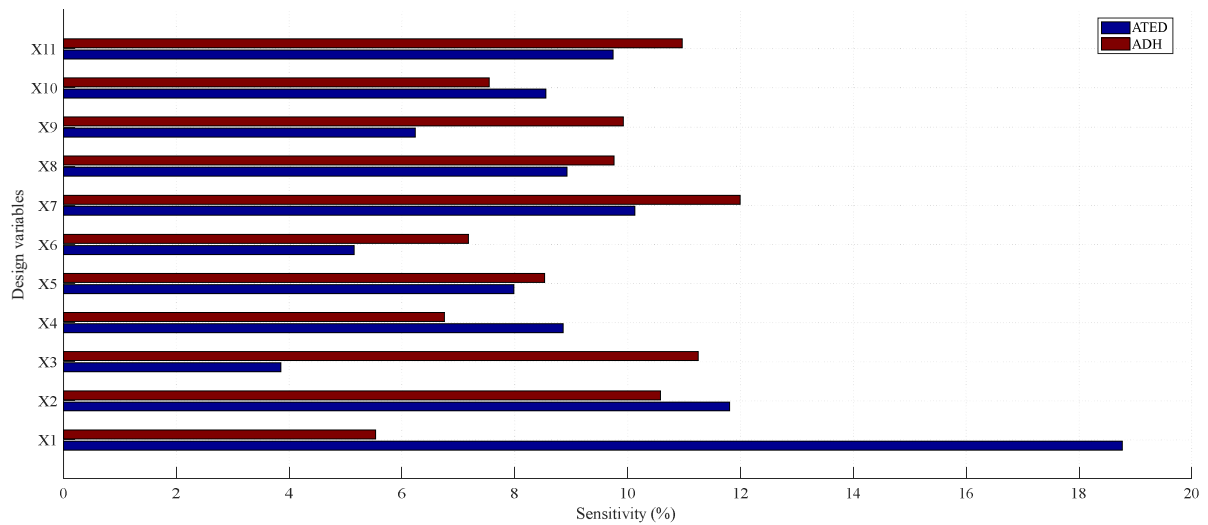


Figure 13. Relative importance of each input variable for estimating ATED and ADH

6. Discussion and results

In this section, we will discuss possible recommendations for designing a building envelope that perfectly meets the requirements of energy-efficient buildings. This will be addressed once the appropriate multi-objective algorithm has been selected.

6.1. Appropriate metaheuristic algorithm

The optimization is generally defined by the selection of the best candidate from a set of available alternatives according to certain criteria. In the simplest case, an optimization problem aims to find the minimum or maximum value of a function by choosing a number of variables subjected to a number of constraints according to specific problems. The optimization function is also called a fitness or objective function, which is often calculated by scientific simulation tools. In this study, the optimization problem consists of minimizing the two functions defined by Eq. (2) and Eq. (3) as mathematically described by Eq. (12):

$$\min_x f(X_z) = \begin{cases} f_1 = \text{Net}_1(X_z) \\ f_2 = \text{Net}_2(X_z) \end{cases} \quad \forall X \in \mathbb{R}^+ \quad (12)$$

Subject to the constraints presented in Eq. (13):

$$\left\{ \begin{array}{l} f_1 > 0 \text{ and } f_2 > 0 \\ 0.1 \leq x_1 \leq 1.9 \\ 0.1 \leq x_2 \leq 2.5 \\ 0.1 \leq x_3 \leq 2.9 \\ 0.1 \leq x_4, x_5 \leq 0.9 \\ 0.01 \leq x_6 \leq 1 \\ 0 \leq x_7, x_8, x_9, x_{10} \leq 1 \\ 1 \leq x_{11} \leq 5 \end{array} \right. \quad (13)$$

6.1.1. Application of metaheuristic algorithms

It appears from the literature, particularly that presented in Table 1, that a number of metaheuristic optimization algorithms have been used in different cases, involving different parameters and obviously different approaches, although some of them are frequently reproduced, namely evolutionary algorithms and those based on particle swarms. These have been compared with each other in numerous research works [64]–[66]. Furthermore, Nguyen et al. [67] showed in a very detailed review of simulation-based optimization methods applied to building performance analysis that, according to 200 published papers in this field, genetic algorithms ranked first in terms of use, followed by PSO algorithms and then hybrid algorithms. In this respect, considering the rank of use of genetic and PSO algorithms, three population-based stochastic multi-objective optimization algorithms, namely NSGA-II [68], MOGA [69] and MOPSO [70], were selected for application to the proposed optimization problem. All these algorithms were implemented on Matlab R2016a according to their operating principle referenced above. It is well known that the performance of optimization algorithms does not only depend on the optimization problem but also on the control parameters. In this study, the parameters of each optimization algorithm were taken according to the default parameters chosen by Li et al. [12] (Table 8). With the exception of population size and iteration number, since these parameters have an important impact on the optimization algorithms convergence. Indeed, several tests have been carried out to define the interval in which the desired optimums are frequently

found, taking into account as priorities population size, iteration number and simulation time. These tests show that this interval ranges between 25 and 100, both for population size and iteration number, as long as their product is the same throughout the interval. Thus, the greatest convergence leading to a better solution was evaluated according to 4 tests as shown in Table 9, within the same interval, in order to select the appropriate algorithm.

Table 8. Setting of the applied optimization algorithms

Algorithms	Settings	Values
NSGA-II	Iteration number	25-100
	Population Size	25-100
	Crossover probability	0.9
	Mutation probability	0.5
MOPSO	Iteration number	25-100
	Population Size	25-100
	Acceleration coefficient c_1	2
	Acceleration coefficient c_2	2
	Inertia Weight	0.4
	Inertia Weight Damping Rate	0.9
MOGA	Iteration number	25-100
	Population Size	25-100
	Crossover probability	0.9
	Mutation probability	0.5

Table 9. Setting the iteration number and population size for the four tests

Settings	Test 1	Test 2	Test 3	Test 4
Iteration number	100	75	50	25
Population Size	25	50	75	100

6.1.2. Selection of the appropriate algorithm

The selection of the appropriate multi-objective algorithm is based on the performance evaluation of the set of implemented algorithms, according to several criteria that depend mainly on the expected objective. An important concept of multi-objective optimization is called the Pareto front, which is a set of solutions that are not dominated by each other [71] (i.e. no design objective can be improved without first judging the others). Indeed, the performance evaluation of a multi-objective algorithm depends on the evaluation of the optimal Pareto set properties, estimated by this algorithm, as well as the computational resources required to generate this set. These properties are diverse, including diversity, generational distance, normalized inverted generational distance, etc [72], [73]. In this study, the implementation of an optimization algorithm aims, in general, towards responding to the present issue while guaranteeing a minimum calculation time, which is partially taken into account when defining the range of tests presented in Table 9. In addition, three criteria have been highlighted in order to select the appropriate algorithm, i.e. calculation time, optimality and diversity of solutions.

Fig. 14, Fig. 15 and Fig. 16 show the Pareto-optimal spectrum of the different applied optimization algorithms, respectively NSGA-II, MOPSO and MOGA. It should be noted that this Pareto-optimal spectrum, derived from the multi-objective algorithm performance, represents the optimums with respect to the objective space rather than the decision space, since the most important reason for using multi-objective algorithms is to examine the balance between conflicting objectives. These figures can be better understood by looking at Table 10, which shows the three best Pareto-optimal solutions obtained by each algorithm in the four proposed tests. Thus, the performance of the applied optimization algorithms can be assessed with respect to the three considered criteria:

- Firstly, computation time constitutes the main criterion of this study. The MOPSO was therefore able to show that it could beat the other algorithms regarding the moment at which convergence is perfectly achieved. However, this outperformance could only be useful if the other evaluation criteria are the same for all algorithms, since this latter does not represent a very significant response time (See Table 11).
- As for optimality, which is a basic criterion for all studies aimed at optimizing any kind of need, it turns out that each of NSGA-II and MOPSO have succeeded, at the end of their convergence, in providing well-optimized pareto-optimal solutions compared to MOGA (i.e., the best achievable pareto-optimal solutions in the objective plan). These solutions are virtually identical in all the tests proposed. Moreover, their particular property in terms of proximity between their Pareto-optimal solutions becomes more important as the number of iterations increases.
- Finally, the third criterion, which is diversity, serves to offer decision-makers a multiple option in terms of Pareto-optimal solutions, in order to provide sufficient flexibility in case where there are constraints regarding certain factors, i.e. feasibility, availability, cost, etc. Indeed, all of the implemented algorithms, i.e. NSGA-II, MOPSO and MOGA have shown in each of the 4 tests that they can generate distinct Pareto-optimal solutions, but in a rather limited way.

Finally, the comparative analysis can show that NSGA-II and MOPSO present the most efficient multi-objective algorithms compared to MOGA, in terms of balance between the considered criteria. However, the MOPSO is the one that will be selected because it offers a slight advantage in computation time compared to NSGA-II. It should be noted that, in this study, only the spectrum that meets the objective plan is concerned.

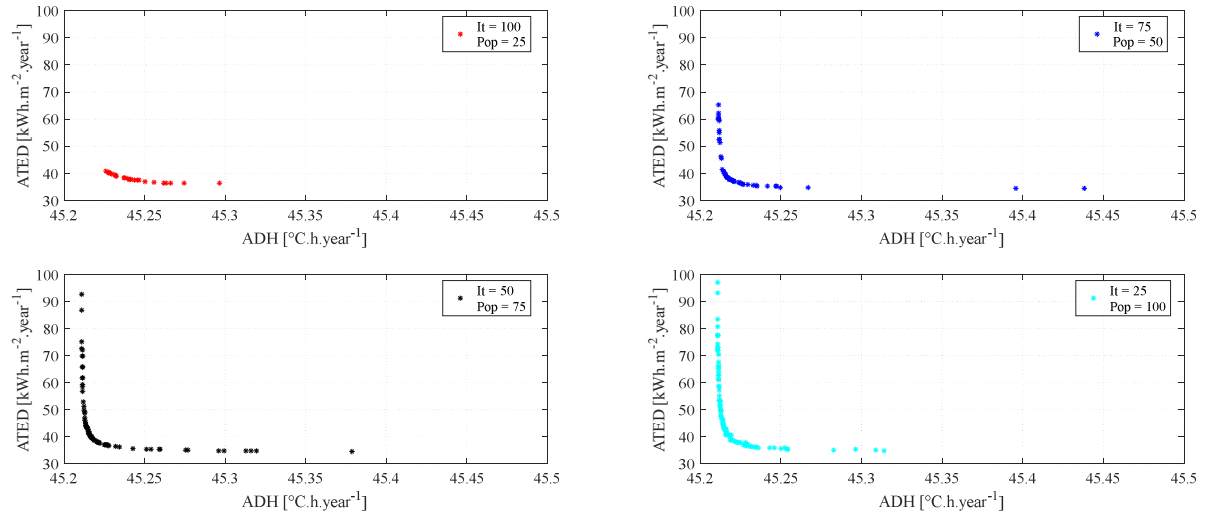


Figure 14. Pareto frontiers evolution in 4 tests for NSGA-II

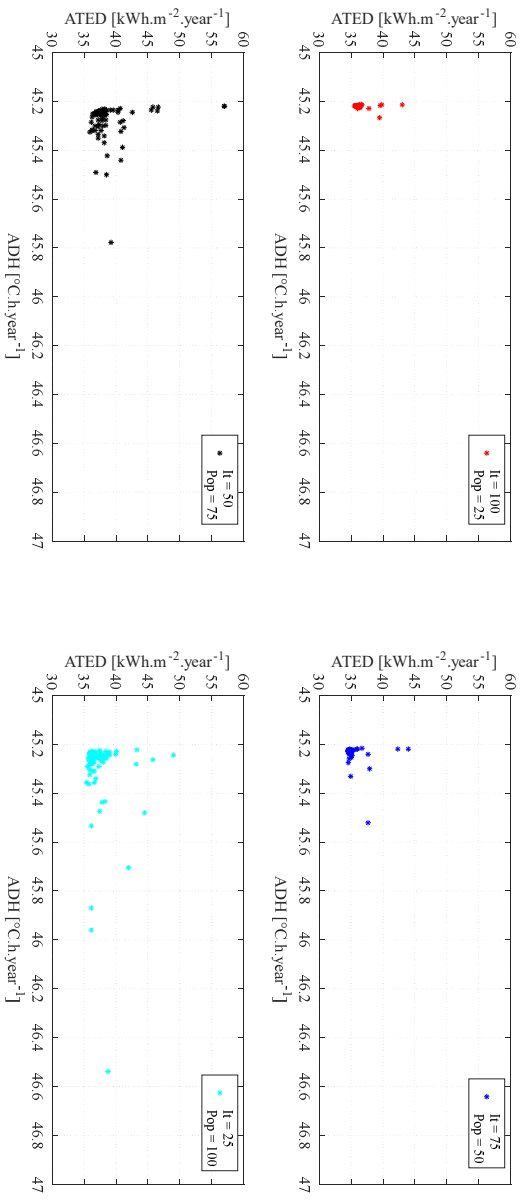


Figure 15. Pareto frontiers evolution in 4 tests for MOPSO

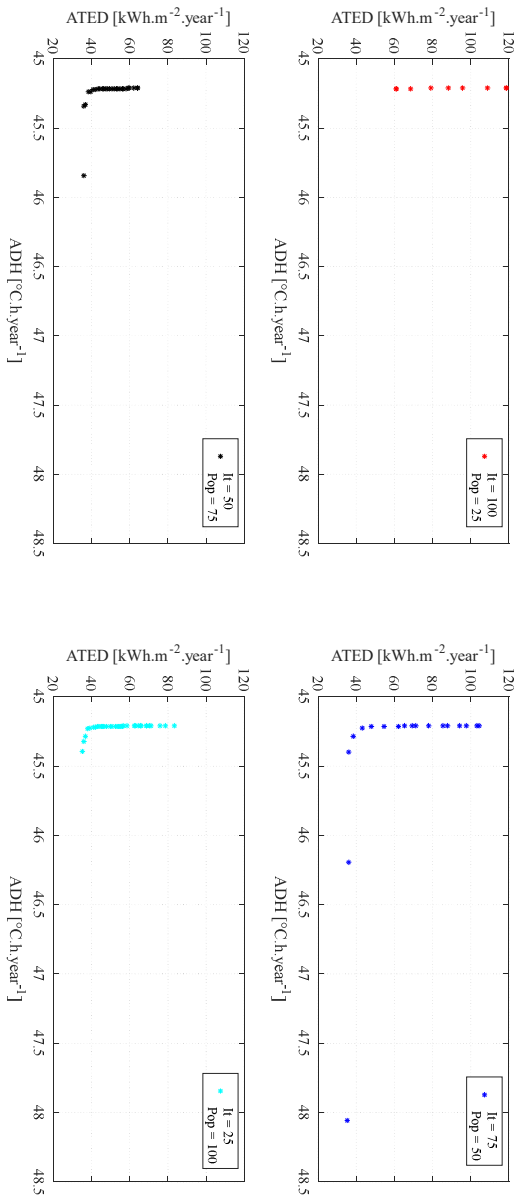


Figure 16. Pareto frontiers evolution in 4 tests for MOGA

Table 10. The Top three Pareto-optimal solutions obtained by each algorithm across the four tests.

Algorithm	Test	Top 3 POS	x ₁	x ₂	x ₃	x ₄	x ₅	x ₆	x ₇	x ₈	x ₉	x ₁₀	x ₁₁	ATED	ADH
NSGA-II	1	1	0.45	0.41	2.17	0.48	0.10	0.50	0.54	0.46	0.55	0.54	Glz ₄	36.40	45.30
		2	0.27	0.70	2.14	0.49	0.10	0.50	0.53	0.46	0.55	0.53	Glz ₄	36.42	45.27
		3	0.34	0.62	2.13	0.49	0.10	0.49	0.52	0.46	0.54	0.53	Glz ₄	36.47	45.27
	2	1	0.18	0.16	2.82	0.37	0.11	0.26	0.30	0.41	0.38	0.72	Glz ₄ - Glz ₅	34.51	45.44
		2	0.18	0.16	2.82	0.43	0.11	0.26	0.30	0.41	0.38	0.72	Glz ₄ - Glz ₅	34.59	45.40
		3	0.23	0.37	2.55	0.36	0.10	0.26	0.30	0.39	0.58	0.75	Glz ₄ - Glz ₅	34.89	45.27
	3	1	0.40	0.28	2.46	0.37	0.10	0.51	0.11	0.39	0.45	0.54	Glz ₅	34.69	45.38
		2	0.40	0.28	2.46	0.37	0.10	0.51	0.29	0.39	0.45	0.54	Glz ₅	34.72	45.32
		3	0.40	0.28	2.46	0.37	0.10	0.51	0.29	0.40	0.45	0.54	Glz ₅	34.73	45.32
	4	1	0.12	0.37	2.27	0.41	0.11	0.24	0.52	0.72	0.37	0.76	Glz ₄ - Glz ₅	34.95	45.31
		2	0.13	0.42	2.38	0.34	0.11	0.22	0.51	0.75	0.41	0.75	Glz ₄	35.09	45.28
		3	0.11	0.51	2.19	0.40	0.10	0.17	0.59	0.75	0.44	0.76	Glz ₃ - Glz ₄	35.48	45.25
MOPSO	1	1	0.51	0.34	2.73	0.10	0.10	0.09	0.44	0.77	0.64	0.97	Glz ₄ - Glz ₅	35.58	45.22
		2	0.56	0.21	2.90	0.10	0.10	0.11	0.50	0.82	0.64	0.95	Glz ₄	35.63	45.22
		3	0.53	0.24	2.68	0.10	0.10	0.13	0.53	0.77	0.65	1.00	Glz ₄	35.72	45.22
	2	1	0.14	0.10	2.81	0.10	0.10	0.04	0.41	0.55	0.65	1.00	Glz ₄	34.53	45.27
		2	0.18	0.19	2.90	0.11	0.10	0.06	0.28	0.52	0.76	0.95	Glz ₄	34.55	45.23
		3	0.12	0.22	2.83	0.10	0.10	0.05	0.40	0.57	0.78	0.97	Glz ₄ - Glz ₅	34.56	45.23
	3	1	0.36	0.59	2.44	0.29	0.10	0.37	0.56	0.53	0.50	0.50	Glz ₄	35.93	45.33
		2	0.24	0.85	2.25	0.40	0.10	0.42	0.55	0.50	0.47	0.52	Glz ₄ - Glz ₅	36.17	45.28
		3	0.36	0.52	1.96	0.35	0.10	0.41	0.42	0.54	0.53	0.52	Glz ₄	36.20	45.32
	4	1	0.23	0.25	2.25	0.50	0.10	0.44	0.58	0.51	0.57	0.58	Glz ₄	35.40	45.36
		2	0.41	0.22	2.37	0.46	0.10	0.43	0.44	0.59	0.40	0.71	Glz ₄	35.58	45.29
		3	0.32	0.31	2.51	0.40	0.10	0.37	0.53	0.61	0.54	0.72	Glz ₃ - Glz ₄	35.71	45.26
MOGA	1	1	1.20	0.76	1.99	0.34	0.16	0.37	0.65	0.62	0.57	0.73	Glz ₃ - Glz ₄	61.09	45.22
		2	1.20	1.04	1.99	0.32	0.16	0.37	0.62	0.62	0.58	0.73	Glz ₃ - Glz ₄	68.32	45.21
		3	1.30	1.20	1.99	0.27	0.16	0.37	0.67	0.63	0.59	0.73	Glz ₃ - Glz ₄	79.27	45.21
	2	1	0.45	0.63	2.57	0.51	0.31	0.41	0.22	0.24	0.35	0.54	Glz ₄	35.98	46.19
		2	0.43	0.57	2.36	0.51	0.22	0.39	0.28	0.30	0.46	0.61	Glz ₄	36.16	45.40
		3	0.42	0.78	2.55	0.51	0.14	0.42	0.58	0.58	0.35	0.64	Glz ₃ - Glz ₄	38.56	45.28
	3	1	0.18	0.51	2.55	0.39	0.18	0.38	0.63	0.56	0.58	0.64	Glz ₄	36.15	45.34
		2	0.13	0.50	2.71	0.42	0.23	0.38	0.60	0.56	0.59	0.57	Glz ₄	35.83	45.84
		3	0.30	0.60	2.44	0.41	0.19	0.38	0.64	0.56	0.59	0.61	Glz ₄	36.71	45.33
	4	1	0.32	0.51	2.39	0.27	0.22	0.26	0.42	0.69	0.36	0.65	Glz ₄ - Glz ₅	35.28	45.40
		2	0.46	0.51	2.40	0.21	0.22	0.38	0.49	0.69	0.48	0.57	Glz ₄ - Glz ₅	35.86	45.33
		3	0.51	0.51	2.40	0.24	0.22	0.34	0.49	0.75	0.58	0.62	Glz ₄	36.75	45.28

Note that the composition [Glz_j - Glz_j] means that this variable corresponds to the middle of the two boundaries.

Table 11. Computation time features of the proposed algorithms in the four tests.

Features	NSGA-II				MOPSO				MOGA			
Tests	1	2	3	4	1	2	3	4	1	2	3	4
Calculation time (s)	58	98	107	66	38	62	64	42	41	60	68	49
Convergence time (s)	7	32	79	54	29	40	10	26	5	20	50	40
Efficiency (%)	99.99	99.99	99.95	99.99	99.93	99.96	99.99	99.98	98.18	99.14	99.06	98.54

6.2. Building envelope recommendations

It is well-known that the BPO technique brings gains at the end of its application. In this study, it led to a significant improvement in the energy performance, in particular that related to heating and cooling, as well as indoor thermal comfort, of a residential building located in Marrakech region. Indeed, this reference building is based on assumptions concerning the same characteristics as a building constructed before 2014 in the same region, when

the RTCM was not yet mandatory. As a result, it is not a monitored building, i.e., it does not have an energy and data management system. In this respect, its optimised performance can only be compared to the RTCM recommendations, as it represents the thermal building code in Morocco as described in section 4. In fact, the RTCM doesn't have any specific recommendations regarding thermal comfort, except for the set temperatures, which implies that the optimised ADH in this study can only be compared to that of the base building. In contrast, a thermal performance indicator, particularly for heating and cooling, is well recommended for the same region, i.e. $130 \text{ kWh.m}^{-2}.\text{yr}^{-1}$ as an upper limit that should not be exceeded.

6.2.1. Optimal building design

The application of the different multi-objective optimization algorithms used in this study showed that the NSGA-II and MOPSO are the most appropriate for addressing the present issue. In this respect, as the MOPSO is the one selected in section 6.1.2, four solutions have been selected among the different alternatives proposed by this latter, i.e. one solution from each of the four tests, in order to construct the most efficient solutions as presented in Table 11. This Table shows that each solution presents some diversity with respect to the others in terms of design variables, with the exception of the variable x_5 , which is constant in all of the proposed solutions. The reason for this is that the roof constitutes a critical component that must be taken with some caution compared to other opaque walls, in order to limit heat loss as much as possible. In addition, it should be noted that the variable x_{11} is also important, since it represents the glazed part of the building envelope. This is why it varies between the most efficient glazings proposed in this study.

Table 12. Design variables of several solutions

Design variable	Unit	Solution 1	Solution 2	Solution 3	Solution 4
Transmission coefficient of the exterior walls	$\text{W.m}^{-2}.\text{K}^{-1}$	0,51	0,14	0,36	0,23
Transmission coefficient of the Roof	$\text{W.m}^{-2}.\text{K}^{-1}$	0,34	0,10	0,59	0,25
Transmission coefficient of the Floor	$\text{W.m}^{-2}.\text{K}^{-1}$	2,73	2,81	2,44	2,25
Absorption coefficient of the exterior walls	-	0,10	0,10	0,29	0,50
Absorption coefficient of the Roof	-	0,10	0,10	0,10	0,10
Linear coefficient of thermal bridges	$\text{W.m}^{-1}.\text{K}^{-1}$	0,09	0,04	0,37	0,44
Air change per hour	v.h^{-1}	0,44	0,41	0,56	0,58
Shading coefficient for north-facing windows	-	0,77	0,55	0,53	0,51
Shading coefficient for south-facing windows	-	0,64	0,65	0,50	0,57
Shading coefficient for east-facing windows	-	0,97	1,00	0,50	0,58
Glazing	-	$\text{Glz}_4 - \text{Glz}_5$	Glz_4	Glz_4	Glz_4

6.2.2. Improvement potential

Following the selection of the four building design solutions, it appears from Table 12 that they represent suitable solutions for this study, due to the successful performance of both ATED and ADH. Thus, in case only one solution should be selected, it will be solution 2, although it presents only a slight difference in advantage, which seems negligible compared to the others. Consequently, the studied building will have to be in full compliance with the RTCM since the ATED varies around $35 \text{ kWh.m}^{-2}.\text{yr}^{-1}$, which represents about 4 times less than the regulatory upper limit. Furthermore, the ADH has practically improved through a reduction of about 2 °C.h.yr^{-1} with respect to the reference building, which remains a simultaneous improvement of its thermal performance.

In this study, the solution 2, using Eq. (14), provided a very significant potential of improvement in the building's energy performance, particularly in terms of thermal needs (Table 13). This solution averaged 74.52%, which means that the achieved savings on the energy consumption of the air-conditioning systems represent more than half of the total. In addition, a further improvement of 4.32% has been made for the occupants in terms of thermal comfort.

$$I_p (\%) = \frac{f_{OD} - f_{BD}}{f_{BD}} \quad (14)$$

Note that the I_p can only be calculated if the f_{OD} and the f_{BD} have the same unit.

Table 13. Improvement potential of several solutions compared to the base design

Building design	Optimization objective	Value	Improvement potential (%)
Base	ATED	135.50	-
	ADH	47.32	-
Solution 1	ATED	35.58	73,74
	ADH	45,22	4,44
Solution 2	ATED	34,53	74,52
	ADH	45,27	4,32
Solution 3	ATED	35,93	73,48
	ADH	45,33	4,22
Solution 4	ATED	35,40	73,87
	ADH	45,36	4,15

7. Conclusion

In this study, the BPO technique was well applied in order to design energy-efficient buildings, i.e. a GFFF residential building located in Marrakech region of Morocco (5th climatic zone according to the RTCM). The purpose is minimizing its energy demand, especially for heating and cooling, as well as maximizing indoor thermal comfort, which are the two most important targets for building designers. The design variables considered in this optimization include the thermo-physical parameters of all opaque and glazed walls, shading devices, thermal bridges and ventilation.

Indeed, a surrogate model with good predictive accuracy has been developed by the ANN in order to target the overall research space of the two expected objectives. This was accomplished by using a database of 35 samples, which were simulated by a platform developed in TRNSYS software environment. Actually, this value represents a major contribution regarding computation time since it is very reduced compared to the existing literature. Then, the selection of the appropriate algorithm, which perfectly meets the requirements of this study, was initiated after comparing the performance of three commonly used multi-objective optimization algorithms, namely NSGA-II, MOPSO and MOGA, using the criteria mentioned in section 6.1.2. The results indicate that the MOPSO achieved the greatest desired performance, followed by the NSGA-II and finally the MOGA.

The final optimization results of the studied building design showed that there is a very significant improvement potential, representing 74.52% and 4.32% respectively for ATED and ADH, compared to the base design. These results show that the BPO technique is highly suitable for difficult building design optimization problems, where no more efficient classical method is available, especially in the case of introducing artificial intelligence. In this context, the proposed methodology presented in this paper, which is based on several modeling, automatic learning and optimization tools, has been carried out successfully by responding quite sufficiently to the gap in knowledge on this issue. However, some other tools may be introduced in further work to improve this approach, especially more powerful tools for machine learning, deep learning and new generation algorithms.

Appendix-A. Supplementary data

Data uploaded

Acknowledgments

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Reference :

- [1] Ministère de l'Energie des Mines de l'Eau et de l'Environnement, "Stratégie Energétique Nationale - Horizon 2030," 2015.
- [2] "BUILDINGS - ENERGY EFFICIENCY - Department of Housing and Urban Policy." [Online]. Available: http://www.mhpv.gov.ma/?page_id=3605. [Accessed: 01-Jan-2021].
- [3] AMEE, *Règlement thermique de construction au Maroc (RTCM)*, vol. 91. 2014.
- [4] V. Machairas, A. Tsangrassoulis, and K. Axarli, "Algorithms for optimization of building design: A review," *Renew. Sustain. Energy Rev.*, vol. 31, no. 1364, pp. 101–112, Mar. 2014.
- [5] F. Bre, N. Roman, and V. D. Fachinotti, "An efficient metamodel-based method to carry out multi-objective building performance optimizations," *Energy Build.*, vol. 206, p. 109576, Jan. 2020.
- [6] Y. Zhai, Y. Wang, Y. Huang, and X. Meng, "A multi-objective optimization methodology for window design considering energy consumption, thermal environment and visual performance," *Renew. Energy*, vol. 134, pp. 1190–1199, Apr. 2019.
- [7] L. Shi, H. Zhang, Z. Li, Z. Luo, and J. Liu, "Optimizing the thermal performance of building envelopes for energy saving in underground office buildings in various climates of China," *Tunn. Undergr. Sp. Technol.*, vol. 77, no. 66, pp. 26–35, Jul. 2018.
- [8] S. Papadopoulos and W. L. Woon, *Data Analytics for Renewable Energy Integration. Technologies, Systems and Society*, vol. 11325. Cham: Springer International Publishing, 2018.
- [9] R. Yao, V. Costanzo, X. Li, Q. Zhang, and B. Li, "The effect of passive measures on thermal comfort and energy conservation. A case study of the hot summer and cold winter climate in the Yangtze River region," *J. Build. Eng.*, vol. 15, no. June 2017, pp. 298–310, Jan. 2018.
- [10] K. Bamdad, M. E. Cholette, L. Guan, and J. Bell, "Building energy optimisation under uncertainty using ACOMV algorithm," *Energy Build.*, vol. 167, pp. 322–333, May 2018.
- [11] S. Gou, V. M. Nik, J. L. Scartezzini, Q. Zhao, and Z. Li, "Passive design optimization of newly-built residential buildings in Shanghai for improving indoor thermal comfort while reducing building energy demand," *Energy Build.*, vol. 169, pp. 484–506, 2018.
- [12] K. Li, L. Pan, W. Xue, H. Jiang, and H. Mao, "Multi-Objective Optimization for Energy Performance Improvement of Residential Buildings: A Comparative Study," *Energies*, vol. 10, no. 2, p. 245, Feb. 2017.
- [13] E. Mostavi, S. Asadi, and D. Boussaa, "Development of a new methodology to optimize building life cycle cost, environmental impacts, and occupant satisfaction," *Energy*, vol. 121, pp. 606–615, Feb. 2017.
- [14] A. Zhang, R. Bokel, A. van den Dobbelsteen, Y. Sun, Q. Huang, and Q. Zhang, "Optimization of thermal and daylight performance of school buildings based on a multi-objective genetic algorithm in the cold climate of China," *Energy Build.*, vol. 139, pp. 371–384, Mar. 2017.
- [15] N. Harmathy, Z. Magyar, and R. Folić, "Multi-criterion optimization of building envelope in the function of indoor illumination quality towards overall energy performance improvement," *Energy*, vol. 114, pp. 302–317, Nov. 2016.
- [16] N. Delgarm, B. Sajadi, F. Kowsary, and S. Delgarm, "Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO)," *Appl. Energy*, vol. 170, pp. 293–303, May 2016.
- [17] R. Azari, S. Garshasbi, P. Amini, H. Rashed-Ali, and Y. Mohammadi, "Multi-objective optimization of building envelope design for life cycle environmental performance," *Energy Build.*, vol. 126, pp. 524–534, Aug. 2016.
- [18] N. C. Brown and C. T. Mueller, "Design for structural and energy performance of long span buildings using geometric multi-objective optimization," *Energy Build.*, vol. 127, pp. 748–761, Sep. 2016.
- [19] T. Méndez Echenagucia, A. Capozzoli, Y. Cascone, and M. Sassone, "The early design stage of a building envelope: Multi-objective search through heating, cooling and lighting energy performance analysis," *Appl. Energy*, vol. 154, pp. 577–591, Sep. 2015.

- [20] Z. Romani, A. Draoui, and F. Allard, "Metamodeling the heating and cooling energy needs and simultaneous building envelope optimization for low energy building design in Morocco," *Energy Build.*, vol. 102, pp. 139–148, 2015.
- [21] W. Yu, B. Li, H. Jia, M. Zhang, and D. Wang, "Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design," *Energy Build.*, vol. 88, pp. 135–143, Feb. 2015.
- [22] C. Yang *et al.*, "High throughput computing based distributed genetic algorithm for building energy consumption optimization," *Energy Build.*, vol. 76, pp. 92–101, Jun. 2014.
- [23] E. D. Giouri, M. Tenpierik, and M. Turrin, "Zero energy potential of a high-rise office building in a Mediterranean climate: Using multi-objective optimization to understand the impact of design decisions towards zero-energy high-rise buildings," *Energy Build.*, vol. 209, p. 109666, Feb. 2020.
- [24] T. Hong, J. Kim, and M. Lee, "A multi-objective optimization model for determining the building design and occupant behaviors based on energy, economic, and environmental performance," *Energy*, vol. 174, pp. 823–834, May 2019.
- [25] N. Perez, P. Riederer, and C. Inard, "Development of a multiobjective optimization procedure dedicated to the design of district energy concept," *Energy Build.*, vol. 178, pp. 11–25, Nov. 2018.
- [26] S. Chatzinikolaou, N. Ventikos, L. Bilgili, and U. B. Celebi, *Energy, Transportation and Global Warming*. Cham: Springer International Publishing, 2016.
- [27] S. G. Attia, "Early Design Simulation Tools for Net Zero Energy Buildings : a Comparison of Ten Tools Design Process & Tools of Nzeb," in *Buildings*, 2011, pp. 14–16.
- [28] Z. Romani, "Développement d ' une méthode d ' aide à la décision multicritère pour la conception des bâtiments neufs et la réhabilitation des bâtiments existants à haute efficacité énergétique Zaid Romani To cite this version : HAL Id : tel-01373443," 2016.
- [29] J. Bois, "Outil d ' aide à la décision pour la conception de maisons solaires à énergie positive To cite this version : HAL Id : tel-01679255 Outil d ' Aide à la Décision pour la Conception de Maisons Solaires à," 2018.
- [30] P. de Wilde, *Building Performance Analysis*. Chichester, UK: John Wiley & Sons, Ltd, 2018.
- [31] S. Salimi, M. Mawlana, and A. Hammad, "Performance analysis of simulation-based optimization of construction projects using High Performance Computing," *Autom. Constr.*, vol. 87, no. October 2017, pp. 158–172, Mar. 2018.
- [32] "AutoCAD For Mac & Windows | CAD Software | Autodesk." [Online]. Available: <https://www.autodesk.eu/products/autocad/overview>. [Accessed: 24-Apr-2019].
- [33] "SketchUp Pro Software | Create 3D Model Online | SketchUp." [Online]. Available: <https://www.sketchup.com/products/sketchup-pro>. [Accessed: 24-Apr-2019].
- [34] B. Chegari, M. Tabaa, F. Moutaouakkil, E. Simeu, and H. Medromi, "Local energy self-sufficiency for passive buildings: Case study of a typical Moroccan building," *J. Build. Eng.*, vol. 29, no. December 2019, p. 101164, May 2020.
- [35] B. Chegari, M. Tabaa, F. Moutaouakkil, E. Simeu, and H. Medromi, "Shading Devices' Benefits on Thermal Comfort and Energy Performance of a Residential Building in Different Climates in Morocco," 2020, pp. 1094–1111.
- [36] B. Chegari, E. Simeu, M. Tabaa, H. Medromi, and F. Moutaouakkil, "Energy savings and thermal comfort benefits of shading devices: Case study of a typical Moroccan building," in *ACM International Conference Proceeding Series*, 2019, pp. 1–8.
- [37] B. Chegari, M. Tabaa, F. Moutaouakkil, E. Simeu, and H. Medroumi, "The impact of the thermos-physical parameters of insulation on the energy performance of a building in Morocco," in *Proceedings of 2019 International Conference of Computer Science and Renewable Energies, ICCSRE 2019*, 2019, pp. 1–6.
- [38] S.A KLEIN *et al.*, *TRNSYS: A Transient System Simulation Program*. In : . Madison, USA : Solar Energy Laboratory, University of Wisconsin. 2010 - CSTB. 2010.

- [39] S.A KLEIN et al., *Multizone Building modeling with Type56 and TRNBuild - CSTB*, vol. 6. 2007.
- [40] "Centre Scientifique et Technique du Bâtiment - CSTB." [Online]. Available: <http://www.cstb.fr/fr/>. [Accessed: 31-May-2019].
- [41] *American Society of Heating Refrigerating and Air Conditioning Engineers*. 2007.
- [42] "Bibliothèque BINAYAT perspective 2014." .
- [43] "Les charges thermiques internes pour les bureaux." [Online]. Available: <https://www.energieplus-lesite.be/index.php?id=11245#>. [Accessed: 17-Apr-2019].
- [44] "Meteonorm Global Meteorological databas Version 7." [Online]. Available: <https://meteonorm.com/download>. [Accessed: 11-Feb-2019].
- [45] "AMEE, Cadre réglementaire." [Online]. Available: http://www.amee.ma/index.php?option=com_content&view=article&id=482&Itemid=865&lang=fr. [Accessed: 08-Jun-2019].
- [46] S. Li, L. Liu, and C. Peng, "A review of performance-oriented architectural design and optimization in the context of sustainability: Dividends and challenges," *Sustain.*, vol. 12, no. 4, p. 1427, Feb. 2020.
- [47] Z. Tian, X. Zhang, X. Jin, X. Zhou, B. Si, and X. Shi, "Towards adoption of building energy simulation and optimization for passive building design: A survey and a review," *Energy Build.*, vol. 158, pp. 1306–1316, Jan. 2018.
- [48] L. De Boeck, S. Verbeke, A. Audenaert, and L. De Mesmaeker, "Improving the energy performance of residential buildings: A literature review," *Renew. Sustain. Energy Rev.*, vol. 52, pp. 960–975, Dec. 2015.
- [49] G. S. Georgiou, P. Christodoulides, and S. A. Kalogirou, "Implementing artificial neural networks in energy building applications - A review," in *2018 IEEE International Energy Conference, ENERGYCON 2018*, 2018, pp. 1–6.
- [50] D. Guyot, F. Giraud, F. Simon, D. Corgier, C. Marvillet, and B. Tremeac, "Overview of the use of artificial neural networks for energy-related applications in the building sector," *Int. J. Energy Res.*, vol. 43, no. 13, p. er.4706, Jul. 2019.
- [51] S. Pandey, D. A. Hindoliya, and R. Mod, "Artificial neural network for predation of cooling load reduction using green roof over building in sustainable city," *Sustain. Cities Soc.*, vol. 3, no. 1, pp. 37–45, Jul. 2012.
- [52] A. S. Jihad and M. Tahiri, "Forecasting the heating and cooling load of residential buildings by using a learning algorithm 'gradient descent', Morocco," *Case Stud. Therm. Eng.*, vol. 12, no. February, pp. 85–93, Sep. 2018.
- [53] Y. Lin, S. Zhou, W. Yang, L. Shi, and C. Q. Li, "Development of building thermal load and discomfort degree hour prediction models using data mining approaches," *Energies*, vol. 11, no. 6, p. 1570, Jun. 2018.
- [54] M. A. Shahin, H. R. Maier, and M. B. Jaksa, "Data division for developing neural networks applied to geotechnical engineering," *J. Comput. Civ. Eng.*, vol. 18, no. 2, pp. 105–114, 2004.
- [55] N. D. Roman, F. Bre, V. D. Fachinotti, and R. Lamberts, "Application and characterization of metamodels based on artificial neural networks for building performance simulation: A systematic review," *Energy Build.*, vol. 217, p. 109972, Jun. 2020.
- [56] B. Wierenga and J. Kluytmans, "Neural nets versus marketing models in time series analysis: A simulation study," *Marketing: Its Dynamics and Challenges*. EMAC, pp. 1139–1153, 1994.
- [57] V. Venugopal and W. Baets, "Neural networks and statistical techniques in marketing research," *Mark. Intell. Plan.*, 1994.
- [58] V. Venugopal and W. Baets, "Neural networks & their applications in marketing management," *J. Syst. Manag.*, vol. 45, no. 9, p. 16, 1994.
- [59] D. Shepard, R. Batra, A. Deutsch, G. Orme, and B. Ratner, *The new direct marketing How to implement a profit-driven database marketing strategy*. Business One Irwin, 1990.
- [60] A. Keshtkarbanaemoghadam, A. Dehghanbanadaki, and M. Hadi, "Estimation and optimization of

heating energy demand of a mountain shelter by soft computing techniques,” *Sustain. Cities Soc.*, vol. 41, no. January, pp. 728–748, 2018.

- [61] G. D. Garson, “Interpreting neural-network connection weights,” *Artif. Intell. Expert*, vol. 6(7), pp. 47–51.
- [62] G. Calleja, A. Carrillo, F. Domínguez, J. Manuel, C. López, and Y. Zhang, “Uncertainties and sensitivity analysis in building energy simulation using macroparameters,” vol. 67, pp. 79–87, 2013.
- [63] T. Laine, F. Forns-Samso, P. Katranuschkov, R. Hoch, and P. Freudenberg, “Application of multi-step simulation and multi-eKPI sensitivity analysis in building energy design optimization,” in *eWork and eBusiness in Architecture, Engineering and Construction-Proceedings of the 10th European Conference on Product and Process Modelling, ECPPM 2014*, 2015, pp. 799–804.
- [64] T. C. N. De Souza, E. F. G. Goldbarg, and M. C. Goldbarg, “Comparing PSO and NSGA II for the biobjective Oil Derivatives Distribution Problem,” *2010 IEEE World Congr. Comput. Intell. WCCI 2010 - 2010 IEEE Congr. Evol. Comput. CEC 2010*, 2010.
- [65] Z. Anwar and A. Ahsan, “Comparative Analysis of MOGA, NSGA-II and MOPSO for Regression Test Suite Optimization,” *Int. J. Softw. Eng.(IJSE)* 7, vol. 7, no. 1, pp. 41–56, 2014.
- [66] V. Babaveisi, M. M. Paydar, and A. S. Safaei, “Optimizing a multi-product closed-loop supply chain using NSGA-II, MOSA, and MOPSO meta-heuristic algorithms,” *J. Ind. Eng. Int.*, vol. 14, no. 2, pp. 305–326, 2018.
- [67] A. Nguyen, S. Reiter, and P. Rigo, “A review on simulation-based optimization methods applied to building performance analysis,” *Appl. Energy*, vol. 113, pp. 1043–1058, 2014.
- [68] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.
- [69] H. Isibushi, T. Isibushi, “T. Murata and H. Ishibuchi, ‘MOGA: Multi-objective genetic algorithms,’” *IEEE*, no. November, pp. 289–294, 1995.
- [70] C. A. Coello Coello and M. S. Lechuga, “MOPSO: a proposal for multiple objective particle swarm optimization,” in *Proceedings of the 2002 Congress on Evolutionary Computation. CEC’02 (Cat. No.02TH8600)*, 2002, vol. 2, pp. 1051–1056.
- [71] K. Deb and K. Deb, “Multi-objective Optimization,” in *Search Methodologies*, E. K. Burke and G. Kendall, Eds. Boston, MA: Springer US, 2014, pp. 403–449.
- [72] M. Hamdy, A.-T. Nguyen, and J. L. M. Hensen, “A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems,” *Energy Build.*, vol. 121, pp. 57–71, Jun. 2016.
- [73] B. Si, J. Wang, X. Yao, X. Shi, X. Jin, and X. Zhou, “Multi-objective optimization design of a complex building based on an artificial neural network and performance evaluation of algorithms,” *Adv. Eng. Informatics*, vol. 40, no. November 2018, pp. 93–109, Apr. 2019.