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# Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application

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ABSTRACT

Retrofitting of existing buildings offers significant opportunities for improving occupants' comfort and well-being, reducing global energy consumption and greenhouse gas emissions. This is being considered as one of the main approaches to achieve sustainability in the built environment at relatively low cost and high uptake rates. Although a wide range of retrofit technologies is readily available, methods to identify the most suitable set of retrofit actions for particular projects are still a major technical and methodological challenge.

This paper presents a multi-objective optimization model using genetic algorithm (GA) and artificial neural network (ANN) to quantitatively assess technology choices in a building retrofit project. This model combines the rapidity of evaluation of ANNs with the optimization power of GAs. A school building is used as a case study to demonstrate the practicability of the proposed approach and highlight potential problems that may arise. The study starts with the individual optimization of objective functions focusing on building's characteristics and performance: energy consumption, retrofit cost, and thermal discomfort hours. Then a multi-objective optimization model is developed to study the interaction between these conflicting objectives and assess their trade-offs.



## 1. Introduction

The energy sector faces significant challenges that everyday become more acute. The current energy trends raise great concerns about the "three Es": environment, energy security and economic prosperity, as defined by the International Energy Agency [1]. The building sector is among the greatest energy consumers, using large amounts of energy and releasing considerable amounts of green house gases (GHG). In the United States in 2010, buildings accounted for 41% of total primary energy consumption and 74% of electricity consumption [2]. About 40% of $CO_2$ emissions, 54% of $SO_2$, and 17% of $NO_x$ produced in the U.S. are due to building-related energy consumption. A similar situation is also observed in the European Union (EU), where the building sector uses 40% of total final energy consumed and releases about 40% of total $CO_2$ emissions. In the last ten years (1999–2009), EU-27 dependency on imported energy has grown, reaching 53.9% in 2009. This represents an increase of 9 percentage points from 1999 [3]. As a consequence, the cornerstone of the European energy policy

*Abbreviations:* ANN, Artificial Neural Network; DM, Decision Maker; EC, Energy Consumption; EPBD, Energy Performance of Buildings Directive; EU, European Union; EWAL, External Wall insulation material; GA, Genetic Algorithm; HVAC, Heating, Ventilation, and Air-Conditioning; LHS, Latin Hypercube Sampling; MCA, Multi Criteria Analysis; MOGA, Multi-Objective Genetic Algorithm; MOO, Multi-Objective Optimization; PMV, Predicted Mean Vote; QHEAT, Energy consumption for space heating; QCOOL, Energy consumption for space cooling; QSC, Heating production by Solar Collector; QSHW, Energy consumption for sanitary hot water; ReCost, Retrofit Cost; ROF, Roof insulation material; SC, Solar Collector; SHW, Sanitary Hot Water; TPMVD, total percentage of discomfort hours; WIN, Window.

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has an explicit orientation toward the conservation and rational use of energy in buildings as the Energy Performance of Buildings Directive (EPBD) 2002/91/EC [4] and its recast [5] indicate.

Most European countries have succeeded in reducing energy consumption of new dwellings by more than 50% without increasing their building cost, and therefore energy efficiency has achieved great acceptance among building owners [6]. These buildings represent about 20% of the building stock but consume only 5% of the energy. However, even if all future buildings were to be built so that their electrical energy and heat energy demands were very low, it would still only mean that the increase in energy demand would be reduced. It would not reduce present demand. For many years to come, measures taken in existing buildings will have the most significant effect on the total energy demands in the building stock [7].

When designing new buildings, only relatively limited additional investments are often needed to make them very energy-efficient. On the other hand, it is more difficult and costly to bring about substantial energy savings in existing buildings, though it is nearly always possible to identify a number of measures that are both energy-saving and cost-effective [8]. However, both in designing new buildings and carrying out measures in existing buildings, it is extremely important that the solution applied and the measures taken are well founded and correctly chosen [9]. That is, when buildings are subject to retrofit, it is very important to select the optimal strategy in a timely manner, since if other solutions are chosen and implemented it will just be possible to change the building at a later occasion at a much higher cost.

The works involved in retrofit are usually of complex and heterogeneous nature that require various specialties to be integrated in highly variable conditions. Furthermore, a thorough building's retrofit evaluation is quite difficult to undertake, because a building and its environment are complex systems regarding technical, technological, ecological, social, comfort, esthetical, and other aspects, where every sub-system influences the total efficiency performance and the interdependence between sub-systems plays a critical role [10].

This paper has five sections, including the introduction. Section 2 presents a brief overview of models and methodologies developed to support decisions regarding building retrofit. The modules in the proposed approach are discussed in detail in Section 3. The application of the model to the retrofit of a school building is described in Section 4. Finally, Section 5 summarizes conclusions and discusses topics for future research.

## 2. Literature review

There are a number of models and methods developed to assess conditions and support decisions pertaining to building retrofit. These methodologies can be categorized into two main approaches: the models in which alternative retrofit solutions are explicitly known a priori (see e.g. [11–14]) and the models in which alternative retrofit solutions are implicitly defined in the setting of an optimization model (see e.g. [7,15–17]).

The most common a priori approach is one in which the decision maker (DM) assigns weights to each criterion, the weighted sum of the criteria then forming a single design criterion. It is then possible to find the single design solution that optimizes the weighted sum of the criteria. Gero et al. [11] were among the first to propose a multi-criteria analysis (MCA) model to be used at the process of building design in order to explore the trade-offs between the building thermal performance and other criteria such as capital cost and usable area. More recently, other researchers have also employed MCA techniques to similar problems. Jaggs and Palmer [12], Flourentzou and Roulet [13], and Rey [14] proposed approaches for the evaluation of retrofitting scenarios. Kaklauskas et al. [10] developed a multivariate design method and MCA for building retrofit, determining the significance, priorities and utility degree of building retrofit alternatives and selecting the most recommended variant.

These lines of research have allowed addressing many problems as far as buildings retrofit is concerned. However, most of them consider that a list of predefined and pre-evaluated alternative variants of the building retrofit options is given. In case a small number of such solutions have been defined, there is no guarantee that the solution finally reached is the best one (from the DM's perspective). On the opposite case, when a large number of solutions are defined the required evaluation and selection process may become extremely difficult to handle. Moreover, MCA-based methodologies do not provide the designer with information about how sensitive each criterion is to changes of the other criteria [18].

The second approach (based on multi-objective optimization, MOO) enables to consider a large set of building retrofit options implicitly defined by the constraints defining the search space and grasp the trade-offs between the objective functions helping to reach a satisfactory compromise solution. However, so far, relatively little attention has been paid to tackling building retrofit decision support with multiple objective optimization [19]. Diakaki et al. [15] investigated the feasibility of applying MOO techniques to the problem of improving energy efficiency in buildings, considering a simplified model for building thermal simulation. Asadi et al. [16] proposed an MOO model that supports the definition of retrofit actions aimed at minimizing energy use in a cost effective manner. Following this work, they developed an MOO model combined with TRNSYS (building performance simulation program) and GenOpt (an optimization program). The proposed model was used for the optimization of retrofit cost, energy savings, and thermal comfort of a residential building, in a framework of an MOO model [7].

Considering all the possibilities that the DM has available for building retrofit (e.g. HVAC systems and renewable energy sources), as well as all the objectives that he/she may wish to optimize ($CO_2$ emissions, social objectives, etc.) may lead to the combinatorial explosion of the decision problem, thus making the solving procedure extremely difficult and time-consuming. In such case, other optimization techniques, namely multi-objective genetic algorithms are necessary for tackling the problem. Wright et al. [20] used a multi-objective GA to find the trade-offs between the energy cost and occupant thermal comfort for the design of a single zone HVAC system. Hamdy et al. [21] proposed an MOO approach based on GA to tackle the problem of designing low-emission cost-effective dwellings, minimizing the carbon dioxide emissions and the investment cost for a two-story house and its HVAC system.

A main drawback of GA is the high burden whenever it is necessary to make a large number of calls to an evaluation function involving a high computational cost. In building applications, these evaluations are generally estimated by an external simulation program such as Computational Fluids Dynamics (CFD) or other simulation packages. If accurate results are required, each evaluation can be time consuming, and thus the complete computational process becomes extremely unattractive [22]. Accordingly, building optimization studies using GA generally tend to reduce the computational time by using two methods. The first method consists in using very simplified models instead of complex simulation software [23]. However, this method presents a risk of oversimplification and inaccurate modeling of building phenomena. The second method commonly used is to select very small GA populations and/or relatively small number of generations [24]. Again, the optimization can be significantly affected and may lead to narrow or non-optimal solution sets [25].

One very efficient, yet widely not exploited, solution to reduce the computational time associated with GA is to use a Response

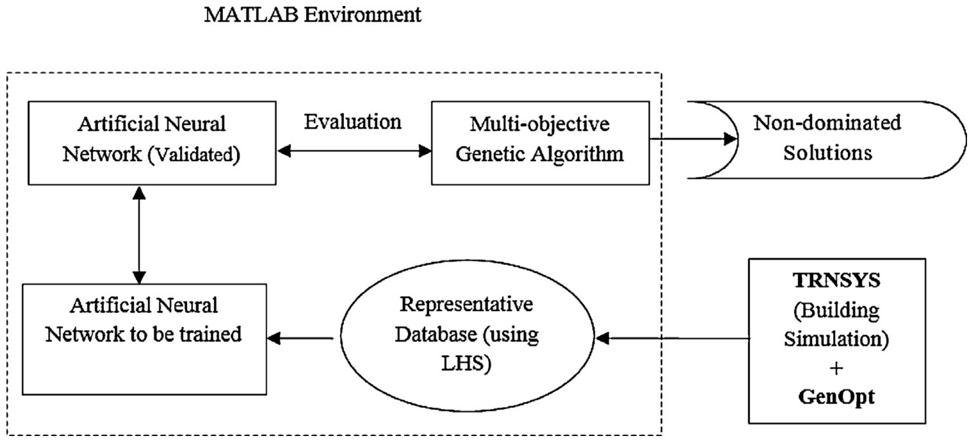


**Fig. 1.** Optimization framework.

Surface Approximation Model (RSA) to first mimic the behavior of the base building model, and then use this RSA inside the GA for the evaluation of individuals [22]. By doing so, the computational time associated with each evaluation becomes negligible, while a good accuracy is maintained in the results. While several RSA methods exist, there is no common agreement regarding which technique is the best one [26]. Recently, Magnier et al. [22] used a simulation-based ANN combined with GA to optimize thermal comfort and energy consumption in designing a residential building.

The current study proposes a MOO method for building retrofit strategies, based on the combination of GA and ANN. The proposed methodology is used for the optimization of energy consumption, retrofit cost, and thermal discomfort hours in a school building retrofit project. A wide decision space is considered, including alternative materials for the external walls insulation, roof insulation, different window types, installation of a solar collector to the existing building, and a wide range of HVAC system types to meet heating and cooling requirements.

## 3. Description of the Optimization approach

The optimization framework is summarized in Fig. 1. First, a model of the existing building is created in TRNSYS and validated through the comparison with utility billing data. Then, using this model, a representative database of simulation cases is created using Latin hypercube sampling (LHS) algorithm. It is then used to train and validate the ANN. Finally, a multi-objective genetic algorithm (MOGA) is run using the ANN to evaluate potential solutions and find the non-dominated solutions.

### 3.1. Parametric runs

In order to create a database for ANN training, parametric runs have to be executed. In order to automate TRNSYS runs, GenOpt (version 3.0.3) [27] is used. GenOpt is an optimization program for the minimization of a cost function that is evaluated by an external simulation program. When associated with TRNSYS, GenOpt can automatically generate building (.bui) and deck (.dck) files based on the chosen templates, run TRNSYS with those files, save results and restart again.

### 3.2. Design of experiments

In order to reduce the size of the training database while keeping the sample representative, LHS is used. LHS is one of the most common methods used to generate a small and representative sample of a population, for specified numbers and ranges of variables. Studies have shown that using LHS, a number of cases greater than twice the number of parameters is sufficient to correctly sample the search space [28]. In this study, LHS is computed in MATLAB, using the Model-Based Calibration Toolbox (version 4.1).

### 3.3. Artificial neural network

ANNs are information processing systems that are non-algorithmic, non-digital, and intensely parallel [29]. They learn the relationship between the input and output variables by studying previously recorded data. An ANN resembles the biological neural system, composed by layers of parallel elemental units, called neurons. The neurons are connected by a large number of weighted links, over which signals or information can pass. Basically, a neuron receives inputs over its incoming connections, combines the inputs, performs generally a non-linear operation, and then outputs the final results. The most known, simple and used network arrangement is the feed-forward model. In this model, the neurons are placed in several layers. The first one is the input layer, which receives inputs from outside. The last layer, called output layer, supplies the result evaluated by the network. Between these two layers, a network can have none, one or more intermediate layers called hidden layers.

Fig. 2 shows a three-layer feed-forward neural network with input, hidden, and output layers, which is the model used in this study. Each node in the input layer represents the value of one independent variable while the output nodes indicate the dependent variables.

MATLAB computing environment has been chosen to generate the ANN model from the data using the neural network toolbox (version 7.0). It has been trained using a first sample from LHS, and checked for validation using a second and smaller sample.

### 3.4. Multi-objective optimization

MOO models aim at capturing the multiple, conflicting and incommensurate aspects of evaluation of the merits of potential solutions, in order to identify their trade-offs and provide a sound technical basis to decision support. In general, due to the conflicting objective functions there is no unique solution to MOO but a set of non-dominated (Pareto optimal) solutions. In our model the simultaneous optimization of energy consumption, retrofit cost and thermal discomfort hours is sought. This MOO model is of combinatorial nature because of its structure and decisions to be made, and it is nonlinear due to the building performance calculations. Therefore, an MOGA has been selected to characterize the non-dominated front.

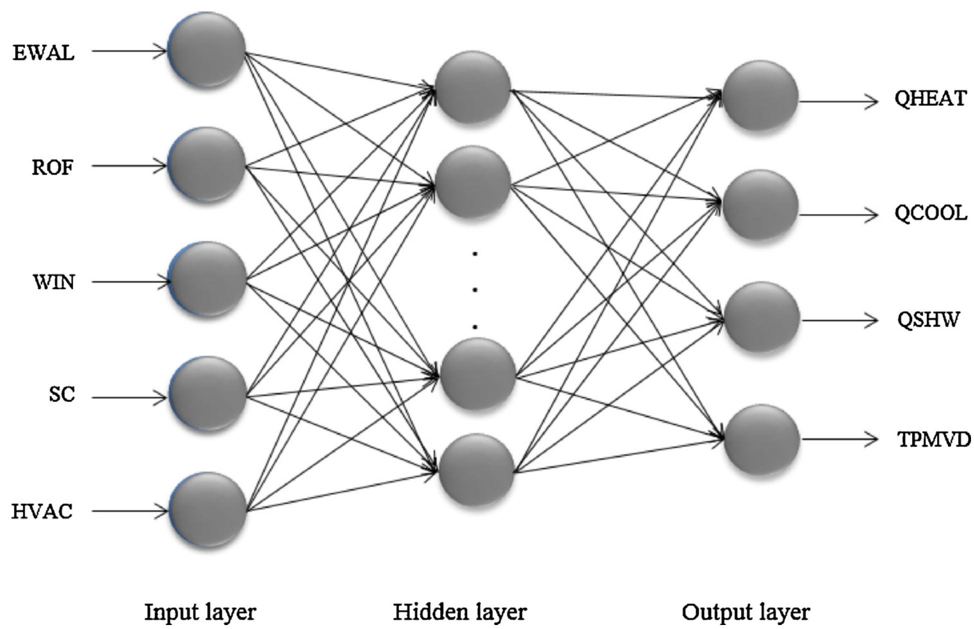


**Fig. 2.** ANN architecture.

Once trained and validated, the ANN is used as the evaluation function for energy consumption and thermal discomfort estimation within the MOGA. The GA toolbox (version 5.1) in MATLAB is used for optimization using the 'gamultiobj' function to identify the set of non-dominated solutions.

MATLAB's 'gamultiobj' function uses a controlled elitist GA (a variant of NSGA-II [30]). Like any other GA, this is based on the evolution of a population of individuals, each of which is a solution to the optimization problem. In this study, an individual represents a retrofit option (embodying different technologies and types of intervention) to be carried out on a building. To use a genetic analogy, each individual is represented by a chromosome whose genes correspond to a number of the individual's characteristics, as in Fig. 3.

### 3.5. Decision variables

The decision variables reflect the total set of alternative measures that are available for building retrofitting (e.g. windows, insulation materials, etc.). The set of retrofit actions concerns combinations of choices regarding external wall insulation material, roof insulation material, windows, installation of solar collector and different HVAC systems to the existing building. Five types of decision variables are defined concerning the alternative choices regarding:

- the external wall insulation materials;
- the roof insulation materials;
- the windows type;
- the solar collectors type;
- the HVAC systems.

For simplicity, it is assumed that only one retrofit action, from each one of the five sets of actions, may be selected for the building retrofit.

Assuming the availability of $I$ alternative types of external wall insulation material, $J$ alternative types of roof insulation material, $K$ alternative types of windows, $L$ alternative types of solar collector, and $M$ alternative types of HVAC system, integer decision variables $x^{EWAL}$, $x^{ROF}$, $x^{WIN}$, $x^{SC}$, and $x^{HVAC}$ are defined as follows:

$$x^{EWAL}: \text{ external wall insulation material type identifier} \quad (1)$$

$$x^{ROF}: \text{ roof insulation material type identifier} \quad (2)$$

$$x^{WIN}: \text{ window type identifier} \quad (3)$$

$$x^{SC}: \text{ solar collector type identifier} \quad (4)$$

$$x^{HVAC}: \text{ HVAC system type identifier} \quad (5)$$

A list of alternative retrofit actions applied in this study is based on a CYPE rehabilitation price generator database (CYPEingenieros [31]) and presented in Appendix A. This list includes 24 different external wall insulation materials, 18 roof insulation materials, 3 windows types, 4 solar collectors and 4 HVAC systems.

### 3.6. Objective functions

#### 3.6.1. Energy consumption

The energy consumption of the building is directly assessed by TRNSYS. The total energy consumption, EC, consists in the sum of energy demands for space heating (QHEAT), space cooling (QCOOL) and sanitary hot water (QSHW) systems. SHW production by solar collector (QSC) is subtracted from the total energy consumption. Moreover, energy consumption for lighting is not included because this is not expected to significantly change as a result of the implementation of the considered retrofit actions. After training the neural network model, the MOGA uses the ANN model to calculate energy consumption.

#### 3.6.2. Retrofit cost

The overall investment cost for the building retrofit is ReCost ($X$), (where $X$ denotes the vector of all decision variables defined in Section 3.5) is calculated by adding individual retrofit action costs as follows:

$$\begin{aligned}\text{ReCost}(X) &= A_{EWAL} \times C^{EWAL}(X) + A_{ROF} \times C^{ROF}(X) \\ &\quad + A_{WIN} \times C^{WIN}(X) + C^{SC}(X) + C^{HVAC}(X)\end{aligned} \quad (6)$$

where $A_{EWAL}$ is the exterior wall surface area [m$^2$]; $C^{EWAL}$ is the cost in [€/m$^2$] for selected external wall insulation material; $A_{ROF}$ is the

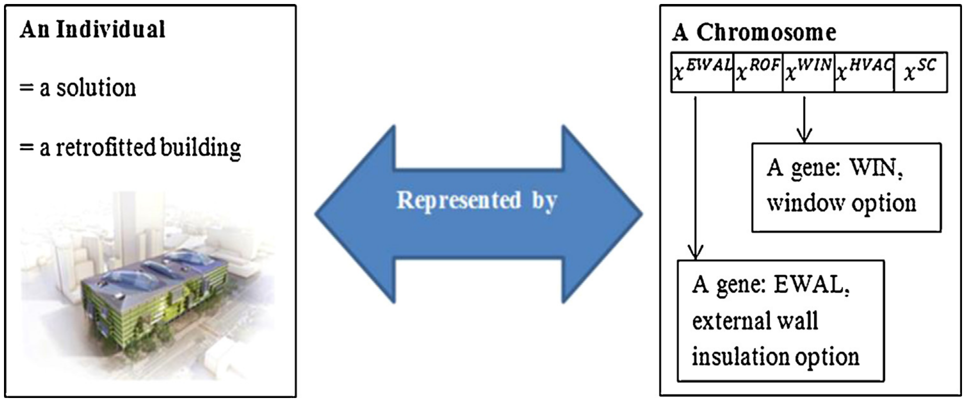


**Fig. 3.** A solution to the retrofit optimization problem, as presented by a chromosome.

roof surface area [m$^2$]; $C^{ROF}$ is the cost in [€/m$^2$] for selected roof insulation material; $A_{WIN}$ is the windows surface area [m$^2$]; $C^{WIN}$ is the cost in [€/m$^2$] for selected window; $C^{SC}$ is the cost for selected solar collector [€]; $C^{HVAC}$ is the cost for selected HVAC system [€].

The retrofit actions (RAs) corresponding costs ($C^{EWAL}$, $C^{ROF}$, $C^{WIN}$, $C^{SC}$, $C^{HVAC}$) are extracted from RAs characteristics tables presented in Appendix A. A MATLAB function using expression (6) is written and incorporated into the MOGA to estimate the retrofit cost objective function ReCost.

### 3.6.3. *Total percentage of discomfort hours (TPMVD)*

The metric used to assess thermal comfort is the predicted mean vote (PMV), based on Fanger's model [32]. PMV is representative of what, in average, a large population would think about a thermal environment, and is used to assess thermal comfort in standards such as ISO 7730 [33] and ASHRAE 55 [34]. It ranges from −3 (too cold) to +3 (too warm), and a PMV value of zero is expected to provide the lowest predicted percentage of dissatisfied people (PPD) among a population. In this study, an absolute value of 0.7 for PMV, the upper limit of category C, the less exigent comfort category in ISO 7730, is considered as the borderline of the comfort zone. Therefore, in order to maximize the thermal comfort, the total percentage of cumulative time with discomfort ($|PMV| > 0.7$) over the whole year during the occupancy period, TPMVD($X$), should be minimized. The total percentage of discomfort hours is also predicted by TRNSYS. After training the neural network model, the MOGA uses the ANN model to estimate TPMVD.

## 4. Model application on a school building

This section is aimed at illustrating how the approach described in Section 3 can be used to provide decision support for selecting a satisfactory compromise solution based on the proposed model. The building under study is a school building constructed in 1983.

The school building is located in Coimbra, Portugal and serves some 800 students and 117 staff. The building consists of 6 blocks, the main block designed for administration purposes. 4 blocks (A, B, C and D), include classrooms and laboratories. These four blocks have similar architecture, with different number of stories. Blocks A and D have three stories and blocks B and C have two stories. The last block is the sport pavilion. Total occupied space floor area is 9850 m$^2$ and is divided between the six mentioned blocks.

In this project block A, one of the four identical blocks (Class rooms) is selected as a case study. The central zone in this block is a big atrium with visibility to all other sections in the building. This central zone uses natural lighting.

Fig. 4 illustrates the schematic plan of ground, first and second floor for Block A. Six classrooms (A1–A6) are located in ground floor, besides bathroom and three storage rooms. There are nine classrooms in the first floor of Block A, as well as one bathroom and one laboratory. In the second floor, there are eight more classrooms and two storage rooms.

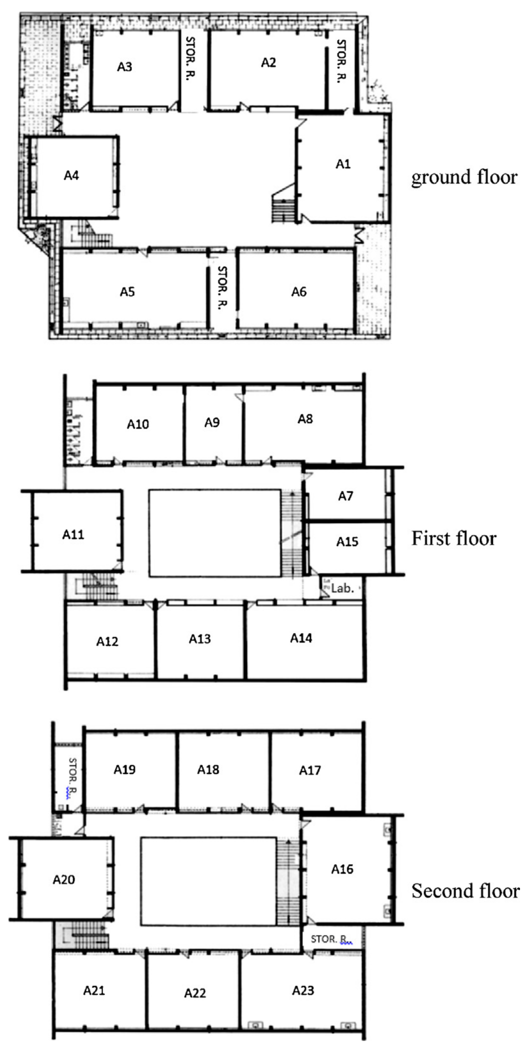


**Fig. 4.** Schematic plan of ground, first and second floor of the case study.

**Table 1**
Brief description of the base building parameters for simulation.

| Location | | Coimbra, Portugal |
|---|---|---|
| Building type | | School building |
| Floor areas | utility floor area | 1886 [m$^2$] |
| | conditioned floor area | 1622 [m$^2$] |
| Dimension and Heights | Average floor height | 3.02 [m] |
| | Window height | 2.7 [m] |
| | Window-to-wall ratio | 65%, except south façade 59% |
| Construction of building envelope | External walls | 2 cm plaster + 11 cm brick + 4 cm air space + 11 cm brick + 2 cm plaster (*U*-value = 1.737 W/m$^2$ K) |
| | Roof | 2 cm plaster + 22 cm concrete + 1 cm bitumen + 4 cm cement (*U*-value = 2.654 W/m$^2$ K) |
| | Windows | Single-pane simple glass (U-value = 5.68 W/m$^2$ K, g-value = 0.855) |
| Operating hours | Monday to Friday | 8:00–20:00 |
| | Weekend | Closed |
| HVAC parameters | Total number of persons | 200 |
| | Lighting + equipment | Lighting 10 W/m$^2$, Equipment 12 W/m$^2$ |
| | Infiltration rate | 0.9 ACH |
| | Cooling system | None |
| | Heating system | electric resistance radiators |
| | Thermal set points | 20 °C–no max. |

### 4.1. Building simulation

Table 1 presents summary of the set-up for the building. Based on this table, a building model is developed in TRNSYS. The type-56 multi-zone building is a reproduction of the reference building. The building model is divided into five zones: North zone, East zone, South zone, West zone, and Atrium zone. Heating is supplied locally in each room by electric resistance radiators; the buildings have no cooling system. However, as some of the considered HVAC retrofit actions include cooling systems, therefore, an estimation of cooling needs was required. This has been taken into account by considering the recommended set point for cooling according to Portuguese national regulation RSECE [35] which is equal to 25 °C. The atrium is not heated nor cooled. In order to validate the TRNSYS model, simulation results have been compared with utility billing data. The TRNSYS model has been run using the existing building parameters described earlier, with 1 h time step, using DOE typical meteorological year version 2 (TMY2) weather data.

### 4.2. Artificial neural network training and validation

As mentioned before, the MATLAB Neural Network toolbox has been used to train and develop the neural network model for simulating the building energy consumption and thermal discomfort. In general, designing an ANN model follows three main steps:

- Design of experiments including collecting and pre-processing the data;
- Building the network, and train the ANN model;
- Validate the model and test the model performance.

#### 4.2.1. Parametric runs

A sample of 950 cases was used for ANN training. This sample was created by using LHS, based on the decision variables (retrofit actions). All the cases have been simulated with TRNSYS, using GenOpt capability for automatic parametric runs.

Simulations were performed with 1 h time step. The total simulation time of the 950 cases took around 3 days (5.19 min for each simulation) using an Intel Core2 Duo CPU workstation at 2.66 GHz speed.

#### 4.2.2. Artificial neural network training

The ANN model adopted in this study was composed of one input layer representing the 5 decision variables (different retrofit action types, i.e. EWAL, ROF, WIN, SC, and HVAC), one hidden layer composed of 15 neurons, and one output layer composed of the three energy consumption and one thermal comfort variables (QHEAT, QCOOL, QSHW, and TPMVD) (Fig. 2). Selection of the optimal number of hidden layer neurons in the ANN architecture falls in the rubric of bias-variance dilemma. Bias indicates the degree of agreement between the model and the training data whereas variance represents the complexity of the approximating model. The number of hidden neurons determines the model complexity of an ANN. Increasing the number of hidden layer neurons compromises the generalization ability of the ANN at the cost of minimizing the training data set error. The number of neurons in the hidden layer, in this study, has been found by trial-and-error. Transfer functions used are hyperbolic tangent sigmoid functions in the initial and hidden layers, and linear functions in the output layer. The method used for the ANN training is back-propagation, associated with Levenberg–Marquardt and Bayesian regularization algorithms. All inputs and outputs were scaled to the [−1,1] range prior to training to enable a better efficiency as recommended in MATLAB [36].

The ANN was trained with 950 cases. The training is considered to have reached convergence if the root mean square errors (RMSE) stabilizes over a certain number of iterations. The ANN training reached this goal after 150 epochs, with a final RMSE of 0.0240. Regression correlation coefficients between the network outputs and the corresponding TRNSYS simulation outputs were found very close to 1 for the four outputs studied, thus demonstrating a very good correlation between outputs and target values.

#### 4.2.3. Artificial neural network validation

A sample of 95 cases, different from the previous ones, has been used for ANN validation. The distribution of the relative errors for the four outputs is summarized in Table 2. The average relative errors regarding energy consumption outputs are good, with 1.4% for heating, 0.5% for cooling and 0.4% for sanitary hot water. Regarding the thermal discomfort output TPMVD, the average error is a bit higher but still acceptable, with 2.5% for TPMVD.

### 4.3. Multi-objective optimization

The final goal of the optimization problem in this phase is the simultaneous optimization of energy consumption, retrofit cost, and total percentage of discomfort hours. An MOGA is used to tackle this MOO problem and identify the set of non-dominated solutions. A modified version of MATLAB 'gamultiobj' function is used. The MOO problem can be summarized as follows, using integer decision variables stated in (1)–(5):

$$
\begin{gathered}
\operatorname{Min} Z_1(X) = \mathrm{EC}(X) \\
\operatorname{Min} Z_2(X) = \mathrm{ReCost}(X) \\
\operatorname{Min} Z_3(X) = \mathrm{TPMVD}(X) \\
\text{S.t.} \\
x^{\mathrm{EWAL}}\{1,\ldots I\}, \quad (I = 24) \\
x^{\mathrm{ROF}}\{1,\ldots J\}, \quad (J = 18) \\
x^{\mathrm{WIN}}\{1,\ldots K\}, \quad (K = 3) \\
x^{\mathrm{SC}}\{1,\ldots L\}, \quad (L = 4) \\
x^{\mathrm{HVAC}}\{1,\ldots M\}, \quad (M = 4) \\
X = \{xEWAL, xROF, xWIN, xSC, xHVAC\}
\end{gathered}
\tag{7}
$$

**Table 2**
Statistical repartition of relative errors in ANN validation.

| Relative error | | <1% | <2.5% | <5% | <10% | <25% | Average relative error (%) |
|---|---|---|---|---|---|---|---|
| Percentage of cases when error falls into the range | QHEAT | 47% | 70% | 89% | 99% | 100% | 1.4 |
| | QCOOL | 92% | 100% | 100% | 100% | 100% | 0.5 |
| | QSHW | 93% | 100% | 100% | 100% | 100% | 0.4 |
| | TPMVD | 33% | 60% | 89% | 98% | 100% | 2.5 |

EC and TPMVD are calculated by the neural network, whereas ReCost is calculated by a MATLAB function written using expression (6). Moreover, a MATLAB function using an ANN model as the input was written for creating a fitness function for the MOGA. The five decision variables encode the type of retrofit action for each category.

After setting up the optimization variables and parameters, the results of the optimization process are illustrated in Figs. 5–10. Three sets of optimizations were carried out. The first set focused on single-objective optimization, i.e. individually minimizing energy consumption, retrofit cost, and thermal discomfort objective functions, in order to have an overview of the range of their values over the non-dominated solution set. The second set involved the MOO of pairs of objective functions, with the aim of understanding the specific trade-offs between them, and how much each could affect the building's characteristics and performance. The third set involved the MOO of all three objectives. The aim is to further exploit the trade-offs at stake and find out how the results varies between the first two sets of optimizations and the last one as more evaluation aspects are considered. The visualization of results is intended to offer the decision makers an interactive tool suited for their analysis.

### 4.4. First set of optimization (single-objective)

In this first optimization set, the three objective functions (energy consumption, retrofit cost, and total percentage of discomfort hours) have been individually minimized.

#### 4.4.1. Single-objective minimization of Energy Consumption

The goal is to minimize energy consumption for heating, cooling and SHW purposes. The results are given in Table 3

In the EC optimized building, the insulation level is high with thick layers of insulating material with lowest *U*-values for external wall and roof. In addition, window type 3, which has the lowest thermal transmittance, is selected. Regarding the HVAC system, an oil-based boiler without cooling option is recommended. Furthermore, the flat solar collector with highest area among all the systems considered is recommended. However, this set of retrofit actions resulted in a significant increase of the retrofit cost with respect to the ReCost optimized building.

#### 4.4.2. Single-objective minimization of retrofit cost

The results of this optimization are given in Table 3. Minimizing retrofit cost results in low insulation level and single glazed window. Besides, the cheapest HVAC system (oil-based boiler without cooling system) and the cheapest solar collector are recommended. However, this results in a significant increase of the energy consumption and thermal discomfort hours compared to the EC and TPMVD optimized buildings.

#### 4.4.3. Single-objective minimization of total percentage of discomfort hours

The aim is to minimize the total percentage of thermal discomfort hours in the building. There is no cooling system in the existing building, either active or passive. The results are given in Table 3.

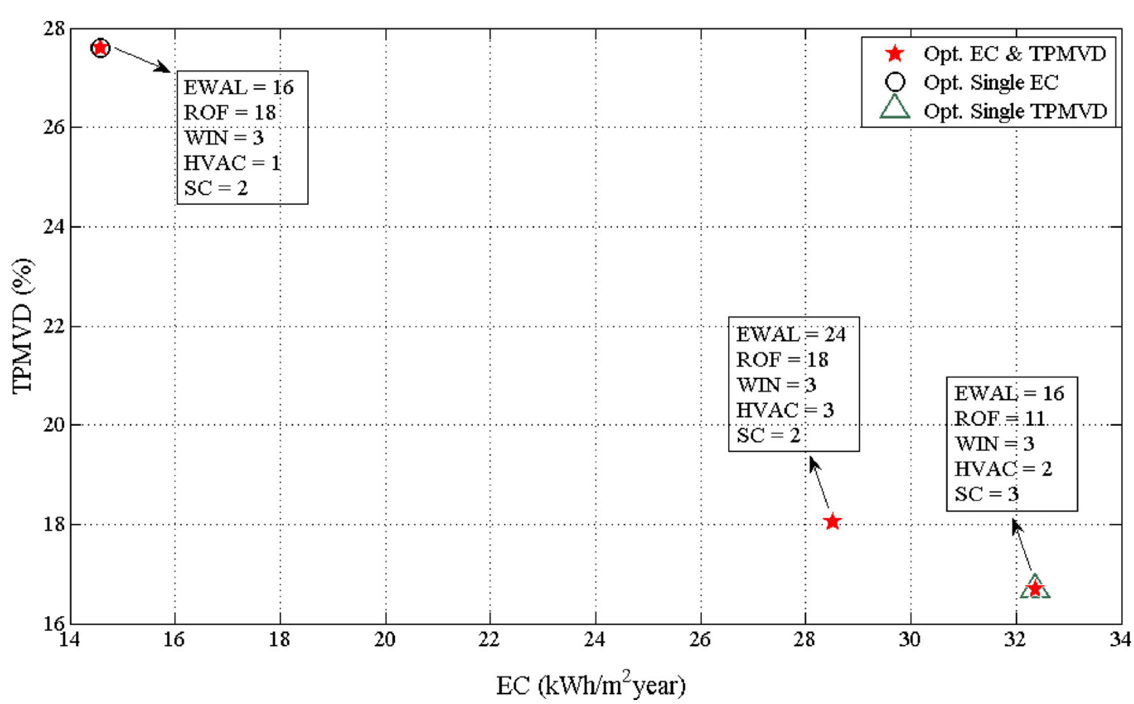


**Fig. 5.** Multi-objective solutions for the building retrofit strategies (EC–TPMVD) (Refer to Appendix A for RAs characteristics).

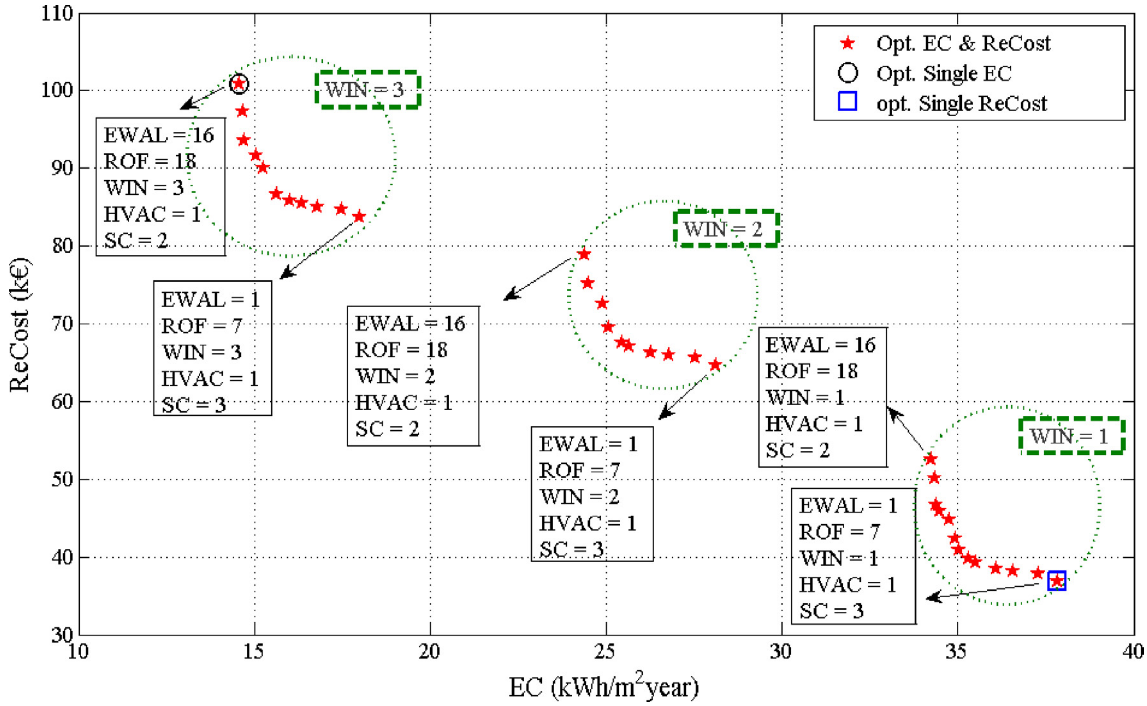


**Fig. 6.** Multi-objective solutions for the building retrofit strategies (EC–ReCost) (Refer to Appendix A for RAs characteristics.

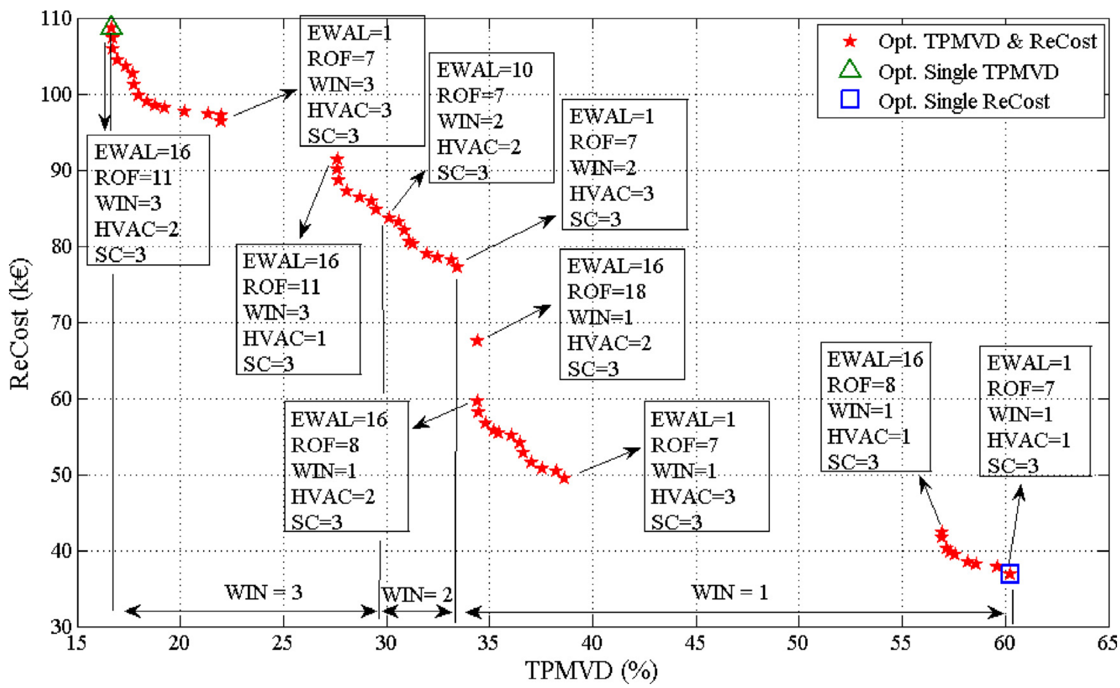


**Fig. 7.** Multi-objective solutions for the building retrofit strategies (TPMVD–ReCost) (Refer to Appendix A for RAs characteristics).

**Table 3**
Results of single-objective optimization (Refer to Appendix A for RAs characteristics).

| Type of solution | EC [kW h/m$^2$ year] | ReCost [k€] | TPMVD [%] | EWAL | ROF | WIN | HVAC | SC |
|---|---|---|---|---|---|---|---|---|
| [min] EC | ***14.58*** | 100.840 | 27.61 | 16 | 18 | 3 | 1 | 2 |
| [min] ReCost | 37.82 | ***36.859*** | 60.24 | 1 | 7 | 1 | 1 | 3 |
| [min] TPMVD | 32.37 | 108.69 | ***16.70*** | 16 | 11 | 3 | 2 | 3 |

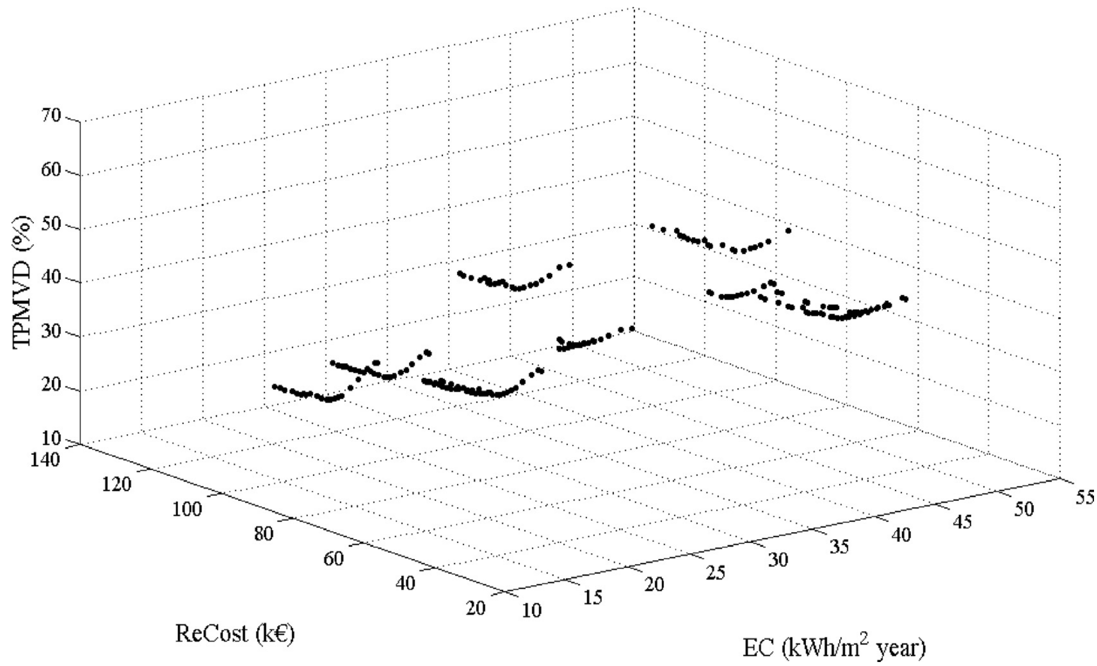


**Fig. 8.** Results of multi-objective optimization—3D visualization.

Minimizing TPMVD results in high insulation level and double glazed windows, similarly to minimization of energy consumption. Regarding HVAC system, HVAC type 2 with natural gas boiler for heating and chiller for cooling is selected that leads to significantly better indoor comfort compared to the existing building.

As can be seen from Table 3, the results for minimization of retrofit cost diverged significantly from the others. The solutions that minimizes energy consumption and thermal discomfort are comparable, which is due to the nature of retrofit actions considered and objective functions. This table can be used to shape the expectation of the DMs and help them to elicit appropriate constraints to objective function values for further considerations, namely contribution to focus the search for new solutions in restricted regions of the search space.

### 4.5. *Second set of optimization (two-objective)*

In each of these multi-objective optimizations, two objectives were chosen from among energy consumption, retrofit cost, and total percentage of discomfort hours.

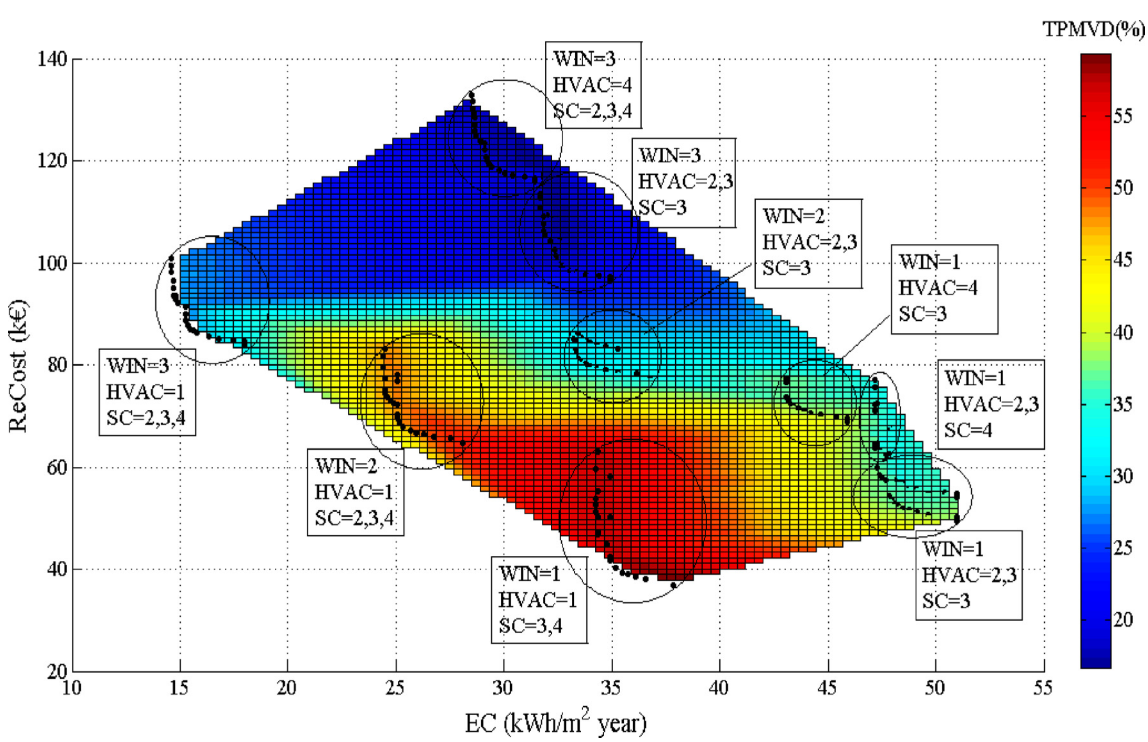


**Fig. 9.** Results of multi-objective optimization of EC, ReCost and TPMVD–2D projection (EC–ReCost) (Refer to Appendix A for RAs characteristics).

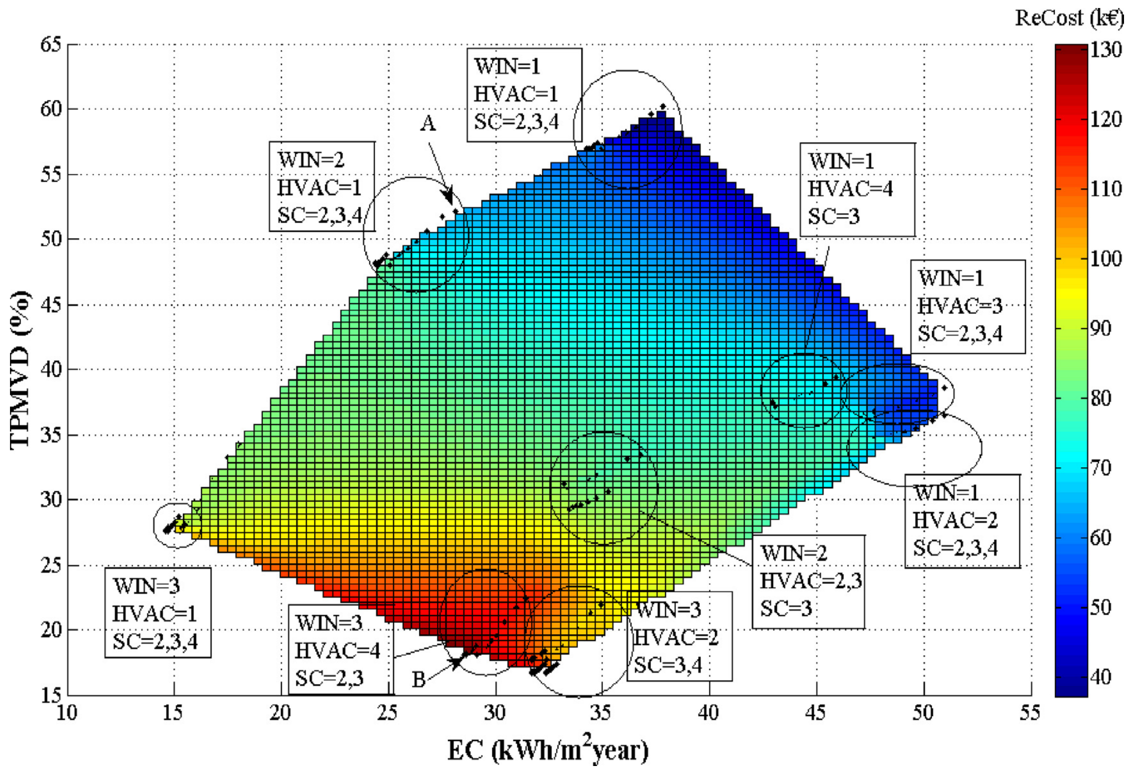


**Fig. 10.** Results of multi-objective optimization of EC, ReCost and TPMVD–2D projection (EC–TPMVD) (Refer to Appendix A for RAs characteristics).

*4.5.1. Multi-objective optimization of energy consumption and total percentage of discomfort hours*

The aim is to simultaneously minimize EC and TMPVD. The results are given in Fig. 5. Each point on the Pareto front is a solution associated with a set of decision variables representing retrofit actions.

The optimization process generates three solutions, which form the Pareto front. The single-objective optimization results for EC and TPMVD are similar, with one major difference which was the HVAC system. The external wall insulation material and window type are the same. The roof insulation material characteristic is also similar. In the multi-objective optimization, there was a minimization of the energy consumption by changing HVAC system type from the system with cooling (HVAC = 2) to the system without cooling option (HVAC = 1).

It is worthwhile also to mention that the small number of non-dominated solutions is due to the fact that the lower EC values are mainly achieved with the HVAC system type 1 without cooling option (HVAC = 1) that leads to high TPMVD values. Therefore, a large number of potential solutions are dominated by the EC optimal solution. Moreover, Air Source Heat Pump (HVAC = 3) has been replaced by oil-based boiler with no cooling option, a significant decrease in energy consumption resulted, which explains the large step at EC equal 28.52 [kW h/m$^2$ year] in the Pareto front as exhibited in Fig. 5.

*4.5.2. Multi-objective optimization of energy consumption and retrofit cost*

The single-objective optimization suggests that these objectives are strongly opposed. The results are given in Fig. 6. There is a larger number of non-dominated solutions than in the case of EC and TPMVD.

Regarding the HVAC system the solutions are all similar, consisting of oil-based boiler without cooling option. None of the HVAC systems with cooling option is selected since this requires additional investment cost and energy consumption compared to the other non-dominated solutions already computed. This can be explained since there is no constraint on summer overheating (or TPMVD), and therefore there is no reason for additional investment in a cooling option.

Wall and roof insulation material as well as windows and solar collector systems vary in different non-dominated solutions. Also, it is worthwhile to mention that the obtained solutions on the Pareto front are found to be grouped according to the window types. This reveals that the window type has a stronger influence on the low EC cost-effective solutions than the other decision variables.

To obtain minimum solutions of ReCost, single glazed window (WIN = 1), the lowest price window, and the cheapest solar collector (SC = 3), is found to be optimal with incrementally additional insulation compared to the existing building to lower the energy consumption. However, since the thickest insulation with lowest U-values for external wall and roof (EWAL = 16, ROF = 18) as well as the largest solar collector (SC = 2) are selected, the optimization leads to double-glazed window (WIN = 2). This leads to a significant reduction in the EC, explaining the discontinuity (EC step) in the Pareto front at 34.24 kW h/m$^2$ year of EC as illustrated in Fig. 6. The same phenomenon happens at the second step in the EC (EC = 24.38) in the Pareto front, where the optimization leads to window type 3 with lowest U-value resulting to a significant reduction in the EC.

*4.5.3. Multi-objective optimization of total percentage of discomfort hours and retrofit cost*

The results of this optimization are given in Fig. 7. The different non-dominated solution all fall between two single-objective optima.

Regarding the solar collector, all the recommended solutions are equal: the cheapest solar collector is recommended. All the other retrofit actions vary in different non-dominated solutions. The optimization solver tries to minimize TPMVD using optimal combinations between the building envelope parameters (including external wall and roof insulation materials, and window type) and the HVAC system type.

Double glazed window with lowest thermal transmittance, thick layer of insulation with low U-values for external wall insulation and roof, and the HVAC system type 2 with cooling option are selected giving the lowest TPMVD value. A cheaper HVAC system (HVAC = 3) is utilized to obtain a set of solutions which produce smaller amounts of ReCost without sacrificing thermal comfort too much. For more reduction in ReCost, HVAC system type 1 is used. Moreover, window type 2 then type 1 is selected to reduce the ReCost. There is a large discontinuity in the Pareto front at 38.62% of TPMVD. This can be explained by changing the HVAC type 3 to 1 with no cooling option. As can be seen, a relatively small amount of reduction in ReCost leads to a large reduction in thermal comfort. Therefore, in the current case, the DM could be convinced to slightly increase the amount of investment from 42 k€ to 50 k€ to improve the thermal comfort in the building by 20 percentage points.

The three sets of optimization presented above results in the following conclusions:

- The number of non-dominated solutions for objectives with not much in conflict characteristics is lower than for those with dissimilar characteristics.
- The analysis of the results shows the physical characteristics of solutions and helps to understand the simultaneous influence of the decision variables on the EC, ReCost, and TPMVD.
- Without considering a constraint on summer overheating, the influence of the window type on the results is more significant than the influence of the other decision variables.
- There are often discontinuities in the Pareto front where it is possible to gain a lot in one objective by sacrificing only a little in the other objective.

### 4.6. Third set of optimization (three-objectives)

The three objectives dealt with in this set of optimization are energy consumption, retrofit cost, and total percentage of discomfort hours. They are treated simultaneously, and the Pareto optimal surface is displayed in three dimensions. The results are given in 3D in Fig. 8, and in 2D projections in Figs. 9 and 10.

Fig. 9 illustrates a 2D projection for energy consumption and retrofit cost, including the corresponding TPMVD color map. Fig. 10 presents a 2D projection for energy consumption and TPMVD, including the corresponding ReCost color map. This color map is not a surface and is used as a visual aid to help determining the values of the third objective function (not in the horizontal and vertical axes). It is worthwhile to mention that the obtained non-dominated solutions on the Pareto front are found to be mainly classified according to the window type and HVAC or solar collector type in each set.

From Figs. 9 and 10, it can be seen that achieving EC values lower than 20 [kW h/m$^2$ year] is possible with thick wall and roof insulation material and double glazed window type 3. Besides, an HVAC system with no cooling option should necessarily be selected to obtain the lowest EC values. This set of non-dominated solutions leads to TPMVD values not greater than 30%. Except this sub-set of non-dominated solutions, the other solutions with the HVAC type 1 results in high thermal discomfort hours (more than 45%).

The HVAC system and window type play a major role in changing the TPMVD values of the set of non-dominated solutions. For example, to attain TPMVD values lower than 20%, the HVAC type 2 or 4 with cooling option and window type 3 with lowest thermal transmittance value are selected to minimize the thermal discomfort hours in the building, as depicted in Fig. 9.

To obtain non-dominated solutions of minimum ReCost, the HVAC system type 1 with no cooling option, and the window type 1 single glazed window, both with lowest price among the set of HVAC and window retrofit actions, is found to be optimal. However, this set of non-dominated solutions results in the highest number of thermal discomfort hours in the building. Therefore, the optimization leads to HVAC option 2 and 3, with the same window type, to achieve better thermal comfort in the building (Fig. 9). Nevertheless, this set of non-dominated solutions results in higher energy consumption (EC more than 42 [kW h/m$^2$ year]).

Fig. 10 shows that at the value of EC 28 [kW h/m$^2$ year], reaching TPMVD values less than 25% or more than 45% is possible. This can be shown by points (A) and (B). Point (A) has TPMVD of 51.92%, which is higher than that for point (B), which is 18.19%. For the latter, a double glazed window with lowest thermal transmittance (WIN = 3) among all the windows considered, and HVAC system type 4 with cooling option are selected to lower summer overheating and consequently decrease the TPMVD value. To keep the same level of EC, the optimization solver selects HVAC system type 1 without cooling option and window type 2, which has lower cost. This leads to sacrificing thermal comfort (TPMVD value reached to 51.92% from 18.19%). However, moving from point (A) to point (B), requires an additional investment of 60 k€.

The most important conclusions from the optimization presented above are:

- Regarding the characteristics of the envelope, the simultaneous optimization of three objectives gives a larger diversity of retrofit solutions to be presented to the DM.
- The obtained non-dominated solutions are found to be classified mainly according to the window type and HVAC or solar collector type in each set. The influence of the window type and HVAC system on the results is more significant than the influence of the other decision variables.
- For achieving the best indoor thermal comfort (lowest TPMVD values), investing in high price HVAC system could be a better solution than investing in additional insulation and other low-energy measures.
- TPMVD values in the range of 20 to 30% are achievable even with a HVAC type without cooling option. In case this range of TPMVD value is acceptable by the DM, the set of non-dominated solutions with HVAC system type 1, window type 3 and thick layer of external wall and roof insulation would be the cheapest means to attain low EC and ReCost values. However, if the DM is slightly more ambitious at the investment stage (retrofit cost), coupling HVAC system type 2 would provide very low TPMVD values.
- The large number of solutions might be considered either as an advantage or a disadvantage: on the one hand, there is a large variety of interesting retrofit actions recommendation; on the other hand, it may be difficult to choose between them.

This set of optimizations highlights the major advantage of a multi-objective formulation, which is to provide a thorough understanding of the trade-offs between the competitive objectives, and bring the potential of each investment into focus.

## 5. Conclusions and future works

A multi-objective optimization model using GA and ANN was applied to a school building case study. Although it required a significant amount of training data, the ANN was able to accurately approximate the existing building simulation software results. Using the ANN, each multi-objective optimization was undertaken with a computational time as low as 9 min. The total computational time associated with the whole optimization (i.e. including ANN training and validation) is approximately 3 days. In case an exhaustive-computation search method is implemented, then $24 \times 18 \times 3 \times 4 \times 4 = 20{,}736$ simulation runs are needed to obtain all possible candidate solutions. The execution time of one simulation run is about 5.19 min. This means that 75 days would be required to get the exhaustive search results for the predefined problem. In other words, this optimization would have never been practical without using the proposed approach.

Regarding the optimization results, the single-objective optimization provided an understanding of the impact of each set of retrofit actions and objective function on the building's overall performance after retrofit. Following that, the proposed multi-objective algorithm produced a wide range of non-dominated solutions. The model assessed their overall performance, while at the same time quantifying the impact of their individual components. Furthermore, 2D and 3D graphical representation of non-dominated frontier unveils the trade-offs between the competitive objectives.

Moreover, using the graphs, one can ascertain the impact on thermal comfort and retrofit cost of any reduction or increase in the energy consumption. The final decision can therefore be based on a real understanding of the situation, and of the impact of energy consumption on thermal comfort and retrofit cost. The search space, and therefore the set of non-dominated solutions, depends on the alternative retrofit actions considered and the constraints that may be imposed to allow their combination.

The proposed approach shows a great potential for the solution of multi-objective building retrofit problems, and can be used as an aid to decision-making in the context of a retrofit project. Knowing what can be feasibly achieved and what trade-offs are at stake, the DMs can progress toward the choice of the best compromise solutions by inserting constraints of the levels of the objective functions, for instance, or look for the solution that is closer to their aspiration levels.

The further consideration of a larger range of possible choices for renewable energy should be included in the future work, for example allowing for solar collector sizes that range from those equal to or exceeding the total roof area at the upper level to no collectors at the lower. Also, other choices such as natural ventilation could be explored within a wider group of possible design choices.

Furthermore, it would be necessary as a future work to combine the proposed model with mechanism to incorporate the DM's preferences into the decision aid process. Besides, since a building retrofit is subject to many uncertainty factors, such as in savings estimation, weather forecast, retrofit actions cost data, therefore uncertainty assessment is essential to provide the DMs with a sufficient level of confidence to select and determine the best retrofit solutions.

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## Appendix A. Appendix A: List of retrofit actions

In this appendix the alternative retrofit actions (RAs) considered are presented. Alternative RAs related to different external wall and roof insulation materials are displayed in Tables A.1 and A.2. Different alternative choices regarding windows are displayed in Table A.3. Finally different solutions for solar collectors and HVAC systems are presented in Tables A.4 and A.5.

**Table A.1**
Characteristics of alternative external wall insulation materials.

| No. | Insulation type | Name | *t* thickness (m) | *U*-value (W/m$^2$ K) | *c* Cost (€/m$^2$) |
|---|---|---|---|---|---|
| 1–8 | Cork | OUTWALL_CORKHIGH3 to OUTWALL_CORKHIGH 10 | 0.03–0.1 (with 0.01 step) | 1.408–0.508 | 5.55–17.95 |
| 9–16 | EPS | OUTWALL_EPSLOW3 to OUTWALL_EPSLOW10 | 0.03–0.1 (with 0.01 step) | 0.8–0.265 | 7.64–13.68 |
| 17–24 | XPS | OUTWALL_XPSLOW3 to OUTWALL_XPSLOW10 | 0.03–0.1 (with 0.01 step) | 0.8–0.265 | 9.65–26.78 |

**Table A.2**
Characteristics of alternative roof insulation materials.

| No. | Insulation types | Name | t Thickness (m) | U-value (W/m$^2$ K) | c Cost (€/m$^2$) |
|---|---|---|---|---|---|
| 1–6 | XPS | ROOF_XPS3 to ROOF_XPS8 | 0.03–0.08 (with 0.01 step) | 0.8–0.328 | 9.65–22.78 |
| 7–12 | EPS | ROOF_EPS3 to ROOF_EPS8 | 0.03–0.08 (with 0.01 step) | 0.8–0.328 | 4.32–10.7 |
| 13–18 | Polyurethane | ROOF_PU3 to ROOF_PU8 | 0.03–0.08 (with 0.01 step) | 0.658–0.265 | 8.34–20.18 |

**Table A.3**
Characteristics of alternative windows.

| No. | Name | Thermal transmittance (W/m$^2$ °C) | Effective solar energy transmittance (%) | Cost (€/m$^2$) |
|---|---|---|---|---|
| 1 | Single glazing Typical glazing | 5.16 | 68.20 | 34.08 |
| 2 | 2bl glazing Luxguard SunGuard clear Argon 6/16/4 | 2.54 | 58.90 | 100.05 |
| 3 | 2bl glazing window Argon-filled 4/16/4 | 1.4 | 44.00 | 145.53 |

**Table A.4**
Characteristics of alternative HVAC systems.

| N | Type | Name | Brand | Generation efficiency (%) or COP(summer/Winter) | Cost (€) |
|---|---|---|---|---|---|
| 1 | Heating system only | Oil-based boiler | CR Remeha P320/4 90 kW | 88 | 6911.52 |
| 2 | Heating and cooling systems | Natural gas boiler (16,368.37€) + chiller (7821.47€) | CR Remeha P320/4 90 kW + York YCSA-80TP 80 kW | 88/3 | 24,189.84 |
| 3 | | Air source heat pump (6506.05€) | MITSUISHI FDC250 VS/25 kW (3 unit) | 2.5/3 | 19,518.15 |
| 4 | | Ground source heat pump | Kensa Compact Plantroom 80 kW | 4.6/15 | 39,000 |

**Table A.5**
Characteristics of alternative solar collector systems.

| N | Type | Name | Brand | Module No. | Collector area ($m^2$) | E_Solar (MW h) | Total cost (€) |
|---|---|---|---|---|---|---|---|
| 1 | Flat collector | FSD10 | Saunier Duval | 10 | 20.1 | 8.640 | 12,918 |
| 2 | | FSD15 | Saunier Duval | 15 | 30.1 | 10.260 | 19,377 |
| 3 | CPC (Compound Parabolic Concentrating) Collector | AS10 | Ao Sol | 10 | 19.9 | 8.640 | 9950 |
| 4 | | AS15 | Ao Sol | 15 | 29.85 | 9.990 | 14,925 |

*Note*—E_Solar (MW h) that is the energy production from solar collector has been calculated by SOLTERM software which is developed by the Portuguese National Laboratory for Energy and Geology (LNEG).

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